Measuring the Connectedness of the Global Economy*

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Abstract

The introduction of the panel and global VAR frameworks and the increasing sophistication of large simulated systems provides opportunities to analyse international linkages in unprecedented depth. However, the considerable volume of statistical output generated by such models introduces a secondary curse of dimensionality, whereby the limits of the modeller’s ability to process the output become a binding constraint. This paper develops a family of Generalized Connectedness Measures (GCMs) which provide a simple means to summarise the linkages embodied in such models non-selectively either with recourse to geographic aggregation or aggregation into desired groups of similar variables. These GCMs are derived from generalized forecast error variance decompositions in a manner that extends the connectedness measures developed by Diebold and Yilmaz (2009, 2011). Our GCMs preserve information across horizons and are robust both to the reordering of variables and to aggregation. We apply our approach using the 26 country 176 variable GVAR model developed by Greenwood-Nimmo, Nguyen and Shin (2012, Journal of Applied Econometrics) and derive vivid representations of the linkages embodied in the model. Our results indicate that the US, the Eurozone and the crude oil market are hot-spots for the transmission of shocks in the global economy and that shocks transmitted through equity markets can strongly affect real magnitudes.

JEL Codes: C32, C53, E17.

Keywords: Generalized Connectedness Measures (GCMs), Global VAR, international linkages, multi-country multi-variable connectedness, processing constraints.

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Globalization makes it impossible for modern societies to collapse in isolation

Jared Diamond

1 Introduction

It is often said that the world has become smaller as the economic and political spheres have become increasingly globalised. This simple observation has far-reaching implications for those working in the joint fields of economics and finance, as the borders between national, regional and global issues have become ever more ill-defined. As the global financial crisis has highlighted emphatically, we are citizens of a brave new world, a globalised world comprised of a network of intricately interconnected entities. These linkages introduce new opportunities and new challenges for economic agents and regulators alike, yet their nature is poorly understood. The development of techniques to quantify and map the connectedness of the global economy must therefore be afforded a high priority.

Attempts to empirically quantify the linkages embedded within economic and financial models have preoccupied academics and practitioners alike for many years. The most widely used methodology to be found in the existing empirical literature employs combinations of impulse response analysis and forecast error variance decomposition to model the interactions among variables in dynamic multivariate models. Recent examples of global models analysed in this manner include Dees, di Mauro, Pesaran and Smith (2007, DdPS), Dees, Holly, Pesaran and Smith (2007, DHPS), Bussière et al. (2009) and Greenwood-Nimmo, Nguyen and Shin (2013, GNS2). A closely related literature has sought to model the (co)dependence structure among variables using pairwise correlation analysis, Granger causality testing and, more recently, equi-correlation analysis (Liu and Bahadori, 2012; Engle and Kelly, 2012). In relation to financial applications, a third strand of literature has considered spillover effects (e.g. the heatwave and meteor shower hypotheses advanced by Engle, Ito and Lin, 1990) and has developed measures of contagion effects, value-at-risk and systemic expected shortfall (Fry, Martin and Tang, 2010; Acharya, Perdersen, Phillippe and Richardson, 2010; Adrian and Brunnermeier, 2011).

A notable feature of the literature which applies these established methods is its selectivity; in general, results are presented only for a subset of the variables in the system, or else the system under consideration is small and therefore selective in its construction. This relatively narrow focus is troublesome in light of the GFC, which has stressed emphatically the need for careful and comprehensive analysis of the channels of risk transmission in detailed models of the global economic and financial system. Particularly in the case of impulse response analysis and forecast error variance decomposition (which are the tools that arguably provide the richest insights into the linkages between variables) detailed analysis becomes largely infeasible as the dimensionality of the model under scrutiny increases. Indeed, it will be a central contention of this paper that as models become larger so the limits of an individual’s ability to comprehensively process and interpret the reported statistics will increasingly bind; we refer to this as a processing constraint. It follows, therefore, that as our desire and our ability to construct large scale macrofinancial
models increases, so the need for reductive methods to analyse their interlinkages will become increasingly acute.

Little research effort has yet been dedicated to the construction of non-selective summary measures appropriate for use with large models in macroeconomics and finance. The first step in this direction was taken by Diebold and Yilmaz (2009), who provide a simple and intuitive measure of the interdependence (spillovers) of asset returns and volatilities by aggregating orthogonalized forecast error variance decompositions (OFEVDs) across markets. In their analysis of nineteen global equity markets over the period January 1992–November 2007, they find striking evidence of divergent dynamics in the sense that return spillovers display a gently increasing trend but no bursts while volatility spillovers display no trend but clear bursts.

This approach suffers from a major limitation, however, as it is well known that the Cholesky decomposition is not unique but is sensitive to the ordering of the variables. It is, therefore, only appropriate to employ Cholesky-factor exact identification when one is confident that the structural model can be well approximated by a particular recursive ordering of the variables. In light of this issue, Diebold and Yilmaz (2010; 2011) consider the use of generalized forecast error variance decompositions (GFEVDs) which do not rely on triangular factorization of the covariance matrix of the residuals. The results are therefore unique, although their interpretation is complicated by the fact that the sum of the variance shares will generally exceed 100% due to the correlation structure of the residuals. The authors opt to overcome this difficulty by normalizing the variance share of each variable by the sum of the variance shares of all variables at any given horizon.

The connectedness measures proposed in the sequence of papers by Diebold and Yilmaz (collectively the DY approach) represent a significant contribution to the literature but they are not without limitations. Firstly, they are not generally applicable in the sense that they are designed for the multi-country univariate or single-country multivariate cases. This is a severe limitation given that the authors stress that connectedness is “central to understanding underlying fundamental macroeconomic risks, in particular business cycle risk (intra- and inter-country real activity connectedness)” (Diebold and Yilmaz 2011, p. 1). However, without refinement, the DY connectedness measures could only model the linkages between a combination of macroeconomic and financial variables within a single country or the linkages between a single variable like real GDP growth across multiple countries. Furthermore, although the DY connectedness measures are computed from a dynamic model, their presentation is essentially comparative static in nature, as the authors choose to report results for a single fixed horizon over rolling windows. This comparative static presentation may be related to the limitations introduced by the authors’ choice of normalization scheme, which obscures inter-horizon scale differences by virtue of the fact that renormalization occurs at each horizon. Clearly a different approach is required if one wishes to present comparable connectedness measures across multiple horizons.

Our purpose in this paper is to develop an intuitively pleasing, readily calculable and robust approach to map both the strength and the direction of the connections between entities in the global economy in a truly dynamic manner. To this end, we propose a family of generalized Connectedness Measures (GCMs) which extend the DY approach to the multi-country, multivariate context and which are therefore appropriate for use with modern multi-country and
global models in macroeconomics and finance. Relative to the DY connectedness measures, our approach is generalized in the sense that it preserves information without loss across horizons and it is robust to both variable re-ordering and aggregation.

Our proposed GCM framework has a number of appealing features. Firstly, it is readily calculable using standard econometric software without the need for advanced programming skills. As such, its application will be very transparent and easily replicable by independent researchers. Moreover, our GCMs are very widely applicable by virtue of their ‘model-independence’, in the sense that they can be generated from the output of any model from which FEVDs can be computed. This implies that they are not reliant on the imposition of strong identifying assumptions, although equally they do not preclude such assumptions. The interpretation of our GCMs is very straightforward and intuitive, and requires only a basic knowledge of economic modelling techniques. Furthermore, our framework can be used to effectively condense the output generated by large economic models, thereby alleviating the processing constraint and unlocking more of the potential of existing techniques for the estimation of large-scale models in macroeconomics and finance. As will shortly become clear, we achieve this distillation of information by defining our GCMs with explicit reference to geographical units and regional aggregation, which is not only appealing given our focus on multi-country and global modelling but also greatly facilitates presentation and communication to non-economists. Finally, the level of aggregation of our measures may be freely chosen by the modeller (or potentially user-defined) which ensures that the analysis is focused at a level of aggregation appropriate to the task at hand, thereby achieving a singularly clear representation. These attributes collectively render our approach ideally suited to dissemination among non-specialist audiences, a feature which is likely to be of significant appeal in policymaking and regulatory environments.

To demonstrate its applicability, we employ our technique to evaluate the connectedness of the global economy using the macro-financial GVAR model developed by Greenwood-Nimmo, Nguyen and Shin [2012a, GNS]. This model is ideally suited to our purpose, comprising of a 176 variable system covering 26 countries/regions that collectively account for the large majority of world trade. Such a model will contain a wealth of information, much of which could not be analysed directly using established methods due to the severity of the processing constraints in such a large system. By computing GCMs at the level of individual variables (V-GCMs) or variable groups (G-GCMs), at the country-level (C-GCMs) and at the regional level (R-GCMs), we are able to explicitly measure and map both the relative strength and direction of the connections embedded within the model in a parsimonious and readily interpretable manner.

Our results provide many interesting insights into the dynamic connectedness between variables, countries and regions in the system. One particularly interesting finding at the national and regional level is that the degree to which external (i.e. international) factors influence the domestic economy generally increases with the horizon, indicating that spillover effects intensify over a number of periods after the initial shock. This suggests that policymakers must adopt a long planning horizon following a shock and must not become complacent at the early signs of recovery. The slow recovery of many Western nations following the GFC could be interpreted in this light if one believes that the switch from fiscal stimulus to austerity came too soon.

Furthermore, our results accurately reflect a number of widely held beliefs about the global economy. We find that the US, the Eurozone and the crude oil market are the overwhelm-
ingly dominant shock transmitters in the global economy, while a number of other important economies on the world stage, including the UK, Japan and the Asian tigers and tiger cubs, are net shock receivers. This offers an intuitively pleasing explanation of why the GFC and the various oil shocks in our sample exerted profound impacts on the global economy while events such as the Japanese real-estate crash, the UK Black Wednesday episode and the 1997 Asian Financial Crisis were not strongly transmitted beyond their respective localities. Similarly, our results provide fresh support for the interventions that have so far managed the Eurozone Debt Crisis, as a collapse in Europe would be rapidly and strongly passed through to the rest of the world. Our results also reflect the growing importance of the BRICs, and as global models are updated with the release of new data this trend can be expected to continue and to accelerate.

This paper proceeds in 5 Sections. Section 2 provides a brief summary of the 33 country GVAR model developed by Greenwood-Nimmo et al. (2012a) which forms a basis for the elaboration of our GCMs in Section 3. The results of GCM analysis of the linkages embodied in the global model are presented in Section 4, while Section 5 concludes.

2 The GNS GVAR Model

As mentioned above, the GCMs that we propose here are model independent in the sense that they can be applied to any model from which FEVDs can be computed. This classification covers a wide array of estimated and simulated models in macroeconomics and finance. To provide context and to facilitate the derivation of our GCMs, we will first introduce the 176 variable GNS GVAR model which will later be used to illustrate their application. However, it should be clear that our GCMs could equally be derived from a wide range of alternative models.

The GNS model is ideally suited to our purpose, not least because of our familiarity with its properties but also because it comprises of a 176 variable system covering 33 countries (26 regions once the 8 Eurozone states in the model have been aggregated) that collectively account for the large majority of world trade. Although international linkages have been evaluated in similar models in the literature (e.g. DdPS, DHPS, Bussière et al., 2009, GNS2), their treatment is necessarily highly selective, and this very selectivity reduces the transparency of the analysis and introduces an ad hoc element. It follows, however, that conducting a comprehensive evaluation of the international and intervariable linkages in such a model using the standard tools of dynamic analysis is all but impossible. To satisfy oneself of the validity of this assertion, it is sufficient to note that it would be necessary to present $176^2 = 30,976$ separate impulse response functions to reveal the time-path of the effect of every possible individual shock on each variable in the system. This is precisely the type of situation that we identify with binding processing constraints.

Indeed, as new techniques such as GVAR and panel VAR allow modellers to increasingly circumvent the curse of dimensionality associated with the limits imposed by the range and frequency of existing macroeconomic and financial datasets, so they intensify the processing constraints, in effect introducing a new curse of output dimensionality. The application of our GCMs in such situations is therefore very natural.

\footnote{The link to the bounded rationality literature is readily seen.}
2.1 Combining National Models into a Global Model

Our presentation of the GNS model adopts and slightly adapts the notation used in Pesaran, Schuermann and Weiner (2004, PSW) and GNS. The global model comprises $N$ economies indexed by $i = 1, \ldots, N$. For each country-specific model, the set of domestic variables are denoted by an $m_i \times 1$ vector, $y_{it}$, and the associated country-specific foreign variables by an $m_i^* \times 1$ vector, $y_{it}^*$ defined as $y_{it}^* = \sum_{j=1}^{N} w_{ij} y_{jt}$, where $w_{ij} \geq 0$ are the weights with $\sum_{j=1}^{N} w_{ij} = 1$, and $w_{ii} = 0$.

Following GNS, we consider the following country-specific VARX*(p,p) model

$$y_{it} = p \sum_{j=1}^{p} \Phi_{ij} y_{i,t-j} + \sum_{j=0}^{p} \Phi_{ij}^* y_{i,t-j}^* + u_{it}$$

(1)

where $\Phi_{ij}$ and $\Phi_{ij}^*$ are $m_i \times m_i$ and $m_i \times m_i^*$ matrices of unknown coefficients and where $u_{it} \sim iid (0, \Sigma_{u,ii})$ is a vector of serially uncorrelated Gaussian error processes with the positive definite covariance matrix $\Sigma_{u,ii}$. To enhance the clarity of our exposition, we will derive a general form of the GVAR model which abstracts from the deterministic components. Once this framework is in place, we will outline the key features of the GNS specification – for a detailed derivation of the GNS GVAR model including the introduction and testing of country-specific structural breaks see Shin (2009) and GNS.

By defining $z_{it} = (y_{it}', y_{it}^*)'$, we may rewrite (1) more compactly as

$$A_{i0} z_{it} = p \sum_{j=1}^{p} A_{ij} z_{i,t-j} + u_{it}$$

(2)

where $A_{i0} = (I_{m_i}, -\Phi_{i0}^*)$ and where $A_{ij} = (\Phi_{ij}, \Phi_{ij}^*)$ for $j = 1, \ldots, p$.

The first step in constructing the GVAR model is to define the $m \times 1$ vector of global endogenous variables $y_t$, where $m = \sum_{i=1}^{N} m_i$. Insodoing, we collect all of the endogenous variables from each of the country-specific (national) VAR models as follows

$$y_t = (y_{1t}', \ldots, y_{Nt}')'$$

This carries the important implication that all of the variables included in a GVAR model must be endogenous to at least one country in the system.

Next, we define the $(m_i + m_i^*) \times m$ link matrices, denoted $W_i$. The typical approach is to use time-invariant bilateral trade weights in the construction of the link matrices, although a wide range of options can be entertained. For example, Chen et al. (2009) employ time-invariant financial weights in their analysis of bank and financial sector risk transmission while Cesa-Bianchi et al. (2012) use a time-varying weighting scheme to evaluate the changing position of financial weights in their analysis of bank and financial sector risk transmission.

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2 It is conventional to assign the country index 0 to the reference country, usually the US. This implies that the exchange rate of the reference country is determined in the remaining $N$ country-specific models in the global system. See DdPS and GNS for more details.

3 PSW show that the definition of the weakly exogenous foreign variables for country $i$ as weighted averages for countries/regions $i \neq j$ results in a simultaneous system of regional equations that may be solved to form a global system.

4 See DdPS and GNS for details of the construction of the link matrices using bilateral trade-weights retrieved from the IMF’s DOTS database.
China and the Latin American economies in the global system. Alternatively, one could employ appropriately defined spatial matrices or even a combined (variable-specific) weighting scheme. Using these link matrices, the $z_{it}$’s for each country-specific model may be re-written in terms of the vector of global variables as follows

$$z_{it} = W_i y_t$$

It is now possible to express (2) in stacked form as

$$H_0 y_t = \sum_{j=1}^{p} H_j y_{t-j} + u_t$$  \hspace{1cm} (3)

where

$$H_j = \begin{pmatrix} A_{1j} W_1 \\ \vdots \\ A_{Nj} W_N \end{pmatrix}, j = 0, 1, \ldots, p; \quad u_t = \begin{pmatrix} u_{1t} \\ \vdots \\ u_{Nt} \end{pmatrix}$$

Finally, we obtain the reduced-form GVAR model in the usual way by pre-multiplying (3) throughout by $H_0^{-1}$ as follows:

$$y_t = \sum_{j=1}^{p} G_j y_{t-j} + \varepsilon_t$$  \hspace{1cm} (4)

where $G_j = H_0^{-1} H_j$, $j = 1, \ldots, p$, denotes the $m \times m$ matrices of GVAR coefficients and where $\varepsilon_t = H_0^{-1} u_t$.

In light of the derivation above, it is clear that all of the GVAR parameters, the $G_j$’s, are obtained by transformation of the parameters of the corresponding CVAR models using the link matrices, $W_i$. Global interactions take place through three channels. Firstly, there is direct dependence of the country/region-specific variables, $y_{it}$ on the corresponding foreign variables, $y_{it}^*$ and their lagged values. Secondly, the $y_{it}$’s depend on any common global variables in the system. The oil price is often included in this manner in GVAR models to account for common (global) business cycle effects. Finally, in the general case in which the off-diagonal blocks of the global covariance matrix, $(\Sigma_u)$, are populated with non-zero values then the contemporaneous correlation of shocks across countries introduces a third channel of global interaction. We will return to this issue shortly.

2.2 Specification of the GNS GVAR Model

The GNS model is a second order GVAR which includes country-specific one-time permanent intercept shifts following [Shin (2009)](#), where the breaks are assumed common to all equations in a given national model. The model is estimated on quarterly data from 1980Q2 to 2007Q2 for the same set of 33 countries/26 regions studied by DdPS. A summary of the model specification is presented in Table 1, which reproduces much of Table 1 in GNS. For a more detailed

5The countries modelled by GNS are: (1) USA; (2) Eurozone; (3) Japan; (4) UK; (5) Norway; (6) Sweden; (7) Switzerland; (8) Canada; (9) Australia; (10) New Zealand; (11) South Africa; (12) Argentina; (13) Brazil; (14) Chile; (15) Mexico; (16) India; (17) Korea; (18) Malaysia; (19) Philippines; (20) Singapore; (21) Thailand; (22) China; (23) Indonesia; (24) Peru; (25) Turkey; and (26) Saudi Arabia. Pre-testing results reported in GNS confirm the non-stationarity of the variables, the presence of the selected structural breaks in the data as well as
discussion, the reader is referred to GNS and also to its Statistical Annex.

[Insert Table 1 about here]

The variables included in the GNS model are the short-term nominal interest rate (\( r_{it} \)), the log of real imports (\( im_{it} \)), the log of real exports (\( ex_{it} \)), the log of real equity prices (\( q_{it} \)), the rate of inflation (\( \Delta p_{it} \)), the log of real output (\( y_{it} \)) and the log of the oil price (\( p_{it}^e \)). As discussed above, the weakly exogenous foreign variables are computed as weighted averages of the data for the remaining \( N \) countries in the model, where we adopt the convention of DdPS and define the link matrices using bilateral trade averages over the period 1999-2001.

Following DHPS, we define the log real effective exchange rate as \( re_{it} = ee_{it} + p_{it}^e - p_{it} \), where \( ee_{it} + p_{it}^e - p_{it} = (e_{it} - p_{it}) - (e_{it}^* - p_{it}^e) = \tilde{e}_{it} + \tilde{p}_{it}^e \) and where, in turn, \( e_{it} \) is the nominal exchange rate vis-à-vis the US$\.), \( e_{it}^* = \sum_{j=0}^{N} w_{ij} e_{jt} \), \( ee_{it} = \sum_{j=0}^{N} w_{ij} e_{ijt} \) is the nominal effective exchange rate, \( p_{it} \) the national price level and \( p_{it}^e \) the foreign price level.

GVAR models are sufficiently flexible to allow for some variability in the set of included in each country specific model. This is a very desirable feature given the paucity of reliable data provided by some nations including, for example, China. Where data availability was not a binding constraint (i.e. for countries \( i = 2, 3, \ldots, 21 \)), the CVAR\( X^* \) models comprising the GNS model include the following endogenous I(1) variables: \( x_{it} = (re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it})' \).

For countries \( i = 22, 23, \ldots, 25 \), we were unable to source reliable stock market data and so we set \( x_{it} = (re_{it}, r_{it}, im_{it}, ex_{it}, \Delta p_{it}, y_{it})' \), while for country \( i = 26 \), \( x_{it} = (re_{it}, im_{it}, ex_{it}, \Delta p_{it}, y_{it})' \).

In all cases except the US model, to which we will return shortly, the vector of weakly exogenous I(1) foreign variables is defined as \( x_{it}^* = (p_{it}^e, r_{it}^*, q_{it}^*, \Delta p_{it}^*, y_{it}^*)' \). The omission of \( ex_{it}^* \) and \( im_{it}^* \) from the model reflects the fact that in a model with complete coverage of world trade, \( im_{it} = ex_{it}^* \) and \( im_{it}^* = ex_{it} \).

The US (\( i = 1 \)) is treated as the reference country in the GNS model, and it is assumed that its exchange rate is determined in the \( N \) remaining country-specific models. Hence \( re_{1t} \) is excluded from the endogenous variable set for the US model while \( \tilde{e}_{1t} \) is included among its weakly exogenous foreign variables. Furthermore, the oil price must be included as an endogenous variable somewhere in the system and we choose to follow DdPS and include it here, reflecting the dominant position of the US in the world economy. We are also obliged to treat the vector of weakly exogenous foreign variables slightly differently in this case, as the US economy is sufficiently large to drive events in global financial markets, for example. We therefore exclude both \( r_{1t}^* \) and \( q_{1t}^* \) for the US model as they are unlikely to be weakly exogenous. Therefore, we have \( x_{1t} = (p_{1t}^e, r_{1t}, im_{1t}, ex_{1t}, q_{1t}, \Delta p_{1t}, y_{1t})' \) and \( x_{1t}^* = (\tilde{e}_{1t}, \Delta p_{1t}^*, y_{1t}^*) \). Given that \( \tilde{e}_{1t} \) is not included in the set of US variables used to estimate the CVAR\( X^* \) model but it is implicitly included in the global system, we must impose one additional restriction. Given that we define nominal exchange rates vis-à-vis the US$, it follows that \( e_{1t} = 0 \) and therefore that \( \tilde{e}_{1t} = -p_{1t} \). By imposing this restriction we are able to solve the system of equations, although it follows that we are now solving for the price level in the US as opposed to inflation in the remainder of the countries in the model – see DHPS, GNS and the statistical annex to GNS for details.

the weak-exogeneity of the vast majority of the foreign variables.

Our initial experimentation with alternative weighting schemes suggests that the choice of weights is of secondary importance in this case.
2.3 Estimating the Global Covariance Matrix

It follows that the construction of the $m \times m$ global covariance matrices for the structural disturbances ($\Sigma_u$) and the reduced form disturbances ($\Sigma_e$) will impact significantly on the results of dynamic analysis of the GVAR model. Using the standard result that $\Sigma_e = H_0^{-1} \Sigma_u H_0^{-1'}$, we elect to focus on the structural covariance matrix, $\Sigma_u$ without loss of generality.

Recall that the $i$-th country-specific $m_i \times m_i$ covariance matrix of $\mathbf{u}_{it}$, denoted $\Sigma_{u,ii}$, can be consistently estimated from the corresponding CVAR model allowing for non-zero contemporaneous correlation among the shocks to each variable in $\mathbf{y}_{it}$ without difficulty. Therefore, the prime diagonal blocks of $\Sigma_u$ representing the ‘in-country’ covariances are already uncontentiously defined. There are, however, a number of options by which to estimate the contemporaneous cross-country covariances, $E(\mathbf{u}_{it} \mathbf{u}'_{jt}) = \Sigma_{u,ij}$. First, one may allow the shocks in $\mathbf{u}_{it}$ to be contemporaneously correlated across countries/regions and estimate their covariances nonparametrically. In this case we have:

$$\Sigma_u = \begin{bmatrix}
\Sigma_{u,11} & \Sigma_{u,12} & \cdots & \Sigma_{u,1N} \\
\Sigma_{u,21} & \Sigma_{u,22} & \cdots & \Sigma_{u,2N} \\
\vdots & \vdots & \ddots & \vdots \\
\Sigma_{u,N1} & \Sigma_{u,N2} & \cdots & \Sigma_{u,NN}
\end{bmatrix} \quad (5)$$

and, as mentioned above, countries can now be interlinked via the contemporaneous cross-country residual covariances, $\Sigma_{u,ij}$. However, considering that the relatively high dimensional nature of most GVAR models, many of the off-diagonal blocks in $\Sigma_u$ may be imprecisely estimated or statistically insignificant in practice, especially those blocks associated with relatively small or developing countries/regions. In such cases, it may be advisable to impose zero restrictions in the relevant blocks of the global covariance matrix. A parsimonious if seemingly overly restrictive solution would be to impose block-diagonality of $\Sigma_u$, yielding

$$\Sigma_u^d = \begin{bmatrix}
\Sigma_{u,11} & 0 & \cdots & 0 \\
0 & \Sigma_{u,22} & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & \Sigma_{u,NN}
\end{bmatrix} \quad (6)$$

This was the approach that we pursued in GNS3 which was found to yield good results in practice. Furthermore, on careful consideration, it follows that block-diagonality is not overly restrictive since the direct impacts of the weighted average of the foreign variables have already been incorporated in the estimated parameters and residuals of the country-specific CVAR models, including the country-specific covariance matrices, $\Sigma_{u,ii}$. However, a more general and statistically robust approach would be to test directly for cross-sectional dependence between blocks following Pesaran (2013). In such a setting, the global variance matrix has the following

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7Assuming that the lag order of the CVARX model is sufficiently large and that the residuals do not follow a moving average process, the $\mathbf{u}_{it}$’s will be serially uncorrelated.
general form

$$
\Sigma_{csd}^{u} = \begin{bmatrix}
\Sigma_{u,11} & \ast & \cdots & \ast \\
\ast & \Sigma_{u,22} & \cdots & \ast \\
\vdots & \vdots & \ddots & \vdots \\
\ast & \ast & \cdots & \Sigma_{u,NN}
\end{bmatrix}
$$

(7)

where the asterisks denote the corresponding blocks in (5) which are to be tested for cross sectional dependence. In each case, if the null of cross sectional independence is rejected then the asterisk is replaced with the corresponding block from (5). When the null is not rejected, then the asterisk is replaced with a null (zero) block.

The test is based on the correlation matrix of $u_t$ which corresponds to $\Sigma_u$

$$
\rho_u = \begin{bmatrix}
\rho_{u,11} & \rho_{u,12} & \cdots & \rho_{u,1N} \\
\rho_{u,21} & \rho_{u,22} & \cdots & \rho_{u,2N} \\
\vdots & \vdots & \ddots & \vdots \\
\rho_{u,N1} & \rho_{u,N2} & \cdots & \rho_{u,NN}
\end{bmatrix}
$$

(8)

where $\rho_{u,k\ell}$, $k, \ell = 1,\ldots,N$, contains the pair-wise correlation coefficients among the variables of blocks $k$ and $\ell$. By construction, the correlation matrix is symmetric and so $\rho_{u,k\ell} = \rho_{u,\ell k}$.

The statistic testing cross sectional dependence between blocks $k$ and $\ell$, for $k \neq \ell$, is defined as follows

$$
CSD_{k,\ell} = \sqrt{\frac{T}{m_k \times m_\ell}} (\mathbf{1}_{m_k}^\prime \rho_{u,k\ell} \mathbf{1}_{m_\ell})
$$

(9)

where $m_k$ ($m_\ell$) denotes the number of variables in block $k$ ($\ell$) and $\mathbf{1}_{m_k}$ is a $m_k \times 1$ vector of ones. Under the null of cross sectional independence between blocks $k$ and $\ell$, the test statistic follows an asymptotic standard normal distribution. The empirical results reported below are computed on the basis of $\Sigma_{csd}^{u}$ where the cross-sectional dependence test was implemented as a significance level of 5%. Full details are available on request.

3 Generalizing the Diebold-Yilmaz Connectedness Measures

The Diebold-Yilmaz concept of connectedness is founded upon the notion that the share of the forecast error variance of variable $i$ explained by variable $j$ at any given horizon in a vector autoregressive model provides a directional measure of the association between these variables. This approach has the appealing feature that FEVDs are computed directly from the estimated parameters and covariance matrix of the VAR system subject to minimal identifying restrictions. To see this more clearly, first recast the GVAR model in (4) in infinite order Global Vector Moving Average (GVMA($\infty$)) form as follows

$$
y_t = \sum_{j=0}^{\infty} B_j \varepsilon_{t-j},
$$

(10)

where the $B_j$'s are evaluated recursively as

$$
B_j = G_1 B_{j-1} + G_2 B_{j-2} + \cdots + G_{p-1} B_{j-p+1}, \text{ } j = 1,2,\ldots, \text{ } \text{with } B_0 = I_m, \text{ } B_j = 0 \text{ for } j < 0.
$$
Following Pesaran and Shin (1998), the orthogonalized and generalized FEVDs may be written as follows

\[
OFEVD(y_{jt}; u_{it}, h) = \sum_{\ell=0}^{h-1} \left( e_j' B_{i\ell} H_0^{-1} P e_i \right)^2 \sum_{\ell=0}^{h-1} e_j' B_{i\ell} \Sigma_{\varepsilon} B_{j\ell} e_j
\]

\[
GFEVD(y_{jt}; u_{it}, h) = \frac{\sigma_{u,ii}^{-1} \sum_{\ell=0}^{h-1} \left( e_j' B_{i\ell} H_0^{-1} \Sigma_u e_i \right)^2}{\sum_{\ell=0}^{h-1} e_j' B_{i\ell} \Sigma_{\varepsilon} B_{j\ell} e_j}
\]

for \(i, j = 1, ..., m\), where \(h = 1, 2, ...\) is the forecast horizon, \(\Sigma_{\varepsilon} = H_0^{-1} \Sigma_u H_0^{-1}'\) and \(P\) is the lower triangular matrix resulting from the Cholesky decomposition of \(\Sigma_u = PP'\). In the OFEVD case, recursive identification is achieved by Cholesky factorization, although the drawback of this simplicity is the well-known order dependence property of OFEVDs. To mitigate this concern, Diebold and Yilmaz (2009) consider a wide but non-exhaustive range of possible orderings and show that in no case does the ordering materially affect their conclusions. However, it seems unlikely that this result can be safely generalized beyond their application. Moreover, any assumption about Wold causality is acutely problematic when working with global models, as it introduces a structure in which countries are assumed to respond to given shocks in a specific order; this is clearly untenable in most cases.

These concerns collectively caution against the use of OFEVDs in the computation of connectedness measures. By contrast, GFEVDs overcome the order dependence problem by working directly with the full residual covariance matrix rather than one of its triangular factors. An intuitive way to view GFEVDs is that they are equivalent to OFEVDs with the exception that all variables are essentially ordered first in the system (see Pesaran and Shin, 1998). However, working with non-orthogonalized shocks carries the implication that the sum of the variance shares will exceed 100% wherever the correlation across shocks is non-zero (i.e. when \(\Sigma_{\varepsilon}\) is non-diagonal). While this is not a fundamental problem, it often thought to complicate the interpretation of GFEVDs. Therefore, Diebold and Yilmaz (2011) compute normalized GFEVDs to ease their interpretation. If the variance share of \(y_{jt}\) in the generalized forecast error variance (FEV) of \(y_{jt}\) is denoted by

\[
\phi_{ji} = GFEVD(y_{jt}; u_{it}, h)
\]

then the normalized \(GFEVD\) may be defined simply as

\[
\eta_{ji} = \frac{\phi_{ji}}{\sum_{i=1}^{m} \phi_{ji}}
\]

where \(\sum_{i=1}^{m} \eta_{ji} = 1\) and \(\sum_{j=1}^{m} (\sum_{i=1}^{m} \eta_{ji}) = m\). By normalizing such that the sum of the FEV shares of each variable is precisely equal to 100%, Diebold and Yilmaz aim to achieve a representation that is robust to the presence of scale differences between forecast error variances of the variables under consideration.

The DY connectedness measures are computed directly from the FEVDs by a process of aggregation. In particular, Diebold and Yilmaz (2011) show that cross-tabulating the \(h\)-step ahead FEVDs for all variables in a VAR system results in a weighted directional network for the chosen horizon. This is easily seen by considering the connectedness matrix for a simple 3
variable system. Table 2 presents the connectedness matrix using general notation and shows how the own-variable FEV share and the spillovers in each direction are defined. Meanwhile, Table 3 presents a simple aid to visualisation of the directional linkages in a trivariate system – the generalisation to larger connectedness matrices is trivial.

[Insert Tables 2 and 3 about here]

The normalization scheme proposed by Diebold and Yilmaz suffers from two significant shortcomings which render it inappropriate given our interest in measuring connectedness dynamically and subject to geographical aggregation. Firstly, given that re-normalization occurs at each horizon, it follows that information is lost across horizons. In particular, variation in the total forecast error variance across horizons is obscured, hindering attempts to compare the strength of connections on a like-for-like basis through time. Secondly, the use of normalized GFEVDs ensures that the sum of each row in a connectedness table such as Table 2 will be precisely equal to 100%. However, this property is violated by the construction of variable groups. This can be seen clearly in Table 4, where it follows that the row sum corresponding to the variable group \( y + z \) will be equal to 200%. Attempts to rectify this distortion by re-weighting are likely to jeopardise the comparability of the scales of the spillovers to and from the newly created variable group. For this reason, we opt to use raw GFEVDs in the construction of our GCMs and not normalized GFEVDs.

[Insert Table 4 about here]

It is important to note, therefore, that in the GCM framework that we will develop over the following pages, the row sums of the connectedness tables need not sum to 100%. The connectedness values that we compute are, however, directly comparable both between variables at the same horizon and also across horizons.

3.1 Connectedness Among \( m \) Global Variables

The DY connectedness measures represent a significant conceptual step, but they are intended for use either in the case of a single variable for each of a set of countries/markets (as studied by Diebold and Yilmaz, 2009) or in the case of multiple variables in a single country/market (as in Diebold and Yilmaz, 2011). The DY measures are most applicable when each variable in the system fully captures an entity of interest, where that entity may be a country or a market, for example. However, without further refinement, they are of limited use when working in the context of multiple countries/markets each of which is represented by more than one variable. That is not to deny that the DY connectedness measures can be applied in such settings, simply that they will be neither very informative nor very tractable without further refinement. Indeed, it is actually rather straightforward to apply the DY connectedness measures to the multi-country multivariate context. At any horizon, \( h \), one simply cross-tabulates the FEVDs for the \( m \times 1 \) vector of global variables as in Table 2 resulting in the following \( m \times m \) global connectedness matrix:

\[
\text{Table 2: Connectedness Matrix}
\]
where the $\phi$’s denote raw GFEVDs as opposed to normalized GFEVDs for the reasons outlined above. Note that we suppress the horizon index to avoid cluttering our notation but it should be clear that the connectedness tables will vary with the forecast horizon; indeed, our interpretation of connectedness is as a fundamentally dynamic phenomenon. Note also our use of non-standard subscript notation. The use of an arrow indicates the direction of the effect under scrutiny. For example, $\phi_{1 \leftarrow 2}$ represents the contribution of variable 2 to the $h$-step ahead FEV of variable 1. Similarly, $\phi_{1 \leftarrow 1}$ denotes the contribution of variable 1 to its own $h$-step ahead FEV. Lastly, note that the connectedness matrix $C$ is, at present, ordered according to the order of the variables in our GVAR system, which are themselves ordered by country. This choice is purely made for convenience and has no bearing on the resulting connectedness measures as they are based on order-invariant generalized FEVDs. To keep track of the notation and definitions that will be introduced over the following pages, each of the key connectedness measures is collected in Table 5 for the reader’s convenience.

Applying the connectedness measures developed by Diebold and Yilmaz (2009) to the multi-country multivariate case reveals considerable scope for further development. We start with the own-variable FEV share $\left( H_{j \leftarrow j}^V \right)$, which is defined as follows

$$H_{j \leftarrow j}^V = \phi_{j \leftarrow j}$$

(16)
where the superscript $V$ indicates that we are working with connectedness measures defined from the V-GCM matrix rather than at a higher level of aggregation. It follows that the own-variable FEV shares lie on the prime diagonal of $C$. If we denote the $m$ global variables in the system in very general notation as $y_t = (a_{1,t}, a_{2,t}, \ldots, a_{m,t})'$ then, for the $j$-th row of $C$, each of the elements excluding $\phi_{j \leftarrow j}$ represent FEV contributions from the other variables in the system to $a_{j,t}$. These are defined as from contributions because they measure the directional connectedness from other variables to $a_{j,t}$ in terms of the contribution to the $h$-step-ahead error variance in the forecasts of $a_{j,t}$ resulting from shocks to $a_{i,t}$, where $i = 1, \ldots, m$ and $i \neq j$. Therefore, we may write the cross-variable from FEV contribution as

$$F_{j \leftarrow \bullet}^V = \sum_{i=1, i \neq j}^{m} \phi_{j \leftarrow i}$$

where the subscript $j \leftarrow \bullet$ indicates that the directional effect under scrutiny is from all variables to variable $j$. Diebold and Yilmaz (2009) refer to this measure as the spillover index in the context of individual returns or volatilities across multiple stock markets. Note that the following is true by construction

$$H_{j \leftarrow j}^V + F_{j \leftarrow \bullet}^V = FEV_{j \leftarrow \bullet}^V = \sum_{i=1}^{m} \phi_{j \leftarrow i}.$$ (18)

where $FEV_{j \leftarrow \bullet}^V$ denotes the total FEV of variable $j$ attributable to all sources. This property can be readily seen by reference to Table 2.

Similarly, we define the total contributions of $a_{j,t}$ to all other variables (denoted $T^V$) as the $j$-th column sum minus the own-variable FEV contribution, $\phi_{j \leftarrow j}$, yielding

$$T_{\bullet \leftarrow j}^V = \sum_{i=1, i \neq j}^{m} \phi_{i \leftarrow j}$$

which measures the total directional connectedness from $a_{j,t}$ to the other variables in the system. The net directional connectedness of $a_{j,t}$ is then defined simply as

$$N_{\bullet \leftarrow j}^V = T_{\bullet \leftarrow j}^V - F_{j \leftarrow \bullet}^V.$$ (20)

It is now straightforward to develop the following aggregate (non-directional) connectedness measures for the $m \times 1$ vector of global variables:

$$H^V = \sum_{j=1}^{m} H_{j \leftarrow j}^V$$ (21)

$$S^V = \sum_{j=1}^{m} F_{j \leftarrow \bullet}^V = \sum_{j=1}^{m} T_{\bullet \leftarrow j}^V$$ (22)

$$H^V + S^V = FEV_{\bullet \leftarrow \bullet}^V = \sum_{j=1}^{m} FEV_{j \leftarrow \bullet}^V.$$ (23)
\[ \sum_{j=1}^{m} N_j = 0 \quad (24) \]

We refer to \( H^V \) and \( S^V \) respectively as the aggregate heatwave index and the aggregate cross-variable FEV contribution, or spillover. This nomenclature follows broadly in the tradition of Engle et al. (1990) and Diebold and Yilmaz (2009). Equation (23) simply states that the sum of the aggregate heatwave and spillover measures accounts for all of the forecast error variance in the entire system at any given horizon, denoted \( FEV \). Similarly, equation (24) notes that the aggregate net connectedness among all the \( m \) variables in the system is simply equal to zero.

Diebold and Yilmaz developed the aggregate measures \( H^V \) and \( S^V \) for use in the multi-market univariate and single-market multivariate contexts. In these specific cases, they provide useful summary measures at a high level of aggregation but they are poorly suited to the multi-market multivariate case as they obscure the directionality of the connections being modelled. In particular, in the context of multi-country multivariate models, the DY measures do not provide a means by which to evaluate the connectedness between countries or regions, for example. It follows that when working with global models, one is likely to be interested in assessing the relative importance of within-country and external shocks from the perspective of any individual variable in the system or from the perspective of an entire country or region. Changes in the relative importance of internal and external factors over different horizons will convey useful information to help managers/regulators plan for and mitigate the effects of shocks during challenging periods of instability. It is to these issues that we now turn.

3.2 Connectedness Among \( b \) Groups

The measures that we define above provide a stylised representation of the interlinkages or connections among the variables in large models but this is unlikely to be the principal interest in many applications, especially in global models where sovereign states and economic blocs are readily identifiable. Therefore, we now show how one may transform the variable-connectedness table in (15) into block form by grouping variables together in an appropriate fashion. A simple illustration using general notation is sufficient to illustrate the principle. Consider the case in which we simply wish to create two groups, and we place half of the variables in the system in group 1 and the remainder in group 2. Recall that the V-GCMs are invariant to the variable ordering so we are free to re-order the elements of (15) as necessary to suit our purpose. In this case, the variable-level connectedness table may be re-written as follows, where the relevant blocks are separated by solid lines:

\[
\begin{array}{cccccc}
  a_1 & \ldots & a_{m/2} & \ldots & a_m \\
  \phi_{a_1} & \ldots & \phi_{a_{m/2}} & \ldots & \phi_{a_m} \\
  \vdots & \ddots & \vdots & \ddots & \vdots \\
  \phi_{a_{m/2}} & \ldots & \phi_{a_m} \\
  a_{m/2+1} & \ldots & a_m \\
  \phi_{a_{m/2+1}} & \ldots & \phi_{a_m} \\
  \vdots & \ddots & \vdots & \ddots & \vdots \\
  \phi_{a_m} \\
\end{array}
\]

This block representation of \( C \) will facilitate the distinction between within-block and cross-
block FEV contributions. All within-block information is contained in the blocks on the prime diagonal, with cross-block information being captured by the off-diagonal blocks. No information is lost in this process, but by grouping variables in this way we introduce a new stratum in between the variable level and the systemwide aggregate level at which we may evaluate connectedness. Not only does this approach explicitly focus the analysis at the appropriate level of aggregation, but insodoing it achieves a significant reduction in the output dimensionality of the model.

It follows that the blocks can be defined in any number of ways depending on the desired grouping of the variables. For example, if one’s interest was in connectedness between the $N$ countries in the system, then one would identify $N$ groups where each group is a country and then re-write $C$ in terms of the resulting $N^2$ blocks. Based on this structure, one could then evaluate connectedness between countries. For now, however, we will abstract from the issues of block selection and provide a general derivation of the block-level directional connectedness measures. When we apply our GCMs to the GNS GVAR model we will exploit these measures to evaluate country-level connectedness (C-GCMs), regional connectedness (R-GCMs) and variable-group connectedness (G-GCMs).

As mentioned above, by selecting the relevant $b$ groups and the associated $b^2$ blocks from the variable-connectedness table in (15), we can express $C$ as

$$C = \begin{bmatrix}
B_{1\leftarrow 1} & B_{1\leftarrow 2} & \cdots & B_{1\leftarrow b} \\
B_{2\leftarrow 1} & B_{2\leftarrow 2} & \cdots & B_{2\leftarrow b} \\
\vdots & \vdots & \ddots & \vdots \\
B_{b\leftarrow 1} & B_{b\leftarrow 2} & \cdots & B_{b\leftarrow b}
\end{bmatrix}$$

(25)

where the $B_{k\leftarrow \ell}$’s are $m_k \times m_\ell$ blocks, where $m_k$ denotes the number of variables in group $k$ and $m_\ell$ the number of variables in group $\ell$. As mentioned above, the blocks lying on the prime diagonal of $C$ (i.e. the $B_{k\leftarrow k}$’s) contain all of the within-block connectedness information. We therefore define the total within-block variance contribution for block $k$ as follows

$$O_{k\leftarrow k}^B = 1_{m_k}^t B_{k\leftarrow k} 1_{m_k}$$

(26)

where the superscript $B$ indicates that we are now working at the block level as opposed to the variable level and $1_k$ is an $m_k \times 1$ column vector of ones. That is, the within-block FEV contribution for block $k$ is simply equal to the sum of all of the elements of the the block $B_{k\leftarrow k}$.

In many cases, it may be useful to decompose the total within-block FEV contribution, $O_{k\leftarrow k}^B$, into the own-variable and cross-variable FEV contributions within block $k$, such that

$$O_{k\leftarrow k}^B = O_{k\leftarrow k}^{B,O} + O_{k\leftarrow k}^{B,C}$$

(27)

where the total within-block own-variable FEV contribution is given by

$$O_{k\leftarrow k}^{B,O} = trace(B_{k\leftarrow k})$$

(28)
and the total within-block cross-variable FEV contribution is obtained as

\[ O_{k \leftarrow k}^{B,C} = O_{k \leftarrow k}^{B} - O_{k \leftarrow k}^{B,O} \]  

(29)

By analogy, the \( B_{k \leftarrow \ell}'s \) for \( k \neq \ell \) relate to the transmission of information from block \( \ell \) to block \( k \). We are therefore able to define the total between-block FEV contribution from block \( \ell \) to block \( k \) as

\[ F_{k \leftarrow \ell}^{B} = 1'_{m_k} B_{k \leftarrow \ell} 1_{m_{\ell}} \]  

(30)

and the to contribution from block \( k \) to block \( \ell \) as

\[ T_{\ell \leftarrow k}^{B} = 1'_{m_{\ell}} B_{\ell \leftarrow k} 1_{m_k} \]  

(31)

Based on these block-level connectedness measures, it is a simple matter to obtain the following \( b \times b \) block-connectedness matrix

\[
\mathbb{C}^B = \begin{bmatrix}
  O_{1 \leftarrow 1}^{B} & F_{1 \leftarrow 2}^{B} & \cdots & F_{1 \leftarrow b}^{B} \\
  F_{2 \leftarrow 1}^{B} & O_{2 \leftarrow 2}^{B} & \cdots & F_{2 \leftarrow b}^{B} \\
  \vdots & \vdots & \ddots & \vdots \\
  F_{b \leftarrow 1}^{B} & F_{b \leftarrow 2}^{B} & \cdots & O_{b \leftarrow b}^{B}
\end{bmatrix}
\]  

(32)

Note that we have chosen to write (32) in terms of the \( F_{k \leftarrow \ell}'s \) but of course we could achieve an equivalent representation in terms of the \( T_{\ell \leftarrow k}'s \) by definition. We refer to (32) as a block-level GCM matrix. Using (32), we can develop the associated aggregate block-level connectedness measures. The total from, to and net contributions for block \( k \) are defined as follows

\[ F_{k \leftarrow \bullet}^{B} = \sum_{\ell=1,\ell \neq k}^{b} F_{k \leftarrow \ell}^{B} \]  

(33)

\[ T_{\bullet \leftarrow k}^{B} = \sum_{\ell=1,\ell \neq k}^{b} T_{\ell \leftarrow k}^{B} \]  

(34)

\[ N_{\bullet \leftarrow k}^{B} = T_{\bullet \leftarrow k}^{B} - F_{k \leftarrow \bullet}^{B} \]  

(35)

where \( F_{k}^{B} \) measures the total between-block FEV contributions from all other blocks to block \( k \) (i.e. the total from contribution affecting block \( k \)), \( T_{k}^{B} \) measures the total between-block FEV contributions from block \( k \) to all other blocks (i.e. the total to contribution arising from block \( k \)), and \( N_{k}^{C} \) is the net FEV contribution associated with block \( k \).

Finally, it is possible to define the aggregate Heatwave and Spillover indices in terms of the \( b \) blocks as follows

\[ O^{B} = \sum_{k=1}^{b} O_{k \leftarrow k}^{B} \]  

(36)

\[ S^{B} = \sum_{k=1}^{b} F_{k \leftarrow \bullet}^{B} = \sum_{k=1}^{b} T_{\bullet \leftarrow k}^{B} \]  

(37)

\*Note that \( O_{k \leftarrow \bullet}^{B} + F_{k \leftarrow \bullet}^{B} = FEV_{k \leftarrow \bullet}^{B} \) by construction.
where, once again, $O^B + S^B = FEV_{\cdots}$ and $\sum_{k=1}^{b} N_{\cdot \cdot \cdot \cdot k}^B = 0$ by construction.

### 3.2.1 Aggregating Into $N$ Countries

Defining country-level connectedness measures will facilitate the distinction between within-country and cross-country FEV shares. The former may be particularly relevant for national policymakers and regulators, while the latter lies more within the realm of supranational bodies such as the IMF. Moreover, as we will show later in the paper, careful consideration of the nature of spillovers between countries will provide a simple and intuitive means to distinguish between those that act as risk transmitters and risk receivers in the global economy. By selecting the relevant country blocks from the variable-connectedness table in (15), we can express $C$ as

$$C = \begin{bmatrix}
C_{1\leftarrow1} & C_{1\leftarrow2} & \cdots & C_{1\leftarrow N} \\
C_{2\leftarrow1} & C_{2\leftarrow2} & \cdots & C_{2\leftarrow N} \\
\vdots & \vdots & \ddots & \vdots \\
C_{N\leftarrow1} & C_{N\leftarrow2} & \cdots & C_{N\leftarrow N}
\end{bmatrix} \tag{38}$$

where the $C_{k\leftarrow \ell}$’s are $m_k \times m_\ell$ matrices corresponding to each country-specific block such that

$$C_{k\leftarrow \ell} = \begin{bmatrix}
\phi \tilde{m}_{k+1\leftarrow \ell+1} & \cdots & \phi \tilde{m}_{k+1\leftarrow \ell+m_\ell} \\
\vdots & \ddots & \vdots \\
\phi \tilde{m}_{k+m_k\leftarrow \ell+1} & \cdots & \phi \tilde{m}_{k+m_k\leftarrow \ell+m_\ell}
\end{bmatrix}, \quad k, \ell = 1, \ldots, N \tag{39}$$

and where $\tilde{m}_k = \sum_{k=1}^{k-1} m_k$ while $m_k$ denotes the number of endogenous variables included in the country-specific CVARX model for country $k$.

### 3.2.2 Aggregating Into $R$ Regions

In many practical applications, it may be preferable to evaluate connectedness among regions or blocs as opposed to countries. Such geographical aggregation may achieve considerable reductions in the output dimensionality of large models while also providing interesting insights into global linkages at a relatively low resolution. Regional connectedness measures can be derived in a similar fashion to the country case outlined above. By selecting the relevant regional blocks in (15), we can express $C$ as

$$C = \begin{bmatrix}
R_{1\leftarrow1} & R_{1\leftarrow2} & \cdots & R_{1\leftarrow R} \\
R_{2\leftarrow1} & R_{2\leftarrow2} & \cdots & R_{2\leftarrow R} \\
\vdots & \vdots & \ddots & \vdots \\
R_{R\leftarrow1} & R_{R\leftarrow2} & \cdots & R_{R\leftarrow R}
\end{bmatrix} \tag{40}$$

where the $R_{r\leftarrow s}$’s are $m_r \times m_s$ matrices relating to each region-specific block, the definition of which follows easily from (39) and where $m_r$ and $m_s$ denote the number of variables in region $r$ and region $s$, respectively.

**Remark 1** In many applications of high dimensional models in economics and finance including GNS1, GNS2 and GNS3, for example, the researcher is principally interested in a subset of focus countries. In such cases, one could reduce the output dimensionality of the model by...
considering one or more focus countries separately while aggregating the remaining countries into appropriately defined blocks. In the case of a single focus country, this can be achieved by setting up the R-GCM matrix such that the first region is simply the country of interest. It is then straightforward to examine the total country–region connectedness measures as follows:

\[
\begin{align*}
F^{R}_{1\rightarrow\bullet} &= \sum_{s=2}^{R} F^{R}_{1\rightarrow s}, \\
T^{R}_{\bullet\rightarrow 1} &= \sum_{s=2}^{R} F^{R}_{s\rightarrow 1}, \\
N^{R}_{\bullet\rightarrow 1} &= T^{R}_{\bullet\rightarrow 1} - F^{R}_{1\rightarrow \bullet}
\end{align*}
\] (41)

where \(F^{R}_{1\rightarrow \bullet}\) measures the total inter-regional variance contributions from all other regions to the country of interest, \(T^{R}_{\bullet\rightarrow 1}\) measures the total variance contributions from the country of interest to all other regions and \(N^{R}_{\bullet\rightarrow 1}\) is the net contribution associated with the country of interest. The extension to the case of multiple focus countries follows trivially.

### 3.2.3 Aggregating Into \(G\) Variable Groups

In addition to the national and regional-level connectedness measures defined above, many practical applications may call for connectedness measures defined in terms of groups of variables. At a very high level of aggregation, one may consider separating nominal variables and real variables, for example. Alternatively, when working with global macroeconometric models, defining common variable groups across countries would allow the modeller to evaluate the time-varying directional linkages between global stock markets and economic output, for example.

Based on the preceding discussion, it is a simple matter to derive a family of variable-group connectedness measures. Given the nature of the GNS GVAR model, the obvious choice is to group common variables across countries (i.e. grouping real GDP across countries, inflation across countries etc). As before, the first step is to regroup the V-GCM matrix (15) according to the relevant \(G\) variable groups, in which case we can express \(\mathbf{C}\) as

\[
\mathbf{C} = \begin{bmatrix}
G_{1\leftarrow 1} & G_{1\leftarrow 2} & \cdots & G_{1\leftarrow G} \\
G_{2\leftarrow 1} & G_{2\leftarrow 2} & \cdots & G_{2\leftarrow G} \\
\vdots & \vdots & \ddots & \vdots \\
G_{G\leftarrow 1} & G_{G\leftarrow 2} & \cdots & G_{G\leftarrow G}
\end{bmatrix}
\] (42)

where, in our application, \(G_{f\leftarrow g}\) is the \(n_f \times n_g\) common variable block and where \(n_f\) and \(n_g\) denote the number of countries in variable groups \(f\) and \(g\), respectively. By analogy with the previous cases, it is clear that \(G_{f\leftarrow f}\) contains the total within-group variance contributions while \(G_{f\leftarrow g}\) contains the total between-group variance contributions from group \(g\) to group \(f\).

**Remark 2** When working with variable groups, in some cases it may be useful to further decompose the from and to contributions into own-country and cross-country effects. Recall that we may decompose \(O^{G}_{f\leftarrow f}\) as follows:

\[
O^{G}_{f\leftarrow f} = O^{G,O}_{f\leftarrow f} + O^{G,C}_{f\leftarrow f}
\] (43)

where \(O^{G,O}_{f\leftarrow f}\) measures the within-block own variable FEV contribution and \(O^{G,C}_{f\leftarrow f}\) measures the within-block cross-variable FEV contribution. For example, where the block in question collects all of the GDP series for the \(N\) countries in the model, then the former magnitude represents the
share of the h-step ahead FEV of GDP attributable to GDP in the same country, while the latter
measures the h-step ahead FEV of GDP attributable to GDP in the remaining \( N - 1 \) countries.

By analogy we may also decompose \( F_{f \leftarrow g}^G \) as follows:

\[
F_{f \leftarrow g}^G = F_{f \leftarrow g}^{G,O} + F_{f \leftarrow g}^{G,C}
\]  

(44)

where, assuming that variable group \( f \) represents GDP and variable group \( g \) represents the ex-
change rate, for example, then \( F_{f \leftarrow g}^{G,O} \) measures the contribution to the h-step ahead FEV of GDP
attributable to the exchange rate for the same country, while \( F_{f \leftarrow g}^{G,C} \) measures the contribution
attributable to the exchange rate for the remaining \( N - 1 \) countries in the model. \( F_{f \leftarrow g} \) is defined as:

\[
F_{f \leftarrow g} = \text{trace} (G_{f \leftarrow g})
\]

(45)

It follows that the to contributions can be decomposed similarly. Now suppose that we wish to
further decompose (43) and (44). First, rewrite \( \mathcal{C} \) as follows

\[
\mathcal{C} = \mathcal{C}^{G,O} + \mathcal{C}^{G,C}
\]

(46)

Using (46), we may now define the following aggregate connectedness measures at the level of
the common variable groups

\[
F_{f \leftarrow \bullet}^{G,O} = \sum_{g=1, g \neq f}^G F_{f \leftarrow g}^{G,O}, \quad T_{\bullet \leftarrow f}^{G,O} = \sum_{g=1, g \neq f}^G F_{g \leftarrow f}^{G,O}, \quad N_{\bullet \leftarrow f}^{G,O} = T_{\bullet \leftarrow f}^{G,O} - F_{f \leftarrow \bullet}^{G,O}
\]

(47)

\[
F_{f \leftarrow \bullet}^{G,C} = \sum_{g=1, g \neq f}^G F_{f \leftarrow g}^{G,C}, \quad T_{\bullet \leftarrow f}^{G,C} = \sum_{g=1, g \neq f}^G F_{g \leftarrow f}^{G,C}, \quad N_{\bullet \leftarrow f}^{G,C} = T_{\bullet \leftarrow f}^{G,C} - F_{f \leftarrow \bullet}^{G,C}
\]

(48)

where \( F_{f \leftarrow \bullet}^{G,O} \) measures the total contribution to the h-step ahead FEV of variable group \( f \) arising
from all other variables (not including variable group \( f \)) in the same country while \( F_{f \leftarrow \bullet}^{G,C} \) measures
the total contribution arising from all other variables in the remaining \( N - 1 \) countries in the model. The interpretation of \( T_{G \leftarrow f}^{G,O}, T_{G \leftarrow f}^{G,C}, N_{G \leftarrow f}^{G,O} \) and \( N_{G \leftarrow f}^{G,C} \) follows easily. Note that the following
equality holds by construction

\[
O_{f \leftarrow f}^{G,O} + O_{f \leftarrow f}^{G,C} + F_{f \leftarrow \bullet}^{G,O} + F_{f \leftarrow \bullet}^{G,C} = \text{FEV}_{f \leftarrow \bullet}.
\]

(49)

Remark 3 Consider the case in which we are interested in measuring the connectedness between
a single variable from a specific country (or a common factor such as the oil price) and all of
the other grouped variables. In this case we simply place the single variable of interest in the
first group variable block, \( G_{1 \leftarrow -1} \) in (43) with \( G - 1 \) groups of variables. In this case \( G_{1 \leftarrow -1} \) is

\( ^9 \)Where the variable of interest is a single variable from a particular country, we adopt the convention of placing
the corresponding variables from the remaining \( N - 1 \) countries in the second block.
a scalar and $G_{1\to f}$ is a $1 \times n_f$ row vector. It is straightforward to construct the following total connectedness measures

$$
F_{1\to \bullet}^G = \sum_{g=2}^{G} F_{1\to g}^G, \quad T_{\bullet \to 1}^G = \sum_{g=2}^{G} F_{g\to 1}^G, \quad N_{\bullet \to 1}^G = T_{\bullet \to 1}^G - F_{1\to \bullet}^G
$$

(50)

where $F_{1\to \bullet}^G$ measures the total FEV contribution from all other variable groups to the single variable of interest, $T_{\bullet \to 1}^G$ measures the total FEV contribution from the single variable of interest to all other variable groups, and $N_{\bullet \to 1}^G$ is the net contribution associated with the single variable of interest.

4 Measuring the Connectedness of the Global Economy

In this section, we will show how the our GCMs can be used to measure and to map the connectedness of the variables, countries and regions modelled in the GNS GVAR framework. In order to place these connectedness measures in context, we will first study the raw GFEVDs for the same four focus countries analysed in GNS and Greenwood-Nimmo et al. (2013), namely the US, the Eurozone, Japan and China. We will then consider aggregate system-wide connectedness measures computed from the V-GCM matrix before moving on to the country-level, regional and variable group cases.

4.1 Exploratory Analysis of the Raw GFEVDs

In order to analyse the GFEVDs for our four focus countries, we draw area plots showing the FEV contributions for each variable in their respective national models over a range of horizons. To facilitate the interpretation of the plots, we do not follow the usual convention of multiplying the FEV by 100 as this would simply inflate the scale on the vertical axis. Therefore, in the figures, the sum of the FEV contributions may exceed 1 as we are not working with orthogonalized shocks. Note also that the total FEV for some variables is larger than for others, and this reflects the accuracy with which a given equation in the VAR system fits the data; it follows that using normalized GFEVDs would obscure these differences and would also obscure the time-variation which is observed in the total FEV as the horizon changes.

The FEV in each case is decomposed into four components as follows: (i) Own – the contribution to a variable’s FEV explained by the variable itself; (ii) Domestic – the contribution explained by the other domestic variables excluding the own contribution; Oil – the contribution explained by the oil price; and (iv) Foreign – the contribution explained by all foreign variables excluding the oil price.\[10\]

Several stylized facts are easily observed. Firstly, the influence of the oil price is generally rather muted in the US, the Eurozone and China, while it is considerable in Japan. We observed

\[10\] Since our analysis involves aggregation of the FEV contributions of the domestic and foreign variables, it is important to recall that the number of domestic variables varies by country in the GNS GVAR model. Among our focus countries, the Eurozone and Japan have a full complement of seven domestic variables while China has just six due to the absence of reliable stock market data. Meanwhile, the US also has six domestic variables once one treats the oil price as a global common factor. Moreover, note that it is the price level and not inflation which is included among the domestic variables for the US.
the same effect via impulse response analysis in Greenwood-Nimmo et al. (2013), where we attribute it to the interaction of the relative energy intensity of production and the relative reliance on energy imports for each country. Secondly, in many cases, the own contribution is a dominant factor in the short-run after which its importance tends to recede, albeit to varying degrees across countries and variables. A similar result is reported in Greenwood-Nimmo et al. (2012b) for the case of Korea. This will be a recurring theme throughout our analysis and one to which we will return shortly. Thirdly, the influence of domestic factors (i.e. the sum of ‘Own’ and ‘Domestic’) is very considerable and often dominates the collective influence of the oil price and the remaining foreign variables at all horizons in the US and also in most cases in the Eurozone and China (the notable exception is the case of the Eurozone stock market which is heavily influences by foreign variables at all horizons). By contrast, the Japanese results reveal the overwhelming dominance of foreign factors, especially in the medium- to long-term. This finding reflects the combination of Japan’s status as a liberally governed and export-oriented open economy. Fourthly, as one may expect, foreign influence is typically felt more strongly in relation to exports than imports.

Finally, while the own contribution overwhelmingly dominates the influence from other sources in the case of the US stock market, foreign influence, on the contrary, is the dominant force affecting the stock markets of the Eurozone and Japan. A closer analysis shows that the US stock market innovation contributes between 17% and 35% to the FEVDs of the Eurozone and Japanese stock indices across all horizons. This finding illustrates both the dominant role of the US stock market in the global financial system and the close linkages between the world’s major stock markets. Furthermore, in conjunction with our other results, it suggests that financial ties may generally be stronger than real ties among the world’s major economies, reflecting the breadth and depth of international financial markets.

4.1.1 The USA

Figure 1 presents the aggregated GFEVDs for the US. The most striking feature of the graphs is that the total foreign influence on the US economy (i.e. the sum of oil and foreign) is of secondary importance relative to domestic factors at most horizons and is, in fact, rather muted in the case of the stock market and interest rate. The largest foreign contributions relate to US imports, exports and the general price level, as one would expect, and also to real output at the longer horizons. The oil price exerts a significant influence on the price-level in the short- to medium-term (contributing almost 20% of the FEV in the short-run) and on real output in the medium- to long-term (up to 10%). These are intuitively plausible results given the dominant position of the US in the global economic system; indeed, the US economy is often thought to drive outcomes in the global economy as much or more than it responds to them.

While China has become an increasingly export-oriented economy over our sample period, its institutional framework is likely to significantly insulate its economy from foreign influence. In particular, the pursuit of capital controls and exchange rate management is likely to be a key factor.

Note that in this figure the oil price is included alongside the US-specific variables. This reflects the fact that the oil price was modelled as an endogenous variable in the US country-specific CVARX model, which itself was then included in the GVAR system. In subsequent figures we will treat the oil price separately rather than including it among the set of US variables to isolate the impact of oil shocks on the global system from the effect of shocks emanating strictly from the US economy.
The GFEVDs of the US interest rate suggest that the Fed focuses largely on domestic conditions for policy purposes, with the contribution from other domestic variables accounting for approximately 60% of the FEV from the second quarter onwards. Furthermore, the pattern of gradual decay of the own-variable variance share is suggestive of inertial policymaking. The dominance of within-country variables in the case of the interest rate also reflects the fact that the rate of price level inflation and output growth are among the key determinants of the policy stance of the Fed, and that their respective FEVDs shows considerable sensitivity to the oil price (i.e. this information is already included in the inflation rate forecasts employed by policymakers). Once again, the pattern of decay of the own-variable variance share for inflation is suggestive of a moderate degree of inflation persistence in the US on average across our sample.

Interestingly, the within-country cross-variable contributions are very significant contributors to the import and export FEVs in all but the very short-run. The dependence of the US trade variables on the state of the US economy once again underscores the country’s dominance in the global system; in a small open economy framework one may expect the trade variables to be predominantly affected by conditions overseas. Further evidence of the US hegemony is to be seen in the case of the US stock market, where the own contribution overwhelmingly dominates, with foreign influence accounting for just 25% of the FEV in the long-run. Similarly, domestic influence is strongly felt in the case of real output, which is a natural observation given that domestic consumption is the largest component of US GDP.

4.1.2 The Eurozone

Figure 2 displays the results for the Eurozone. Abstracting for now from the case of the European stock market, as with the US, the domestic contribution is considerable in all cases, although the degree of foreign influence is generally somewhat higher in the Eurozone than in the US as one would expect. Interestingly, we observe considerably more foreign influence in the interest rate FEVD for Europe than the US, suggesting that European interest rates are more responsive to conditions overseas, a result that aligns with the notion of a leader-follower relationship between the Fed and the ECB.

The most striking difference between Figures 1 and 2 is the behaviour of the stock market. While the US stock market was found to depend largely on domestic conditions, the Eurozone stock market is largely determined by foreign factors, which collectively account for approximately 60% of its FEV at all horizons. Similarly, we find considerable foreign influence on European inflation in the short-run, although interestingly the oil price is found to play no significant role. We observe a similar phenomenon in GNS2, which we attribute to the relative energy intensity of production in the Eurozone relative to our other focus countries, and also perhaps to the presence of large oil producers in the European area (Britain, for example, is a large oil producer and is also part of the European Union but is not included in our composite Eurozone as it does not use the Euro). Lastly, and significantly, our results indicate that the real exchange rate is strongly influenced by domestic factors, reflecting the collective size of the
Euro Area economies and the importance of the Euro in the global financial system. Indeed, the Euro may reasonably be considered the world’s second reserve currency behind the US Dollar but ahead of both the Yen and Sterling.

4.1.3 Japan

Even a cursory inspection of Figure 3 reveals that Japan behaves quite differently to either the US or the Eurozone. In this case, foreign factors exert a dominant influence in the medium- to long-term. The largest own contribution is observed in the short-term in the case of the interest rate and real output, while the largest within-country cross-variable contribution is recorded for the real exchange rate.

[Insert Figure 3 about here]

A further difference in the Japanese case is the important role played by the oil price, reflecting Japan’s reliance on imported minerals and energy. Moreover, the large contribution of the oil price to the interest rate FEV may reflect attempts by policymakers to manage the influence of oil price fluctuations on the Yen and/or to offset their negative impact on the large Japanese manufacturing sector. It is also interesting to note that oil price shocks are passed through to Japanese real activity with a considerable lag of approximately 18 months, perhaps reflecting the Japanese government’s maintenance of the world’s second largest strategic petroleum reserve over much of our sample.

These results bear many similarities to those reported in GNS3 for the case of Korea. This is to be expected given the similarities between the two economies, in particular their mutual export-orientation, their reliance on mineral imports and the prevailing doctrine of economic openness and liberal governance. Against the backdrop of such institutional arrangements, the importance of external factors is entirely natural.

4.1.4 China

Figure 4 presents results for Chinese economy which are generally qualitatively similar to those recorded in the US and the Eurozone. Our findings indicate that the degree of foreign influence on the Chinese economy is rather limited, with the largest foreign contribution being associated with the real exchange rate and inflation. As with the US and the Eurozone, the own contribution typically dominates in the short- to medium-term while the contribution from other domestic variables dominates at longer horizons. The large own variable FEV contribution of real output neatly captures the impact of the unprecedented and sustained high level of fixed investment and government spending in China over our sample period.

[Insert Figure 4 about here]

A crude summary of the key findings based on the raw GFEVDs above is that the US in particular, and the Eurozone to a lesser extent, exhibit the characteristics of large economies which tend to drive the global economy perhaps to a greater extent than they respond to it. China behaves in a somewhat similar manner, exhibiting many of the characteristics of a large closed economy despite its export-orientation and the prevalence of imported intermediate inputs.
in Chinese manufactures. The factors underlying these unusual characteristics include China’s relatively restrictive institutional framework, its reliance on capital controls and exchange rate management and the fact that while it is a major industrial centre it is yet to develop deep financial markets. Lastly, our results indicate that the Japanese economy is very strongly affected by conditions overseas, reflecting its economic openness, its export-orientation and, indeed, its specialisation within specific export markets, notably hi-tech and automotive goods.

4.2 Applying the Generalized Connectedness Measures

The simple visual analysis of GFEVDs presented above provides some interesting insights and is suggestive of the wealth of interlinkages contained within the global model but much of the detail is obscured. Furthermore, it is clear that this manner of presentation does not achieve significant reductions in the output dimensionality of the model, as we must analyse one FEVD figure for each variable of interest. In this section, we demonstrate how our GCMs can be used to summarise the interlinkages embedded in the global framework at various levels of aggregation, and how the use of appropriate aggregate representations facilitates the analysis of connectedness between various entities in the global economic system. Starting with the 176 variable V-GCM case, we then construct country-level C-GCMs where each of the 26 countries in the GNS model (including the composite Eurozone) are treated separately. We then aggregate further and compute regional-level R-GCMs based on 11 regions as follows: the USA, Eurozone, Japan, UK, Canada, Other European, Brazil-India-China (BIC), Australia and New Zealand, Latin America, South Korea and Asean and the Rest of the World (ROW). Finally, we construct G-GCMs by selecting groups of common variables across countries where we distinguish between the following groups: real exchange rates, interest rates, imports, exports, the stock market, inflation and output. In all cases, the oil price is treated separately as a global common factor.

4.2.1 Aggregate Connectedness

Figure 5 plots the aggregate connectedness measures at various levels of aggregation. Note that to maintain a roughly comparable scale of the vertical axis with those of Figures 1–4, the total FEV is divided by the number of global variables, $m$ without loss of generality. It follows trivially that the aggregate own contribution is the same in each of the four subfigures by construction since we do not identify separate blocks in the system (either countries, regions or common variable groups). The figure reveals that, on average across the entire system, the own variable FEV contribution is initially considerable, explaining almost 40% of the total FEV. This figure gradually drops as the horizon increases, settling at less than 20% in the long-run. The main implication arising from this representation of the GCMs is that cross-variable connections typically exert a dominant influence, particularly at longer
horizons. It therefore follows that modelling connectedness between variables appropriately is fundamental to understanding the behaviour of the global economic system. It is also interesting to note that the total FEV decreases slightly before levelling out after roughly 4 quarters. This decline is associated with the sharp initial decreases in the own-variable FEV contribution which are not fully offset by the growth of cross-variable spillovers.

Moving on to panels (b)–(d), we can now separate within unit and between block contributions, which will obviously differ depending on whether the block under consideration is defined at the country, region or variable-group level. The most striking feature of these figures is that the within and between contributions exhibit remarkably similar patterns in the country and region cases. Closer scrutiny reveals that the within contribution is slightly bigger in the region case because when several countries are combined into a region then the connections that previously existed between these countries will now be considered internal within that region. The country-level and region-level results reveal a significant finding in the sense that domestic factors (i.e. the sum of the own and within contributions) are found to be dominant in the short-term, while between contributions come to dominate at the longer horizons. This suggests that domestic and regional factors are likely to preoccupy national policymakers given their planning horizon and the widely discussed implications of the political business cycle in many countries, leaving an important role for supranational bodies in the longer-term.

The patterns of the within and between contributions in the variable-group case are broadly similar to the country and region cases in the sense that the between group FEV contribution becomes increasingly important at longer horizons. However, the within group contribution is considerably smaller in the variable group case, suggesting that cross-variable connections (e.g. between GDP and the stock market) are generally more important than common-variable connections (e.g. between GDP and GDP) in the system. The details underlying this general observation will be discussed in more depth below.

4.2.2 C-GCMs: Country Connectedness

Figure 6 plots the from-between, to-between and net connectedness results at the country level, including the oil price separately as a global common factor. In each subfigure, the bars in the upper panel represent the to-between contribution while the solid red line represents the net contribution across horizons. By contrast, the lower panel shows an area plot of the from-between, within and own contributions. By definition, the net contribution for any country is equal to the difference between its to-between and from-between values.

[Insert Figure 6 about here]

Even a cursory glance over the figures proves informative, showcasing the ease of interpretation and usefulness of our aggregation scheme and, in particular, of our C-GCM representation. Rather than attempting to discuss each figure in turn, we may save considerable space while maintaining a focus on the key phenomena by summarising the C-GCM results via the following stylised findings:

(i.) The to-between contribution measures the extent to which a country influences the rest of the world. As one might expect, we find that the largest to-between contributions are
associated with the US, the EU and the oil price.

(ii.) The *net* contribution measures the degree to which a country transmits shocks to others relative to the degree to which it receives them from others. We find that the largest *net* contributions are also observed for the US and the EU, indicating that they tend to drive events in the global economy. We also note that the oil price is almost wholly a shock transmitter, reflecting the fact that oil supply is managed to a large extent by OPEC and that the price is not allowed to respond freely to demand;

(iii.) The *within* contribution measures the extent to which an economy is driven by its own domestic conditions. The *within* contributions associated with the US and the EU are strong, indicating that they play a dominant role in the world economy and that their own shocks will have a significant effect not just on the rest of the world but also on their own economies;

(iv.) Excluding the US and the EU for the reasons discussed in (v.) above, large *within* contributions are often associated with developing countries, particularly the Latin American countries that experienced hyperinflation during our sample period and also South Africa. In the case of South Africa, this reflects the embargo related to the apartheid era, while for the Latin American countries it suggests that they may have become somewhat decoupled from the global economy during their hyperinflationary crises;

(v.) The *from-between* contribution measures the extent to which an economy is susceptible to conditions overseas. The largest *from-between* contributions are associated with the smaller and more open economies such as the UK, Sweden, Switzerland and the South-East Asian nations. This group receives international shocks to a greater degree than they propagate shocks internationally.\(^{13}\)

(vi.) Despite being a large economy, Japan also exhibits a very strong *from-between* contribution reflecting its heavily export-oriented economic structure and its extensive reliance on imported energy;

(vii.) China, and to a lesser extent Brazil and India, are notable for their weak *from-between* connections, indicating that they have exhibited the behaviour of relatively closed economies, at least over our sample period; and

(viii.) China is a net contributor, although its significance is likely to be considerably greater using more recent trade weights and also newer data. We also find that Brazil is a net contributor, reflecting not only the size and rapid growth of the Brazilian economy but also its role as the largest economy in Latin America (in particular, we observe very large *to-between* contributions from Brazilian inflation and interest rates to other Latin American countries).

These stylized findings arising from the analysis of our C-GCMs accurately capture many of the key interrelationships in the global economy in a simple and intuitive manner. This is

\(^{13}\)Saudi Arabia also exhibits a strong *from-between* contribution although this may be misleading since its dominant role within OPEC is not fully reflected here because the oil price is shown separately as a global common factor.
all the more impressive for the fact that they are computed based on a global model which is not subject to theoretical restrictions either on its short-run or long-run parameters. To further exploit the geographical element of our country-connectedness results, we now construct the following transmission ratio:

\[ V_k = \frac{T_k}{T_k + F_k} \]

(51)

Note that \( V_k \) can be computed for any desired horizon and that it is bounded between zero and one. Its value provides useful information about the relative position of country \( k \) as either a net shock transmitter or receiver at horizon \( h \). More precisely, for any horizon \( h \), country \( k \) is a net shock receiver if \( 0 \leq V_k < 0.5 \), a net shock transmitter if \( 0.5 < V_k \leq 1 \), and neither a net transmitter or receiver if \( V_k = 0.5 \) (country \( k \)'s to-between and from-between contributions are precisely equal in this case). By overlaying these measures onto a world map, at any given horizon we are able to identify hot spots for the transmission of shocks, as well as countries and regions which are particularly vulnerable to shocks emanating from overseas. Figures 7–9 present shock transmission maps at the one, four and twelve quarter ahead horizons. Note that the contribution of oil is drawn on the maps in the Gulf region, reflecting the fact that eighty percent of the founding members of OPEC are gulf states. Strictly speaking, however, the effect of oil should not be interpreted as emanating from this region in our model as oil is modelled as a common factor; it is merely a stylised representation. Note also that the entirety of the Eurozone is shaded despite the fact that our composite Eurozone economy does not contain data for each member state.

It is clear across all three figures that the dominant shock transmitters are the US, the Eurozone and the oil price. Furthermore, the transmission ratio increases through time for the US and the oil price but not for the Eurozone, indicating that the latter receives global shocks more strongly and therefore cannot be considered as a driver of the world economy to quite the same extent. China and Brazil (and also Argentina to some extent) also transmit shocks within the world economy, but not as strongly. The remainder of the economies in our model are net receivers at all horizons.

This stylised representation is very informative, and provides a simple means of assessing the risks to the global economy posed by shocks occurring in different states. Given that the US is found to be such a strong transmitter, it is not surprising to note that the effects of the subprime crisis were passed through to the world economy rapidly, strongly and catastrophically. Similarly, the various oil shocks that have occurred throughout the last four decades have had considerable global impact. Therefore, economic instability in the US and shocks occurring in major oil producing regions (particularly the gulf states) should be of great concern to national governments and supranational bodies such as the Bretton Woods institutions.

Our risk maps also demonstrate why some regional crises have not proven overly damaging to the global economy. For example, the real-estate and stock-market collapse which was the forerunner of the so-called ‘lost decade’ in Japan was not passed through in any significant way to the rest of the world because the Japanese economy does not exhibit strong to-between
connectedness. Similarly, the UK Black Wednesday event and the South-East Asian financial crisis of 1997 were not felt strongly beyond their respective regions for exactly the same reason. The case of Brazil and Argentina is to some extent a special one, since shocks in these economies seem to have played a very significant regional role in Latin America during our sample but they do not seem to have been felt strongly beyond the continent.

These figures also provide strong support for the range of interventions that have so far staved off a dramatic unwinding of the debt crisis in Europe. Our results indicate unambiguously that shocks within the Eurozone are strongly transmitted to the world economy. It follows, therefore, that any traumatic shocks within the Eurozone are likely to prove very damaging to global prosperity. It also seems likely that the importance of China as a shock transmitter is likely to increase dramatically with its growing prominence in the world economy.

4.2.3 R-GCMs: Region Connectedness

Figure 10 repeats the country-connectedness analysis above at the regional level for the eleven regions defined earlier, as well as the oil price.

The results are generally similar to the country-level case, although the patterns are somewhat more marked. The oil price, the US and the Eurozone are again found to be the dominant contributors in the global economy, although the role of the BICs is non-negligible when they are considered collectively. Similarly, once Brazil is excluded, the Latin American countries are major net receivers. The largest net receivership of foreign shocks is observed in the case of South Korea and the ASEAN economies, in which the level of shock transmission is approximately half the level of receivership. This is a plausible finding given the widespread adoption of export-orientated growth strategies in the region. The case of the non-Eurozone European countries is rather similar.

By further aggregating into just five regions (the US, Eurozone, Japan, BICs and ROW, plus the oil price), we are able to present R-GCMs in a very vivid manner in Figure 11. The figure plots the time-varying connectedness patterns of the USA, the Eurozone and Japan over four quarters. In each case, the area of the central circle represents the own region FEV contribution, while the area of the five surrounding circles represents the FEV contribution from the named region (or the oil price). All of the circles are on the same scale so the figures are directly comparable. The distance of the outer circles from the inner circle in each case is inversely proportional to the to-between contribution, where the distances are normalised against the FEV contribution from the US to ROW in the first horizon for convenience. Note that in the specific case of oil in the figures for the Eurozone and Japan, the scale is multiplied by a factor of three to avoid distorting the figure because the FEV contributions from these countries to the oil price is so weak.

Consider the case of the USA first. The own FEV contribution is very significant in this case and remains roughly constant through time. The FEV contribution from the ROW to
the US is approximately one-third as large as the own contribution and is the largest external factor followed by the oil price, the BICs and the Eurozone (each of which are of roughly equal magnitude) and then by Japan, which exerts only a modest influence on the US economy. Interestingly, we find that the contribution from the Eurozone to the US strengthens through time, while the others remain relatively constant.

The FEV contributions to the other regions from the US are very interesting. The US exerts a dominant influence on the ROW at all horizons as one may expect. Similarly, it exerts a very strong effect on the BICs and Japan and a strong effect on Europe, all of which strengthen through time. By contrast, the influence of the US on the oil price is relatively weak, and weakens gradually as the horizon increases. As noted above, this reflects OPEC’s supply management policies which insulate the crude oil market from demand shifts to a large extent.

Moving on to the case of the Eurozone, we find that the own contribution is again considerable, and weakens very gradually at longer horizons. The effect of the ROW on Europe is stronger than it was for the US, while the US also exerts a strong influence on the Eurozone economy, particularly at longer horizons. The effect of the BICs is roughly the same as it was in the US case, although Japan has a considerably stronger effect on the Eurozone economy than on the US, reflecting the stronger bilateral trading relationship. Looking at the FEV contributions from the Eurozone to the other regions, we observe a strong connection to the ROW and to the BICs, and a moderately strong connection to Japan, all of which are largely constant over the four quarter horizon. By contrast, the Eurozone does not affect the USA as strongly as the USA affects the Eurozone, but its influence increases rapidly with the horizon. Finally, the Eurozone does not exert any significant influence over the oil price.

Finally, consider the case of Japan. Here, we find that the own contribution is much smaller than it was for the US or the Eurozone, and that it weakens at longer horizons. The ROW and the USA are major contributors to the Japanese FEVD at all horizons, with the influence of the USA strengthening through time. The BICs and the Eurozone are also significant contributors, and exert a roughly equal influence on the Japanese economy. The FEV contributions from Japan to the other regions are much weaker than in the previous two cases, reflecting the fact that the Japanese economy is not a principal factor driving outcomes in the world economy. The strongest linkages are from Japan to ROW and the BICs, and in each case the strength of the linkage does not vary significantly through time. Japan exerts a non-negligible influence on the Eurozone, although it rapidly weakens with time. Meanwhile, its influence on the US economy is fairly weak, while its influence on the oil price is negligible.

4.2.4 G-GCMs: Variable-Group Connectedness

Our final exercise considers the case of connections between groups of common variables across the countries in our sample. Figure 12 plots the from-between, to-between and net contributions among the eight variable-groups, as well as the own and within-group FEV contributions. As before, the oil price is a strong net contributor. Among the remaining variable groups, the only notable net transmitter is the stock market, reflecting its role as a leading indicator of real economic activity and as a gauge of economic sentiment more broadly, and its important underlying role in influencing the level of investment spending by many private enterprises.
The largest net receivers are exports and imports, which is an intuitively pleasing result. Similarly, the interest rate is a large net receiver, which is an appropriate reflection of its role as a policy instrument used in stabilising national economies in the wake of shocks, particularly shocks to inflation and growth. It is, therefore, appropriate to note that inflation acts as a modest net contributor in the short-run, while the same is true of output in the long-run. Interestingly, while it is a major net receiver in the short-run the exchange rate reaches a net position of roughly zero in the long-run. It also exhibits the largest within contribution by some way, reflecting the fact that the exchange rate of one currency is defined relative to others and hence a change in the value of the Euro, for example, will have an impact on the relative value of Sterling, the Yen etc. The only other variable group which exhibits non-negligible within-group effects is the stock market, which is a plausible finding. The relatively weak within-group effects are interesting, as they suggest that the main linkages are not between common variables across countries but between different groups of variables.

5 Concluding Remarks

In this paper, we have developed a family of Generalized Connectedness Measures (GCMs) which extend upon the work of Diebold and Yilmaz (2009; 2011). We demonstrate that our approach is more general than theirs because it preserves information without loss across horizons and it is robust to both variable re-ordering and aggregation. Furthermore, and most importantly, we introduce a new stratum between the level of individual variables and the level of systemwide aggregates which allows us to measure connectedness between countries, regions and variable groups.

Throughout the paper, we demonstrate that our GCMs possess a wide array of desirable attributes. They are readily calculable using standard software and their interpretation requires nothing more than a basic knowledge of economic modelling techniques. These two features greatly facilitate their replication by independent researchers and will naturally enhance their transparency. Moreover, they may be computed based upon any model from which one can derive FEVDs, whether it is an estimated model or a simulated model, and regardless of whether one wishes to impose theoretical or statistical restrictions on either the long-run or short-run model parameters. Our GCMs effectively condense the output generated by large economic models, thereby alleviating the processing constraint and unlocking more of the potential of existing techniques for the estimation of multi-country and global models. This reduction of the output dimensionality of large models is achieved by making explicit reference to geographical units and employing regional aggregation. This is not only a natural direction to pursue when working with multi-country and global models, but it also greatly facilitates the presentation and communication of our connectedness measures to non-economists. Finally, we note that the level of aggregation of our GCMs may be freely chosen by the modeller (or even user-defined if one were to develop an appropriate interactive platform), thereby naturally focusing the analysis at an appropriate level of aggregation and achieving a singularly clear representation. These attributes collectively render our approach ideally suited to dissemination among non-specialist
audiences, a feature which is likely to be of significant appeal in policymaking and regulatory environments.

By computing GCMs at various levels of aggregation based on the 176 variable 26 country GNS GVAR model, we derive a rich and vivid representation of the connectedness of the global economy. The quote with which we open this paper promotes a simple but widely held view of globalisation whereby domestic shocks are not contained by national boundaries and may, therefore, spread rapidly and forcefully within the global economy. A careful analysis of our results partially validates this view. We find that spillovers between countries and regions are very significant and that, in many cases, domestic factors are not the dominant force driving domestic conditions in anything but the short horizon. This observation fundamentally underscores the importance of our work, providing an unambiguous impetus to model these spillovers in a comprehensive manner.

However, our results also reveal that the majority of the spillovers come from the US, the Eurozone and the crude oil market, which therefore act as the key shock transmitters in the global economy. Shocks within these regions (including the Gulf states in terms of oil production) are therefore of global significance. This has been demonstrated with unusual clarity by the unprecedented global fallout of the GFC and the ongoing concern over the nascent European debt crisis. On the other hand, we identify another group of economies in which domestic shocks are not strongly transmitted beyond their boundaries but where foreign shocks may exert profound effects on the domestic economy. These are not just small peripheral economies, but globally significant open economies such as Japan and the UK. This provides a simple explanation of why the GFC, rooted as it was in the US economy, was so much more damaging than the UK Black Wednesday event, the 1997 Asian financial crises and the collapse of the Japanese bubble earlier in the same decade. Simply put, these regions are not strongly connected to the global economy in an outward (shock-propagating) sense, rather in an inward (shock-receiving) sense. We are therefore able to identify and map the risk hot-spots in the global economy, providing a focus of attention for risk managers and for policymakers charged with economic stabilisation, whether at the national or supra-national level.

Our contribution to the literature is undeniably timely. In the wake of the GFC, economists and practitioners alike were faced with an urgent imperative to develop a detailed understanding of the channels by which shocks are transmitted through the global economy. Our approach offers a simple and intuitive means to illuminate these linkages in existing multi-country and global models. Furthermore, one of the key premises of this paper is that the use of such large models is typically highly selective due to the large volume of statistical output which they generate. Our GCMs provide a non-selective and comprehensive means of analysing the linkages embodied in large models without running into the processing constraints that one would typically encounter. As the range and sophistication of global models increases, and as their use becomes increasingly widespread among policy institutions in particular, so the potential to employ our methodology grows.
References


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**Note:** r, n and k are the numbers of cointegrating vectors, endogenous variables and exogenous variables for each country/region, respectively. (●) is our chosen break point.

* For our purposes, the Eurozone includes Austria, Belgium, Finland, France, Germany, Italy, the Netherlands and Spain only. Eurozone data are constructed by aggregating the contributions of these member states using a PPP-GDP weighting scheme. The only exceptions are the Eurozone’s export and import series, which are the total of member states’ exports and imports, respectively.

Table 1: Details of the Specification of the GNS GVAR Model
### Table 2: The Trivariate Connectedness Matrix at Horizon \( h \)

<table>
<thead>
<tr>
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<th>( x )</th>
<th>( y )</th>
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<td>( \eta_{xz,h} )</td>
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<td>( y )</td>
<td>( \eta_{yx,h} )</td>
<td>( \eta_{yy,h} )</td>
<td>( \eta_{yz,h} )</td>
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<td>( z )</td>
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<td>( \eta_{zy,h} )</td>
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<td>( \eta_{xx,h} + \eta_{yy,h} + \eta_{zz,h} )</td>
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<td>Spillovers to others</td>
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### Table 3: Visualising the Directional Network at a Given Horizon

#### Table 3: Visualising the Directional Network at a Given Horizon

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<thead>
<tr>
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### Table 4: Aggregation of Normalized GFEVDs

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<tr>
<td>( y + z )</td>
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Table 3: Visualising the Directional Network at a Given Horizon
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<td>0.a</td>
<td>$H^V_{j\leftarrow j} = \phi_{j\leftarrow j}$</td>
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<td>$T^V_{\bullet \leftarrow j} = \sum_{i=1,i\neq j}^m \phi_{i\leftarrow j}$</td>
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<tr>
<td>Cross-variable NET contribution</td>
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<td>$N^V_{\bullet \leftarrow j} = T^V_{\bullet \leftarrow j} - F^V_{j \leftarrow \cdot}$</td>
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<td>Within</td>
<td>Total Contribution</td>
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<td>$O^B_k = \sum_{b=1}^{b} B_{k\leftarrow b} 1^b_{m_k} 1^b_{m_k}$</td>
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<td>$O^B_{k\leftarrow k}^{O} = \text{tr}(B_{k\leftarrow k})$</td>
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<td>1.a.ii</td>
<td>$O^B_{k\leftarrow k}^{C} = O^B_{k\leftarrow k} - O^B_{k\leftarrow k}^{O}$</td>
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<td>$S^B_{k\leftarrow \ell} = \sum_{b=1}^{b} B_{k\leftarrow \ell} 1^b_{m_k} 1^b_{m_{\ell}}$</td>
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<td></td>
<td>FROM Block $\ell$ to Block $k$</td>
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<td>$S^B_{k\leftarrow \ell} = 1^b_{m_k} B_{k\leftarrow \ell} 1^b_{m_{\ell}}$</td>
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<td>1.c</td>
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<td>from Block $k$ TO Block $\ell$</td>
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<td>Cross-variable total NET contribution</td>
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<td>$S^B_{\bullet\leftarrow k} = T^B_{\bullet\leftarrow k} - F^B_{k\leftarrow \cdot}$</td>
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<td>from Block $k$ TO Block $\ell$</td>
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<td>$S^B_{\bullet\leftarrow k} = T^B_{\bullet\leftarrow k} - F^B_{k\leftarrow \cdot}$</td>
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</table>

*m* denotes the number of global endogenous variables in the system, *b* the number of blocks used in aggregation and *m* (*m*) the number of variables in blocks *k* (*\ell*). To enhance the clarity of our notation we suppress the horizon index although it should be clear that all of the connectedness measures derived in this Table vary with the forecast horizon.

Table 5: Summary of Terminology and Key Measures
Figure 1: GFEVDs of US variables

Figure 2: GFEVDs of Eurozone variables
Figure 3: GFEVDs of Japanese variables

Figure 4: GFEVDs of Chinese variables
Figure 5: Aggregate Connectedness Measures
Figure 6: Connectedness Among 26 Countries
Figure 7: Transmission Ratio at $h = 1$

Figure 8: Transmission Ratio at $h = 4$

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Figure 9: Transmission Ratio at $h = 12$
Figure 10: Connectedness Among 11 Regions
Figure 11: Connectedness of the USA, the Eurozone and Japan
Figure 12: Connectedness Among 8 Variable Groups