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Abstract

We develop a technique to evaluate macroeconomic connectedness in any multi-country macroeconomic model with an approximate VAR representation. We apply our technique to a large Global VAR covering 25 countries and derive vivid representations of the connectedness of the system. We show that the US, the Eurozone and the crude oil market exert a dominant influence in the global economy and that the Chinese and Brazilian economies are also globally significant. Recursive analysis over the period of the global financial crisis shows that shocks to global equity markets are rapidly and forcefully transmitted to real trade flows and real GDP.

JEL classification: C32, C53, E17

Keywords: Generalised Connectedness Measures (GCMs), international linkages, network analysis, macroeconomic connectedness

Globalization makes it impossible for modern societies to collapse in isolation
— Jared Diamond

1 Introduction

Globalisation is the process of increasing interdependence among entities in the global economy. In layman's terms, the world is becoming 'smaller' and the distinction between national, regional and global issues less well-defined. Established views of the benefits of globalisation in relation to openness, liberalisation and development have been challenged in light of the Global Financial Crisis (GFC), which has drawn renewed attention to the risks posed by aspects of financial globalisation (Mishkin, 2011). Recent research into financial connectedness has reshaped our understanding of systemic linkages and has shed new light on the identification and supervision of institutions which are 'too big' or 'too connected' to fail (IMF, 2009). However, our understanding of international macroeconomic linkages has not advanced to the same degree and the network structure of the global economy remains poorly understood. We address this lacuna by developing an innovative and highly adaptable graph-theoretic framework to evaluate macroeconomic connectedness in a wide class of multi-country and global macroeconomic models.

International linkages may arise through diverse channels including financial linkages, trade linkages and relative price changes (Dees et al., 2007). We therefore consider macroeconomic connectedness to be an intrinsically multi-dimensional concept. However, the existing literature has focused almost exclusively on a single aspect of macroeconomic connectedness, namely the apparent convergence of business cycles across countries. A degree of consensus has emerged around the notion of a global business cycle which induces some common behaviour in national business cycles (e.g. Kose et al., 2003, 2008; Hirata et al., 2013, inter alia). Much of this research has modelled the global business cycle as a latent factor, an approach which is attractive by virtue of its parsimony. This an important consideration in light of the relatively short sample lengths and low sampling frequencies associated with much macroeconomic data. Indeed, the dimensional constraint was a key motivation underlying Croux et al.'s (2001) development of a synthetic measure of synchronisation across countries/regions which is defined in the frequency domain as opposed to the time domain.

Their ‘cohesion’ measure can be used to trace the comovement of multiple costationary time series and its application to European sovereign and US state-level business cycles further supports the synchronisation hypothesis.

Although Croux et al. stress that estimating VAR models may be ‘problematic when the number of time series is large’ (p. 232), subsequent innovations in the estimation of large multi-country VAR models — notably panel/global VAR (Pesaran et al., 2004), factor augmented VAR (Bernanke et al., 2005) and large Bayesian VAR (De Mol et al., 2008) — have relaxed this constraint. Consequently, it is now possible to estimate large macroeconometric models in the time domain. Canova et al. (2007) were among the first to apply these techniques to the analysis of business cycle convergence, estimating a Bayesian panel VAR model which again highlights the importance of a global cycle relative to idiosyncratic effects.

In principle, a sufficiently detailed multi-country system provides a route to model the global business cycle as an observable process defined by the interaction of the countries comprising the model without recourse to latent factors. Consequently, sophisticated multi-country models may provide a new perspective on the issues of globalisation and regionalisation that have emerged prominently in the existing literature, most recently in Hirata et al. (2013). A further advantage of these sophisticated models is that, by easing the dimensional constraint, they are able to accommodate a far greater wealth of interactions among countries and regions than was previously possible. This opens a new avenue to study macroeconomic connectedness in a truly multi-dimensional sense as opposed to focusing simply on business cycle convergence.

Unfortunately, however, the development of techniques for global macroeconometric modelling has yet to be met by concomitant advances in techniques for the analysis of the linkages embedded within these models. Even as progress in the estimation of large VAR models has mitigated the curse of dimensionality associated with the limits imposed by the range and frequency of existing macroeconomic datasets, so it has introduced a new curse of dimensionality associated with one’s ability to adequately process the model output. Consequently, the analysis of such models tends to be highly selective and does not properly illuminate the network of linkages among variables in the system.

Significantly, unlike much of the recent literature on financial connectedness, the existing business cycle literature is largely ungrounded in network theory (Diebold and Yilmaz, 2015). Yet network models provide a natural vehicle for the analysis of complex systems — such as the global economy — which are composed of many interconnected entities. Our key contribution is therefore to unite recent advances in global macroeconomic modelling with state of the art developments in network analysis from the finance literature. Leading examples of financial network models include Billio et al. (2012) and Diebold and Yilmaz (2009, 2014; henceforth DY).[1] In this literature, financial institutions are characterised as nodes within a network. Analysing the network topology provides a means to identify systemically important institutions and to study the propagation of shocks. Billio et al. propose the use of a Granger causal network, while Diebold and Yilmaz develop connectedness measures based on error variance decomposition of a vector autoregression. The DY approach has the considerable advantage that it fully accounts for contemporaneous effects and it also directly measures not only the direction but also the strength of linkages among nodes in the network.

Our approach requires an innovative and non-trivial generalisation of the DY connectedness measures. The DY approach was originally developed to study connectedness either in the multi-country univariate case (e.g. Diebold and Yilmaz, 2009) or in the single-country multivariate case (e.g. Diebold and Yilmaz, 2014). To see this, note that the DY approach operates at two extremes: complete aggregation where the $m(m-1)$ bilateral linkages in an m variable model are aggregated into a single spillover index, or no aggregation where the $m(m-1)$ bilateral linkages are studied individually. In a multi-country model with multiple variables per country — a setting which is typical of sophisticated global models and which is central to our notion of multi-dimensional macroeconomic connectedness — one may wish to analyse linkages among countries or regions rather than among individual variables.

Our solution to this issue is to introduce intermediate levels of aggregation, yielding a framework for the construction of *generalised connectedness measures* (GCMs). We show that one is free to use any desired aggregation scheme and that by defining an appropriate aggregation scheme one may evaluate connectedness among a wide variety of entities in

[1] Financial network models have also been developed by simulation. Such simulations typically employ data on bilateral exposures among financial institutions to measure the strength of pairwise connections between nodes in the network. With this structure in place, modellers are able to simulate a credit event at a chosen 'trigger' institution and then trace the subsequent propagation of the shock through the system. Such analyses contributed significantly to our understanding of contagion during the GFC (see IMF, 2009, and the references therein). However, this method cannot be readily generalised to the study of macroeconomic connectedness as no uncontroversial proxy exists to measure the degree to which one country/region is exposed to another in a general sense (Gray et al., 2013).

the global economy. For example, by defining an aggregation scheme based on geographic units, one is able to distill a wealth of information on the multitude of connections among countries/regions into an easily interpreted form. Similarly, by aggregating real variables and financial variables into separate groups, one may evaluate real–financial linkages in the global economy. As such, our approach provides a considerably more general representation of macroeconomic connectedness than the literature on business cycle synchronisation and it also mitigates the processing constraints encountered with large and detailed macroeconomic models. Consequently, we unlock the potential of such models to study macroeconomic connectedness in unparalleled breadth and detail.

We apply our technique to an updated version of the macro-financial global VAR model developed by Greenwood-Nimmo, Nguyen and Shin (2012, hereafter GNS) which is initially estimated using data prior to the GFC to provide a benchmark. The model contains 169 endogenous variables covering 25 countries/regions that collectively account for the large majority of global trade and output. We exploit the conceptual links between a country's macroeconomic connectedness, its dependence on (or openness to) overseas conditions and the extent of its economic influence to draw out several key results. Firstly, our analysis identifies the US, the Eurozone, China and Brazil as the World's most influential economies. Although the US acts as the principal driver of global conditions as in Diebold and Yilmaz (2015), the emergence of regional centres is consistent with the regionalisation documented by Hirata et al. (2013). The high degree of US influence relative to that of other economies which have experienced crises in our sample period provides an intuitive explanation of the global impact of the GFC compared to the local and regional effects of Black Wednesday in the UK, the 1997 Asian financial crisis and the collapse of the Japanese bubble earlier in the same decade.

Our analysis indicates that the countries which are most dependent on external conditions are Canada, Singapore and Switzerland, all of which are strongly affected by conditions within their respective free trade areas. We also show that analysing a country's relative dependence and influence provides an elegant summary of its role within the global economy, ranging from small open economies at one extreme (high dependence, low influence) to large dominant and/or closed economies at the other (high influence, low dependence). The resulting ranking is closely consistent with that of Gwartney et al. (2013) which is based on a considerably broader information set including measures of freedom and institutional quality.

Having established a pre-GFC baseline, we recursively update our estimation sample over the GFC period. The results are striking, indicating a massive increase in total spillover activity originating from the US financial system which coincides with the collapse of Lehman Brothers. Further analysis shows that the original US financial shock was rapidly and strongly passed through to foreign exchange markets and thereafter to both nominal variables and to real economic magnitudes, with real exports and imports being particularly strongly affected. Existing research has studied each of these links separately but, to the best our knowledge, ours is the first analysis to capture all of these links in the propagation of the GFC simultaneously. Importantly, as of the end of our estimation sample in 2012q2, global connectedness remains at a higher level than it was prior to the GFC. This substantial increase in the connectedness of the global economic system raises concerns over the speed and force with which future shocks may propagate through the global economy.

Aside from the connectedness literature, our paper is most closely related to the panel VAR approach of Canova et al. (2007) and the dynamic factor model developed by Hirata et al. (2013). Both of these papers distinguish between global, regional and local effects. Canova et al. emphasise the role of a global factor influencing G7 business cycles, while Hirata et al. stress that regional factors have come to play a prominant role since the mid 1980s, during which time the role of global factors has diminished. These observations furnish an a priori case for the development of new techniques such as ours which offer a new perspective on the nature of international macroeconomic linkages.

This paper proceeds in 5 Sections. Section 2 introduces the concept of connectedness in VAR systems and provides a detailed derivation of our GCMs. Section 3 then introduces an updated version of the global VAR model developed by Greenwood-Nimmo et al. (2012) which forms the basis of our empirical analysis. The results of GCM analysis of the linkages embodied in this model are presented in Section 4, while Section 5 concludes. Further details of the derivation and the model set-up are contained in a separate Technical Annex.

2 Measuring Economic Connectedness

Following Diebold and Yilmaz (2009, 2014), the connectedness measures that we shall develop are based on the forecast error variance decomposition (FEVD) of a p-th order vector autoregression for the $m \times 1$ vector of endogenous variables $\boldsymbol{y}_t$. This approach is founded on the notion that the share of the forecast error variance (FEV) of variable i explained by shocks to variable j provides a directional measure of the association between these variables. An appealing feature of this framework is that FEVDs are computed directly from the estimated parameters and covariance matrix of the VAR system subject to no additional restrictions beyond those required for estimation and identification. As such, they provide an unadulterated reflection of the connections embedded in the model.

Abstracting from any deterministic terms, we may write the structural form of the VAR(p) model in general notation as follows:

$$\boldsymbol{H}_0 \boldsymbol{y}_t = \sum_{j=1}^{p} \boldsymbol{H}_j \boldsymbol{y}_{t-j} + \boldsymbol{u}_t \tag{1}$$

where $\boldsymbol{H}_0$ is the $m \times m$ contemporaneous matrix, the $\boldsymbol{H}_j$'s are the vector autoregressive parameter matrices and the residuals $\boldsymbol{u}_t \sim (0, \boldsymbol{\Sigma}_u)$ where $\boldsymbol{\Sigma}_u$ is positive definite. The reduced form of the model is written as:

$$\boldsymbol{y}_t = \sum_{j=1}^{p} \boldsymbol{G}_j \boldsymbol{y}_{t-j} + \boldsymbol{\varepsilon}_t \tag{2}$$

where $\boldsymbol{G}_j = \boldsymbol{H}_0^{-1} \boldsymbol{H}_j$ and $\boldsymbol{\varepsilon}_t = \boldsymbol{H}_0^{-1} \boldsymbol{u}_t$. Throughout the derivations to follow, we remain intentionally agnostic about the nature of the contemporaneous effects in the model. Indeed, a key feature of the generalised connectedness measures that we develop is that they may be derived from either the structural model (1) or the reduced form model (2) or, indeed, from any model with an approximate VAR representation, including Dynamic Stochastic General Equilibrium (DSGE) models in their state-space form (Giacomini, 2013). As always, one's choice of the underlying model will be guided by the intended application. Where one seeks to draw structural inferences then robust identification of the structural shocks is necessary. Meanwhile, if one's main interest is in characterising cyclical synchronisation and/or measuring the intensity and direction of spillover effects then a reduced form model will suffice. In a general sense, connectedness measures derived from reduced form models can be viewed as dynamic directional measures of correlation.

We will proceed with the derivation based on the reduced form model (2) without loss of generality. By Wold's Representation Theorem, it is well established that (2) has the following infinite order vector moving average representation:

$$\boldsymbol{y}_t = \sum_{j=0}^{\infty} \boldsymbol{B}_j \boldsymbol{\varepsilon}_{t-j}, \tag{3}$$

where the $\boldsymbol{B}_j$'s are evaluated recursively as $\boldsymbol{B}_j = \boldsymbol{G}_1 \boldsymbol{B}_{j-1} + \boldsymbol{G}_2 \boldsymbol{B}_{j-2} + \cdots + \boldsymbol{G}_{p-1} \boldsymbol{B}_{j-p+1}$, with $\boldsymbol{B}_0 = \boldsymbol{I}_m$ and $\boldsymbol{B}_j = \boldsymbol{0}$ for $j < 0$ such that the $\boldsymbol{B}_j$'s are square-summable and causal.

In their original paper, Diebold and Yilmaz (2009) compute connectedness measures based on orthogonalised FEVDs, whereby recursive identification of shocks is achieved by Cholesky factorization with the drawback that the results are order dependent. This is likely to be problematic in many practical applications even when working with small VAR systems. Furthermore, the assumption of Wold causality is likely to become increasingly untenable as the dimension of the VAR system increases. Therefore, in their subsequent work, Diebold and Yilmaz (2014) employ order-invariant Generalised FEVDs (GFEVDs), which may be defined following Pesaran and Shin (1998) as follows:

$$GFEVD\left(y_{it}; u_{jt}, h\right) = \varphi_{i\leftarrow j}^{(h)} = \frac{\sigma_{u,jj}^{-1} \sum_{\ell=0}^{h-1} \left(\mathbf{e}_i' \boldsymbol{B}_\ell \boldsymbol{H}_0^{-1} \boldsymbol{\Sigma}_u \mathbf{e}_j\right)^2}{\sum_{\ell=0}^{h-1} \mathbf{e}_i' \boldsymbol{B}_\ell \boldsymbol{\Sigma}_\varepsilon \boldsymbol{B}_\ell' \mathbf{e}_i} \tag{4}$$

for $i, j = 1, ..., m$, where $h = 1, 2, ...$ is the forecast horizon, $\sigma_{u,jj}^{-1}$ is the standard deviation of the residual process of the j-th equation in the VAR system, $\boldsymbol{\Sigma}_\varepsilon = \boldsymbol{H}_0^{-1} \boldsymbol{\Sigma}_u \boldsymbol{H}_0^{-1\prime}$ and $\boldsymbol{e}_i$ ($\boldsymbol{e}_j$) is an $m \times 1$ selection vector whose i-th element (j-th element) is unity with zeros elsewhere. Note our use of non-standard subscript notation which will serve to highlight the directionality of the connectedness measures in the derivations to follow. $\varphi_{i\leftarrow j}^{(h)}$ represents the contribution of variable j to the h-step ahead FEV of variable i. Similarly, $\varphi_{i\leftarrow i}^{(h)}$ denotes the contribution of variable i to its own h-step ahead FEV.

The interpretation of GFEVDs is complicated by the fact that the sum of the variance shares will exceed 100% if $\boldsymbol{\Sigma}_\varepsilon$ is non-diagonal. Therefore, Diebold and Yilmaz (2014) employ normalised GFEVDs (NGFEVDs) defined as:

$$\phi_{i\leftarrow j}^{(h)} = \varphi_{i\leftarrow j}^{(h)} / \sum_{j=1}^{m} \varphi_{i\leftarrow j}^{(h)} \tag{5}$$

such that $\sum_{j=1}^{m} \phi_{i\leftarrow j}^{(h)} = 1$ and $\sum_{i=1}^{m} \left(\sum_{j=1}^{m} \phi_{i\leftarrow j}^{(h)} \right) = m$. This restores a percentage interpretation to the GFEVDs. The key conceptual foundation of the DY framework is the recognition that cross-tabulating the h-step ahead NGFEVDs for the $m \times 1$ vector of global variables forms a weighted directed network. The resulting $m \times m$ connectedness matrix is given by:

$$\underset{(m\times m)}{\mathbb{C}^{(h)}} = \begin{bmatrix} \phi_{1\leftarrow 1}^{(h)} & \phi_{1\leftarrow 2}^{(h)} & \cdots & \phi_{1\leftarrow m}^{(h)} \\ \phi_{2\leftarrow 1}^{(h)} & \phi_{2\leftarrow 2}^{(h)} & \cdots & \phi_{1\leftarrow m}^{(h)} \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{m\leftarrow 1}^{(h)} & \phi_{m\leftarrow 2}^{(h)} & \cdots & \phi_{m\leftarrow m}^{(h)} \end{bmatrix}. \tag{6}$$

Note that the elements of the i-th row of $\mathbb{C}^{(h)}$ record the proportion of the h-step ahead FEV of the i-th variable attributable to each variable in the system. The contribution of the shock to the i-th variable itself, denoted $H_{i\leftarrow i}^{(h)}$, is recorded by the i-th diagonal element of $\mathbb{C}^{(h)}$:

$$H_{i\leftarrow i}^{(h)} = \phi_{i\leftarrow i}^{(h)}, \tag{7}$$

while the off-diagonal elements of the i-th row of $\mathbb{C}^{(h)}$ capture spillovers from the other variables in the system to variable i. Specifically, the (i, j)-th element, $\phi_{i\leftarrow j}^{(h)}$, represents the contribution to the h-step-ahead FEV of variable i from variable $j \neq i$. Adopting the terminology of Diebold and Yilmaz, this is known as a *from* contribution because it measures the directional connectedness to the i-th variable *from* variable j. By summing over j, we may define the total spillover from the system to variable i as:

$$F_{i\leftarrow \bullet}^{(h)} = \sum_{j=1, j\neq i}^{m} \phi_{i\leftarrow j}^{(h)}, \tag{8}$$

where the subscript $i \leftarrow \bullet$ indicates that the directional effect under scrutiny is from all other variables to variable i. It follows that $H_{i\leftarrow i}^{(h)} + F_{i\leftarrow \bullet}^{(h)} = \sum_{j=1}^{m} \phi_{i\leftarrow j}^{(h)} = 1$.

Spillovers from the i-th variable to the other variables in the system are recorded in the i-th column of $\mathbb{C}^{(h)}$. The contribution of variable i *to* the h-step ahead FEV of the j-th variable in the system is given by $\phi^{(h)}_{j\leftarrow i}$. By summing over j, we can compute the total spillovers from variable i to the system as:

$$T^{(h)}_{\bullet\leftarrow i} = \sum_{j=1, j\neq i}^{m} \phi^{(h)}_{j\leftarrow i}. \tag{9}$$

The net directional connectedness of variable i is then defined simply as:

$$N^{(h)}_{\bullet\leftarrow i} = T^{(h)}_{\bullet\leftarrow i} - F^{(h)}_{i\leftarrow \bullet}, \tag{10}$$

such that $\sum_{i=1}^{m} N^{(h)}_{\bullet\leftarrow i} = 0$ by construction. It is now straightforward to develop the following aggregate (non-directional) connectedness measures for the $m \times 1$ vector of global variables:

$$H^{(h)} = \sum_{i=1}^{m} H^{(h)}_{i\leftarrow i} \text{ and } S^{(h)} = \sum_{i=1}^{m} F^{(h)}_{i\leftarrow \bullet} \equiv \sum_{i=1}^{m} T^{(h)}_{\bullet\leftarrow i}. \tag{11}$$

We refer to $H^{(h)}$ and $S^{(h)}$ respectively as the h-step ahead aggregate heatwave and spillover indices, respectively, a nomenclature which follows broadly in the tradition of Engle et al. (1990) and Diebold and Yilmaz (2009).[2] Note that $H^{(h)} + S^{(h)} = m$ by definition.

2.1 Generalised Connectedness Measures

The DY connectedness measures are well suited to use in relatively small VAR systems. However, their usefulness diminishes as m — the number of variables entering the VAR system — becomes large. This is true for two reasons. Firstly, the DY approach is subject to 'processing constraints' which intensify sharply with m. That is, for a sufficiently large value of m, it will become infeasible to interpret (or process) the elements of the connectedness matrix individually. Consequently, as the system becomes larger, attention is increasingly likely to focus only the aggregate spillover and heatwave indices for reasons of expediency. Since the dimension of $\mathbb{C}^{(h)}$ is quadratic in m, the addition of an $(m+1)$th variable to the system enlarges $\mathbb{C}^{(h)}$ by $2m+1$ elements. In practice, therefore, the processing constraint may bind for a relatively low value of m.

Secondly, consider a model with $k = 1, \ldots, N$ countries each of which is described by m_k

[2]Diebold and Yilmaz (2009) define the spillover index as $100\left[S^{(h)}/\left(S^{(h)} + H^{(h)}\right)\right]$ which measures the relative importance of spillovers between variables in the system as a percentage of the systemwide FEV at horizon h.

variables such that $m = \sum_{k=1}^{N} m_k$. The DY technique is best suited to simple models where either $N = 1$ or $m_k = 1\ \forall k$.[3] This is true because the DY approach operates at two extremes: (i) one may study connectedness among the m variables in the system in a disaggregated fashion (via equations (6) to (10)); and (ii) one may study systemwide connectedness in a wholly aggregated fashion (via equation (11)). Without modification, the DY method does not accommodate intermediate levels of aggregation. Now consider the more general setting in which both $N > 1$ and $m_k > 1$, a setting which is typical of sophisticated multi-country and global models. In this case, the DY approach does not provide a simple representation of the spillover effect from country ℓ to country k because it is captured by $m_\ell m_k$ elements of $\mathbb{C}^{(h)}$ rather than by a single value. A good example of this issue arises in Greenwood-Nimmo et al. (2014), which explores the connectedness of a small Global VAR model containing two endogenous variables for each of eight foreign exchange spot markets.

We propose a simple approach to overcome both issues based on re-normalisation and block aggregation of the connectedness matrix. First, we re-normalise such that $\mathbb{C}_R^{(h)} = m^{-1}\mathbb{C}^{(h)}$. This subtly alters the interpretation of the elements of the connectedness matrix. Recall that the (i, j)-th element of $\mathbb{C}^{(h)}$ represents the proportion of the h-step ahead FEV of variable i explained by variable j. After re-normalisation, the (i, j)-th element of $\mathbb{C}_R^{(h)}$ represents the proportion of the total h-step ahead FEV of the system accounted for by the spillover effect from variable j to variable i. This subtle modification ensures that we may achieve a clear percentage interpretation even after aggregating groups of variables in the system. This would not be the case under the DY framework where the aggregation of variables into groups may lead to spillovers that exceed 100% (recall that the elements of $\mathbb{C}^{(h)}$ sum to $m \times 100\%$).

Our use of block aggregation exploits the fact that GFEVDs are invariant to the ordering of the variables in $\boldsymbol{y}_t$. We may therefore re-order $\boldsymbol{y}_t$ so that the variables are gathered together into desired groups. For example, if $\boldsymbol{y}_{k,t}$ denotes the variables that relate to country k, then we may express $\boldsymbol{y}_t$ in country order as $\boldsymbol{y}_t = \left(\boldsymbol{y}'_{1,t}, \boldsymbol{y}'_{2,t}, \ldots, \boldsymbol{y}'_{N,t}\right)'$. In this case, we may write

[3] Diebold and Yilmaz (2009) work with 19 equity markets where each market is represented by a single variable: hence $N = 19$ and $m_k = 1$ for $k = 1, \ldots, 19$. Likewise, Diebold and Yilmaz (2015) study industrial production in a group of six countries: hence, $N = 6$ and $m_k = 1$ for $k = 1, \ldots, 6$. By contrast, in their full-sample analysis, Diebold and Yilmaz (2014) work with data for 13 financial institutions drawn from the same market: hence, $N = 1$ and $m_1 = 13$.

$\mathbb{C}_R^{(h)}$ as follows:

$$\underset{(m\times m)}{\mathbb{C}_R^{(h)}} = m^{-1}\begin{bmatrix} \phi^{(h)}_{1\leftarrow 1} & \cdots & \phi^{(h)}_{1\leftarrow m_1} & \phi^{(h)}_{1\leftarrow m_1+1} & \cdots & \phi^{(h)}_{1\leftarrow m_1+m_2} & \cdots & \phi^{(h)}_{1\leftarrow m} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & & \vdots \\ \phi^{(h)}_{m_1\leftarrow 1} & \cdots & \phi^{(h)}_{m_1\leftarrow m_1} & \phi^{(h)}_{m_1\leftarrow m_1+1} & \cdots & \phi^{(h)}_{m_1\leftarrow m_1+m_2} & & \phi^{(h)}_{m_1\leftarrow m} \\ \phi^{(h)}_{m_1+1\leftarrow 1} & \cdots & \phi^{(h)}_{m_1+1\leftarrow m_1} & \phi^{(h)}_{m_1+1\leftarrow m_1+1} & \cdots & \phi^{(h)}_{m_1+1\leftarrow m_1+m_2} & & \phi^{(h)}_{m_1+1\leftarrow m} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & & \vdots \\ \phi^{(h)}_{m_1+m_2\leftarrow 1} & \cdots & \phi^{(h)}_{m_1+m_2\leftarrow m_1} & \phi^{(h)}_{m_1+m_2\leftarrow m_1+1} & \cdots & \phi^{(h)}_{m_1+m_2\leftarrow m_1+m_2} & & \phi^{(h)}_{m_1+m_2\leftarrow m} \\ \vdots & & & & & & \ddots & \vdots \\ \phi^{(h)}_{m\leftarrow 1} & \cdots & \phi^{(h)}_{m\leftarrow m_1} & \phi^{(h)}_{m\leftarrow m_1+1} & \cdots & \phi^{(h)}_{m\leftarrow m_1+m_2} & \cdots & \phi^{(h)}_{m\leftarrow m} \end{bmatrix} \tag{12}$$

The block structure of $\mathbb{C}_R^{(h)}$ is easily seen. The (k,ℓ)th block in (12), denoted $\mathbf{B}^{(h)}_{k\leftarrow\ell}$, is given by:

$$\underset{(k\times\ell)}{\mathbf{B}^{(h)}_{k\leftarrow\ell}} = m^{-1}\begin{bmatrix} \phi^{(h)}_{\tilde{m}_k+1\leftarrow\tilde{m}_\ell+1} & \cdots & \phi^{(h)}_{\tilde{m}_k+1\leftarrow\tilde{m}_\ell+m_\ell} \\ \vdots & \ddots & \vdots \\ \phi^{(h)}_{\tilde{m}_k+m_k\leftarrow\tilde{m}_\ell+1} & \cdots & \phi^{(h)}_{\tilde{m}_k+m_k\leftarrow\tilde{m}_\ell+m_\ell} \end{bmatrix} \tag{13}$$

for $k,\ell = 1,...,N$ where $\widetilde{m}_k = \sum_{k=1}^{k-1} m_k$. While the preceding example highlights the formation of country-level blocks, we stress that $\boldsymbol{y}_t$ can be re-ordered freely to support *any desired block aggregation scheme*, whether one is interested in connectedness among countries, regions, economic blocs or other arbitrary groups of variables. Furthermore, there is no requirement that the groups contain the same number or even a similar number of variables. For example, in a model with a global common factor such as the oil price (e.g. Dees et al., 2007), the factor could be treated as a separate group when evaluating connectedness among countries and, in turn, each country could be represented by a different number of variables. We provide several additional examples of group selection and the associated block structure of the connectedness matrix in the Technical Annex.

Having ordered $\boldsymbol{y}_t$ into b groups which define the b^2 blocks consistent with one's desired aggregation scheme, $\mathbb{C}_R^{(h)}$ can be expressed in block form as follows:

$$\underset{(m\times m)}{\mathbb{C}_R^{(h)}} = \begin{bmatrix} \mathbf{B}_{1\leftarrow 1}^{(h)} & \mathbf{B}_{1\leftarrow 2}^{(h)} & \cdots & \mathbf{B}_{1\leftarrow b}^{(h)} \\ \mathbf{B}_{2\leftarrow 1}^{(h)} & \mathbf{B}_{2\leftarrow 2}^{(h)} & \cdots & \mathbf{B}_{2\leftarrow b}^{(h)} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{B}_{b\leftarrow 1}^{(h)} & \mathbf{B}_{b\leftarrow 2}^{(h)} & \cdots & \mathbf{B}_{b\leftarrow b}^{(h)} \end{bmatrix}. \tag{14}$$

No information is lost in this process but by grouping variables in this way we introduce a new stratum between the variable level and the systemwide aggregate level at which we may evaluate connectedness. The blocks lying on the prime diagonal of $\mathbb{C}_R^{(h)}$ (i.e. the $\mathbf{B}_{k\leftarrow k}^{(h)}$'s) contain all of the within-group FEV contributions. We therefore define the total within-group FEV contribution for the k-th group as follows:

$$\mathcal{W}_{k\leftarrow k}^{(h)} = \mathbf{e}'_{m_k}\mathbf{B}_{k\leftarrow k}^{(h)}\mathbf{e}_{m_k} \tag{15}$$

where $\mathbf{e}_{m_k}$ is an $m_k \times 1$ column vector of ones and where we employ caligraphic notation to distinguish our GCMs defined at the group level from the Diebold-Yilmaz connectedness measures defined at the variable level. That is, the within-group FEV contribution for the k-th group is equal to the sum of the elements of the block $\mathbf{B}_{k\leftarrow k}^{(h)}$.[4] By analogy, the $\mathbf{B}_{k\leftarrow \ell}$'s for $k \neq \ell$ relate to the transmission of information across groups. We are therefore able to define the spillover from group ℓ to group k as:

$$\mathcal{F}_{k\leftarrow \ell}^{(h)} = \mathbf{e}'_{m_k}\mathbf{B}_{k\leftarrow \ell}^{(h)}\mathbf{e}_{m_\ell} \tag{16}$$

and the spillover to group k from group ℓ as:

$$\mathcal{T}_{\ell\leftarrow k}^{(h)} = \mathbf{e}'_{m_\ell}\mathbf{B}_{\ell\leftarrow k}^{(h)}\mathbf{e}_{m_k}. \tag{17}$$

With these definitions in hand, it is straightforward to obtain the following h-step ahead

[4]In some cases it may be useful to decompose the within-group FEV contribution, $\mathcal{W}_{k\leftarrow k}^{(h)}$, into the own-variable and cross-variable FEV contributions within group k, denoted $O_{k\leftarrow k}^{(h)}$ and $C_{k\leftarrow k}^{(h)}$ respectively. Hence, we may write $\mathcal{W}_{k\leftarrow k}^{(h)} = O_{k\leftarrow k}^{(h)} + C_{k\leftarrow k}^{(h)}$ where $O_{k\leftarrow k}^{(h)} = \text{trace}\left(\mathbf{B}_{k\leftarrow k}^{(h)}\right)$ and $C_{k\leftarrow k}^{(h)} = \mathcal{W}_{k\leftarrow k}^{(h)} - O_{k\leftarrow k}^{(h)}$.

group connectedness matrix:

$$\underset{(b\times b)}{\mathbb{B}^{(h)}} = \begin{bmatrix} \mathcal{W}^{(h)}_{1\leftarrow 1} & \mathcal{F}^{(h)}_{1\leftarrow 2} & \cdots & \mathcal{F}^{(h)}_{1\leftarrow b} \\ \mathcal{F}^{(h)}_{2\leftarrow 1} & \mathcal{W}^{(h)}_{2\leftarrow 2} & \cdots & \mathcal{F}^{(h)}_{2\leftarrow b} \\ \vdots & \vdots & \ddots & \vdots \\ \mathcal{F}^{(h)}_{b\leftarrow 1} & \mathcal{F}^{(h)}_{b\leftarrow 2} & \cdots & \mathcal{W}^{(h)}_{b\leftarrow b} \end{bmatrix} \equiv \begin{bmatrix} \mathcal{W}^{(h)}_{1\leftarrow 1} & \mathcal{T}^{(h)}_{1\leftarrow 2} & \cdots & \mathcal{T}^{(h)}_{1\leftarrow b} \\ \mathcal{T}^{(h)}_{2\leftarrow 1} & \mathcal{W}^{(h)}_{2\leftarrow 2} & \cdots & \mathcal{T}^{(h)}_{2\leftarrow b} \\ \vdots & \vdots & \ddots & \vdots \\ \mathcal{T}^{(h)}_{b\leftarrow 1} & \mathcal{T}^{(h)}_{b\leftarrow 2} & \cdots & \mathcal{W}^{(h)}_{b\leftarrow b} \end{bmatrix} \tag{18}$$

Note that the dimension of the group connectedness matrix is $b^2 < m^2$ which implies that working with the group connectedness matrix can significantly ease the processing constraints encountered in large models. Using (18), it is straightforward to develop aggregate connectedness measures at the group level. The total *from*, *to* and *net* connectedness of the k-th group are defined as follows:

$$\mathcal{F}^{(h)}_{k\leftarrow\bullet} = \sum_{\ell=1,\ell\neq k}^{b} \mathcal{F}^{(h)}_{k\leftarrow\ell} \ , \ \mathcal{T}^{(h)}_{\bullet\leftarrow k} = \sum_{\ell=1,\ell\neq k}^{b} \mathcal{T}^{(h)}_{\ell\leftarrow k} \ \text{ and } \ \mathcal{N}^{(h)}_{\bullet\leftarrow k} = \mathcal{T}^{(h)}_{\bullet\leftarrow k} - \mathcal{F}^{(h)}_{k\leftarrow\bullet}, \tag{19}$$

where $\mathcal{F}^{(h)}_{k\leftarrow\bullet}$ measures the total spillover from all other groups to group k (i.e. the total *from* contribution affecting group k), $\mathcal{T}^{(h)}_{\bullet\leftarrow k}$ measures the total spillover to all other groups from group k (i.e. the total *to* contribution arising from group k) and $\mathcal{N}^{(h)}_{\bullet\leftarrow k}$ is the net connectedness of group k. Similarly, it is possible to define the aggregate heatwave and spillover indices in terms of the b groups as follows:

$$\mathcal{H}^{(h)} = \sum_{k=1}^{b} \mathcal{W}^{(h)}_{k\leftarrow k} \ \text{ and } \ \mathcal{S}^{(h)} = \sum_{k=1}^{b} \mathcal{F}^{(h)}_{k\leftarrow\bullet} \equiv \sum_{k=1}^{b} \mathcal{T}^{(h)}_{\bullet\leftarrow k} \tag{20}$$

where $\mathcal{H}^{(h)} + \mathcal{S}^{(h)} = 1$ and $\sum_{k=1}^{b} \mathcal{N}^{(h)}_{\bullet\leftarrow k} = 0 \ \forall h$ by construction. Note that unlike the DY heatwave and spillover measures, $\mathcal{H}^{(h)}$ and $\mathcal{S}^{(h)}$ measure the heatwave and spillover effects consistent with the chosen aggregation routine.

Finally, we define a pair of indices to succinctly address two questions of particular interest when measuring macroeconomic connectedness: (i) '*how dependent is the k-th group on external conditions?*' and (ii) '*to what extent does the k-th group influence/is the k-th group influenced by the system as a whole?*'. These measures are especially relevant when evaluating connectedness among geo-political units such as countries and economic blocs within the global economy. In response to the first question, we propose the following *dependence index*:

$$\mathcal{O}_k^{(h)} = \frac{\mathcal{F}_{k\leftarrow\bullet}^{(h)}}{\mathcal{W}_{k\leftarrow k}^{(h)} + \mathcal{F}_{k\leftarrow\bullet}^{(h)}}, \tag{21}$$

where $0 \leq \mathcal{O}_k^{(h)} \leq 1$ expresses the relative importance of external shocks for the k-th group. Specifically, as $\mathcal{O}_k^{(h)} \rightarrow 1$ then conditions in group k are dominated by external shocks while group k is unaffected by external shocks if $\mathcal{O}_k^{(h)} \rightarrow 0$. In a similar vein, we develop the *influence index*:

$$\mathcal{I}_k^{(h)} = \frac{\mathcal{N}_{\bullet\leftarrow k}^{(h)}}{\mathcal{T}_{\bullet\leftarrow k}^{(h)} + \mathcal{F}_{k\leftarrow\bullet}^{(h)}} \tag{22}$$

where $-1 \leq \mathcal{I}_k^{(h)} \leq 1$. For any horizon h, the k-th group is a net shock recipient if $-1 \leq \mathcal{I}_k^{(h)} < 0$, a net shock transmitter if $0 < \mathcal{I}_k^{(h)} \leq 1$, and neither a net transmitter or recipient if $\mathcal{I}_k^{(h)} = 0$. As such, the influence index measures the extent to which the k-th group influences or is influenced by conditions in the system.[5] When studying connectedness among countries, the coordinate pair $\left(\mathcal{O}_k^{(h)}, \mathcal{I}_k^{(h)}\right)$ in dependence–influence space provides an elegant representation of country k's role in the global system. A classic small open economy would be located close to the point $(1, -1)$ while, by contrast, an overwhelmingly dominant economy would exist in the locale of $(0, 1)$. In this way, we are able to measure the extent to which the different economies of the world correspond to these stylised concepts.

3 The GNS Global Model

We apply our framework to an updated version of the global cointegrating VAR model developed by Greenwood-Nimmo et al. (2012) which, in turn, owes a significant intellectual debt to Dees et al. (2007). This model provides an ideal basis for the evaluation of macroeconomic connectedness as it is a large system composed of multiple countries which collectively account for the majority of global activity. Furthermore, the model includes a range of key macroeconomic and financial indicators relating to real output, real trade flows, price level

[5] In some cases, one may be interested in measuring bilateral influence between two countries, such as the US and China. The bilateral influence index between groups k and ℓ can be defined analogously as follows:

$$\mathcal{I}_{\ell\leftarrow k}^{(h)} = \frac{\mathcal{N}_{\ell\leftarrow k}^{(h)}}{\mathcal{T}_{\ell\leftarrow k}^{(h)} + \mathcal{F}_{k\leftarrow \ell}^{(h)}}$$

which is also bounded between -1 and 1 and is interpreted in a similar manner to (22). Note that $\mathcal{I}_{\ell\leftarrow k}^{(h)} = -\mathcal{I}_{k\leftarrow \ell}^{(h)}$ by definition.

inflation and the financial markets. Recall, however, that our technique can be applied to any model with an approximate VAR representation.

Our updated model (henceforth the GNS25 model) differs from that of Greenwood-Nimmo et al. (2012) in two respects. Firstly, the GNS25 model excludes Argentina, as this proves necessary to ensure dynamically stable solutions once the sample period is extended to include the crisis period. This does not significantly alter the essential features of the model. Secondly, the global covariance matrix in the GNS25 model is estimated with greater precision. Specifically, we exclude any covariance terms which are found to be insignificant using the cross section dependence test of Pesaran (2004). This increased precision is particularly important because our GCMs depend upon both the parameter matrices and the covariance matrix of the global VAR. In all other respects, the GNS25 model is identical to that of Greenwood-Nimmo et al. (2012). We therefore limit our discussion to a concise summary of the model, with further details in the Technical Annex.

The GNS25 model is estimated using quarterly data spanning the reference sample period 1980q2–2007q2[6] for the $i = 1, 2, \ldots, 25$ economies listed in Table 1. Our dataset covers all major economies for which reliable data are available. The 25 countries that we include account for approximately 90% of world output and for the large majority of bilateral trade. For each economy, $i = 1, 2, \ldots, 25$, we estimate a country-specific VARX*(2,2) model of the following form:

$$\boldsymbol{y}_{it} = \boldsymbol{\gamma}_{i0} + \boldsymbol{\gamma}_{i1} t + \sum_{j=0}^{2} \boldsymbol{\delta}_{ij} d_{i,t-j} + \sum_{j=1}^{2} \boldsymbol{\Phi}_{ij} \boldsymbol{y}_{i,t-j} + \sum_{j=0}^{2} \boldsymbol{\Phi}^{*}_{ij} \boldsymbol{y}^{*}_{i,t-j} + \boldsymbol{u}_{it} \tag{23}$$

where $\boldsymbol{y}_{it}$ is an $m_i \times 1$ vector of endogenous variables, $\boldsymbol{y}^{*}_{it}$ is a corresponding $m^{*}_{i} \times 1$ vector of weakly exogenous country-specific foreign variables defined below, d_{it} is a country-specific one-time permanent intercept shift term, $\boldsymbol{u}_{it}$ is a serially uncorrelated mean-zero process with positive definite covariance matrix $\boldsymbol{\Sigma}_{u,ii}$ and Greek letters represent unknown parameters to be estimated. The country-specific structural breaks included in the GNS25 model are detailed in Table 1.[7] The inclusion of country-specific break dummies accounts for local

[6] This is the same sample period considered by Greenwood-Nimmo et al. (2012) and is used here to provide benchmark results for the period prior to the GFC. As discussed below, we also estimate the GNS25 model recursively using samples starting in 1980q2 and ending in 2005q2,. . .,2012q3.

[7] Where no structural break can be detected for the i-th country using the CUSUM test advanced by Brown et al. (1975), then the i-th model is estimated excluding the break dummies.

structural breaks which are not accommodated by co-breaking. In principle, one could model the GFC as a global break but, instead, we elect to study it via recursive estimation which allows the model parameters and the associated functions of these paramaters — including our GCMs — to evolve with the sample.

— Insert Table 1 about here —

The foreign variables from the perspective of the i-th country, $\boldsymbol{y}_{it}^* = \left(y_{1,it}^*, y_{2,it}^*, \ldots, y_{m_i^*,it}^*\right)'$, are constructed as a weighted average of the variables from the other countries in the system such that $y_{1,it}^* = \sum_{j=1}^N w_{ij} y_{1,jt}$ and likewise for variables $2, \ldots, m_i^*$. Following Dees et al. (2007), the weights (the w_{ij}'s) are computed using bilateral trade averages over the period 1999–2001 and they satisfy $\sum_{j=0}^N w_{ij} = 1$ and $w_{ii} = 0$.[8]

Unit root testing reveals that the series used in estimation are difference stationary, so the country-specific VARX*(2,2) models are estimated in error correction form where the deterministic time trends are restricted to the cointegrating vectors while the intercepts and break dummies enter the model in an unrestricted manner. The variables entering each country-specific model are recorded in Table 1. For all countries apart from the US, the variables are drawn from the following: the real effective exchange rate (re_{it}), 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 (Δp_{it}) and the log of real output (y_{it}). The omission of stock market data for China, Indonesia, Peru and Turkey and the omission of both stock market data and the short-term interest rate for Saudi Arabia is necessitated by the lack of reliable data spanning our sample period. Furthermore, ex_{it}^* and im_{it}^* are excluded from the set of weakly exogenous variables in all cases because, in a model such as ours with considerable coverage of world trade, $im_{it} \approx ex_{it}^*$ and $ex_{it} \approx im_{it}^*$ by definition.

As the dominant economy in the system, the US is modelled slightly differently. Specifically, the log of the spot oil price (p_t^o) is treated as endogenous to the US while the Dollar exchange rate e_{it} is assumed to be determined in the other country-specific models in the system and is, therefore, treated as weakly exogenous to the US.[9] Furthermore, due to the

[8]A range of alternative weighting schemes were tested in Greenwood-Nimmo et al. (2012) and were found to yield qualitatively and quantitatively similar results. A similar conclusion was reached by Dees et al. (2007).

[9]Following Dees et al. (2007), the log real effective exchange rate is defined as $re_{it} = ee_{it} + p_{it}^* - p_{it}$. Note that $ee_{it} + p_{it}^* - p_{it} = (e_{it} - p_{it}) - (e_{it}^* - p_{it}^*) = \tilde{e}_{it} - \tilde{e}_{it}^*$, where e_{it} is the nominal exchange rate *vis-à-vis* the

dominance of the US in the world economy, r^*_{1t} and q^*_{1t} are likely to respond to conditions in the US, violating the assumption of their weak exogeneity — both are therefore excluded from the US model.

The country-specific VARX* models, (23), may be expressed compactly as:

$$\boldsymbol{A}_{i0}\boldsymbol{z}_{it} = \boldsymbol{\gamma}_{i0} + \boldsymbol{\gamma}_{i1}t + \sum_{j=0}^{2}\boldsymbol{\delta}_{ij}d_{i,t-j} + \sum_{j=1}^{2}\boldsymbol{A}_{ij}\boldsymbol{z}_{i,t-j} + \boldsymbol{u}_{it} \tag{24}$$

where $\boldsymbol{z}_{it} = (\boldsymbol{y}_{it}, \boldsymbol{y}^*_{it})'$, $\boldsymbol{A}_{i0} = (\boldsymbol{I}_{m_i}, -\boldsymbol{\Phi}^*_{i0})$ and where $\boldsymbol{A}_{ij} = (\boldsymbol{\Phi}_{ij}, \boldsymbol{\Phi}^*_{ij})$ for $j = 1, ..., p$. Next, we may define $\boldsymbol{z}_{it} = \boldsymbol{W}_i\boldsymbol{y}_t$ where $\boldsymbol{y}_t = (\boldsymbol{y}'_{1,t}, ..., \boldsymbol{y}'_{25,t})'$ and $\boldsymbol{W}_i$ denotes the $(m_i + m^*_i) \times m$ 'link matrix' with $m = \sum_{i=1}^{25} m_i$. Note that the link matrix for the i-th country contains the bilateral trade weights used to construct the foreign variables that enter the i-th country-specific model. In light of this linking structure between $\boldsymbol{z}_{it}$ and $\boldsymbol{y}_t$, the country-specific VARX*(2,2) models in (24) may be stacked to yield:

$$\boldsymbol{H}_0\boldsymbol{y}_t = \boldsymbol{\gamma}_0 + \boldsymbol{\gamma}_1 t + \sum_{j=0}^{2}\boldsymbol{\delta}_{ij}d_{i,t-j} + \sum_{j=1}^{2}\boldsymbol{H}_j\boldsymbol{y}_{t-j} + \boldsymbol{u}_t \tag{25}$$

where:

$$\boldsymbol{\gamma}_0 = \begin{pmatrix} \boldsymbol{\gamma}_{1,0} \\ \vdots \\ \boldsymbol{\gamma}_{25,0} \end{pmatrix}, \boldsymbol{\gamma}_1 = \begin{pmatrix} \boldsymbol{\gamma}_{1,1} \\ \vdots \\ \boldsymbol{\gamma}_{25,1} \end{pmatrix}, \boldsymbol{u}_t = \begin{pmatrix} \boldsymbol{u}_{1t} \\ \vdots \\ \boldsymbol{u}_{25t} \end{pmatrix} \text{ and } \boldsymbol{H}_j = \begin{pmatrix} \boldsymbol{A}_{1j}\boldsymbol{W}_1 \\ \vdots \\ \boldsymbol{A}_{25j}\boldsymbol{W}_{25} \end{pmatrix}$$

for $j = 1, \ldots, p$, from which the final reduced-form global VAR(2,2) model can be retrieved as:

$$\boldsymbol{y}_t = \boldsymbol{g}_0 + \boldsymbol{g}_1 t + \sum_{j=0}^{2}\boldsymbol{\delta}_{ij}d_{i,t-j} + \sum_{j=1}^{2}\boldsymbol{G}_j\boldsymbol{y}_{t-j} + \boldsymbol{\varepsilon}_t \tag{26}$$

where $\boldsymbol{g}_0 = \boldsymbol{H}_0^{-1}\boldsymbol{\gamma}_0$, $\boldsymbol{g}_1 = \boldsymbol{H}_0^{-1}\boldsymbol{\gamma}_1$ and $\boldsymbol{G}_j = \boldsymbol{H}_0^{-1}\boldsymbol{H}_j$, $j = 1, ..., p$, denotes the set of $m \times m$ global VAR coefficient matrices. As usual, $\boldsymbol{\varepsilon}_t = \boldsymbol{H}_0^{-1}\boldsymbol{u}_t$ where $\boldsymbol{\varepsilon}_t \sim (0, \boldsymbol{\Sigma}_\varepsilon)$. Since the global VAR model is just a large VAR, it is straightforward to invert (26) into its Wold

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} the foreign price level. Hence, we actually model the US price level rather than US inflation and we carefully account for this fact when stacking the country-specific VARX*(2,2) models into the global VAR(2,2) model. See the Technical Annex, Greenwood-Nimmo et al. (2012) and Dees et al. (2007) for a detailed discussion.

representation, from which the computation of generalised connectedness measures follows easily from Section 2 above.

The covariance matrix is central to the computation of FEVDs and so its accurate estimation is essential. Note that the residual covariance matrices from equations (25) and (26) — $\boldsymbol{\Sigma}_u$ and $\boldsymbol{\Sigma}_\varepsilon$, respectively — are explicitly related according to $\boldsymbol{\Sigma}_\varepsilon = \boldsymbol{H}_0^{-1}\boldsymbol{\Sigma}_u\boldsymbol{H}_0^{-1\prime}$. We elect to focus on $\boldsymbol{\Sigma}_u$, which contains the original contemporaneous correlation structure among shocks across countries and is free from the influence of the estimated parameters in the contemporaneous matrix, $\boldsymbol{H}_0$. In the global VAR literature, $\boldsymbol{\Sigma}_u$ is usually estimated non-parametrically as $\hat{\boldsymbol{\Sigma}}_u = \hat{\boldsymbol{u}}_t\hat{\boldsymbol{u}}_t'$, where $\hat{\boldsymbol{u}}_t = \left(\hat{\boldsymbol{u}}_{1t}', \hat{\boldsymbol{u}}_{2t}', \ldots, \hat{\boldsymbol{u}}_{25t}'\right)'$. Recall from Table 1 that the country-specific VARX* models differ both in terms of their cointegrating rank and also in terms of the domestic and foreign variables that they include. As such, the different country-specific models may contain different numbers of regressors. Consequently, $\hat{\boldsymbol{u}}_{it}$ and $\hat{\boldsymbol{u}}_{jt}$ for $i \neq j$, may be estimated with different degrees of freedom and the established method of computing $\hat{\boldsymbol{\Sigma}}_u$ may yield imprecise estimates. Furthermore, the estimation of the off-diagonal (cross-country) blocks of $\hat{\boldsymbol{\Sigma}}_u$ may be refined by formally testing for cross section dependence or by employing related techniques for the sparse estimation of covariance matrices (Bien and Tibshirani, 2011).

We adopt a simple two-step technique to estimate the global covariance matrix more accurately. Firstly, the prime diagonal (within-country) blocks of $\boldsymbol{\Sigma}_u$ are estimated as $\hat{\boldsymbol{\Sigma}}_{u,ii} = (\hat{\mathbf{u}}_{it}\hat{\mathbf{u}}_{it}')/(T - n_i)$ where n_i is the number of regressors in the i-th country-specific VARX* model. Note that $\hat{\boldsymbol{\Sigma}}_{u,ii}$ is simply the usual consistent estimator of the covariance matrix of the i-th country-specific VARX* model. Secondly, we carry out the cross section dependence (CD) test proposed by Pesaran (2004) for each of the off-diagonal blocks of $\boldsymbol{\Sigma}_u$. Under the null hypothesis, $\hat{\boldsymbol{u}}_{it}$ and $\hat{\boldsymbol{u}}_{jt}$ for $i \neq j$ are cross sectionally independent and the CD test statistic follows an asymptotic standard normal distribution. Results of the cross section dependence test can be found in the Technical Annex. Where the null hypothesis of cross section independence is not rejected at the 5% significance level, we impose a null block in $\boldsymbol{\Sigma}_u$. Where the null hypothesis of cross section independence is rejected, we estimate the block as $\hat{\boldsymbol{\Sigma}}_{u,ij} = (\hat{\mathbf{u}}_{it}\hat{\mathbf{u}}_{jt}')/(T - \sqrt{n_i n_j})$ where n_i and n_j are the number of regressors in the country-specific models for countries i and j, respectively. Consequently, our procedure yields an estimated global covariance matrix which is correctly adjusted for degrees of freedom and which accurately accounts for cross section dependence.

4 Measuring Global Connectedness

4.1 Economic Connectedness Prior to the GFC

The first step in our analysis is to select an appropriate forecast horizon. Existing applications of the DY methodology have mostly considered financial spillovers using daily or weekly data and correspondingly short forecast horizons. The only exception of which we are aware is Diebold and Yilmaz (2015), who work with a 12 month horizon and demonstrate robustness over 6 and 18 months horizons. Therefore, in the absence of a clear precedent, we start by studying the variation in country-level connectedness over horizons $h = 1, 2, \ldots, 12$ quarters, as recorded in Figure 1. In the subfigure for the j-th country, the upper panel plots the *to* contribution ($\mathcal{T}^{(h)}_{\bullet\leftarrow j}$) as a red line and the *from* contribution ($\mathcal{F}^{(h)}_{j\leftarrow\bullet}$) as a blue line. The *net* connectedness ($\mathcal{N}^{(h)}_{\bullet\leftarrow j}$) is shown by the shaded region: red shading indicates a net transmitter at horizon h while blue shading indicates a net recipient. Meanwhile, the bars in the lower panel report the *within* country connectedness ($\mathcal{W}^{(h)}_{j\leftarrow j}$) across horizons. By virtue of the re-normalisation procedure discussed above, all of the values reported in Figure 1 are percentages of the total systemwide FEV at each horizon.

— Insert Figure 1 about here —

In the large majority of cases, the *net* connectedness of the k-th economy does not change sign over the forecast horizon. This suggests that the choice of forecast horizon is unlikely to exert a decisive influence on our results. The only notable exception is Japan, which is a significant net transmitter until $h = 3$, whereupon it becomes a net recipient. Closer inspection reveals that the influence of Japanese shocks rapidly diminishes, both domestically (measured by the *within* contribution) and externally (measured by the *to* contribution). Meanwhile, as a result of Japan's openness, the effect of external shocks on the Japanese economy (the *from* contribution) rapidly intensifies and becomes the dominant influence on domestic economic conditions. This is in constrast to the full sample results of Diebold and Yilmaz (2015), which indicate that Japanese shocks exert a dominant influence on the system with the *to* connectedness of Japan being almost twice as large as that of the US. However, their results are not directly comparable to ours as their model focuses solely on industrial production without any financial variables and with no Asian economies other than Japan. Our results are closer to those of Stock and Watson (2005), who report a reduction in the association between Japanese business cycle fluctuations and those of the remaining G7 economies during the 1990s.

Two further general patterns are noteworthy. First, *within* effects tend to recede while *from* contributions grow with the forecast horizon. The same effect is discussed by Diebold and Yilmaz (2015, pp. 7-8). The observation that spillovers intensify over time suggests that the international transmission of shocks occurs gradually. Second, outward (*to*) spillovers arising from the dominant units in the global system — notably the US, the Eurozone and the oil price — tend to strengthen over the forecast horizon. This increase is rapid in the case of the US, with its *to* contribution rising from 5.99% at $h = 1$ to 12.83% at $h = 8$. Meanwhile, outward spillovers from the Eurozone increase gradually over the forecast horizon, from 4.86% at $h = 1$ to 7.77% at $h = 12$. In most cases, however, the connectedness measures plotted in Figure 1 converge to their long-run value after 3–5 quarters. In light of these considerations, we elect to focus henceforth on the four-quarters-ahead forecasting horizon.

Table 2 records the *within*, *from*, *to* and *net* connectedness among countries in the system at the four-quarters-ahead horizon measured as a percentage of the systemwide FEV. The two rightmost columns of Table 2 report the dependence and influence indices, respectively. To further test the robustness of our results to alternative choices of the forecast horizon, Table 3 records the range of values that are obtained for each of the connectedness measures reported in Table 2 using forecast horizons in the interval $h = 1, 2, \ldots, 12$. In the large majority of cases, the range of possible values is rather narrow, confirming that our results do not depend crucially on the selection of $h = 4$. Furthermore, the connectedness measures evaluated at $h = 4$ typically lie toward the centre of the interval reported in Table 3, indicating that results based on $h = 4$ are representative of the general pattern of connectedness across horizons.

— Insert Tables 2 and 3 about here —

Continuing with the case of $h = 4$, several stylised results emerge from Table 2. Firstly, the importance of within-country (domestic) information provides an indirect indication of relative economic openness. Large within-country effects are indicative of less open economies, where domestic conditions are strongly influenced by local factors but are somewhat insulated from global conditions. Many of emerging economies in our sample exhibit large within-country effects — at $h = 4$, the largest *within* values are recorded by China (2.31%) and Brazil (2.29%), which compares to a corresponding average within-country effect of just 1.68%. Meanwhile, weak within-country effects are predominantly associated with small open economies, especially those that belong to significant free trade areas such as EFTA, ASEAN and NAFTA. Notable examples from these areas include Switzerland (0.80%), Malaysia (1.22%) and Canada (1.25%). This reflects the importance of regional factors documented by Hirata et al. (2013) *inter alia*.

The dependence index (21) provides a more complete picture of economic openness as it combines the *within* and *from* connectedness information for each country to provide a simple metric suitable for ranking exercises. This reveals that the most open economies in our sample are Switzerland (0.81), Japan (0.73) and Malaysia (0.71) while the least open are China (0.35), Turkey (0.42) and Brazil (0.45).[10] The resulting ranking derived from our model is generally consistent with established beliefs about economic openess. Since our network-based dependence index is considerably more general than standard measures of trade openness, we evaluate it relative to one of the broadest measures of economic freedom to be found in the literature. Gwartney et al. (2013) compute a ranking of economic freedom which encompasses the size of government, the legal system and property rights, measures relating to inflation and the exchange rate, trade freedom and various aspects of regulation. We conjecture that the extent to which an economy integrates within the global economic system is likely to be positively related to the quality of its institutions and the degree to which it protects the rights of its citizens and firms. This appears to be the case, as the correlation between our dependence index and Gwartney et al.'s summary index of economic freedom is strongly positive, at 0.52.[11]

[10]Saudi Arabia records the lowest within-country effect in our sample as well as the fourth highest dependence index. However, these results are likely to overstate the external dependence of the Saudi economy as its dominant role within OPEC is not fully reflected within our model because the oil price is modelled separately as a global common factor.

[11]We compare our dependence index against the mean value of Gwartney et al.'s summary index in the years 1990, 1995, 2000, 2005 and 2010. Note that we use Gwartney et al.'s reported values for Germany to proxy for the Eurozone since the authors do not provide values for the Eurozone as a region but only for its constituent states. Furthermore, for Saudi Arabia we use the value of Gwartney et al.'s overall freedom index for 2010 since this is the earliest period for which they provide data.

Figure 2(a) shows the dependence indices overlayed on a political map. As one may expect, the developed and/or trade-oriented economies of Europe, Asia and Australasia stand out as the most externally dependent, while less developed and less liberal economies record lower dependence scores. The USA stands out as a noteworthy special case, as it achieves a lower dependence score than many other developed countries. This reflects the dominant role of the US in the world economy. Not only does the US drive conditions overseas but also domestically, resulting in a strong *within* effect (1.86%) and a correspondingly weaker *from* contribution (1.69%).

— Insert Figure 2 about here —

The leading role of the US economy is manifestly clear in Table 2, which reveals that spillovers from the US to the world economy account for 10.57% of all of the four-quarters-ahead forecast error variance of the system. This represents a considerably stronger spillover effect than any other observed in the model — the next largest values are recorded by the Eurozone (6.13%) and the oil price (3.56%). In fact, the average *to* connectedness recorded by all countries in the system excluding the US is just 1.82%. This is a striking illustration of US economic dominance. Continuing in a similar vein, note the large positive net connectedness of the US, the Eurozone and the oil price. Net outward spillovers from these three sources alone account for 15.74% of systemwide FEV at $h = 4$. China and Brazil are the only other economies which exert net outward spillover effects at $h = 4$, reflecting their importance within the global economy.

The influence index (22) is recorded in the rightmost column of Table 2 and is mapped onto the globe in Figure 2(b). Economic influence measured in this way aligns closely with common perceptions of geo-political influence and with economic mass in particular. Figure 2(b) also provides a simple means of assessing the risks to the global economy posed by shocks occuring in different states. Given its influence, shocks to the US are globally significant, as highlighted by the rapid and forceful transmission of the subprime crisis around the world (Mishkin, 2011; Bagliano and Morana, 2012). Similarly, shocks to the Eurozone and to the market for oil will have considerable global impact. This is also becoming increasingly true of the BRICs, particularly China which has emerged as a major global power during our sample period. The figure also offers an explanation of why some regional crises have not translated into global crises. For example, Japan does not exhibit strong external spillover effects and thus the Japanese real-estate and stock-market collapse was not strongly felt outside Asia. Likewise, Black Wednesday in the UK and the 1997 Asian financial crisis were not strongly propagated beyond their respective regions.

Finally, Figure 3(a) records the location of each country in dependence–influence space in order to empirically measure the extent to which each economy can be viewed as small and open on the one hand (lying below the 45° line) or large, dominant and/or closed on the other hand (above the 45° line). The closer that country k lies to the limiting point $(\mathcal{O}_k = 0, \mathcal{I}_k = 1)$, the more influential it is and, consequently, the less exposed it is to overseas conditions. The US and China are closest to this point, with the US being more influential but China less dependent on external conditions. Brazil and the EU are also classed as dominant economies, with the EU being very much the most externally dependent among this group. This may reflect the strong spillovers from the US to Europe that have been documented elsewhere in the literature (Eickmeier, 2007). Meanwhile, proximity to the limiting point $(\mathcal{O}_k = 1, \mathcal{I}_k = -1)$ indicates the extent to which an economy corresponds to the stylised small open economy which is fundamental to much macroeconomic research. Canada and Switzerland are closest to this point, which is an intuitively pleasing result and which supports the widespread use of Canada as the classic example of a small open economy. We shall return to Figure 3(b) shortly.

— Insert Figure 3 about here —

4.2 Economic Connectedness and the GFC

It has been argued in the global business cycle literature that a sufficiently large shock hitting one economy is likely to spillover to others, resulting in increased business cycle correlation across countries (Doyle and Faust, 2005). Therefore, a large shock — such as the GFC — is likely to influence the observed pattern of macroeconomic connectedness in our framework. By observing the evolution of our GCMs in the wake of the GFC we can analyse how the crisis propagated through the global economy. To this end, we re-estimate the model recursively using 30 samples starting in 1980q2 and ending in 2005q2, . . . ,2012q3.[12]

[12] Note that we retain the same structure of the covariance matrix as employed above throughout our recursive analysis. Specifically, we test for cross section dependence using the reference sample 1980q2–2007q2 and impose null off-diagonal blocks in $\mathbf{\Sigma}_u$ where the null hypothesis of cross section independence cannot be rejected, as described in Section 3. We then retain this pattern of restrictions when estimating the

Figure 4 records the variation in the four-quarters ahead aggregate spillover index over the 30 recursive samples under three different aggregation schemes — (i) no aggregation, where the spillover index is computed directly from the 169×169 connectedness matrix; (ii) aggregation into 25 countries/regions as in the preceding section; and (iii) aggregation into 8 groups of common variables, such that the 25 GDP series are gathered into one group, the 25 export series into another group and so on, with the oil price being treated separately as a global common factor.[13] The GFC is associated with a marked increase in spillover activity under each of the three aggregation schemes, although it is most pronounced among countries where spillovers account for almost 67.17% of the systemwide FEV in late 2008 compared to 57.60% prior to the GFC.

— Insert Figure 4 about here —

Figure 5 records the time-variation in country connectedness at the four-quarters-ahead horizon while Table 4 recreates the analysis in Table 2 for the recursive sample ending in 2008q4, a date which corresponds to the height of the crisis following the collapse of Lehman Brothers. Comparing the two tables reveals that country-specific idiosyncratic effects are much smaller on average in the crisis period (1.26% vs. 1.63% before the GFC) while spillovers intensify markedly. Figure 5 demonstrates that this increase in spillover activity is driven by increased spillovers from the US to the system, reflecting the GFC's roots in the US subprime crisis (Mishkin, 2011). Outward (*to*) spillovers from the US jump from 10.57% prior to the GFC to 17.27% at the height of the GFC, while its *net* connectedness increases by a factor of more than two-thirds from 8.87% to 15.37%.

The majority of countries in the sample show a noticeable increase in their *from* (inward) connectedness during the GFC, as they receive the shock emanating from the US. This is particularly evident for Brazil and China, the *net* connectedness of which falls considerably during the GFC. Interestingly, Japan and, to a lesser extent, the UK and Singapore exhibit strengthening outward spillovers in the wake of the shock, albeit with a modest lag. Each of these countries hosts a significant financial hub, which is suggestive of the key role played by

covariance matrices for all of the recursive samples. This ensures that our results remain comparable across recursive samples and avoids possible distortions arising from changes in the structure of the covariance matrix.

[13]The figures also report intervals which record the range of values that the spillover index takes in each recursive sample over horizons 1 to 12. As in the reference sample 1980q2–2007q2, in each case the range of possible values is relatively narrow and our results using $h = 4$ lie toward its center.

the financial markets in the propagation of the GFC. Japan is particularly noteworthy, as it switches from being a net recipient of shocks prior to the GFC to a modest net transmitter. The particular behaviour of Japan at this time may be rooted in the robustness of its financial services sector. Chor and Manova (2012) show that credit conditions represent a key channel by which the GFC was transmitted to real magnitudes and to trade flows in particular. Their analysis reveals that interbank lending rates in Japan remained remarkably stable throughout the GFC, quite unlike the experience of other major economies.

— Insert Figure 5 and Table 4 about here —

Given our definition of dependence, the massive increase in spillovers from the world's dominant economy is reflected in increased dependence of most other countries. The average dependence index increases from 0.58 prior to the GFC to 0.67, indicating much greater sensitivity to external conditions during the crisis than in previous periods. This is a natural result in the context of contagion where shocks spread forcefully across national borders. This effect can be seen very clearly in Figure 3(b), which reproduces the analysis in Figure 3(a) for selected major economies. As the source of the shock, the US behaves quite differently than any other economy, being the only country to record a significant increase in influence while all others record a marked increase in dependence, often coupled with reduced influence.

As a final exercise, we switch our frame of reference away from geographical units and focus instead on spillovers among different classes of variables in the system. As with the rightmost panel of Figure 4, Figure 6 is computed by aggregating the connectedness matrix $\mathbb{C}^{(h)}$ into 8^2 blocks corresponding to 8 groups: one for the oil price and another for each of the variables in the model (the stock index, exchange rate and so on). The standout feature of Figure 6 is the sharp increase in outward spillovers from global stock markets to the rest of the system, which jumps from 8.57% prior to the GFC to 13.46% at the height of the crisis. No other variable group records such a sharp rise in outward spillover activity, which highlights the central role played by financial markets in the propagation of the GFC.

— Insert Figure 6 about here —

The behaviour of real imports and exports shown in Figure 6 suggests that the volatility in the financial markets rapidly and forcefully spilled over into global trade, as previously documented by Chor and Manova (2012) and discussed by Diebold and Yilmaz (2015). To illustrate this effect more clearly, Figure 7 reports the bilateral connectedness between the stock markets and the 7 remaining variable groups. The impact of financial shocks associated with the GFC on both trade flows and real activity is striking, with a large and sustained increase in spillover activity. This result contributes to the important debate over the linkage between financial and real variables, where notable contributions have been made both in favour of a strong linkage (Blanchard et al., 2010) and against such a linkage (Claessens et al., 2012).

— Insert Figure 7 about here —

Figure 7 also reveals a significant short-lived spike in spillovers from global stock markets to the foreign exchange markets. This illustrates the widespread flight-to-quality instigated by the GFC, in which investors rebalanced their portfolios to favour the safer investment opportunities offered by fixed income markets over the riskier environment afforded by a volatile stock market in the early days of the crisis (Caballero and Krishnamurthy, 2008). The resulting money flows have been identified as a key factor driving significant exchange rate movements, particularly the strong appreciation of high yielding currencies including the Australian Dollar. This provides an excellent illustration of the value of studying global macroeconomic connectedness. An improved ability to model and potentially to predict such spillover effects would have been invaluable during the GFC, where many countries including Switzerland and Japan were obliged to intervene in foreign exchange markets in an effort to control the value of their currencies and, thereby, to mitigate the real impact of the crisis.

5 Concluding Remarks

We develop a technique to measure macroeconomic connectedness in the global economy. Our framework is an innovative and powerful generalisation of that developed by Diebold and Yilmaz (2009, 2014) for the study of financial connectedness. Our principal innovation is to 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 or any arbitrary group of variables within the model. Our approach is therefore well suited to the analysis of sophisticated global models, where multiple variables for each of a potentially large number of countries are modelled simultaneously.

Our method provides a means to distill the wealth of information contained in such sophisticated models into a readily interpreted form, thereby mitigating the processing constraints typically encountered when working with large models. Furthermore, our approach is accessible to non-specialists as it provides a stylised representation of macroeconomic connectedness, the interpretation of which is intuitive and does not require advanced knowledge of economic modelling techniques. Finally, our framework is highly adaptable. It can be applied to any model with an approximate VAR representation, including DSGE models in their state-space form (Giacomini, 2013). It is also not reliant on the imposition of identifying restrictions although, equally, it does not preclude them (Diebold and Yilmaz, 2015).

We apply our technique to a large global VAR model based on Dees et al. (2007) and Greenwood-Nimmo et al. (2012) and derive a vivid representation of the connectedness of the global system. We uncover strong spillovers between countries and regions and find that, in many cases, idiosyncratic country-specific factors are not the main force influencing domestic conditions. The majority of spillovers originate from a small cohort of large and dominant states — the US, the Eurozone, China and Brazil — as well as the crude oil market. Shocks within this group are of global significance. By contrast, shocks to other economies may not be strongly transmitted beyond their respective locales. This offers a simple explanation of why the GFC, rooted as it was in the US economy, was so much more damaging to global prosperity than Black Wednesday in the UK, the 1997 Asian financial crisis and the collapse of the Japanese bubble earlier in the same decade.

Based on estimation over a recursively expanding sample, we gain additional insights into the propagation of the GFC from its origins in the US financial markets. Our analysis captures the initial flight-to-quality of equity investors in favour of foreign exchange. We also observe the subsequent transmission of the shock from the global financial markets to real activity, with a particularly marked effect on global trade flows. Existing research has studied each of these links separately but, to the best our knowledge, ours is the first analysis to capture all of these links in the propagation of the GFC simultaneously.

A number of implications arise from our analysis, two of which we wish to highlight. Firstly, our results reveal profound spillovers from financial markets to real activity, not only during the GFC but also prior to it. This has implications for the 'lean' versus 'clean' debate, as it is not just the burst of asset bubbles that may affect the real economy but also their inflation. Secondly, the world economy is characterised by heterogeneity. Countries play different roles in the global system, being either dominant units or recipients. However, heterogeneity persists even within these groups, as the US and China are mutually dissimilar and are unlike other dominant units, while recipients differ in a number of ways including their openness and the extent and nature of their regional linkages. Accommodating this heterogeneity in stylised macroeconomic models poses a significant challenge but will yield major gains in the degree to which such models approximate reality.

We conclude by returning to our opening quote, which promotes a simple but widely held view of globalisation in which domestic shocks are not contained by national boundaries but may spread rapidly and forcefully within the global economy. Our results partially validate this view subject to an important caveat — connectedness matters and connectedness is asymmetric. Hence, a more accurate statement would be that globalisation makes it impossible for *dominant economies* to collapse in isolation.

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Country	ISO Code	r	Endogenous Variables	Exogenous Variables	Structural Break
United States	US	3	$\{p^o_t, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{e^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
Eurozone*	EU	3	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
Japan	JP	6	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	Burst of Japanese Bubble (1992Q1)
United Kingdom	GB	2	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	Departure from the ERM (1992Q4)
Norway	NO	2	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
Sweden	SE	4	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
Switzerland	CH	5	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
Canada	CA	4	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
Australia	AU	3	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
New Zealand	NZ	5	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
South Africa	ZA	3	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
Brazil	BR	3	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	Effects of the Real Plan (1994Q3)
Chile	CL	4	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
Mexico	MX	4	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	Mexican Peso Crisis (1995Q1)
India	IN	3	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
South Korea	KR	4	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	South East Asian Crisis (1997Q4)
Malaysia	MY	5	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	South East Asian Crisis (1997Q3)
Philippines	PH	4	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	South East Asian Crisis (1997Q4)
Singapore	SG	3	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
Thailand	TH	4	$\{re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	South East Asian Crisis (1997Q3)
China	CN	3	$\{re_{it}, r_{it}, im_{it}, ex_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
Indonesia	ID	4	$\{re_{it}, r_{it}, im_{it}, ex_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	South East Asian Crisis (1997Q3)
Peru	PE	4	$\{re_{it}, r_{it}, im_{it}, ex_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	Effects of Dollarisation (1994Q3)
Turkey	TR	2	$\{re_{it}, r_{it}, im_{it}, ex_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	
Saudi Arabia	SA	4	$\{re_{it}, im_{it}, ex_{it}, \Delta p_{it}, y_{it}\}$	$\{p^o_t, r^*_{it}, q^*_{it}, \Delta p^*_{it}, y^*_{it}\}$	

NOTE: r denotes the numbers of cointegrating vectors in the country-specific models. (•) is our chosen break point. Note that the oil price is included among the set of endogenous variables for the US CVARX model for estimation purposes following the precedent of Dees et al. (2007).
* 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: Specification Details for the GNS25 Model

	Within	From	To	Net	Open.	Infl.
Oil	0.34	0.25	3.56	3.31	0.43	0.87
United States	1.86	1.69	10.57	8.87	0.48	0.72
Eurozone	1.57	2.57	6.13	3.56	0.62	0.41
Japan	1.13	3.02	2.56	-0.46	0.73	-0.08
United Kingdom	1.81	2.33	1.78	-0.55	0.56	-0.13
Norway	1.44	2.70	1.26	-1.44	0.65	-0.37
Sweden	1.38	2.76	2.34	-0.42	0.67	-0.08
Switzerland	0.80	3.34	2.40	-0.94	0.81	-0.16
Canada	1.25	2.89	1.25	-1.64	0.70	-0.40
Australia	2.06	2.08	1.24	-0.84	0.50	-0.25
New Zealand	2.06	2.08	0.50	-1.58	0.50	-0.61
South Africa	2.17	1.97	1.71	-0.26	0.48	-0.07
Brazil	2.29	1.86	3.79	1.93	0.45	0.34
Chile	2.27	1.87	1.08	-0.79	0.45	-0.27
Mexico	1.90	2.24	1.34	-0.90	0.54	-0.25
India	2.13	2.02	0.79	-1.22	0.49	-0.43
South Korea	1.55	2.59	1.68	-0.90	0.63	-0.21
Malaysia	1.21	2.93	1.53	-1.40	0.71	-0.31
Philippines	2.02	2.12	1.57	-0.55	0.51	-0.15
Singapore	1.34	2.81	2.43	-0.38	0.68	-0.07
Thailand	1.77	2.37	1.24	-1.12	0.57	-0.31
China	2.31	1.24	2.31	1.07	0.35	0.30
Indonesia	1.31	2.24	1.65	-0.59	0.63	-0.15
Peru	1.49	2.06	0.77	-1.29	0.58	-0.45
Turkey	2.07	1.48	0.55	-0.93	0.42	-0.46
Saudi Arabia	0.88	2.08	1.56	-0.52	0.70	-0.14
Average	1.63	2.21	2.21	0.00	0.57	-0.11
Average (excl. oil)	1.68	2.29	2.16	-0.13	0.58	-0.14

NOTE: The values of *within*, *from*, *to* and *net* are computed following equations (15) and (19). The unit of measurement for each of these four quantities is the percentage of the total h-step ahead forecast error variance of the system. *Open.* denotes the openness index, $\mathcal{O}_k^h$, which is defined in equation (21). Note that $0 \leq \mathcal{O}_k^h \leq 1$ where higher values denote greater sensitivity to overseas conditions, which indicates greater economic openness. *Infl.* denotes the influence index, $\mathcal{I}_k^h$, which is computed following equation (22). Recall that $-1 \leq \mathcal{I}_k^h \leq 1$ and that country k is a net recipient at horizon h if $-1 \leq \mathcal{I}_k^h < 0$ and a net shock transmitter if $0 < \mathcal{I}_k^h \leq 1$.

Table 2: Connectedness Among Countries, Four-Quarters Ahead

	Within		From		To		Net		Openness		Influence	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Oil	0.29	0.34	0.25	0.31	1.85	4.38	1.58	4.08	0.42	0.52	0.75	0.87
United States	1.85	2.10	1.45	1.70	5.99	12.94	4.54	11.28	0.41	0.48	0.61	0.77
Eurozone	1.50	1.71	2.43	2.64	4.86	7.77	2.43	5.14	0.59	0.64	0.33	0.49
Japan	0.54	2.29	1.85	3.60	1.95	3.29	-1.64	1.44	0.45	0.87	-0.30	0.28
United Kingdom	1.46	1.94	2.20	2.68	1.58	2.05	-0.63	-0.53	0.53	0.65	-0.16	-0.13
Norway	1.40	1.68	2.46	2.74	1.20	1.34	-1.54	-1.13	0.59	0.66	-0.39	-0.30
Sweden	1.20	1.65	2.49	2.94	2.14	2.53	-0.79	0.03	0.60	0.71	-0.16	0.01
Switzerland	0.59	1.42	2.72	3.55	2.34	2.75	-1.21	0.03	0.66	0.86	-0.21	0.01
Canada	1.02	2.03	2.12	3.13	1.11	1.52	-1.72	-1.00	0.51	0.75	-0.40	-0.31
Australia	1.64	2.27	1.87	2.50	1.01	1.55	-1.49	-0.32	0.45	0.60	-0.43	-0.09
New Zealand	1.62	2.38	1.76	2.52	0.41	0.53	-2.11	-1.24	0.43	0.61	-0.72	-0.54
South Africa	1.98	2.20	1.94	2.16	1.52	2.17	-0.43	0.01	0.47	0.52	-0.12	0.00
Brazil	2.01	2.65	1.49	2.13	1.93	3.83	0.44	1.93	0.36	0.51	0.13	0.34
Chile	1.92	2.60	1.55	2.22	1.07	1.09	-1.15	-0.45	0.37	0.54	-0.35	-0.17
Mexico	1.70	2.36	1.79	2.44	1.34	1.62	-0.98	-0.34	0.43	0.59	-0.26	-0.11
India	1.85	2.39	1.75	2.29	0.69	0.94	-1.60	-0.81	0.42	0.55	-0.54	-0.30
South Korea	1.15	2.13	2.02	2.99	1.19	1.99	-1.01	-0.76	0.49	0.72	-0.26	-0.20
Malaysia	0.90	2.00	2.14	3.24	1.31	1.73	-1.55	-0.84	0.52	0.78	-0.32	-0.24
Philippines	1.89	2.32	1.82	2.25	1.32	1.75	-0.56	-0.49	0.44	0.54	-0.16	-0.12
Singapore	1.09	1.82	2.32	3.06	1.36	3.05	-0.96	-0.01	0.56	0.74	-0.26	0.00
Thailand	1.64	2.20	1.94	2.51	1.24	1.67	-1.16	-0.66	0.47	0.61	-0.31	-0.20
China	2.05	2.39	1.16	1.50	1.76	2.80	0.60	1.32	0.33	0.42	0.21	0.33
Indonesia	0.95	1.84	1.71	2.60	1.58	1.89	-1.01	0.18	0.48	0.73	-0.24	0.05
Peru	1.04	2.37	1.18	2.51	0.73	0.79	-1.77	-0.39	0.33	0.71	-0.54	-0.20
Turkey	1.94	2.38	1.17	1.61	0.54	0.58	-1.06	-0.60	0.33	0.45	-0.49	-0.34
Saudi Arabia	0.56	1.16	1.80	2.39	1.55	1.61	-0.81	-0.18	0.61	0.81	-0.20	-0.05

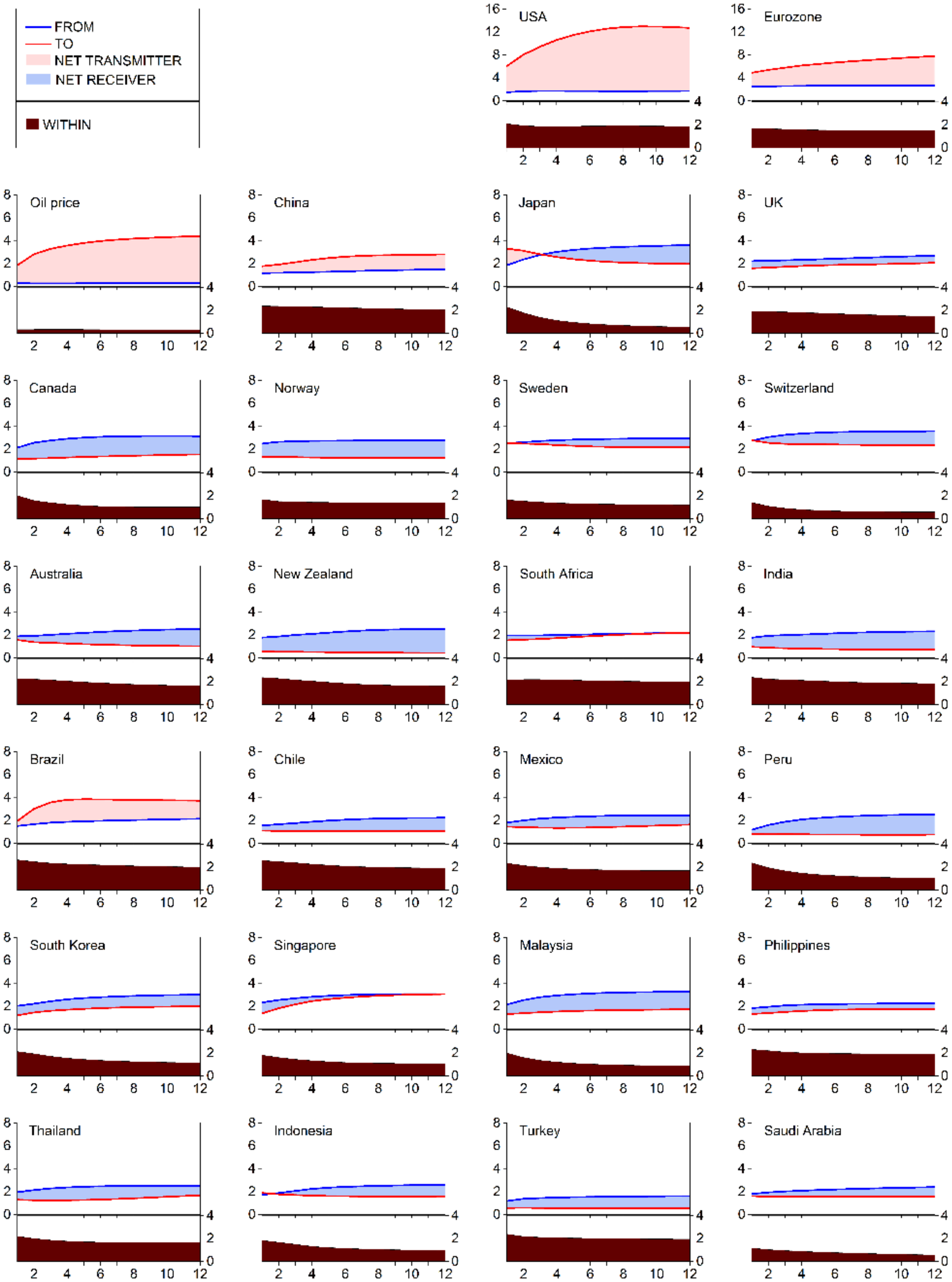
NOTE: The table reports the maximum and minimum values for each of the named connectedness measures over horizons $h = 1, 2, \ldots, 12$ for the estimation sample 1980q2–2007q2.

Table 3: Robustness to the Choice of Forecast Horizon

	Within	From	To	Net	Open.	Infl.
Oil	0.13	0.46	2.89	2.43	0.77	0.73
United States	1.65	1.90	17.27	15.37	0.54	0.80
Eurozone	1.08	3.06	6.44	3.38	0.74	0.36
Japan	0.64	3.50	2.98	-0.52	0.85	-0.08
United Kingdom	1.55	2.59	2.00	-0.59	0.63	-0.13
Norway	1.21	2.93	1.60	-1.34	0.71	-0.30
Sweden	1.00	3.14	1.83	-1.31	0.76	-0.26
Switzerland	0.66	3.48	2.67	-0.81	0.84	-0.13
Canada	0.92	3.22	1.34	-1.88	0.78	-0.41
Australia	1.64	2.51	1.11	-1.40	0.61	-0.39
New Zealand	1.51	2.63	0.45	-2.18	0.64	-0.71
South Africa	1.71	2.43	2.25	-0.19	0.59	-0.04
Brazil	2.13	2.02	3.17	1.15	0.49	0.22
Chile	1.67	2.47	1.03	-1.44	0.60	-0.41
Mexico	1.41	2.73	1.58	-1.15	0.66	-0.27
India	1.59	2.55	0.76	-1.79	0.62	-0.54
South Korea	1.53	2.61	2.17	-0.43	0.63	-0.09
Malaysia	0.82	3.32	1.75	-1.57	0.80	-0.31
Philippines	1.51	2.63	1.65	-0.98	0.64	-0.23
Singapore	0.78	3.37	3.17	-0.19	0.81	-0.03
Thailand	1.02	3.12	1.84	-1.29	0.75	-0.26
China	1.87	1.68	2.30	0.62	0.47	0.16
Indonesia	1.16	2.39	1.87	-0.52	0.67	-0.12
Peru	1.25	2.30	0.68	-1.61	0.65	-0.54
Turkey	1.58	1.97	0.49	-1.48	0.55	-0.60
Saudi Arabia	0.80	2.16	1.88	-0.27	0.73	-0.07
Average	1.26	2.58	2.58	0.00	0.67	-0.14
Average (excl. oil)	1.31	2.67	2.57	-0.10	0.67	-0.18

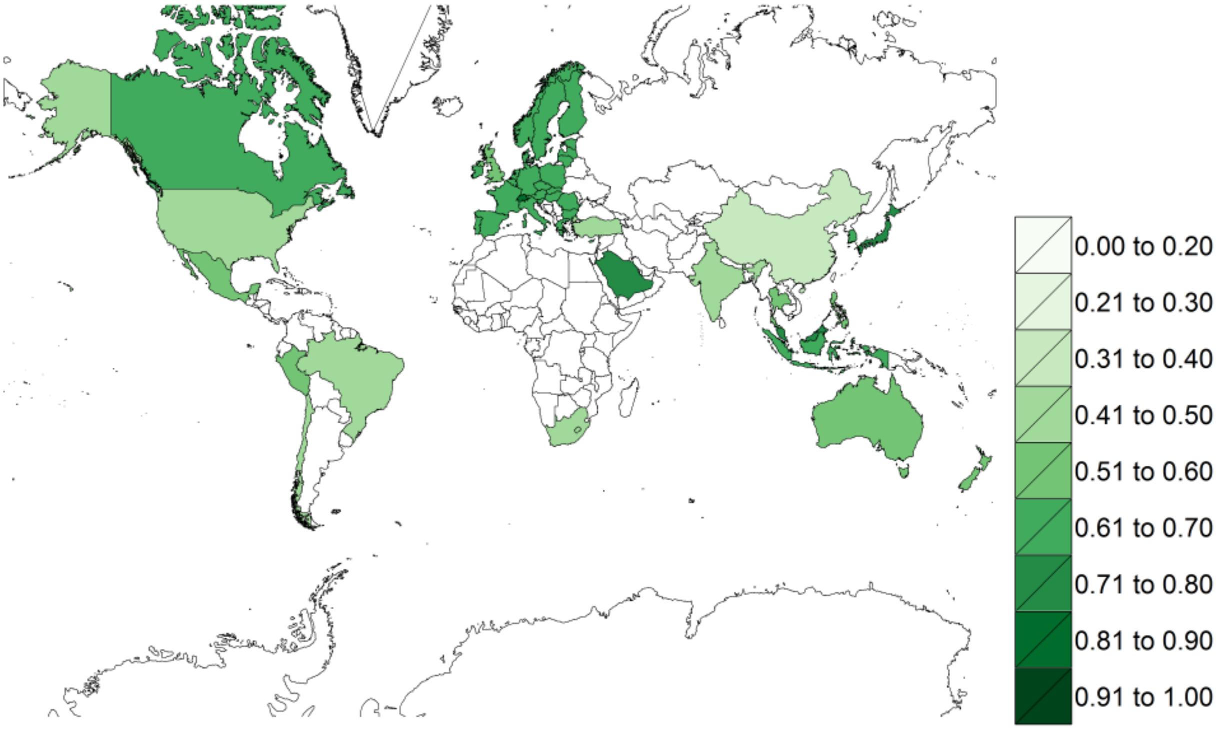
NOTE: The values of *within*, *from*, *to* and *net* are computed following equations (15) and (19). The unit of measurement for each of these four quantities is the percentage of the total h-step ahead forecast error variance of the system. *Open.* denotes the openness index, $\mathcal{O}_k^h$, which is defined in equation (21). Note that $0 \leq \mathcal{O}_k^h \leq 1$ where higher values denote greater sensitivity to overseas conditions, which indicates greater economic openness. *Infl.* denotes the influence index, $\mathcal{I}_k^h$, which is computed following equation (22). Recall that $-1 \leq \mathcal{I}_k^h \leq 1$ and that country k is a net recipient at horizon h if $-1 \leq \mathcal{I}_k^h < 0$ and a net shock transmitter if $0 < \mathcal{I}_k^h \leq 1$.

Table 4: Connectedness Among Countries, Four-Quarters Ahead at 2009q4

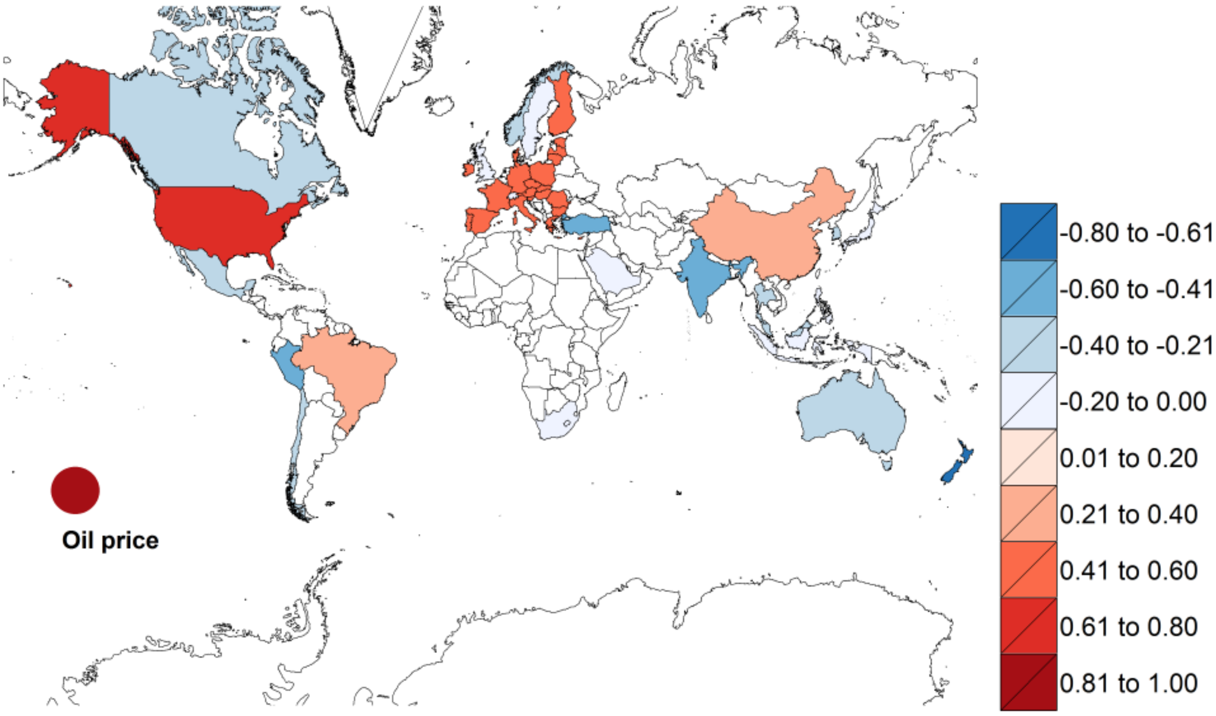


Note: The values of *within*, *from*, *to* and *net* are computed following equations (15) and (19). In all cases, the unit of measurement is the percentage of the total h-step ahead forecast error variance of the system. Note the difference in the scaling of the vertical axes for the US and the Eurozone relative to the other cases.

Figure 1: Connectedness Among Countries



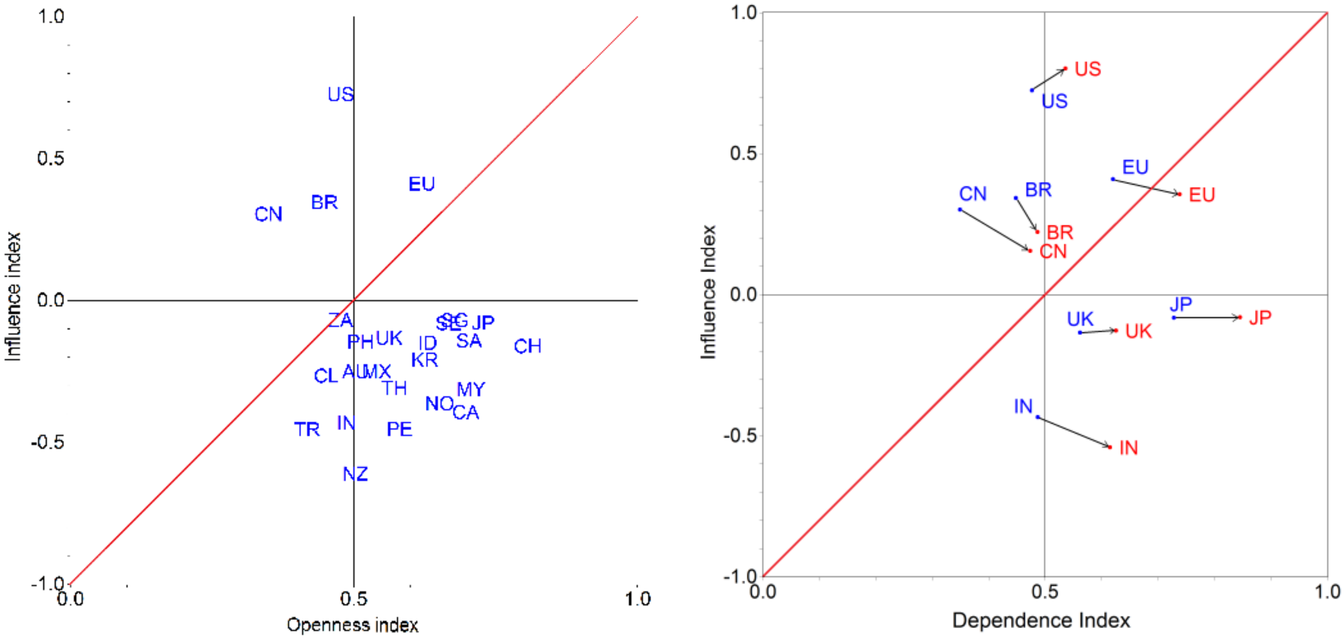
(a) Countries of the World by Openness



(b) Countries of the World by Influence

NOTE: The openness index, $\mathcal{O}_k^h$, is computed following equation (21). Recall that $0 \leq \mathcal{O}_k^h \leq 1$ and that a higher value indicates greater openness to external conditions. The influence index, $\mathcal{I}_k^h$, is computed following equation (22). Country k is a net recipient at horizon h if $-1 \leq \mathcal{I}_k^h < 0$ and a net shock transmitter if $0 < \mathcal{I}_k^h \leq 1$. The entirety of the Eurozone is shaded for visual clarity but recall that the Eurozone economy in our model is comprised of the eight member states listed in the notes to Table 1.

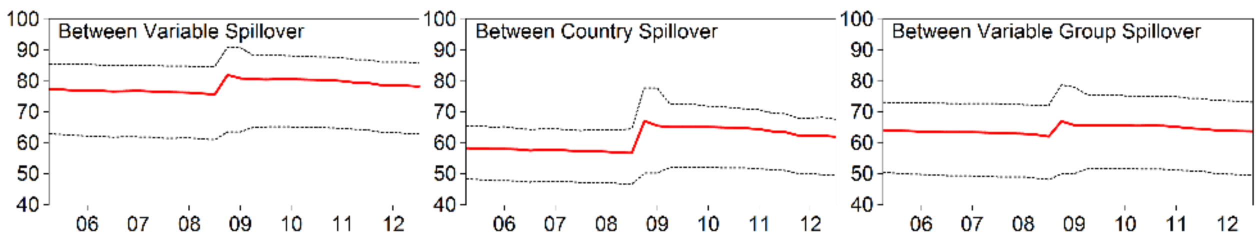
Figure 2: Openness Indices by Country, Four-Quarters-Ahead



(a) All Countries, 1980q2–2007q2 (b) Change by 2009q4, Selected Countries

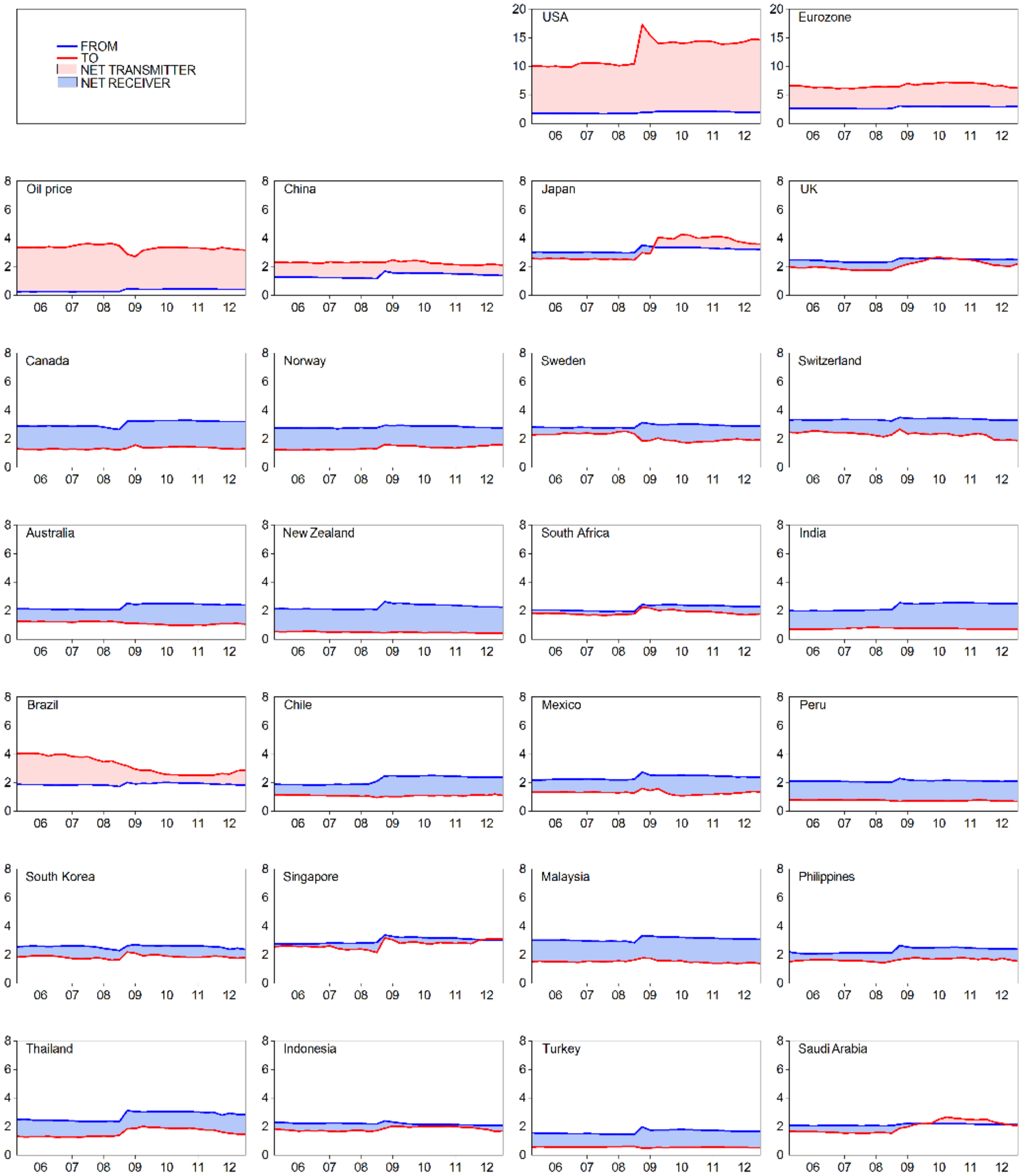
NOTE: Panel (a) records the openness and influence indices for each country over the reference sample period 1980q2–2007q2. Panel (b) records change in influence and openness for seven selected economies between the reference sample (shown in blue) and the sample 1980q2–2009q4 which includes the onset of the GFC (shown in red). Influence and openess are measured following equations (22) and (21). All figures are computed using the four-quarters ahead forecast horizon. The red 45° line is provided as an aid to visualisation.

Figure 3: Influence vs. Openness, Four-Quarters Ahead



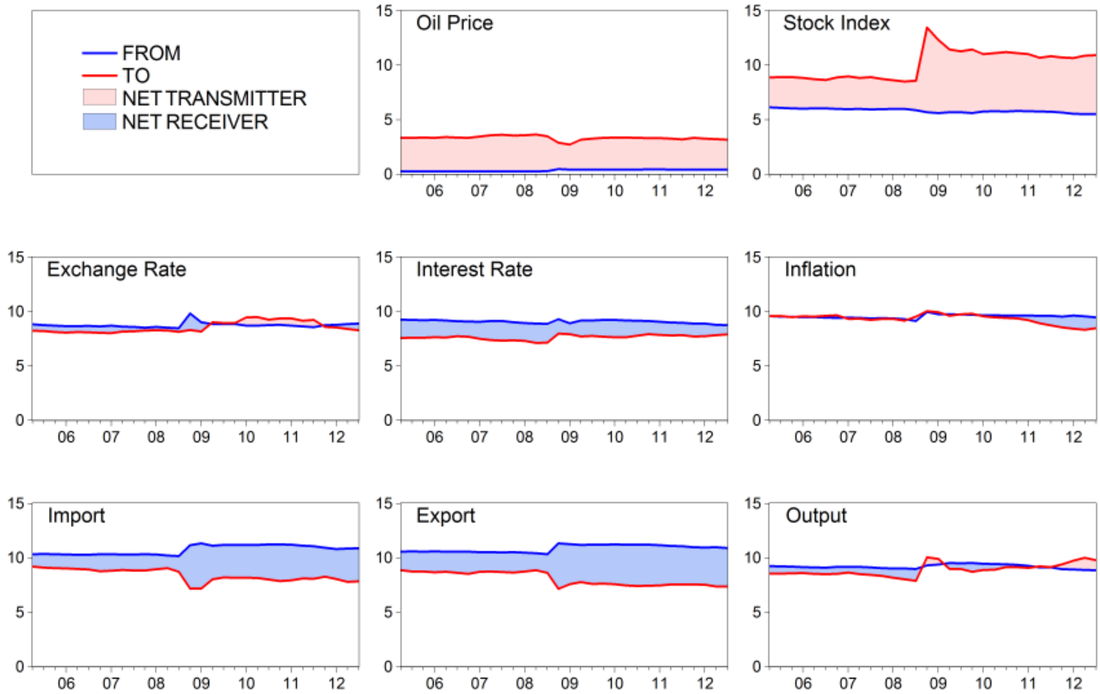
NOTE: The aggregate spillover among variables (the left panel) is computed following equation (11). The aggregate spillovers among countries (middle panel) and variable groups (right panel) are computed following equation (20) subject to the appropriate block structure of $\mathbb{B}^h$. In each case, the interval reports the range of values taken by the spillover index over horizons 1 to 12 in a similar manner to the values reported in Table 3. Note that the time axis records the end of the recursive sample period so that values shown at 2009q4, for example, are derived from the estimation sample 1980q2–2009q4. In all cases, the unit of measurement is the percentage of the total h-step ahead forecast error variance of the system.

Figure 4: Time-Varying Aggregate Spillover Indices, Four-Quarters Ahead



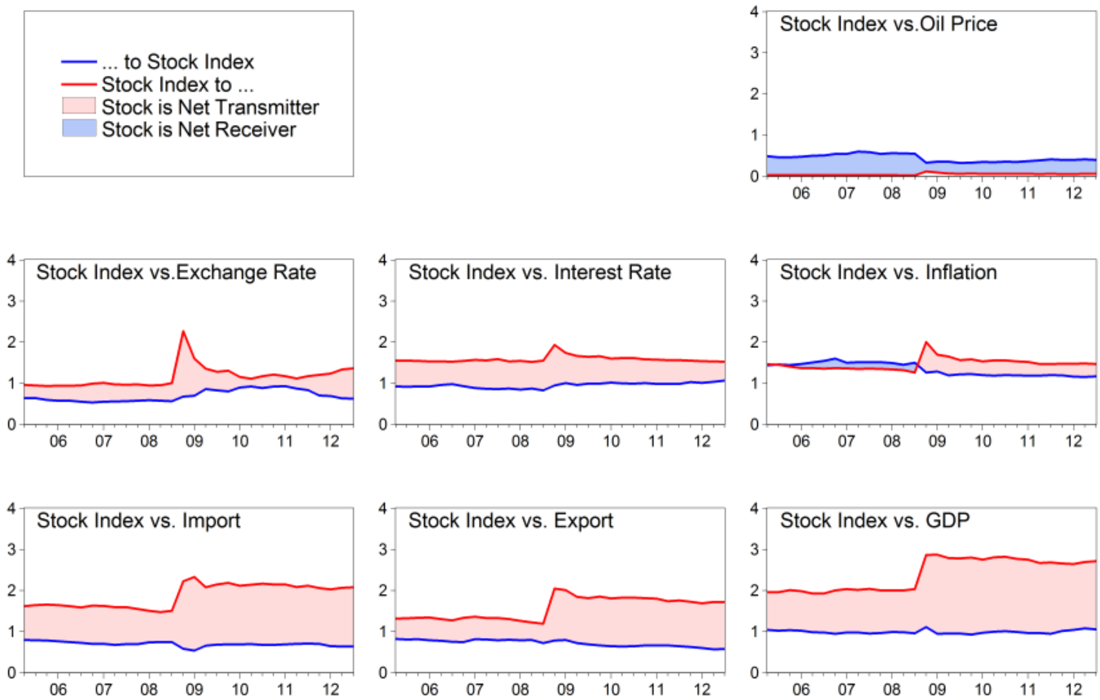
NOTE: The values of *from*, *to* and *net* are computed following equation (19). In all cases, the unit of measurement is the percentage of the total four-quarters-ahead forecast error variance of the system. Note the difference in the scaling of the vertical axes for the US and the Eurozone relative to the other cases.

Figure 5: Time-Varying Connectedness Among Countries, Four-Quarters-Ahead



NOTE: The values of *from*, *to* and *net* are computed following equation (19). In all cases, the unit of measurement is the percentage of the total four-quarters-ahead FEV of the system.

Figure 6: Time-Varying Connectedness Among Variable-Groups, Four-Quarters-Ahead



NOTE: The values of *from*, *to* and *net* are computed following equation (19). In all cases, the unit of measurement is the percentage of the total four-quarters-ahead FEV of the system.

Figure 7: Time-Varying Bilateral Connectedness of the Stock Index, Four-Quarters-Ahead

Technical Annex

A.1 Introduction

This Annex provides supplementary information for *Measuring the Connectedness of the Global Economy* by Matthew Greenwood-Nimmo, Viet Hoang Nguyen and Yongcheol Shin. It proceeds in four sections. Section A.2 outlines the specification of the GNS25 model, which is an updated version of the GVAR model analysed by Greenwood-Nimmo et al. (2012). Detailed notes on the construction of the GVAR link matrices using bilateral trade data are also provided. Section A.3 provides further details on the aggregation schemes used in the paper to evaluate connectedness among countries and groups of common variables. Section A.4 provides a detailed description of the construction of the dataset including a comprehensive list of data sources and full details of the transformations that have been applied to the data.

A.2 The GNS Global Model

Greenwood-Nimmo, Nguyen and Shin (2012, GNS) develop a global VAR model consisting of 26 countries with a total of 176 variables. In the current paper, we employ an updated version of this model (henceforth the GNS25 model) which differs from the original in two respects:

(i) The GNS25 model excludes Argentina, as this proves necessary to ensure dynamically stable solutions once the sample period is extended to include the crisis period. The stability issues encountered in the original 26 country model seem to be rooted in the unstable time series behaviour of the Argentine inflation, interest rate and equity price data, which may experience multiple structural breaks during our sample period.

(ii) The global covariance matrix in the GNS25 model is estimated with greater precision by excluding any covariance terms which are found to be insignificant using the weak cross section dependence test of Pesaran (2004).

In all other respects, the GNS25 model is identical to that of Greenwood-Nimmo et al. (2012). As such, the GNS25 model contains 169 endogenous variables covering 25 countries/regions that collectively account for the large majority of global trade and output. The 25 countries 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) Brazil; (13) Chile; (14) Mexico; (15) India; (16) Korea; (17) Malaysia; (18) Philippines; (19) Singapore; (20) Thailand; (21) China; (22) Indonesia; (23) Peru; (24) Turkey; and (25) Saudi Arabia.

A.2.1 Country-Specific Models

The first step in constructing the GNS25 model is to estimate a country-specific VARX* model for each country in the system. Consider a global economy consisting of N economies, indexed by $i = 1, 2, .., N$. Denote the country-specific variables by an $m_i \times 1$ vector $\boldsymbol{y}_{it}$ and the country-specific foreign variables by an $m_i^* \times 1$ vector $\boldsymbol{y}_{it}^* = \sum_{j=1}^{N} w_{ij} \boldsymbol{y}_{jt}$, where $w_{ij} \geq 0$ is the set of granular weights with $\sum_{j=1}^{N} w_{ij} = 1$, and $w_{ii} = 0$ for all i. The country-specific VARX* $(2, 2)$ model can be written as:

$$\begin{aligned} \boldsymbol{y}_{it} &= \boldsymbol{h}_{i0} + \boldsymbol{h}_{i1} t + \boldsymbol{\delta}_{i0} d_{it} + \boldsymbol{\delta}_{i1} d_{i,t-1} + \boldsymbol{\delta}_{i2} d_{i,t-2} + \boldsymbol{\Phi}_{i1} \boldsymbol{y}_{i,t-1} \\ &+ \boldsymbol{\Phi}_{i2} \boldsymbol{y}_{i,t-2} + \boldsymbol{\Psi}_{i0} \boldsymbol{y}_{it}^* + \boldsymbol{\Psi}_{i1} \boldsymbol{y}_{i,t-1}^* + \boldsymbol{\Psi}_{i2} \boldsymbol{y}_{i,t-2}^* + \boldsymbol{u}_{it}, \end{aligned} \tag{A.1}$$

where d_{it} is a country-specific intercept-shift dummy variable which captures country-specific structural breaks (if any). The choice of whether or not to include an intercept shift dummy for a given country takes account of both statistical evidence derived from the CUSUM test statistics developed by Brown et al. (1975) as well as anecdotal evidence on macroeconomic events that are likely to have contributed to structural changes in specific countries/regions. Examples of such events include the 1997 Asian currency crisis and the South American hyperinflation of the 1980s. The dummy variable, d_{it}, follows the same lag structure as the continuous variables in the model. The dimension of $\boldsymbol{h}_{ij}$ and $\boldsymbol{\delta}_{ij}$, $j = 0, 1, 2$, is $m_i \times 1$ while the dimensions of $\boldsymbol{\Phi}_{ij}$ and $\boldsymbol{\Psi}_{ij}$, $j = 0, 1, 2$, are $m_i \times m_i$ and $m_i \times m_i^*$. As usual, we assume that $\boldsymbol{u}_{it} \sim iid\,(0, \boldsymbol{\Sigma}_{ii})$ where $\boldsymbol{\Sigma}_{ii}$ is an $m_i \times m_i$ positive definite matrix.

Assuming that the country-specific foreign variables are weakly exogenous (an assumption which is borne out by formal tests as documented below), the VECM associated with (A.1) can be written as follows:

$$\begin{aligned} \Delta \boldsymbol{y}_{it} &= \boldsymbol{c}_{i0} + \boldsymbol{c}_{i0}^* \Delta d_{it} + \boldsymbol{c}_{i1}^* \Delta d_{i,t-1} + \boldsymbol{\Lambda}_i \Delta \boldsymbol{y}_{it}^* + \boldsymbol{\Gamma}_i \Delta \boldsymbol{z}_{i,t-1} \\ &+ \boldsymbol{\alpha}_i \boldsymbol{\beta}_i' \left(\boldsymbol{z}_{i,t-1} - \boldsymbol{\mu}_i d_{i,t-1} - \boldsymbol{\gamma}_i (t-1) \right) + \boldsymbol{u}_{it}, \end{aligned} \tag{A.2}$$

where $\boldsymbol{z}_{it} = (\boldsymbol{y}_{it}', \boldsymbol{y}_{it}^{*\prime})'$, $\boldsymbol{\alpha}_i$ is an $m_i \times r_i$ adjustment matrix of rank r_i and $\boldsymbol{\beta}_i$ is an $(m_i + m_i^*) \times r_i$

cointegrating matrix of rank r_i. Notice that (A.1) can be rewritten in terms of $\boldsymbol{z}_{it}$ as:

$$\boldsymbol{A}_{i0}\boldsymbol{z}_{it} = \boldsymbol{h}_{i0}^{*} + \boldsymbol{h}_{i1}t + \boldsymbol{A}_{i1}\boldsymbol{z}_{i,t-1} + \boldsymbol{A}_{i2}\boldsymbol{z}_{i,t-2} + \boldsymbol{u}_{it}, \tag{A.3}$$

where $\boldsymbol{h}_{i0}^{*} = \boldsymbol{h}_{i0} + \boldsymbol{\delta}_{i0}d_{it} + \boldsymbol{\delta}_{i1}d_{i,t-1} + \boldsymbol{\delta}_{i2}d_{i,t-2}$, $\boldsymbol{A}_{i0} = (\boldsymbol{I}_{m_i}, -\boldsymbol{\Psi}_{i0})$, $\boldsymbol{A}_{i1} = (\boldsymbol{\Phi}_{i1}, \boldsymbol{\Psi}_{i1})$, and $\boldsymbol{A}_{i2} = (\boldsymbol{\Phi}_{i2}, \boldsymbol{\Psi}_{i1})$. Note that the parameters of (A.3) can be obtained from those of (A.2) as $\boldsymbol{A}_{i0} = (\boldsymbol{I}_{m_i}, -\boldsymbol{\Lambda}_{i0})$, $\boldsymbol{A}_{i1} = \boldsymbol{A}_{i0} + \boldsymbol{\Pi}_i + \boldsymbol{\Gamma}_i$, $\boldsymbol{A}_{i2} = -\boldsymbol{\Gamma}_i$, $\boldsymbol{h}_{i0}^{*} = \boldsymbol{c}_{i0} + \boldsymbol{c}_{i0}^{*}\Delta d_{it} + \boldsymbol{c}_{i1}^{*}\Delta d_{i,t-1} + (-\boldsymbol{\Pi}_i\boldsymbol{\mu}_i)\, d_{i,t-1}$, $\boldsymbol{h}_{i1} = -\boldsymbol{\Pi}_i\boldsymbol{\gamma}_i$ and $\boldsymbol{\Pi}_i = \boldsymbol{\alpha}_i\boldsymbol{\beta}_i'$.

The variables included in the GNS25 model are drawn from the following:

re_{it}	the real effective exchange rate
r_{it}	the short-term nominal interest rate
im_{it}	the log of real imports
ex_{it}	the log of real exports
q_{it}	the log of real equity prices
Δp_{it}	the rate of inflation
y_{it}	the log of real output
p_t^o	the log of the oil price

The weakly exogenous foreign variables are computed as weighted averages of the data for the remaining $(N-1)$ countries in the model. GNS adopt the convention of Dees, di Mauro, Pesaran and Smith (2007, DdPS) and define the weights using bilateral trade averages derived from the IMF's *Direction of Trade Statistics* over the period 1999-2001. As noted by GNS, the choice of weighting scheme does not exert a dominant influence over the model output. Following Dees, Holly, Pesaran and Smith (2007, DHPS), GNS define the log real effective exchange rate as $re_{it} = ee_{it} + p_{it}^{*} - p_{it}$, where $ee_{it} + p_{it}^{*} - p_{it} = (e_{it} - p_{it}) - (e_{it}^{*} - p_{it}^{*}) = \tilde{e}_{it} - \tilde{e}_{it}^{*}$ and where, in turn, e_{it} is the nominal exchange rate *vis-à-vis* the US\$, $e_{it}^{*} = \sum_{j=1}^{N} w_{ij}e_{jt}$, $ee_{it} = \sum_{j=1}^{N} w_{ij}e_{ijt}$ is the nominal effective exchange rate, p_{it} the national price level and p_{it}^{*} the foreign price level.

Where data availability is unconstrained (*i.e.* for countries $i = 2, 3, \ldots, 20$), the VARX* models include the following endogenous I(1) variables: $\boldsymbol{y}_{it} = (re_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it})'$. For countries $i = 21, 22, \ldots, 24$, where the stock market data were unreliable or unavailable, we have $\boldsymbol{y}_{it} = (re_{it}, r_{it}, im_{it}, ex_{it}, \Delta p_{it}, y_{it})'$. Finally, for country $i = 25$ (Saudi Arabia) without an official interest rate, $\boldsymbol{y}_{it} = (re_{it}, im_{it}, ex_{it}, \Delta p_{it}, y_{it})'$. In all cases but the US, the vector of weakly exogenous foreign variables is given by $\boldsymbol{y}_{it}^{*} = (p_t^o, r_{it}^{*}, q_{it}^{*}, \Delta p_{it}^{*}, y_{it}^{*})'$ where $y_{it}^{*} = \sum_{j=1}^{N} w_{ij}y_{jt}$, $p_{it}^{*} = \sum_{j=0}^{N} w_{ij}p_{jt}$, $\Delta p_{it}^{*} = \sum_{j=1}^{N} w_{ij}\Delta p_{jt}$, $r_{it}^{*} = \sum_{j=1}^{N} w_{ij}r_{jt}$, $e_{it}^{*} = \sum_{j=1}^{N} w_{ij}e_{jt}$, and $q_{it}^{*} = \sum_{j=1}^{N} w_{ij}q_{jt}$, w_{ij} is the share of country j in the trade of country i. The omission of ex_{it}^{*} and im_{it}^{*} from the model reflects the fact that our model covers more than 90% of the world trade in which case $im_{it} \simeq ex^*_{it}$ and $im^*_{it} \simeq ex_{it}$.

The US ($i = 1$) is treated as the reference country such that its exchange rate is determined through the $N - 1$ 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, following DdPS, we include the oil price as an endogenous variable in the US model, reflecting the dominant position of the US in the global economy. We also treat the vector of weakly exogenous foreign variables slightly differently, as the US economy is sufficiently large to drive events in global financial markets. In this regard we exclude both r^*_{1t} and q^*_{1t} from the US model as they are unlikely to be weakly exogenous. Therefore, we have $\boldsymbol{y}_{1t} = (p^o_t, r_{1t}, im_{1t}, ex_{1t}, q_{1t}, \Delta p_{1t}, y_{1t})'$ and $\boldsymbol{y}^*_{1t} = (\tilde{e}^*_{1t}, \Delta p^*_{1t}, y^*_{1t})$.

Table 1 in the main text presents a concise summary of the GNS25 model specification, while Table A.1 records the results of standard statistical tests for structural breaks, co-breaking and weak exogeneity for each of the country-specific models in turn. The tests provide strong foundations for the specification adopted in the paper.

A.2.2 Combining the National Models into the Global Model

GNS define the $(m + 1) \times 1$ vector of intermediate global variables as $\tilde{\boldsymbol{y}}_t = (\tilde{\boldsymbol{y}}'_{1t}, \tilde{\boldsymbol{y}}'_{2t}, ..., \tilde{\boldsymbol{y}}'_{Nt})'$, where $\tilde{\boldsymbol{y}}_{1t} = (\tilde{e}_{1t}, p^o_t, r_{1t}, im_{1t}, ex_{1t}, q_{1t}, \Delta p_{1t}, y_{1t})'$, $\tilde{\boldsymbol{y}}_{it} = (\tilde{e}_{it}, r_{it}, im_{it}, ex_{it}, q_{it}, \Delta p_{it}, y_{it})'$ for $i = 2, ..., N$ and $m = \sum_{i=1}^{N} m_i$. Insodoing, all of the endogenous variables from each of the country-specific VARX* models are collected into the global vector $\tilde{\boldsymbol{y}}_t$.

Next, one must define the $(m_i + m^*_i) \times (m + 1)$ link matrices, denoted $\boldsymbol{W}_i$. We follow the typical approach in the literature, which employs time-invariant bilateral trade weights based on IMF DOTS data in the construction of the link matrices.[1] Employing the country ordering given in Section A.2 and also shown in Table 1 of the main text, the $\boldsymbol{W}_i$'s are given by:

$$\underset{10\times 170}{\boldsymbol{W}_1} = \begin{pmatrix} \boldsymbol{R}_{11} & \boldsymbol{0}_{7\times 7} & \cdots & \boldsymbol{0}_{7\times 7} & \boldsymbol{0}_{7\times 6} & \cdots & \boldsymbol{0}_{7\times 6} & \boldsymbol{0}_{7\times 5} \\ \boldsymbol{0}_{3\times 8} & \boldsymbol{W}_{1,2} & \cdots & \boldsymbol{W}_{1,19} & \boldsymbol{W}_{1,20} & \cdots & \boldsymbol{W}_{1,24} & \boldsymbol{W}_{1,25} \end{pmatrix},$$

$$\underset{12\times 170}{\boldsymbol{W}_i} = \begin{pmatrix} \boldsymbol{R}_{i1} & \boldsymbol{R}_{i2} & \boldsymbol{R}_{i3} & \cdots & \boldsymbol{R}_{i,25} \\ \boldsymbol{W}_{i1} & \boldsymbol{W}_{i2} & \boldsymbol{W}_{i3} & \cdots & \boldsymbol{W}_{i,25} \end{pmatrix}, \; i = 2, ..., 25,$$

[1] It should be noted that a wide range of alternative weighting schemes could be adopted in practice. 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 China and the Latin American economies in the global system. Alternatively, one could employ appropriately defined spatial matrices or even a combined weighting scheme.

ISO Code	Structural Break Test[a]		Co-breaking test[b]	Weak exogeneity test[c]					
	Breaks identified by test	Chosen break		p^o_t	r^*_{it}	q^*_{it}	Δp^*_{it}	y^*_{it}	$\tilde{e}^*_{0t}$
US				–	–	–	1.53	0.12	1.26
EU				1.74	5.25 †	0.26	0.28	2.16	–
JP	r(1993Q2), q(1992Q1)	1992Q1	68.94 [0.00]	1.29	0.97	0.86	0.79	1.81	–
GB	y(1992Q2)	1992Q4	41.03 [0.00]	4.03	0.97	1.86	4.21	0.23	–
NO				2.37	0.29	0.83	0.27	6.04 †	–
SE				1.13	2.20	0.04	2.04	3.31	–
CH				1.03	1.60	3.41 †	4.67 †	0.96	–
CA				0.60	5.60 †	2.04	1.28	0.74	–
AU				0.71	1.77	0.74	1.08	1.12	–
NZ				1.29	2.09	0.43	1.03	0.92	–
ZA				0.50	0.08	0.38	4.03 †	1.51	–
BR	r(1996Q1), im(1993Q2)	1994Q3	60.93 [0.00]	0.55	2.22	1.05	5.71 †	2.56	–
CL				0.72	0.66	1.47	0.67	0.52	–
MX	None	1995Q1	70.98 [0.00]	0.81	1.49	1.55	3.91 †	2.00	–
IN				1.57	0.47	0.27	0.71	0.41	–
KR	y(1998Q1)	1997Q4	52.15 [0.00]	2.76	2.15	0.74	2.36	0.29	–
MY	r(1998Q3)	1997Q3	48.39 [0.00]	1.90	2.91	2.80	4.20 †	3.25 †	–
PH	None	1997Q4	89.66 [0.00]	0.74	2.63	0.60	2.37	1.43	–
SG				0.90	2.91	0.62	2.00	0.72	–
TH	None	1997Q3	72.56 [0.00]	3.96 †	1.33	0.07	1.71	0.85	–
CN				1.10	2.65	0.86	3.95	0.43	–
ID	None	1997Q3	110.32 [0.00]	1.29	0.32	0.99	0.44	3.51 †	–
PE	im(1995Q1), Δp(1997Q1)	1994Q3	34.21 [0.00]	1.02	2.21	0.39	0.54	2.43	–
TR				0.39	0.60	1.05	0.59	0.37	–
SA				0.33	0.39	3.27	0.56	0.45	–

[a] Breaks identified by the CUSUM test where (.) is the break point for the named series. Break points are identified using the 10% significance level. {.} the breakpoints included in the model are chosen as a compromise between the empirical test results and our knowledge of historical economic events.
[b] LR-Stat $\sim \chi^2_r$ for the null of co-breaking, where r is the number of cointegrating vectors and [.] is the p-value.
[c] F-Stat $\sim F(r, T-k)$ for the null of weak exogeneity, where k is the number of regressors in the unrestricted model, and '†' denotes rejection of the null at the 1% level.

Table A.1: Tests for Structural Breaks, Co-breaking and Weak Exogeneity where

$$\boldsymbol{R}_{11} = \begin{bmatrix} \mathbf{0}_{7\times 1} & \boldsymbol{I}_7 \end{bmatrix}, \ \boldsymbol{R}_{i1} = \begin{bmatrix} -w_{i1} & \mathbf{0}_{1\times 7} \\ \mathbf{0}_{6\times 1} & \mathbf{0}_{6\times 7} \end{bmatrix}, \ i = 2, ..., 25,$$

$$\{\boldsymbol{R}_{ij}\}_{j=2}^{20} = \left\{ \begin{array}{cc} \begin{bmatrix} -w_{ij} & \mathbf{0}_{1\times 6} \\ \mathbf{0}_{6\times 1} & \mathbf{0}_{6\times 6} \end{bmatrix} & \text{if } j \neq i \\ \boldsymbol{I}_7 & \text{if } j = i \end{array} \right\}, \ i = 2, ..., 25,$$

$$\{\boldsymbol{R}_{ij}\}_{j=21}^{24} = \left\{ \begin{array}{cc} \begin{bmatrix} -w_{ij} & \mathbf{0}_{1\times 5} \\ \mathbf{0}_{6\times 1} & \mathbf{0}_{6\times 5} \end{bmatrix} & \text{if } j \neq i \\ \boldsymbol{I}_6 & \text{if } j = i \end{array} \right\}, \ i = 2, ..., 25,$$

$$\boldsymbol{R}_{i,25} = \left\{ \begin{array}{cc} \begin{bmatrix} -w_{i,25} & \mathbf{0}_{1\times 4} \\ \mathbf{0}_{6\times 1} & \mathbf{0}_{6\times 4} \end{bmatrix} & \text{if } i \neq 25 \\ \boldsymbol{I}_5 & \text{if } i = 25 \end{array} \right\},$$

$$\{\boldsymbol{W}_{1j}\}_{j=2}^{20} = \begin{bmatrix} w_{1j} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{1j} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{1j} \end{bmatrix},$$

$$\{\boldsymbol{W}_{1j}\}_{j=21}^{24} = \begin{bmatrix} w_{1j} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & w_{1j} & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{1j} \end{bmatrix}, \ \boldsymbol{W}_{1,25} = \begin{bmatrix} w_{1,25} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & w_{1,25} & 0 \\ 0 & 0 & 0 & 0 & w_{1,25} \end{bmatrix},$$

and for $i = 2, ..., 25,$

$$\boldsymbol{W}_{i1} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & w_{i0}^{*} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{i0}^{**} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{i0} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & w_{i0} \end{bmatrix}, \ \{\boldsymbol{W}_{ij}\}_{j=2}^{20} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & w_{ij}^{*} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & w_{ij}^{**} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{ij} & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & w_{ij} \end{bmatrix},$$

$$\{\boldsymbol{W}_{ij}\}_{j=21}^{24} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & w_{ij}^{*} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & w_{ij} & 0 \\ 0 & 0 & 0 & 0 & 0 & w_{ij} \end{bmatrix}, \ \boldsymbol{W}_{i,25} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & w_{i,25} & 0 \\ 0 & 0 & 0 & 0 & w_{i,25} \end{bmatrix}.$$

where w_{ij} is the weight of country i in the trade of country j, w_{ij}^{*} is the ith country's adjusted trade-weight with the jth country after allowing for the lack of Saudi interest rate data, and w_{ij}^{**} is the ith country's trade-weight with the jth country adjusted to accommodate the lack of reliable stock market data for China, Indonesia, Peru, Turkey and Saudi Arabia. Notice that $\sum_{j=1}^{N} w_{ij} = \sum_{j=1}^{N} w_{ij}^{*} = \sum_{j=1}^{N} w_{ij}^{**} = 1$, and $w_{ii} = w_{ii}^{*} = w_{ii}^{*} = 0$ for all i.

Using these link matrices, the $\boldsymbol{z}_{it}$'s for each country-specific model may be re-written in terms of the vector of global variables, $\tilde{\boldsymbol{y}}_t$, as follows:

$$\boldsymbol{z}_{it} = \boldsymbol{W}_i \tilde{\boldsymbol{y}}_t, \ i = 0, 1, ..., N. \tag{A.4}$$

Using (A.4) in (A.3) and stacking the results, we obtain the following global model:

$$\boldsymbol{H}_0 \tilde{\boldsymbol{y}}_t = \boldsymbol{h}_0^* + \boldsymbol{h}_1 t + \boldsymbol{H}_1 \tilde{\boldsymbol{y}}_{t-1} + \boldsymbol{H}_2 \tilde{\boldsymbol{y}}_{t-2} + \boldsymbol{u}_t, \tag{A.5}$$

where $\boldsymbol{H}_i = (\boldsymbol{W}_1' \boldsymbol{A}_{1i}', ..., \boldsymbol{W}_N' \boldsymbol{A}_{Ni}')'$, $\boldsymbol{h}_0^* = \left(\boldsymbol{h}_{10}^{*\prime}, ..., \boldsymbol{h}_{N0}^{*\prime}\right)'$, $\boldsymbol{h}_1 = \left(\boldsymbol{h}_{11}', ..., \boldsymbol{h}_{N1}',\right)'$ and $\boldsymbol{u}_t = \left(\boldsymbol{u}_{1t}', ..., \boldsymbol{u}_{Nt}'\right)'$ for $i = 0, 1, 2$.

Since $\tilde{e}_{1t}$ is not included in the set of US variables for VARX* 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 Dollar, it follows that $e_{1t} = 0$ and thus, $\tilde{e}_{1t} = -p_{1t}$. By imposing this restriction we are able to solve the system, although we are now solving for the price level in the US as opposed to inflation in the remainder of the countries (see DdPS for further details).

Finally, we define the $m \times 1$ vector of global variables: $\boldsymbol{y}_t = \left(\mathring{\boldsymbol{y}}_{1t}', \tilde{\boldsymbol{y}}_{2t}', ..., \tilde{\boldsymbol{y}}_{Nt}'\right)'$, where $\mathring{\boldsymbol{y}}_{1t} = \left(p_t^o, r_{1t}, m_{1t}, x_{1t}, q_{1t}, p_{1t}, y_{1t}\right)'$, and the $\tilde{\boldsymbol{y}}_{it}$'s are defined as above. To solve for the price level in the special case of the US, we set:

$$\tilde{\boldsymbol{y}}_t = \boldsymbol{S}_0 \boldsymbol{y}_t - \boldsymbol{S}_1 \boldsymbol{y}_{t-1}, \tag{A.6}$$

where $\boldsymbol{S}_0$ and $\boldsymbol{S}_1$ are $(m+1)\times m$ selection matrices given by:

$$\boldsymbol{S}_0 = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & -1 & 0 & \mathbf{0} \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & \mathbf{0} \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & \mathbf{0} \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & \mathbf{0} \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & \mathbf{0} \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \boldsymbol{I}_{m-m_1} \end{pmatrix}, \quad \boldsymbol{S}_1 = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & \mathbf{0} \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0}_{m-m_1} \end{pmatrix}$$

Using $(A.6)$, $(A.5)$ can be rewritten in terms of $\boldsymbol{y}_t$ as follows:

$$\boldsymbol{F}_0\boldsymbol{y}_t = \boldsymbol{h}_0^* + \boldsymbol{h}_1 t + \boldsymbol{F}_1\boldsymbol{y}_{t-1} + \boldsymbol{F}_2\boldsymbol{y}_{t-2} + \boldsymbol{F}_3\boldsymbol{y}_{t-3} + \boldsymbol{u}_t, \tag{A.7}$$

where $\boldsymbol{F}_0 = \boldsymbol{H}_0\boldsymbol{S}_0$, $\boldsymbol{F}_1 = \boldsymbol{H}_1\boldsymbol{S}_0 + \boldsymbol{H}_0\boldsymbol{S}_1$, $\boldsymbol{F}_2 = \boldsymbol{H}_2\boldsymbol{S}_0 - \boldsymbol{H}_1\boldsymbol{S}_1$, and $\boldsymbol{F}_3 = -\boldsymbol{H}_2\boldsymbol{S}_1$. The final GVAR model is obtained as:

$$\boldsymbol{y}_t = \boldsymbol{g}_0^* + \boldsymbol{g}_1 t + \boldsymbol{G}_1\boldsymbol{y}_{t-1} + \boldsymbol{G}_2\boldsymbol{y}_{t-2} + \boldsymbol{G}_3\boldsymbol{y}_{t-3} + \boldsymbol{\varepsilon}_t, \tag{A.8}$$

where $\boldsymbol{G}_j = \boldsymbol{F}_0^{-1}\boldsymbol{F}_j$, $j = 1,2,3$, $\boldsymbol{g}_0^* = \boldsymbol{F}_0^{-1}\boldsymbol{h}_0^*$, $\boldsymbol{g}_1 = \boldsymbol{F}_0^{-1}\boldsymbol{h}_1$, and $\boldsymbol{\varepsilon}_t = \boldsymbol{F}_0^{-1}\boldsymbol{u}_t$, and $E\left(\boldsymbol{u}_{it}\boldsymbol{u}_{jt}'\right) = \boldsymbol{\Sigma}_{u,ij}$ for $t = t'$ and 0 otherwise.

Recall from the main text that we construct the covariance matrix from equation (A.7) taking into account the results of the cross section dependence test proposed by Pesaran (2004). Table A.2 records the results of the cross section dependence test. In those off-diagonal blocks where the null of cross section independence is rejected, we estimate the block as $\hat{\boldsymbol{\Sigma}}_{u,ij} = (\hat{\mathbf{u}}_{it}\hat{\mathbf{u}}_{jt}')/(T - \sqrt{n_i n_j})$ where n_i and n_j are the number of regressors in the country-specific models for countries i and j, respectively. Where the null of cross section independence is not rejected, we impose a null block.

A.3 Details of the Aggregation Schemes used in the Paper

In this Section, we provide further details of the block aggregation routines used in the paper to evaluate connectedness among countries and among groups of common variables. Using the block representations of the renormalised connectedness matrix shown below, it is straightforward to compute the associated generalised connectedness measures following the derivations in Section 2.1 of the main text.

A.3.1 Connectedness Among Countries

The updated version of the GNS model used in the paper contains 169 globally endogenous variables covering 25 countries including one common global variable (the oil price, p_t^o). The endogenous variable set for country k, $\boldsymbol{y}_{k,t}$, is detailed in Table 1 in the main text. Maintaining the country order in Table 1, note that we may write the vector of global variables as:

$$\boldsymbol{y}_t = \left(p_t^o, \widetilde{\boldsymbol{y}}'_{US,t}, \ldots, \boldsymbol{y}'_{SA,t}\right)' \tag{A.9}$$

	US	EU	JP	GB	NO	SE	CH	CA	AU	NZ	ZA	BR	CL	MX	IN	KR	MY	PH	SG	TH	CN	ID	PE	TR	SA
US	*NA*	-0.50	1.06	1.39	0.38	-1.44	**2.36**	**2.13**	0.57	0.70	**-2.62**	**-2.77**	-0.15	**3.16**	-0.33	0.77	-1.93	-1.09	**2.10**	0.02	-1.94	-0.51	0.83	0.98	1.22
EU	-0.50	*NA*	**2.82**	**3.94**	0.40	**2.32**	**4.95**	**2.55**	1.37	0.61	0.87	**-2.44**	**-4.44**	-0.16	-1.65	**-3.32**	**2.24**	**2.46**	1.72	**3.33**	**4.80**	**7.11**	1.32	-1.71	**-3.08**
JP	1.06	**2.82**	*NA*	0.42	1.01	-1.58	**4.53**	-0.77	**2.48**	-0.34	1.68	**-2.21**	0.94	1.05	-1.73	-1.26	-1.10	**-2.18**	-1.43	**-3.00**	-1.54	0.82	1.74	-1.92	**-2.81**
GB	1.39	**3.94**	0.42	*NA*	1.85	**2.58**	**4.26**	1.64	**2.17**	0.09	**-2.75**	**-2.05**	-1.46	**3.95**	1.20	-0.90	-1.82	-1.10	-0.83	**2.52**	0.62	**-2.18**	0.84	-0.27	**-2.27**
NO	0.38	0.40	1.01	1.85	*NA*	**3.02**	**3.36**	**2.42**	**2.35**	0.76	**3.07**	**-2.28**	0.47	**2.29**	0.47	-0.19	-0.90	-0.12	**2.32**	1.74	**2.16**	-0.38	0.83	0.87	0.28
SE	-1.44	**2.32**	-1.58	**2.58**	**3.02**	*NA*	**2.40**	**5.21**	**2.51**	-0.15	**2.80**	-0.84	**2.75**	**-3.60**	-0.93	**2.80**	0.77	-0.35	**2.34**	**2.37**	-0.68	-0.02	0.41	1.84	-0.70
CH	**2.36**	**4.95**	**4.53**	**4.26**	**3.36**	**2.40**	*NA*	1.81	1.57	-0.16	**2.72**	-1.46	-0.76	0.18	1.67	-1.31	1.13	-0.54	1.15	0.01	1.90	**3.96**	-1.08	0.74	**-3.30**
CA	**2.13**	**2.55**	-0.77	1.64	**2.42**	**5.21**	1.81	*NA*	**3.40**	1.37	0.30	1.83	1.09	1.89	-0.19	1.21	-0.54	-1.55	0.83	0.21	1.93	-0.41	0.35	0.66	0.43
AU	0.57	1.37	**2.48**	**2.17**	**2.35**	**2.51**	1.57	**3.40**	*NA*	**4.72**	**4.33**	1.74	1.69	0.62	1.00	-1.49	-0.59	-0.24	-1.76	0.56	1.73	0.95	0.89	0.25	-1.48
NZ	0.70	0.61	-0.34	0.09	0.76	-0.15	-0.16	1.37	**4.72**	*NA*	0.21	-0.91	-0.02	-0.77	-0.83	**-3.15**	-1.28	-1.85	**-2.57**	0.23	-0.93	**-2.03**	0.31	-0.94	-1.17
ZA	**-2.62**	0.87	1.68	**-2.75**	**3.07**	**2.80**	**2.72**	0.30	**4.33**	0.21	*NA*	1.46	0.50	-0.42	0.40	-0.39	**2.50**	0.51	-0.41	-0.13	**2.06**	**3.37**	-0.23	-0.64	-0.72
BR	**-2.77**	**-2.44**	**-2.21**	**-2.05**	**-2.28**	-0.84	-1.46	1.83	1.74	-0.91	1.46	*NA*	0.59	-0.44	0.25	1.28	1.64	**2.87**	**-2.87**	0.32	1.43	-0.09	**2.57**	**3.48**	**2.16**
CL	-0.15	**-4.44**	0.94	-1.46	0.47	**2.75**	-0.76	1.09	1.69	-0.02	0.50	0.59	*NA*	-0.17	**-2.21**	0.02	0.34	-0.25	**-2.67**	1.26	-1.31	**-3.26**	**2.25**	-0.45	-0.34
MX	**3.16**	-0.16	1.05	**3.95**	**2.29**	**-3.60**	0.18	1.89	0.62	-0.77	-0.42	-0.44	-0.17	*NA*	1.10	1.03	0.46	-1.40	1.40	-0.33	1.02	**-4.62**	**3.11**	**3.84**	-0.65
IN	-0.33	-1.65	-1.73	1.20	0.47	-0.93	1.67	-0.19	1.00	-0.83	0.40	0.25	**-2.21**	1.10	*NA*	**2.47**	1.80	1.67	**1.99**	1.74	**2.86**	1.04	**-3.14**	1.28	**2.81**
KR	0.77	**-3.32**	-1.26	-0.90	-0.19	**2.80**	-1.31	1.21	-1.49	**-3.15**	-0.39	1.28	0.02	1.03	**2.47**	*NA*	0.62	0.22	-0.59	**2.17**	-1.87	**-3.08**	-0.77	0.86	**3.40**
MY	-1.93	**2.24**	-1.10	-1.82	-0.90	0.77	1.13	-0.54	-0.59	-1.28	**2.50**	1.64	0.34	0.46	1.80	0.62	*NA*	-1.29	0.88	1.44	**3.80**	0.88	-1.35	0.76	-0.34
PH	-1.09	**2.46**	**-2.18**	-1.10	-0.12	-0.35	-0.54	-1.55	-0.24	-1.85	0.51	**2.87**	-0.25	-1.40	1.67	0.22	-1.29	*NA*	1.05	**2.91**	0.91	**2.48**	-0.16	**2.07**	**2.12**
SG	**2.10**	1.72	-1.43	-0.83	**2.32**	**2.34**	1.15	0.83	-1.76	**-2.57**	-0.41	**-2.87**	**-2.67**	1.40	**1.99**	-0.59	0.88	1.05	*NA*	0.07	-1.36	0.43	-0.61	1.06	1.38
TH	0.02	**3.33**	**-3.00**	**2.52**	1.74	**2.37**	0.01	0.21	0.56	0.23	-0.13	0.32	1.26	-0.33	1.74	**2.17**	1.44	**2.91**	0.07	*NA*	-1.34	1.26	-0.41	-0.85	1.27
CN	-1.94	**4.80**	-1.54	0.62	**2.16**	-0.68	1.90	1.93	1.73	-0.93	**2.06**	1.43	-1.31	1.02	**2.86**	-1.87	**3.80**	0.91	-1.36	-1.34	*NA*	-0.07	-0.43	-0.19	-0.72
ID	-0.51	**7.11**	0.82	**-2.18**	-0.38	-0.02	**3.96**	-0.41	0.95	**-2.03**	**3.37**	-0.09	**-3.26**	**-4.62**	1.04	**-3.08**	0.88	**2.48**	0.43	1.26	-0.07	*NA*	-0.15	-0.48	**-2.13**
PE	0.83	1.32	1.74	0.84	0.83	0.41	-1.08	0.35	0.89	0.31	-0.23	**2.57**	**2.25**	**3.11**	**-3.14**	-0.77	-1.35	-0.16	-0.61	-0.41	-0.43	-0.15	*NA*	**-1.97**	-1.19
TR	0.98	-1.71	-1.92	-0.27	0.87	1.84	0.74	0.66	0.25	-0.94	-0.64	**3.48**	-0.45	**3.84**	1.28	0.86	0.76	**2.07**	1.06	-0.85	-0.19	-0.48	**-1.97**	*NA*	0.75
SA	1.22	**-3.08**	**-2.81**	**-2.27**	0.28	-0.70	**-3.30**	0.43	-1.48	-1.17	-0.72	**2.16**	-0.34	-0.65	**2.81**	**3.40**	-0.34	**2.12**	1.38	1.27	-0.72	**-2.13**	-1.19	0.75	*NA*

∗ Note: Numbers in bold face are statistically significant at the 5% level.

Table A.2: Testing for Cross Section Dependence where $\widetilde{\boldsymbol{y}}_{US,t}$ denotes the vector of endogenous variables for the US excluding the oil price. The renormalised connectedness matrix corresponding to these groups is given by:

$$\underset{(m\times m)}{\mathbb{C}_R^{(h)}} = \begin{bmatrix} C^{(h)}_{p^o\leftarrow p^o} & \mathbf{C}^{(h)}_{p^o\leftarrow US} & \cdots & \mathbf{C}^{(h)}_{p^o\leftarrow SA} \\ \mathbf{C}^{(h)}_{US\leftarrow p^o} & \mathbf{C}^{(h)}_{US\leftarrow US} & \cdots & \mathbf{C}^{(h)}_{US\leftarrow SA} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{C}^{(h)}_{SA\leftarrow p^o} & \mathbf{C}^{(h)}_{SA\leftarrow US} & \cdots & \mathbf{C}^{(h)}_{SA\leftarrow SA} \end{bmatrix} \tag{A.10}$$

where $C^{(h)}_{p^o\leftarrow p^o}$ is a scalar measuring the own-variable FEV share of the oil price, $\mathbf{C}^{(h)}_{p^o\leftarrow \ell}$ is a $1\times m_\ell$ row vector collecting spillovers from country ℓ to the oil price, $\mathbf{C}^{(h)}_{k\leftarrow p^o}$ is a $m_k \times 1$ column vector collecting spillovers from the oil price to country k and $\mathbf{C}^{(h)}_{k\leftarrow \ell}$ is an $m_k \times m_\ell$ matrix containing spillovers from country ℓ to country k with $k, \ell = US, EU, \ldots, SA$.

Remark 1 *In many applications of high dimensional models in economics and finance, 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 blocs. This is a straightforward extension of the country-level case described above.*

A.3.2 Connectedness Among Groups of Common Variables

In Figures 4, 6 and 7 of the main text we evaluate connectedness among the following $G = 8$ variable groups: (1) the oil price, (2) the exchange rates for all countries, (3) the interest rates for all countries, (4) the stock indices for all countries, (5) real exports for all countries, (6) real imports for all countries, (7) inflation for all countries and (8) output for all countries. This is achieved by block aggregation of the renormalised connectedness matrix as follows:

$$\underset{(m\times m)}{\mathbb{C}_R^{(h)}} = \begin{bmatrix} G^{(h)}_{p^o\leftarrow p^o} & \mathbf{G}^{(h)}_{p^o\leftarrow re} & \cdots & \mathbf{G}^{(h)}_{p^o\leftarrow y} \\ \mathbf{G}^{(h)}_{re\leftarrow p^o} & \mathbf{G}^{(h)}_{re\leftarrow re} & \cdots & \mathbf{G}^{(h)}_{re\leftarrow y} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{G}^{(h)}_{y\leftarrow p^o} & \mathbf{G}^{(h)}_{y\leftarrow re} & \cdots & \mathbf{G}^{(h)}_{y\leftarrow y} \end{bmatrix} \tag{A.11}$$

where $G^{(h)}_{p^o\leftarrow p^o}$ is a scalar measuring the own-variable FEV share of the oil price, $\mathbf{G}^{(h)}_{p^o\leftarrow \ell}$ is a $1 \times m_\ell$ row vector collecting spillovers from the ℓth variable group to the oil price, $\mathbf{G}^{(h)}_{k\leftarrow p^o}$ is a $m_k \times 1$ column vector collecting spillovers from the oil price to the kth variable group and $\mathbf{G}^{(h)}_{k\leftarrow \ell}$ is an $m_k \times m_\ell$ matrix containing spillovers from variable group ℓ to variable group k with $k, \ell = p^o, re, \ldots, y$. m_k and m_ℓ respectively denote the number of countries for which we have data for variable groups k and ℓ.

A.4 Data Construction

Real GDP — $y_{it} = \ln(Y_{it})$

Real GDP series for 32 countries were taken from the IMF's International Financial Statistics (IFS) database (Index, 2005 = 100). When unavailable, the IFS series were completed from other sources. Data from the OECD's Main Economic Indicators were used for Brazil from 1996Q1 onwards. When data was unavailable at the quarterly frequency, the annual series were interpolated following the method in DdPS (Supplement A). This technique was employed for Brazil from 1980-1995, China from 1980-1999, India from 1980-1996, for Indonesia from 1980-1982, for Malaysia from 1980-1987, for the Philippines for 1980, for Thailand from 1980-1992, for Turkey from 1980-1986, and for Saudi Arabia from 1980-2009. The data for Saudi Arabia from 2010 onwards were extrapolated using GDP growth rate from Saudi Arabian Central Department of Statistics and Information. Where necessary, the data were seasonally adjusted using the US Census Bureau's X12 routine.

Consumer Price Index — $p_{it} = \ln(CPI_{it})$

CPI data were collected from the IMF's IFS database (Index, 2005 = 100). CPI data for China from 1980-1986 and for Germany from 1980-1990 was provided by the Bank of Korea. The Chinese series was completed using IFS data from 1987 onwards.

Nominal Exchange Rate — $e_{it} = \ln(E_{it})$

Nominal exchange rates (E_{it}) measured in units of national currency per US Dollar were collected from the IMF's IFS database. The exchange rate series for the Eurozone are the ECU-EURO/USD rate from the OECD's Main Economic Indicators.

Short-Term Nominal Interest Rate — $r_{it} = 0.25 \times \ln(1 + R_{it}/100)$

Short-term interest rate series (R_{it}) measured in percent per annum were taken from the IFS Money Market Rate series. Where the IFS data was incomplete or unavailable, other IFS series were used. Particularly, the IFS Deposit Rate series was used for Chile, China and Turkey, the IFS Treasury Bill Rate series was used for Mexico and the IFS Discount Rate series was used for New Zealand and Peru. For India, the IFS Money Market Rate series over 1998Q2-2006Q2 were retrieved from the Reserve Bank of India. For Norway, the NIBOR 3-month rates from the OECD were used. Among Eurozone countries, Finland, Germany, Italy, and Spain have their own interest rate series over the full sample period whilst for Austria, Belgium, France, and Netherlands, the IFS Money Market Rate series ended at 1998qQ4 and were then augmented with overnight Euro interbank rates.

Real Exports and Imports — $ex_{it} = \ln\left(\frac{EXPORT_{it} \times E_{it}}{CPI_{it}}\right)$ & $im_{it} = \ln\left(\frac{IMPORT_{it} \times E_{it}}{CPI_{it}}\right)$

IFS Goods, Value of Exports series ($EXPORT_{it}$) and IFS Goods, Value of Imports series ($IMPORT_{it}$), measured in millions of US$, were available for 31 countries. Where necessary, the data were extrapolated backward using export and import growth rates obtained from the World Bank. This technique was applied for Belgium over the period 1980-1992 and for China in 1980. The quarterly series for Saudi Arabia were collected from the IMF's Direction of Trade Statistics (DOTS). All the series were then seasonally adjusted using the US Census Bureau's X12 routine.

Real Equity Price Index — $q_{it} = \ln\left(\frac{Q_{it}}{CPI_{it}}\right)$

Equity price indices (Q_{it}) were collected from the OECD's Main Economic Indicators (all shares/broad, 2005 = 100) for 31 countries. Where the OECD equity price series was incomplete or unavailable, IFS data were used. Specifically, the IFS industrial share price index series were used for Belgium from 1980-1985Q1, for Brazil from 1980-1992, for Chile from 1980-1989, for Korea for 1980, for Norway from 1980-1985, and for Spain from 1980-1984. Datastream series were used for Malaysia from 1980Q2 onwards, for Philippines from 1986Q2 onwards, for Singapore from 1981Q2 onwards, and for Thailand from 1995Q4 onwards.

Spot Price of Crude Oil — $p_t^o = \ln(POIL_t)$

The UK Dated Brent series ($POIL_t$), measured in US$ per barrel, was retrieved from the IMF's IFS Commodity Price database.

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