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Measuring the Connectedness of the Global Economy*

Matthew Greenwood-Nimmo
Department of Economics, University of Melbourne
Centre for Applied Macroeconomic Analysis, Australian National University

Viet Hoang Nguyen
Melbourne Institute of Applied Economic and Social Research

Yongcheol Shin
Department of Economics and Related Studies, University of York

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Abstract

We develop a technique to exploit forecast error variance decompositions to evaluate the macroeconomic connectedness embedded in any multi-country macroeconomic model with an approximate vector autoregressive (VAR) representation. We apply our technique to a large global VAR model covering 25 countries and derive vivid representations of macroeconomic connectedness. We find that the US exerts a dominant influence in the global economy and that Brazil, China and the Eurozone 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 Codes: C32, C53, E17.

Keywords: Generalised Connectedness Measures (GCMs), international linkages, network analysis, macroeconomic connectedness, forecast error variance decomposition.

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*Address for correspondence: M.J. Greenwood-Nimmo, 3.12 Faculty of Business and Economics, 111 Barry Street, University of Melbourne, VIC 3053, Australia. Email: matthew.greenwood@unimelb.edu.au. Tel: +61 (0)3 8344 5354. We are grateful for the insightful comments of Heather Anderson, Sang-Don Bu, Efrem Castelnuovo, Woonkyu Choi, John Hunter, Yong-Min Kim, Vance Martin, Faek Menla Ali, Kostas Mouratidis, Adrian Pagan, Hail Park, Hashem Pesaran, Kalvinder Shields, Peter Smith, Ron Smith, Benjamin Wong and Tomasz Woźniak. This work has benefited greatly from the stimulating discussion of delegates at the 21st Annual Symposium of the Society for Nonlinear Dynamics and Econometrics (Milan, March 2013), the Annual Conference of the Scottish Economic Society (Perth, April 2013), the BMRC-QASS Conference on Macro and Financial Economics (London, May 2013), the Econometrics of Social Interaction Symposium (York, May 2013), the 9th International Symposium on Econometric Theory and Applications (Seoul, July 2013), the Econometric Society Australasian Meeting (Sydney, July 2013), the Asian Meeting of the Econometric Society (Singapore, August 2013), the 45th Annual Conference of the Money, Macro and Finance Research Group (London, September 2013), the Econometrics Workshop at Victoria University of Wellington (November 2013), the 11th World Congress of the Econometric Society (Montreal, August 2015) and the 69th European Meeting of the Econometric Society (Geneva, August 2016), as well as the many detailed comments raised by seminar participants at Deakin and Monash Universities, the Universities of Lecce, Melbourne, Seoul, Sheffield, Sogang, Utah, Yonsei and York, the Melbourne Institute for Applied Economic and Social Research, the Sheffield Methods Institute, the Bank of Korea and the Reserve Bank of New Zealand. Greenwood-Nimmo gratefully acknowledges financial support from the University of Leeds Seedcorn Fund and the kind hospitality of the Universities of Sheffield and York during visits in 2013–5 when a substantial part of this work was conducted. Nguyen acknowledges funding from the Faculty of Business and Economics at the University of Melbourne. Shin acknowledges the hospitality of the Melbourne Institute for Applied Economic and Social Research and the Bank of Korea during research visits in the period April–July 2014. The usual disclaimer applies.

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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 that 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 largely focused 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 that 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 that is attractive by virtue of its parsimony. This is an important consideration in light of the relatively short samples and low sampling frequencies of 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 that is defined in the frequency domain as opposed to the time domain. Their 'cohesion' measure can be used to trace the comovement of multiple 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 vector autoregressive (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 — including 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 that 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 (e.g. 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, 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 in such 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 process the model output. Consequently, the analysis of such models tends to be highly selective and does not properly illuminate the intricate network of linkages among variables in the system.

Significantly, unlike much of the recent literature on financial connectedness, the existing business cycle literature is mostly not grounded 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 — that are composed of many interconnected entities. Our key contribution is therefore to unite modern techniques for global macroeconomic modelling with state of the art developments in financial network analysis. Leading examples of financial network models include Billio et al. (2012) and Diebold and Yilmaz (2009, 2012, 2014).[1] In this literature, financial institutions are characterised as nodes within a network. Analysing the network topology provides a means to

[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).

identify systemically important institutions and to study the propagation of shocks. Billio et al. consider a Granger causal network, while Diebold and Yilmaz develop a weighted directed network (or 'connectedness table') based on the decomposition of the forecast error variance of a VAR. The forecast error variance decomposition (FEVD) measures the proportion of the variance of the h-steps-ahead forecast error of variable i that is due to innovations to variable j. Consequently, it has a natural bilateral interpretation that lends itself to network analysis. Relative to a Granger-causal network, the FEVD approach has the 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.

As originally conceptualised, the framework of Diebold and Yilmaz (2009, 2012, 2014) is not well-suited to the analysis of large and sophisticated multi-country models. Their approach operates at two extremes: (i) complete aggregation, where the $m(m-1)$ bilateral linkages in an m variable model are aggregated into a single spillover index; and (ii) no aggregation, where the $m(m-1)$ bilateral linkages are either studied individually or on a variable-by-variable basis. However, modern multi-country macroeconomic models can contain many variables (often 100 or more). In such cases, as m becomes large, it will rapidly become infeasible to study the network topology on a disaggregated basis and the amount of detail obscured by relying on a single spillover index to summarise the connectedness of the system will increase. Moreover, in a multi-country model with multiple variables per country — a setting that is typical of sophisticated global models and that is central to our notion of multi-dimensional macroeconomic connectedness — one may wish to analyse linkages among countries or regions in the aggregate rather than among individual variables. The Diebold and Yilmaz approach does not provide any straightforward way to achieve this. We therefore require a flexible generalisation of the Diebold and Yilmaz connectedness measures.

Our solution is to introduce intermediate levels of aggregation, yielding a framework for the construction of *generalised connectedness measures* (GCMs). Our approach is to gather the m variables in the model into a set of $b \leq m$ groups and then to aggregate the connectedness matrix according to this group structure. Significantly, aggregation occurs after estimation, so the underlying model is unaffected by the choice of aggregation scheme, facilitating comparisons across different levels of aggregation. The only restrictions on the allocation of variables to groups are that each group must contain one or more variables, no variable may enter more than one group and every variable must be included in the analysis. For example, in a simple model with 5 variables for each of 10 countries (i.e. $m = 50$), one may define 10 groups of 5 variables, with one group corresponding to each country. By aggregating the connectedness matrix accordingly, one may evaluate the connectedness of the system at the country-level. Similarly, suppose that the set of 5 variables for each country contains 2 financial variables and 3 real variables. In this setting, one could define a group containing the 20 financial variables in the system and another containing the 30 real variables in order to evaluate real–financial linkages in the global economy.

Our approach is sufficiently flexible that it can accommodate a very wide variety of aggregation schemes. Consequently, it can shed light on the interactions among a multitude of diverse entities in the global economy. As such, our approach provides a more comprehensive framework for the study of macroeconomic connectedness than the existing literature on business cycle synchronisation. Moreover, our use of aggregation mitigates the processing constraints encountered when analysing large and detailed macroeconomic models. Consequently, our framework unlocks the potential of such models to study macroeconomic connectedness in considerable 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 account for the large majority of global trade and output. In the absence of a precedent, we begin by carefully analysing the sensitivity of the estimated network to the choice of forecast horizon. Our GCMs typically converge to their long-run values after 3–5 quarters. Consequently, we focus on the four-quarters-ahead horizon, which aligns our analysis neatly with the medium-term forecast horizon of many central banks.

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. We identify the US, China, Brazil and the Eurozone 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 presence of additional centres of economic activity is consistent with the rise of China as an economic power and with the regionalisation documented by Hirata et al. (2013). This phenomenon is discernible in the baseline specification of the GNS model but it is particularly evident in robustness tests where time-varying trade weights are used to construct the global VAR system. The high degree of US influence relative to that of other economies that 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 results also reveal that the countries that are most dependent on external conditions include Canada, Singapore and Switzerland, all of which are strongly affected by conditions within their respective free trade areas. We show that analysing a country's relative dependence and influence provides an elegant summary of its role in the global economy, ranging from small open economies at one extreme (high dependence, low influence) to large dominant economies at the other (high influence, low dependence).

Having established a pre-GFC benchmark, we recursively update our estimation sample over the GFC period. The results reveal a marked increase in spillovers originating from the US financial system that coincides with the collapse of Lehman Brothers. Further analysis shows that the US financial shock was rapidly and strongly passed through to both nominal variables and to real economic magnitudes, with real exports and imports being particularly strongly affected.

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 prominent role since the mid-1980s, while the role of global factors has diminished. These observations furnish an a priori case for the development of new techniques such as ours, that 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 introduces an updated version of the GNS global VAR model, which forms the basis of our empirical analysis. The results of GCM analysis of the linkages embedded in this model are presented in Section 4, while Section 5 concludes. Further details of dataset, the model set-up and several robustness exercises are contained in a separate Technical Annex.

2 Measuring Economic Connectedness

Following Diebold and Yilmaz (2009, 2012, 2014), the connectedness measures that we shall develop are based on the FEVD of a p-th order VAR 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 the FEVD is 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, it provides an unadulterated reflection of the connections embedded in the model.

Abstracting from any deterministic terms, the structural VAR(p) model is:

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

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 $\boldsymbol{\varepsilon}_t = \boldsymbol{H}_0^{-1}\boldsymbol{u}_t$. An important feature of the GCMs 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 models in their state-space form (Giacomini, 2013). As always, the choice of underlying model will be guided by the intended application. Where one intends to label shocks and draw structural inferences, then robust identification of the structural shocks is necessary. For example, identification may be achieved by imposing Wold-causality as in Sims (1986), short-run exclusion restrictions as in Blanchard and Watson (1986) or long-run restrictions as in Blanchard and Quah (1989). The framework that we propose below can be applied in each case without limitation. Meanwhile, if one's main interest is in characterising cyclical synchronisation and/or measuring the intensity and direction of bilateral spillover effects, for example, then a reduced form model will often suffice. Although they have no structural interpretation, 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). 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. Following Diebold and Yilmaz (2014), we employ the generalised FEVD (GFEVD) of Pesaran and Shin (1998), which is well-suited to use in reduced form models with correlated shocks. The GFEVD is defined as follows:

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

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

The interpretation of GFEVDs is complicated by the fact that the sum of the variance shares will exceed 100% if $\mathbf{\Sigma}_\varepsilon$ 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 $\sum_{i=1}^{m}\sum_{j=1}^{m} \phi_{i\leftarrow j}^{(h)} = m$. This restores a proportional interpretation to the variance decomposition. The key insight of Diebold and Yilmaz is the recognition that cross-tabulating the h-steps-ahead NGFEVDs for the $m \times 1$ vector of global variables yields a weighted directed network. The resulting $m \times m$ connectedness matrix is given by:

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

The elements of the i-th row of $\mathbb{C}^{(h)}$ record the proportion of the h-steps-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-steps-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

[2]See Diebold and Yilmaz (2009) for an alternative derivation using the orthogonalised FEVD. In principle, the orthogonalised FEVD can support a structural interpretation based on a Wold causal identification scheme, although defining an uncontroversial recursive identification scheme is often infeasible in practice.

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-steps-ahead FEV of the j-th variable in the system is given by $\phi_{j\leftarrow i}^{(h)}$. By summing over j, we can compute the total spillover from variable i to the system as:

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

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

$$N_{\bullet\leftarrow i}^{(h)} = T_{\bullet\leftarrow i}^{(h)} - F_{i\leftarrow\bullet}^{(h)}, \tag{10}$$

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

$$H^{(h)} = \sum_{i=1}^{m} H_{i\leftarrow i}^{(h)} \quad \text{and} \quad S^{(h)} = \sum_{i=1}^{m} F_{i\leftarrow\bullet}^{(h)} \equiv \sum_{i=1}^{m} T_{\bullet\leftarrow i}^{(h)}. \tag{11}$$

We refer to $H^{(h)}$ and $S^{(h)}$ respectively as the h-steps-ahead aggregate heatwave and spillover indices, respectively, a nomenclature that adapts terminology from Engle et al. (1990).[3] Note that $H^{(h)} + S^{(h)} = m$ by definition.

2.1 Generalised Connectedness Measures

The connectedness measures developed by Diebold and Yilmaz (2009, 2012, 2014) 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, one encounters 'processing constraints' that 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. Consequently, as the system becomes larger, attention is increasingly likely to focus only the aggregate spillover and heatwave indices for reasons of expediency. Because the dimension of

[3]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.

$\mathbb{C}^{(h)}$ 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 variables such that $m = \sum_{k=1}^{N} m_k$. The Diebold and Yilmaz technique is best suited to simple models, where either $N = 1$ or $m_k = 1\ \forall k$.[4] This is true because it 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, it does not accommodate intermediate levels of aggregation. Now consider the more general setting in which both $N > 1$ and $m_k > 1$, a setting that is typical of sophisticated multi-country and global models. The Diebold and Yilmaz approach does not provide a simple representation of the spillover from country ℓ to country k because it is not captured by a single element of $\mathbb{C}^{(h)}$ but by $m_\ell m_k$ elements. A good example of this issue arises in Greenwood-Nimmo et al. (2019), which explores the connectedness of a system 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-steps-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-steps-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 Diebold and Yilmaz 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 exposition of the block aggregation routine 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 clarity of presentation.[5] 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

[4] 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 $m_1 = 13$.

[5] As we will show below, our technique simply involves summing desired elements of the connectedness matrix. As such, it does not *require* the re-ordering of $\boldsymbol{y}_t$; it is possible to sum non-adjacent elements. However, re-ordering $\boldsymbol{y}_t$ makes it much easier to visualise how our aggregation routine operates, so we proceed on that basis. One must remain cognisant of the fact that it would be inappropriate to re-order $\boldsymbol{y}_t$ if one were using an order-variant variance decomposition, such as the orthogonalised FEVD discussed by Diebold and Yilmaz (2009).

this case, we may write $\mathbb{C}_R^{(h)}$ as follows:

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

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

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

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 the elements of $\boldsymbol{y}_t$ can be grouped according to *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 collected the variables in $\boldsymbol{y}_t$ into b groups that 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 and 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 $\mathbf{B}_{k\leftarrow k}^{(h)}$.[6] 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-steps-ahead group connectedness matrix:

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

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:

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

where $\mathcal{F}_{k\leftarrow \bullet}^{(h)}$ measures the total spillover from all other groups to group k (i.e. the total *from*

[6] 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 $C_{k\leftarrow k}^{(h)} = \mathcal{W}_{k\leftarrow k}^{(h)} - O_{k\leftarrow k}^{(h)}$.

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:

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

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 variable-level heatwave and spillover measures defined in (11), $\mathcal{H}^{(h)}$ 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 geopolitical units, such as countries and economic blocs within the global economy. In response to the first question, we propose the following *dependence index*:

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

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

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

where $-1 \leq \mathcal{I}^{(h)}_{k} \leq 1$. For any horizon h, the k-th group is a net shock recipient if $-1 \leq \mathcal{I}^{(h)}_{k} < 0$, a net shock transmitter if $0 < \mathcal{I}^{(h)}_{k} \leq 1$, and neither a net transmitter or recipient if $\mathcal{I}^{(h)}_{k} = 0$. As such, the influence index measures the extent to which the k-th group influences or is influenced by conditions in the system.[7] When studying connectedness among countries, the coordinate pair $\left(\mathcal{O}^{(h)}_{k}, \mathcal{I}^{(h)}_{k}\right)$ in dependence–influence space provides an elegant representation of country k's role

[7] 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:

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

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

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 GCM framework to an updated version of the global cointegrating VAR model developed by GNS 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 that collectively account for the majority of global economic activity. Furthermore, the model includes a range of key macroeconomic and financial indicators relating to real output, real trade flows, price level inflation and the financial markets. Recall, however, that our GCM technique can be applied to any model with an approximate VAR representation.

Our updated model (henceforth the GNS25 model) differs from the original 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 GFC. 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 that are found to be insignificant using the cross section dependence test of Pesaran (2020). This increased precision is particularly important because our GCMs depend upon both the parameter matrices and the covariance matrix of the global VAR model. In all other respects, the GNS25 model is identical to the GNS model. 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[8] 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:

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

[8]This is the same sample period considered by GNS 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.

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.[9] The inclusion of country-specific break dummies accounts for local structural breaks that 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 parameters — including our GCMs — to evolve with the sample.

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 $2, \ldots, m_i^*$, where the weights satisfy $\sum_{j=0}^{N} w_{ij} = 1$ and $w_{ii} = 0$. GNS follow Dees et al. (2007) and construct the weights using bilateral trade averages over the period 1999–2001. We adopt the same procedure to obtain baseline estimation results in Sections 4.1 and 4.2. Robustness tests reported by GNS reveal little sensitivity to the choice of weighting scheme in terms of forecasting performance. However, given that our focus is on connectedness as opposed to forecasting, we explore the main implications of alternative weighting schemes in Section 4.3 and conduct a comprehensive robustness exercise in the Technical Annex.

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 world's dominant economy over our sample period, the US is modelled slightly differently.

[9] 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.

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

NOTE: r denotes the number of cointegrating vectors in each country-specific model. ($\bullet$) is our chosen break point. Note that the oil price is included among the set of endogenous variables for the US country-specific 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

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.[10] Furthermore, due to the leading role of the US over our sample period, 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:

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

where $\boldsymbol{z}_{it} = (\boldsymbol{y}_{it}, \boldsymbol{y}_{it}^*)'$, $\boldsymbol{\gamma}_{i0}^* = \boldsymbol{\gamma}_{i0} + \sum_{j=0}^{2} \boldsymbol{\delta}_{ij} d_{i,t-j}$, $\boldsymbol{A}_{i0} = (\boldsymbol{I}_{m_i}, -\boldsymbol{\Phi}_{i0}^*)$ and where $\boldsymbol{A}_{ij} = \left(\boldsymbol{\Phi}_{ij}, \boldsymbol{\Phi}_{ij}^*\right)$ for $j = 1, ..., p$. Next, we may define $\boldsymbol{z}_{it} = \boldsymbol{W}_i \boldsymbol{y}_t$, where $\boldsymbol{y}_t = \left(\boldsymbol{y}_{1,t}', ..., \boldsymbol{y}_{25,t}'\right)'$ 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:

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

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:

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

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 $\boldsymbol{\varepsilon}_t \sim (0, \boldsymbol{\Sigma}_\varepsilon)$. Because the global VAR model is just a large VAR model, it is straightforward to invert (26) into its Wold representation,

[10] 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 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, GNS and Dees et al. (2007) for a detailed discussion.

from which the computation of GCMs follows easily from Section 2 above.

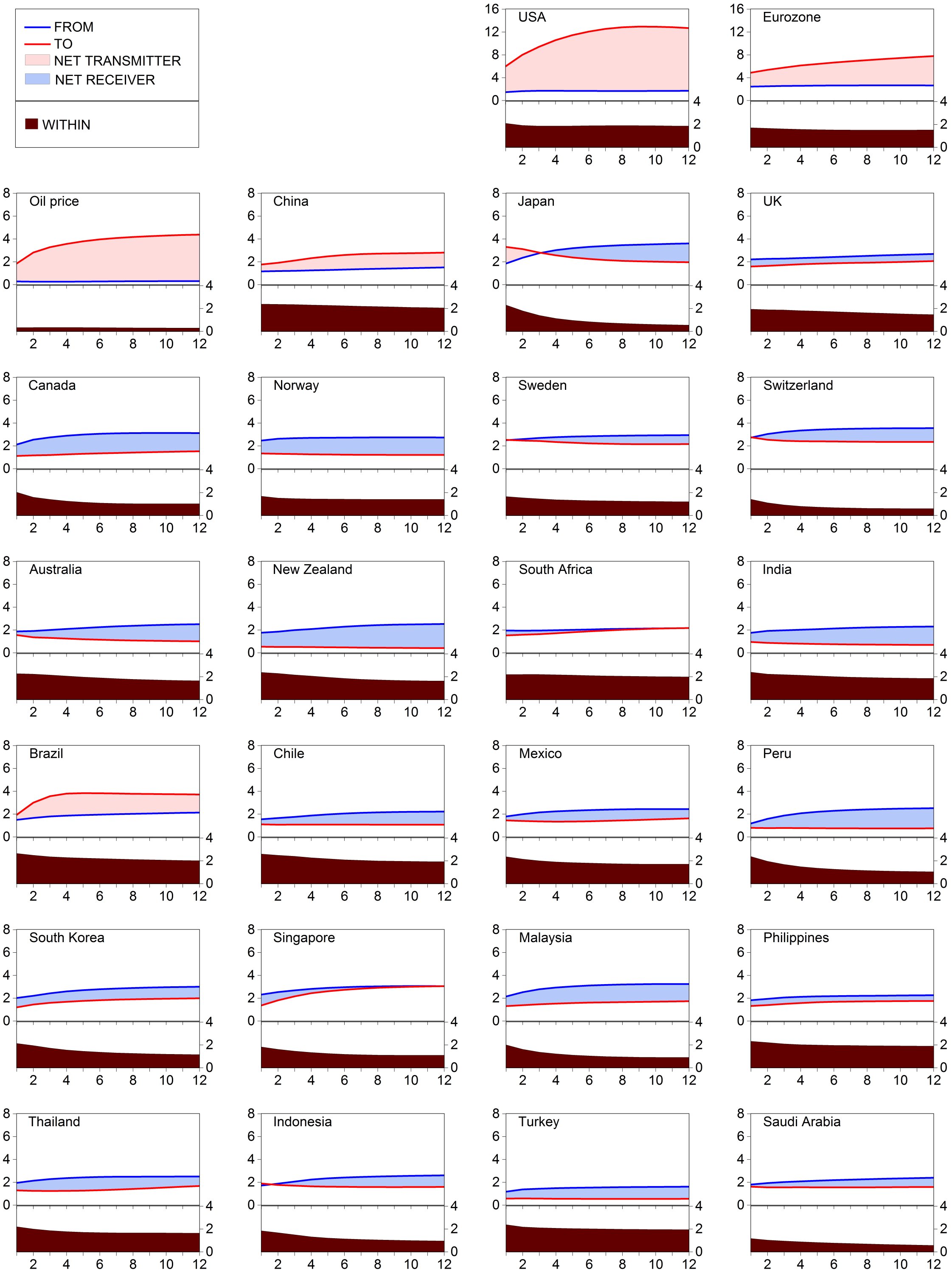
The covariance matrix is central to the computation of FEVDs and so its accurate estimation is essential. Note that the residual covariance matrices from equations (25) and (26) — $\mathbf{\Sigma}_u$ and $\mathbf{\Sigma}_\varepsilon$, respectively — are explicitly related according to $\mathbf{\Sigma}_\varepsilon = \boldsymbol{H}_0^{-1}\mathbf{\Sigma}_u\boldsymbol{H}_0^{-1\prime}$. We elect to focus on $\mathbf{\Sigma}_u$, 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, $\mathbf{\Sigma}_u$ is usually estimated non-parametrically as $\hat{\mathbf{\Sigma}}_u = T^{-1}\sum_{t=1}^{T}\hat{\boldsymbol{u}}_t\hat{\boldsymbol{u}}_t'$, where $\hat{\boldsymbol{u}}_t = \left(\hat{\boldsymbol{u}}_{1t}', \hat{\boldsymbol{u}}_{2t}', \ldots, \hat{\boldsymbol{u}}_{25t}'\right)'$. However, this simple approach may yield imprecise estimates in large systems.[11] We therefore employ an enhanced two-step estimation procedure. First, the prime diagonal (within-country) blocks of $\mathbf{\Sigma}_u$ are estimated as $\hat{\mathbf{\Sigma}}_{u,ii} = (T - n_i)^{-1}\sum_{t=1}^{T}\hat{\mathbf{u}}_{it}\hat{\mathbf{u}}_{it}'$, where n_i is the number of regressors in the i-th country-specific VARX* model. Note that $\hat{\mathbf{\Sigma}}_{u,ii}$ is simply the usual consistent estimator of the covariance matrix of the i-th country-specific VARX* model. Next, we apply the cross section dependence test of Pesaran (2020) to each of the off-diagonal blocks of $\mathbf{\Sigma}_u$ (test results are summarised 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 $\mathbf{\Sigma}_u$; otherwise, the block is estimated as $\hat{\mathbf{\Sigma}}_{u,ij} = (T - \sqrt{n_i n_j})^{-1}\sum_{t=1}^{T}\hat{\mathbf{u}}_{it}\hat{\mathbf{u}}_{jt}'$. Consequently, we obtain an estimated global covariance matrix that employs an appropriate degrees of freedom adjustment and that 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. In the absence of an uncontroversial 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 ($\mathcal{T}_{\bullet\leftarrow j}^{(h)}$) as a red line and the *from* contribution ($\mathcal{F}_{j\leftarrow\bullet}^{(h)}$) as a blue line. The *net* connectedness ($\mathcal{N}_{\bullet\leftarrow j}^{(h)}$) 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 ($\mathcal{W}_{j\leftarrow j}^{(h)}$) across horizons. All of the values reported in Figure 1 are percentages of the total systemwide FEV at each horizon.

[11]For example, 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 $\hat{\mathbf{\Sigma}}_u$ may yield imprecise estimates. In addition, the simple non-parametric routine is unlikely to properly capture any sparsity that may exist, particularly among the off-diagonal (cross-country) blocks of $\hat{\mathbf{\Sigma}}_u$.



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-steps-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 over the Reference Sample, 1980q2–2007q2

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 contrast 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 with the forecast horizon, while *from* contributions grow. 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, China, Brazil 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 $h = 8$. By contrast, 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 values after 3–5 quarters. Consequently, we focus on the four-quarters-ahead horizon below.

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. 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 the 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 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).[12] The resulting ranking derived from our model is generally consistent with established beliefs about economic openness. As 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 that 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 0.55.[13]

Figure 2(a) shows the dependence indices overlaid on a political map. As one may expect, many of 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 US 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%).

The leading role of the US is clear in Table 2, which reveals that spillovers from the US to

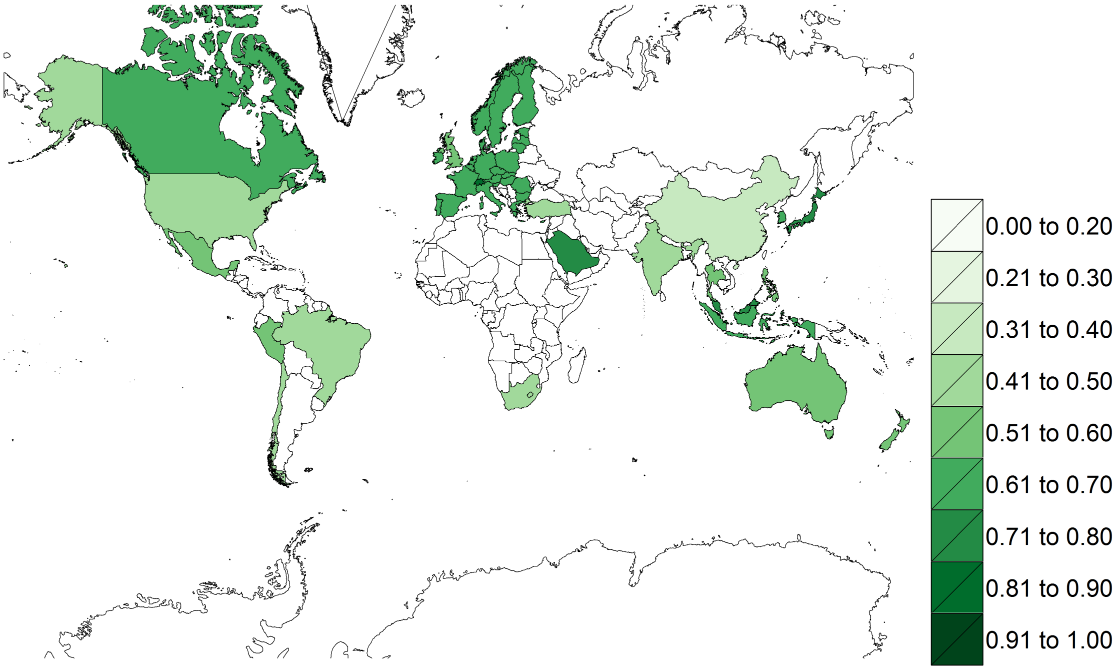
[12]Saudi Arabia records the lowest within-country effect in our sample as well as the fourth highest dependence index. However, these results are likely to overstate the external dependence of the Saudi economy, as its dominant role within OPEC is not fully reflected within our model because the oil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

[13]We compare our dependence index against the mean value of Gwartney et al.'s summary index in the years 1980, 1985, 1990, 1995, 2000, 2005 and 2010. Note that we use Gwartney et al.'s reported values for Germany to proxy for the Eurozone, because 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, as this is the earliest period for which the authors provide data.

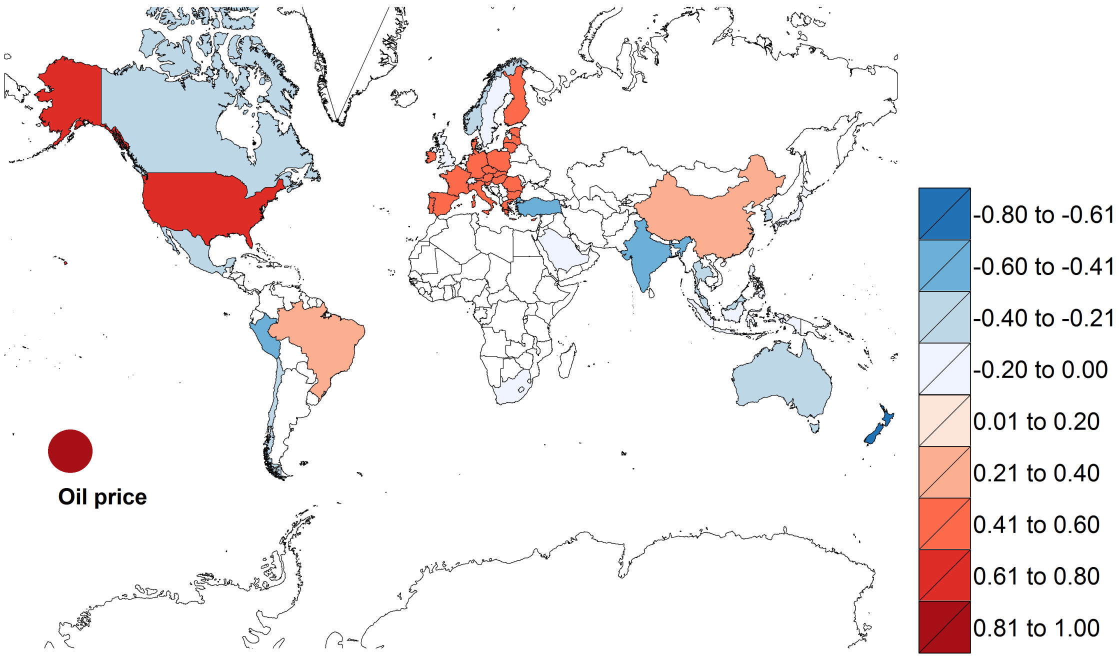
	Within	From	To	Net	Dep.	Infl.
Oil	0.34	0.25	3.56	3.31	0.43	0.87
United States	1.86	1.69	10.57	8.87	0.48	0.72
Eurozone	1.57	2.57	6.13	3.56	0.62	0.41
Japan	1.13	3.02	2.56	-0.46	0.73	-0.08
United Kingdom	1.81	2.33	1.78	-0.55	0.56	-0.13
Norway	1.44	2.70	1.26	-1.44	0.65	-0.37
Sweden	1.38	2.76	2.34	-0.42	0.67	-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-steps-ahead forecast error variance of the system. *Dep.* denotes the dependence 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. *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



(a) Countries of the World by External Dependence



(b) Countries of the World by Influence

NOTE: The dependence 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 dependence on 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: Dependence and Influence Indices by Country, Four-Quarters-Ahead

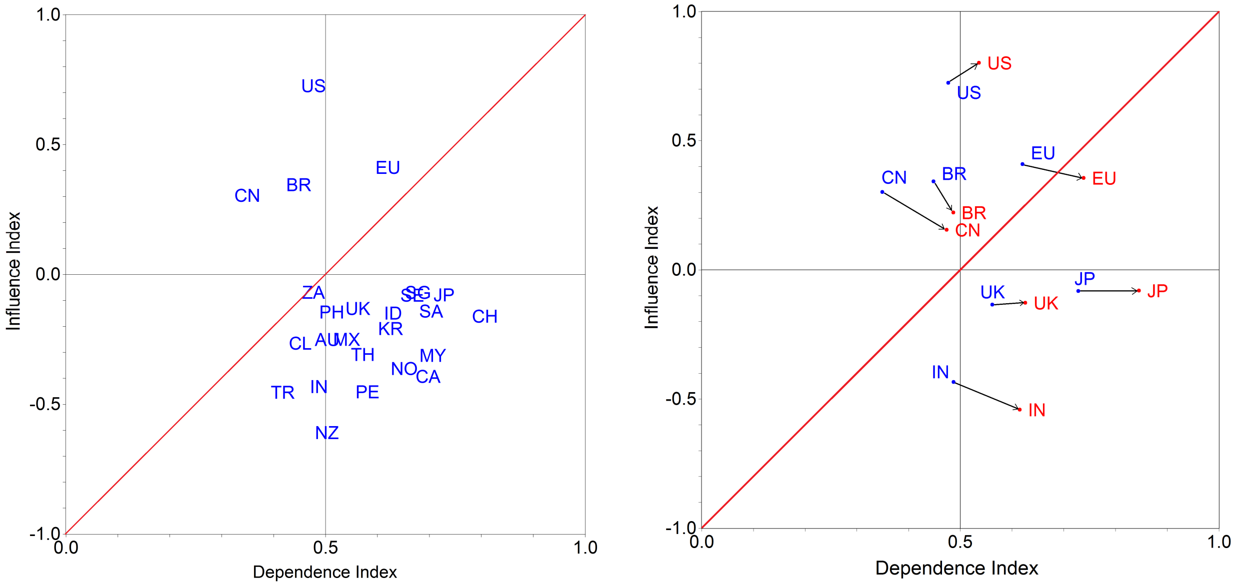
the world economy account for 10.57% of systemwide FEV at $h = 4$. This is a considerably stronger spillover effect than any other observed over the reference sample period — the next largest values are recorded by the Eurozone (6.13%) and the oil price (3.56%). In fact, the average *to* connectedness recorded by all countries in the system excluding the US is just 1.82%. 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 that exert net outward spillover effects at $h = 4$, reflecting their importance within the global economy.[14]

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 geopolitical influence and with economic mass in particular. For example, the correlation between our influence index and each country's share of nominal world GDP on average over the years 1980–2007 is 0.73. Figure 2(b) also provides a simple means of assessing the risks to the global economy posed by shocks occurring 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 and dominant 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 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 onto Europe that have been documented elsewhere in the literature (Eickmeier, 2007). Meanwhile, proximity to the limiting

[14] Note, however, that the estimated influence of China and Brazil is stronger if the model is estimated using time-varying trade weights, as discussed in Section 4.3.

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 is closest to this point, which is an intuitively pleasing result and one that supports the widespread use of Canada as the classic example of a small open economy. We shall return to Figure 3(b) shortly.



(a) All Countries, 1980q2–2007q2

(b) Change during GFC, Selected Countries

NOTE: Panel (a) records the dependence and influence indices for each country over the reference sample period 1980q2–2007q2. Panel (b) records the change in influence and dependence for seven selected economies between the reference sample (shown in blue) and the sample 1980q2–2008q4, which includes the onset of the GFC (shown in red). Influence and dependence 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.

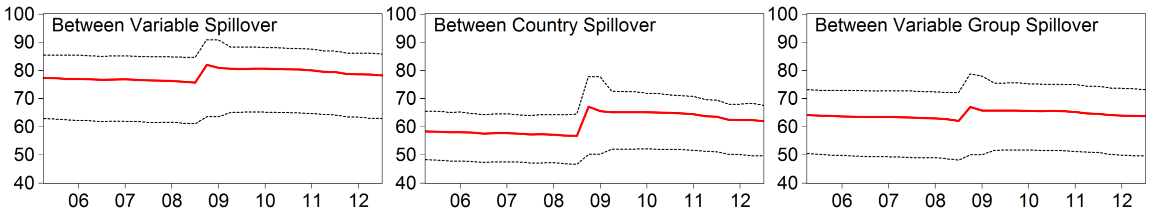
Figure 3: Influence vs. Openness, Four-Quarters-Ahead

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 spill over 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.[15]

[15]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 $\boldsymbol{\Sigma}_u$ whenever 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 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.

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 common global variable. 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.

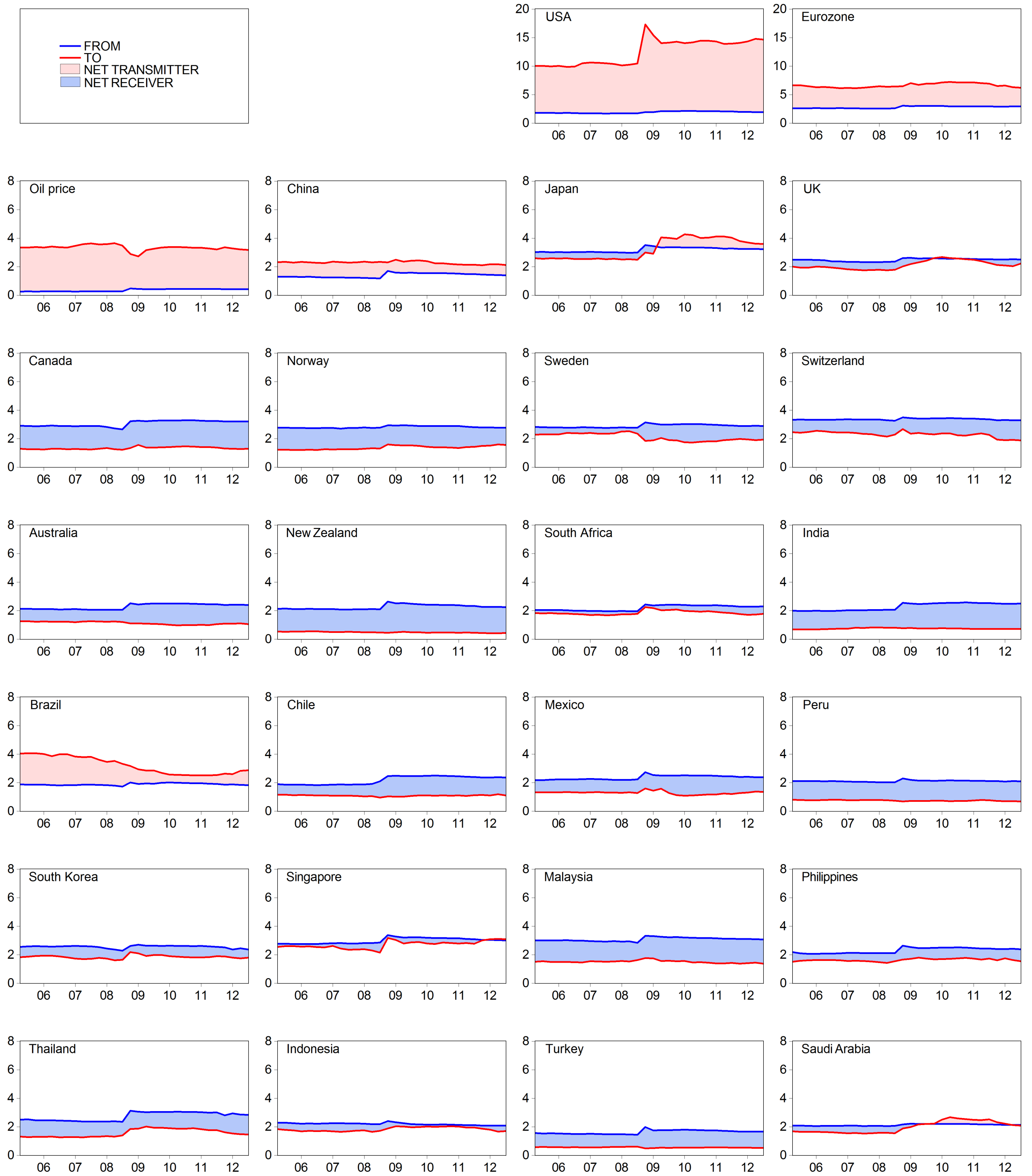


NOTE: The aggregate spillover among variables (the left panel) is computed following equation (11). The aggregate spillovers among countries (middle panel) and variable groups (right panel) are computed following equation (20) subject to the appropriate block structure of $\mathbb{B}^{(h)}$. In each case, the interval reports the range of values taken by the spillover index over horizons 1 to 12, to demonstrate the degree of sensitivity of our recursive estimation results to the choice of forecast horizon. 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. Note that the time axis records the end of the recursive sample period, so that values shown at 2008q4, for example, are derived from the estimation sample 1980q2–2008q4. In all cases, the unit of measurement is the percentage of the total h-steps-ahead forecast error variance of the system.

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

Figure 5 records the time-variation in country connectedness at the four-quarters-ahead horizon, while Table 3 recreates the analysis in Table 2 for the recursive sample ending in 2008q4, a date that corresponds to the height of the GFC, following the collapse of Lehman Brothers. Comparing the two tables reveals that within country effects are much smaller on average in the crisis period (1.26% vs. 1.63% before the GFC), while bilateral 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 origins of the GFC 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 almost three-quarters, 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. 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



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

	Within	From	To	Net	Dep.	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-steps-ahead forecast error variance of the system. *Dep.* denotes the dependence 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. *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 3: Connectedness Among Countries, Four-Quarters-Ahead (1980q2–2008q4)

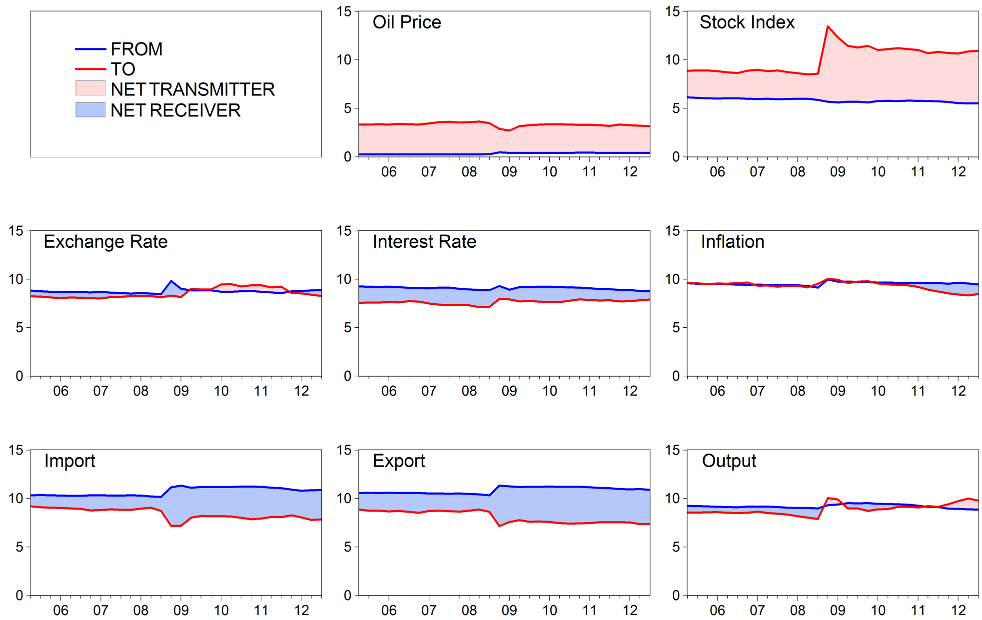
of these countries hosts a significant financial hub, which is suggestive of the key role played by the financial markets in the propagation of the GFC. Japan is particularly noteworthy, as it switches from being a net recipient of shocks prior to the GFC to a modest net transmitter. The particular behaviour 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.

Given our definition of dependence, the substantial increase in spillovers from the US 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 records a notable increase in influence, while the other countries in the figure record increased dependence, often coupled with reduced influence.[16] This finding is also consistent with Starrs (2013), who uses data on transnational corporations to show that American economic power in several sectors has actually increased after 2008 and that America is still the world's dominant economy by some margin.

Next, 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.

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

[16]The high correlation between our dependence index and the summary economic freedom index of Gwartney et al. (2013) is maintained over the extended sample period. Based on the same average values of the summary economic freedom index described in footnote 13, as of 2008Q4, the correlation is 0.57 and, by 2012Q3, it has risen to 0.64. Likewise, our influence index remains strongly correlated with the nominal GDP share over the extended sample period, recording values of 0.74 as of 2008Q4 (relative to the average nominal GDP share over the period 1980–2008) and 0.76 as of 2012Q3 (relative to the average nominal GDP share over the period 1980–2012).

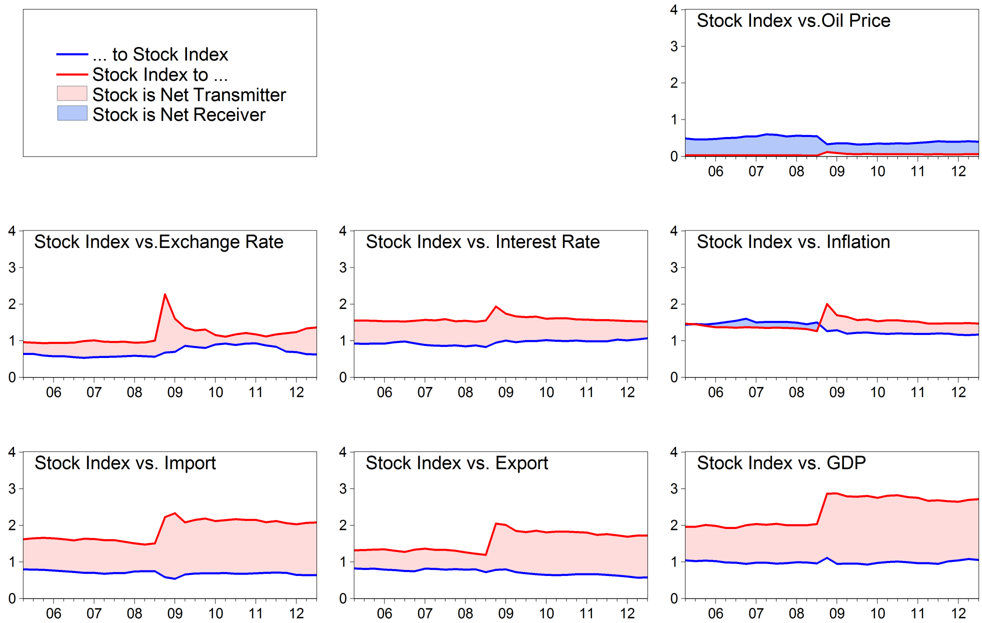


NOTE: The values of *from*, *to* and *net* are computed following equation (19). In all cases, the unit of measurement is the percentage of the total four-quarters-ahead FEV of the system.

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

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).

Figure 7 also reveals a significant short-lived spike in spillovers from global stock markets to the foreign exchange markets (a similar result is documented by Diebold and Yilmaz, 2012). This is consistent 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.



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

4.3 Implications of Alternative Weighting Schemes

The results discussed above are obtained using fixed trade weights over 1999–2001 in the estimation of the GNS25 model, following the precedent of both GNS and Dees et al. (2007). The use of fixed weighting schemes is widespread in the global VAR literature, because time-varying weights have been shown to introduce uncertainty in estimation. However, as highlighted by Cesa-Bianchi et al. (2012), the use of time-varying weights may better account for the emergence of new economic powers, including China. Consequently, we close with a brief analysis of the impact of alternative weighting schemes on our analysis of economic connectedness.

We consider two alternative weighting schemes: (i) more recent fixed trade weights defined over the period 2004–6, just prior to the subprime crisis and the GFC; and (ii) time-varying trade weights defined over rolling three-year windows. To conserve space, we summarise the principal differences arising from the use of these alternative weights by reproducing the analysis in Figure 3 for both weighting schemes in Figure 8. Note that we present and discuss a comprehensive replication of all of our results using both of the alternative weighting schemes in the Technical Annex.

The use of more recent trade data in the construction of the weights matrices leads us to attach relatively less weight to the US and relatively more weight to the fast-growing emerging economies (especially China) in the estimation of the country-specific VARX* models. Over our reference sample period, this manifests as a notable increase in Chinese influence in the model, coupled with a modest decrease in US influence. The overall impact on the system as a whole is an increase in global connectedness, which translates into a general tendency toward increased external dependence. This is visible when using the 2004–6 fixed weights in Figure 8(a) but it is much more apparent when using the time-varying weights in Figure 8(c).

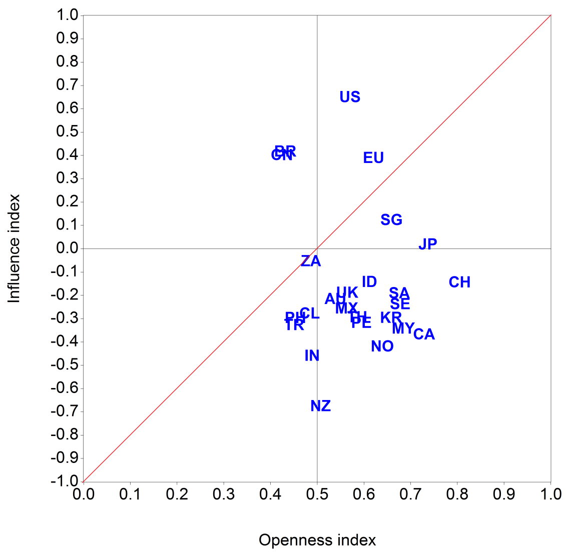
Moving on to the GFC period, we no longer observe an increase in US influence when using time-varying weights, although we still observe a substantial increase in external dependence for each of the seven countries shown in panels (b) and (c) of Figure 8. Nonetheless, the other core elements of our recursive analysis remain largely unchanged relative to the baseline results obtained using 1999–2001 fixed weights. The most marked difference is that the reduction in the weight attached to the US under the alternative weighting schemes reduces the extent to which spillovers from the US intensify during the GFC. Offsetting this, we find evidence of stronger outward spillovers from other sources, most notably the Eurozone and China. This does not alter the finding from our recursive analysis that spillovers from the financial markets onto real GDP and trade flows increased during the GFC, although it does slightly mitigate the magnitude of this effect.

This exercise reveals that the weighting scheme used in the construction of a global VAR model can impact on the network structure embodied by the model and that the use of time-varying trade weights may help to account for the impact of rapidly growing emerging economies over recent decades. Consequently, we recommend that the authors of future studies in the global VAR literature should take these findings into consideration when designing their weighting schemes.

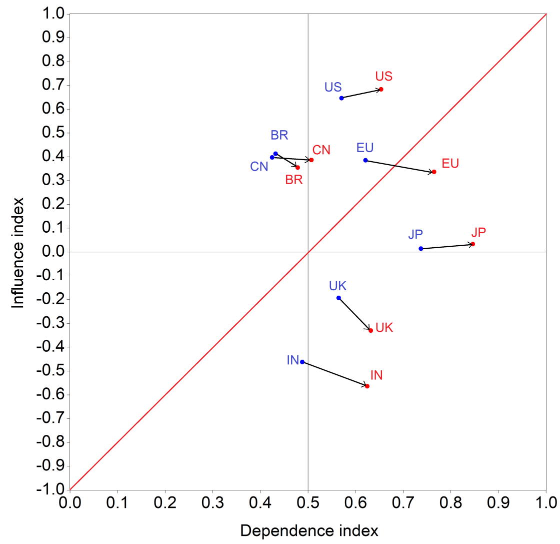
5 Concluding Remarks

We develop a technique to measure macroeconomic connectedness in the global economy. Our GCM framework is an innovative generalisation of the FEVD-based connectedness methodology advanced by Diebold and Yilmaz (2009, 2012, 2014) for the study of financial networks. 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.

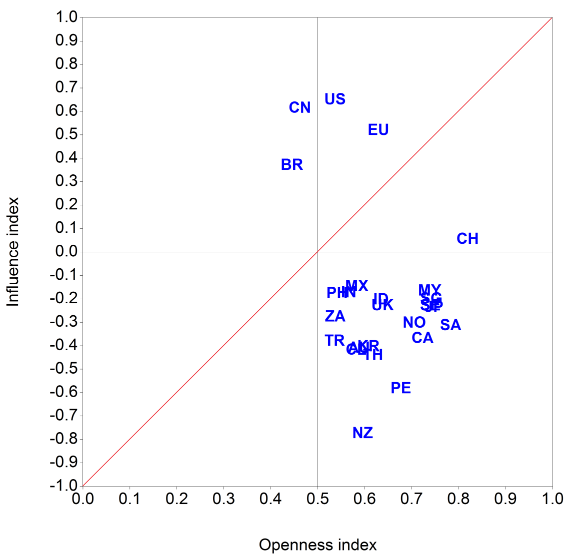
Our method provides a means to distill the wealth of information contained in such sophisticated models into a readily interpreted form, thereby mitigating the processing constraints typically encountered when working with large models. Furthermore, our approach is accessible to non-specialists, as it provides a stylised representation of macroeconomic connectedness, the in-



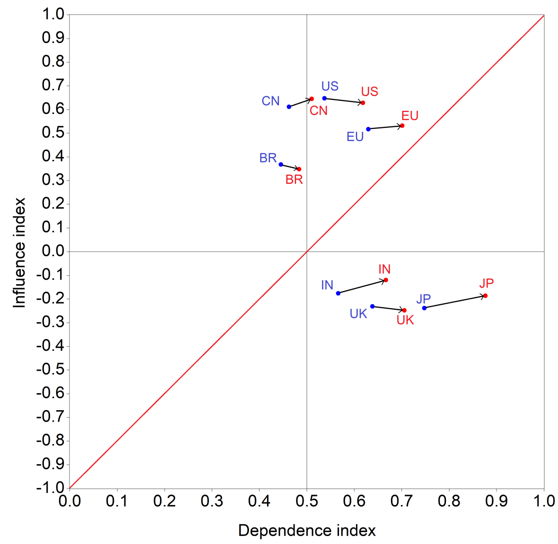
(a) Reference sample period, 2004–6 Weights



(b) Change during GFC, 2004–6 Weights



(c) Reference sample period, T/V Weights



(d) Change during GFC, T/V Weights

NOTE: Panels (a) and (c) record the dependence and influence indices for each country over the reference sample period 1980q2–2007q2 using the 2004–6 fixed weights (panel (a)) and the time-varying weights (panel (c)). Panels (b) and (d) record the change in influence and dependence for seven selected economies between the reference sample (shown in blue) and the sample 1980q2–2008q4 (shown in red) using the 2004–6 fixed weights (panel (b)) and the time-varying weights (panel (d)). Influence and dependence 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 8: Influence vs. Openness under Alternative Weighting Schemes

terpretation 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 dynamic stochastic general equilibrium 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 GNS 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, 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, as well as 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. First, 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. Second, 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 — the connectedness of entities within the global economy matters and their 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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