Measuring the Connectedness of the Global Economy*

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Abstract

We develop a technique to evaluate macroeconomic connectedness among entities in sophisticated multi-country and global macroeconomic models. Our methodology is highly adaptable and may be applied to any model with an approximate VAR representation. We apply our technique to a global vector autoregressive model containing 169 macroeconomic and financial variables for 25 countries. We derive vivid representations of the connectedness of the system and find that the US, the Eurozone and the crude oil market exert a dominant influence over conditions in the global macroeconomy and that China and Brazil are also globally significant economies. 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.

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1 Introduction

Globalisation is the process of increasing interdependence among entities in the global economy. In layman’s terms, the world is becoming ‘smaller’ and the distinction between national, regional and global issues less well-defined. Established views of the benefits of globalisation in relation to openness, liberalisation and development have been challenged in light of the Global Financial Crisis (GFC), which has drawn renewed attention to the risks posed by aspects of financial globalisation [Mishkin, 2011]. Recent research into financial connectedness has reshaped our understanding of systemic linkages and has shed new light on the identification and supervision of institutions which are ‘too big’ or ‘too connected’ to fail [IMF, 2009]. However, our understanding of international macroeconomic linkages has not advanced to the same degree [Eichmeier, 2007]. Our goal in this paper is to develop a general framework to evaluate macroeconomic connectedness.

One aspect of macroeconomic connectedness that has been studied is the apparent convergence of business cycles across countries. A degree of consensus has emerged around the notion of a global business cycle which induces some common behaviour in national business cycles (e.g. Kose et al., 2003, 2008; Hirata et al., 2013, inter alia). Much of this research has modelled the global business cycle as a latent factor, an approach which is attractive by virtue of its parsimony. This is an important consideration in light of the relatively short sample lengths and low sampling frequencies associated with much macroeconomic data. This was a key motivation underlying Croux et al.’s (2001) development of a synthetic measure of synchronisation across countries/regions which is defined in the frequency domain as opposed to the time domain. Their ‘cohesion’ measure can be used to trace the comovement of multiple cointegrated time series and its application to European sovereign and US state-level business cycles further supports the synchronisation hypothesis.

Although Croux et al. stress that estimating VAR models may be ‘problematic when the number of time series is large’ (p. 232), subsequent innovations in the estimation of large multi-country VAR models — notably panel/global VAR (Pesaran et al., 2004), factor augmented VAR (Bernanke et al., 2005) and large Bayesian VAR (De Mol et al., 2008) — have relaxed this constraint. Consequently, it is now possible to estimate large macroeconomic models in the time domain which accommodate a wealth of interactions among countries and regions. Canova et al. (2007) were among the first to apply these techniques to the analysis of business cycle convergence, estimating a Bayesian panel VAR model which again highlights the importance of a global cycle relative to...
idiosyncratic effects. In principle, a sufficiently detailed multicountry 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, such models may provide a new perspective on the issues of globalisation and regionalisation that have emerged prominently in the existing literature, most recently in Hirata et al. (2013).

The development of techniques for global macroeconometric modelling has yet to be met by concomitant advances in techniques for the analysis of the linkages embedded within these models. Unlike much of the recent literature on financial connectedness, the business cycle literature surveyed above is 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 — which are composed of many interconnected entities. Leading examples of network models in finance include Billio et al. (2012) and Diebold and Yilmaz (2009, 2014; henceforth DY). In this literature, financial institutions are characterised as nodes within a network. Analysing the network topography provides a means to identify systemically important institutions and to study the propagation of shocks. Billio et al. propose the use of a Granger causal network, while Diebold and Yilmaz develop connectedness measures based on error variance decomposition of a vector autoregression. The latter approach has the considerable advantage that it fully accounts for contemporaneous effects and it also directly measures not only the direction but also the strength of linkages among nodes in the network.

The DY approach has recently been applied to the analysis of business cycle convergence by Diebold and Yilmaz (2015), who study spillovers in real activity among six developed economies. The authors uncover an intricate pattern of bilateral spillovers, with shocks emanating from the US and Japan exerting a disproportionately large influence over the system. Their paper is noteworthy as the first to apply this type of network analysis to macroeconomic phenomena. However, it is highly stylised, focusing solely on real activity measured by industrial production. While this provides insights into business cycle comovement, there is little reason to believe that this is the only relevant aspect of macroeconomic connectedness. International linkages may arise through diverse channels including financial linkages, trade linkages and relative price changes (Dees et al., 2007). We therefore seek a more holistic approach.

Our contribution is to bring together recent advances in global modelling with the current state

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).
of the art in network analysis to develop a general framework to study macroeconomic connectedness on a global scale. Our approach integrates detailed multivariate country-specific macroeconomic models into a global system and then maps the topography of the resulting global network. This requires a generalisation of the DY connectedness measures which have been developed to study either the multi-country univariate case (e.g. [Diebold and Yilmaz, 2015]) or the single-country multivariate case (e.g. [Diebold and Yilmaz, 2014]). To see this, note that the DY approach operates at two extremes: complete aggregation where the $m(m-1)$ bilateral linkages in an $m$ variable model are aggregated into a single spillover index, or no aggregation where the $m(m-1)$ linkages are studied individually. In a multicountry model with multiple variables per country, one may wish to analyse linkages among countries or regions rather than among individual variables. We therefore introduce intermediate levels of aggregation, yielding a framework for the construction of generalised connectedness measures, or GCMs. The resulting framework is highly adaptable and can be applied to any model with an approximate VAR representation, including DSGE models in their state-space form ([Giacomini, 2013]). Moreover, it is not reliant on the imposition of identifying assumptions although equally it does not preclude them ([Diebold and Yilmaz, 2015]).

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

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

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

Aside from the connectedness literature, our paper is most closely related to the panel VAR approach of Canova et al. (2007) and the dynamic factor model developed by Hirata et al. (2013). Both of these papers distinguish between global, regional and local effects. Canova et al. emphasise the role of a global factor influencing G7 business cycles, while Hirata et al. stress that regional factors have come to play a prominent role since the mid 1980s, during which time the role of global factors has diminished. These observations furnish an a priori case for the development of new techniques such as ours which offer a sophisticated treatment of the foreign sector which does not rely on traditional ‘small open economy’ assumptions and which does not require strong restrictions to identify orthogonal factors.

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

2 Measuring Economic Connectedness

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

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

\[
H_0 y_t = \sum_{j=1}^{p} H_j y_{t-j} + u_t
\] (1)

where \(H_0\) is the \(m \times m\) contemporaneous matrix, the \(H_j\)’s are the vector autoregressive parameter
matrices and the residuals \(u_t \sim (0, \Sigma_u)\) where \(\Sigma_u\) is positive definite. The reduced form of the
model is written as:

\[
y_t = \sum_{j=1}^{p} G_j y_{t-j} + \varepsilon_t
\] (2)

where \(G_j = H_0^{-1} H_j\) and \(\varepsilon_t = H_0^{-1} u_t\). Throughout the derivations to follow, we remain intention-
ally agnostic about the nature of the contemporaneous effects in the model. Indeed, a key feature
of the generalised connectedness measures that we develop is that they may be derived from ei-
ther the structural model (1) or the reduced form model (2) or, indeed, from any model with an
approximate VAR representation, including DSGE models in their state-space form (Giacomini,
2013). As always, one’s choice of the underlying model will be guided by the intended application.
Where one seeks to draw structural inferences then robust identification of the structural shocks
is necessary. Meanwhile, if one’s main interest is in characterising cyclical synchronisation and/or
measuring the intensity and direction of spillover effects then a reduced form model will suffice.

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

\[
y_t = \sum_{j=0}^{\infty} B_j \varepsilon_{t-j},
\] (3)

where the \(B_j\)’s are evaluated recursively as \(B_j = G_1 B_{j-1} + G_2 B_{j-2} + \cdots + G_{p-1} B_{j-p+1}\), with
\(B_0 = I_m\) and \(B_j = 0\) for \(j < 0\) such that the \(B_j\)’s are square-summable and causal.

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

\[
GFEVD(y_{it}; u_{jt}, h) = \varphi_{i \leftarrow j}^{(h)} = \frac{\sigma_{u,jj}^{-1} \sum_{\ell=0}^{h-1} (e_i' B_i H_0^{-1} \Sigma_u e_j)^2}{\sum_{\ell=0}^{h-1} e_i' B_i \Sigma_u B_i' e_i} \quad (4)
\]

for \( i, j = 1, \ldots, m \), where \( h = 1, 2, \ldots \) is the forecast horizon, \( \sigma_{u,jj}^{-1} \) is the standard deviation of the residual process of the \( j \)-th equation in the VAR system, \( \Sigma_u = H_0^{-1} \Sigma_u H_0^{-1}' \) and \( e_i \) (\( e_j \)) is an \( m \times 1 \) selection vector whose \( i \)-th element (\( j \)-th element) is unity with zeros elsewhere. Note our use of non-standard subscript notation which will serve to highlight the directionality of the connectedness measures in the derivations to follow. \( \varphi_{i \leftarrow j}^{(h)} \) represents the contribution of variable \( j \) to the \( h \)-step ahead FEV of variable \( i \). Similarly, \( \varphi_{i \leftarrow i}^{(h)} \) denotes the contribution of variable \( i \) to its own \( h \)-step ahead FEV.

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

\[
\phi_{i \leftarrow j}^{(h)} = \varphi_{i \leftarrow j}^{(h)} \sum_{j=1}^{m} \varphi_{i \leftarrow j}^{(h)} \quad (5)
\]

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

\[
C^{(h)} = \begin{bmatrix}
\phi_{1 \leftarrow 1}^{(h)} & \phi_{1 \leftarrow 2}^{(h)} & \cdots & \phi_{1 \leftarrow m}^{(h)} \\
\phi_{2 \leftarrow 1}^{(h)} & \phi_{2 \leftarrow 2}^{(h)} & \cdots & \phi_{2 \leftarrow m}^{(h)} \\
\vdots & \vdots & \ddots & \vdots \\
\phi_{m \leftarrow 1}^{(h)} & \phi_{m \leftarrow 2}^{(h)} & \cdots & \phi_{m \leftarrow m}^{(h)}
\end{bmatrix} \quad (6)
\]

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

\[
H_{i \leftarrow i}^{(h)} = \phi_{i \leftarrow i}^{(h)} \quad (7)
\]
while the off-diagonal elements of the $i$-th row of $C^{(h)}$ capture spillovers from the other variables in the system to variable $i$. Specifically, the $(i, j)$-th element, $\phi_{i\leftarrow j}^{(h)}$, represents the contribution to the $h$-step-ahead FEV of variable $i$ from variable $j \neq i$. Adopting the terminology of Diebold and Yilmaz, this is known as a *from* contribution because it measures the directional connectedness to the $i$-th variable from variable $j$. By summing over $j$, we may define the total spillover from the system to variable $i$ as:

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

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

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

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

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

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:

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

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

### 2.1 Generalised Connectedness Measures

The DY connectedness measures are well suited to use in relatively small VAR systems. However, their usefulness diminishes as $m$ — the number of variables entering the VAR system — becomes large. This is true for two reasons. Firstly, the DY approach is subject to ‘processing constraints’ which intensify sharply with $m$. That is, for a sufficiently large value of $m$, it will become infeasible

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2 Diebold and Yilmaz (2009) define the spillover index as $100 \left[ S^{(h)}/ (S^{(h)} + H^{(h)}) \right]$ which measures the relative importance of spillovers between variables in the system as a percentage of the systemwide FEV at horizon $h$. }
to interpret (or process) the elements of the connectedness matrix individually. Consequently, as
the system becomes larger, attention is increasingly likely to focus only the aggregate spillover
and heatwave indices for reasons of expediency. Since the dimension of $C^{(h)}$ is quadratic in $m$, the
addition of an $(m + 1)$th variable to the system enlarges $C^{(h)}$ 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 DY technique is best suited to simple models where either
$N = 1$ or $m_k = 1 \ \forall k$\footnote{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 $m_1 = 13$.}. This is true because the DY approach operates at two extremes: (i) one may
study connectedness among the $m$ variables in the system in a disaggregated fashion (via equations\footnote{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 $m_1 = 13.$} 6 to 10); and (ii) one may study systemwide connectedness in a wholly aggregated fashion (via equation (11)). Without modification, the DY method does not accommodate intermediate levels
of aggregation. Now consider the more general setting in which both $N > 1$ and $m_k > 1$, a setting
which is typical of sophisticated multi-country and global models. In this case, the DY approach
does not provide a simple representation of the spillover effect from country $\ell$ to country $k$ because
it is captured by $m_\ell m_k$ elements of $C^{(h)}$ rather than by a single value. A good example of this
issue arises in Greenwood-Nimmo et al. (2014), which explores the connectedness of a small Global
VAR model containing two endogenous variables for each of eight foreign exchange spot markets.

We propose a simple approach to overcome both issues based on re-normalisation and block
aggregation of the connectedness matrix. First, we re-normalise such that $C^{(h)}_R = m^{-1} C^{(h)}$. This
subtly alters the interpretation of the elements of the connectedness matrix. Recall that the $(i, j)$-

th element of $C^{(h)}$ represents the proportion of the $h$-step ahead FEV of variable $i$ explained by
variable $j$. After re-normalisation, the $(i, j)$-th element of $C^{(h)}_R$ represents the proportion of the total
$h$-step ahead FEV of the system accounted for by the spillover effect from variable $j$ to variable $i$.

This subtle modification ensures that we may achieve a clear percentage interpretation even after
aggregating groups of variables in the system. This would not be the case under the DY framework
where the aggregation of variables into groups may lead to spillovers that exceed 100% (recall that
the elements of $C^{(h)}$ sum to $m \times 100\%$).

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

\[
C^{(h)}_R = m^{-1}
\begin{bmatrix}
\phi_{1-1}^{(h)} & \cdots & \phi_{1-m}^{(h)} & \phi_{1-m+1}^{(h)} & \cdots & \phi_{1-m+1}^{(h)} & \cdots & \phi_{1-m+1}^{(h)} & \cdots & \phi_{1-m}^{(h)} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\
\phi_{m_1+1-1}^{(h)} & \cdots & \phi_{m_1+1-m}^{(h)} & \phi_{m_1+1-m+1}^{(h)} & \cdots & \phi_{m_1+1-m+1}^{(h)} & \cdots & \phi_{m_1+1-m+1}^{(h)} & \cdots & \phi_{m_1+1-m}^{(h)} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\
\phi_{m_2+1-1}^{(h)} & \cdots & \phi_{m_2+1-m}^{(h)} & \phi_{m_2+1-m+1}^{(h)} & \cdots & \phi_{m_2+1-m+1}^{(h)} & \cdots & \phi_{m_2+1-m+1}^{(h)} & \cdots & \phi_{m_2+1-m}^{(h)} \\
\vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots & \ddots & \vdots \\
\phi_{m+B-1}^{(h)} & \cdots & \phi_{m+B-m}^{(h)} & \phi_{m+B-m+1}^{(h)} & \cdots & \phi_{m+B-m+1}^{(h)} & \cdots & \phi_{m+B-m+1}^{(h)} & \cdots & \phi_{m+B-m}^{(h)} \\
\end{bmatrix}
\]

(12)

The block structure of \( C^{(h)}_R \) is easily seen. The \((k, \ell)\)th block in (12), denoted \( B_{k,\ell}^{(h)} \), is given by:

\[
B_{k,\ell}^{(h)} = m^{-1}
\begin{bmatrix}
\phi_{m_k+1-k+1}^{(h)} & \cdots & \phi_{m_k+1-k+m_\ell}^{(h)} & \cdots & \phi_{m_k+1-k+m_\ell}^{(h)} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
\phi_{m_k+m_\ell+1-k}^{(h)} & \cdots & \phi_{m_k+m_\ell+1-m_\ell}^{(h)} & \cdots & \phi_{m_k+m_\ell+1-m_\ell}^{(h)} \\
\end{bmatrix}
\]

(13)

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

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

\[
C^{(h)}_R = m^{-1}
\begin{bmatrix}
B_{1-1}^{(h)} & B_{1-2}^{(h)} & \cdots & B_{1-b}^{(h)} \\
B_{2-1}^{(h)} & B_{2-2}^{(h)} & \cdots & B_{2-b}^{(h)} \\
\vdots & \vdots & \ddots & \vdots \\
B_{b-1}^{(h)} & B_{b-2}^{(h)} & \cdots & B_{b-b}^{(h)} \\
\end{bmatrix}
\]

(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 $C^{(h)}_R$ (i.e. the $B^{(h)}_{k+\ell}$’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:

$$W^{(h)}_{k-k} = e'_m B^{(h)}_{k-k} e_m$$

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

$$F^{(h)}_{k-k} = e'_m B^{(h)}_{k-k} e_m$$

and the spillover to group $k$ from group $\ell$ as:

$$T^{(h)}_{\ell-k} = e'_m B^{(h)}_{\ell-k} e_m.$$  

With these definitions in hand, it is straightforward to obtain the following $h$-step ahead group connectedness matrix:

$$B^{(h)} = \begin{bmatrix}
W^{(h)}_{1-1} & F^{(h)}_{2-1} & \cdots & F^{(h)}_{1-b} \\
F^{(h)}_{2-1} & W^{(h)}_{2-2} & \cdots & F^{(h)}_{2-b} \\
\vdots & \vdots & \ddots & \vdots \\
F^{(h)}_{b-1} & F^{(h)}_{b-2} & \cdots & W^{(h)}_{b-b} 
\end{bmatrix} = \begin{bmatrix}
W^{(h)}_{1-1} & T^{(h)}_{1-2} & \cdots & T^{(h)}_{1-b} \\
T^{(h)}_{2-1} & W^{(h)}_{2-2} & \cdots & T^{(h)}_{2-b} \\
\vdots & \vdots & \ddots & \vdots \\
T^{(h)}_{b-1} & T^{(h)}_{b-2} & \cdots & W^{(h)}_{b-b} 
\end{bmatrix}$$

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:

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

where $F^{(h)}_{k-\bullet}$ measures the total spillover from all other groups to group $k$ (i.e. the total from contribution affecting group $k$), $T^{(h)}_{\bullet-k}$ measures the total spillover to all other groups from group $k$, and $N^{(h)}_{\bullet-k}$ measures the total net spillover from all other groups to group $k$. 

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

4
$k$ (i.e. the total to contribution arising from group $k$) and $N_{i\rightarrow k}$ 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:

$$H^{(h)} = \sum_{k=1}^{b} W_{k\rightarrow k}^{(h)} \quad \text{and} \quad S^{(h)} = \sum_{k=1}^{b} F_{k\rightarrow k}^{(h)} \equiv \sum_{k=1}^{b} T_{k\rightarrow k}^{(h)}$$

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

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

$$O_{k}^{(h)} = \frac{F_{k\rightarrow k}^{(h)}}{W_{k\rightarrow k}^{(h)} + F_{k\rightarrow k}^{(h)}}$$

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

$$I_{k}^{(h)} = \frac{N_{i\rightarrow k}^{(h)}}{T_{i\rightarrow k}^{(h)} + F_{i\rightarrow k}^{(h)}}$$

where $-1 \leq I_{k}^{(h)} \leq 1$. For any horizon $h$, the $k$-th group is a net shock recipient if $-1 \leq I_{k}^{(h)} < 0$, a net shock transmitter if $0 < I_{k}^{(h)} \leq 1$, and neither a net transmitter or recipient if $I_{k}^{(h)} = 0$. As such, the influence index measures the extent to which the $k$-th group influences or is influenced by conditions in the system. When studying connectedness among countries, the coordinate pair $(O_{k}^{(h)}, I_{k}^{(h)})$ in dependence–influence space provides an elegant representation of country $k$’s role in the global system. A classic small open economy would be located close to the point $(1, -1)$ while, by contrast, an overwhelmingly dominant economy would exist in the locale of $(0, 1)$. In this

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

$$T_{i\rightarrow k}^{(h)} = \frac{N_{i\rightarrow k}^{(h)}}{T_{i\rightarrow k}^{(h)} + T_{i\rightarrow \ell}^{(h)}}$$

which is also bounded between -1 and 1 and is interpreted in a similar manner to (22). Note that $T_{i\rightarrow k}^{(h)} = -T_{k\rightarrow i}^{(h)}$ by definition.
way, we are able to measure the extent to which the different economies of the world correspond to these stylised concepts.

3 The GNS Global Model

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

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

The GNS25 model is estimated using quarterly data spanning the reference sample period 1980q2–2007q2 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:

\[
y_{it} = \gamma_{i0} + \gamma_{i1}t + \sum_{j=0}^{2} \delta_{ij}d_{i,t-j} + \sum_{j=1}^{2} \Phi_{ij}y_{i,t-j} + \sum_{j=0}^{2} \Phi^*_ijy^*_i,t-j + u_{it} \tag{23}
\]

where \( y_{it} \) is an \( m_i \times 1 \) vector of endogenous variables, \( y^*_it \) 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, \( u_{it} \) is a serially uncorrelated mean-zero process with positive

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6 This is the same sample period considered by Greenwood-Nimmo et al. (2012) and is used here to provide benchmark results for the period prior to the GFC. As discussed below, we also estimate the GNS25 model recursively using samples starting in 1980q2 and ending in 2005q2, 2007q2, 2012q3.
definite covariance matrix $\Sigma_{u,ii}$ and Greek letters represent unknown parameters to be estimated. The country-specific structural breaks included in the GNS25 model are detailed in Table 1. The inclusion of country-specific break dummies accounts for local structural breaks which are not accommodated by co-breaking. In principle, one could model the GFC as a global break but, instead, we elect to study it via recursive estimation which allows the model parameters and the associated functions of these parameters — including our GCMs — to evolve with the sample.

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

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

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

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7Where 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.

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

9Following Dees et al. (2007), the log real effective exchange rate is defined as $re_{it} = e_{it} + p_{it} - p_{i}$. Note that $e_{it} + p_{it} - p_{i} = (e_{it} - p_{i}) - (p_{it} - p_{i}) = \tilde{e}_{it} - \tilde{p}_{it}$, where $e_{it}$ is the nominal exchange rate vis-à-vis the USS, $\tilde{e}_{it} = \sum_{j=0}^{N} w_{ij} e_{jt}$, $\tilde{e}_{it} = \sum_{j=0}^{N} w_{ij} e_{jt}$ is the nominal effective exchange rate, $p_{it}$ the national price level and $p_{i}$ the
economy, $r_{it}$ and $q_{it}$ 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:

\[
A_{i0}z_{it} = \gamma_{i0} + \gamma_{i1}t + \sum_{j=0}^{2} \delta_{ij}d_{i,t-j} + \sum_{j=1}^{2} A_{ij}z_{i,t-j} + u_{it} \tag{24}
\]

where \( z_{it} = (y_{it}, y^*_{it})' \), \( A_{i0} = (I_{m_i}, -\Phi_{i0}) \) and where \( A_{ij} = (\Phi_{ij}, \Phi^*_{ij}) \) for \( j = 1, \ldots, p \). Next, we may define \( z_{it} = W_i y_t \) where \( y_t = (y'_{1,t}, \ldots, y'_{25,t})' \) and \( W_i \) 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 \( z_{it} \) and \( y_t \), the country-specific VARX*(2,2) models in \( (24) \) may be stacked to yield:

\[
H_0 y_t = \gamma_0 + \gamma_1 t + \sum_{j=0}^{2} \delta_{ij}d_{i,t-j} + \sum_{j=1}^{2} H_j y_{t-j} + u_t \tag{25}
\]

where:

\[
\gamma_0 = \begin{pmatrix} \gamma_{1,0} \\ \vdots \\ \gamma_{25,0} \end{pmatrix}, \quad \gamma_1 = \begin{pmatrix} \gamma_{1,1} \\ \vdots \\ \gamma_{25,1} \end{pmatrix}, \quad u_t = \begin{pmatrix} u_{it} \\ \vdots \\ u_{25t} \end{pmatrix} \quad \text{and} \quad H_j = \begin{pmatrix} A_{1j} W_1 \\ \vdots \\ A_{25j} W_{25} \end{pmatrix}
\]

from which the final reduced-form global VAR(2,2) model can be retrieved as:

\[
y_t = g_0 + g_1 t + \sum_{j=0}^{2} \delta_{ij}d_{i,t-j} + \sum_{j=1}^{2} G_j y_{t-j} + \varepsilon_t \tag{26}
\]

where \( g_0 = H_0^{-1} \gamma_0, g_1 = H_0^{-1} \gamma_1 \) and \( G_j = H_0^{-1} H_j, j = 1, \ldots, p \), denotes the set of \( m \times m \) global VAR coefficient matrices. As usual, \( \varepsilon_t = H_0^{-1} u_t \) where \( \varepsilon_t \sim (0, \Sigma_e) \). Since the global VAR model is just a large VAR, it is straightforward to invert \( (26) \) into its Wold representation, from which the computation of generalised connectedness measures follows easily from Section 2 above.

The covariance matrix is central to the computation of FEVDs and so its accurate estimation is essential. Note that the residual covariance matrices from equations \( (25) \) and \( (26) \) — \( \Sigma_u \) and \( \Sigma_e \), respectively — are explicitly related according to \( \Sigma_e = H_0^{-1} \Sigma_u H_0^{-1/2} \). We elect to focus on \( \Sigma_u \), which contains the original contemporaneous correlation structure among shocks across countries.

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foreign price level. Hence, we actually model the US price level rather than US inflation and we carefully account for this fact when stacking the country-specific VARX*(2,2) models into the global VAR(2,2) model. See the Technical Annex, Greenwood-Nimmo et al. (2012) and Dees et al. (2007) for a detailed discussion.
and is free from the influence of the estimated parameters in the contemporaneous matrix, $H_0$. In the global VAR literature, $\Sigma_u$ is usually estimated non-parametrically as $\hat{\Sigma}_u = \hat{u}_t\hat{u}_t'$, where $\hat{u}_t = (\hat{u}'_{1t}, \hat{u}'_{2t}, \ldots, \hat{u}'_{25t})'$. Recall from Table 1 that the country-specific VARX* models differ both in terms of their cointegrating rank and also in terms of the domestic and foreign variables that they include. As such, the different country-specific models may contain different numbers of regressors. Consequently, $\hat{u}_{it}$ and $\hat{u}_{jt}$ for $i \neq j$, may be estimated with different degrees of freedom and the established method of computing $\hat{\Sigma}_u$ may yield imprecise estimates. Furthermore, the estimation of the off-diagonal (cross-country) blocks of $\hat{\Sigma}_u$ may be refined by formally testing for cross section dependence or by employing related techniques for the sparse estimation of covariance matrices (Bien and Tibshirani [2011]).

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

4 Measuring the Connectedness of the Global Economy

4.1 Economic Connectedness Prior to the GFC

The first step in our analysis is to select an appropriate forecast horizon. Existing applications of the DY methodology have mostly considered financial spillovers using daily or weekly data and correspondingly short forecast horizons. The only exception of which we are aware is Diebold and Yilmaz (2015), who work with a 12 month horizon and demonstrate robustness over 6 and 18 months horizons. Therefore, in the absence of a clear precedent, we start by studying the variation in country-level connectedness over horizons $h = 1, 2, \ldots, 12$ quarters, as recorded in Figure 1.

In
the subfigure for the $j$-th country, the upper panel plots the to contribution ($T_{\rightarrow j}^{(h)}$) as a red line and the from contribution ($F_{\rightarrow j}^{(h)}$) as a blue line. The net connectedness ($\Lambda_{\rightarrow j}^{(h)}$) 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 ($W_{\rightarrow j}^{(h)}$) across horizons. By virtue of the re-normalisation procedure discussed above, all of the values reported in Figure 1 are percentages of the total systemwide FEV at each horizon.

--- Insert Figure 1 about here ---

In the large majority of cases, the net connectedness of the $k$-th economy does not change sign over the forecast horizon. This suggests that the choice of forecast horizon is unlikely to exert a decisive influence on our results. The only notable exception is Japan, which is a significant net transmitter until $h = 3$, whereupon it becomes a net recipient. Closer inspection reveals that the influence of Japanese shocks rapidly diminishes, both domestically (measured by the within contribution) and externally (measured by the to contribution). Meanwhile, as a result of Japan’s openness, the effect of external shocks on the Japanese economy (the from contribution) rapidly intensifies and becomes the dominant influence on domestic economic conditions. This is in 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 while from contributions grow with the forecast horizon. The same effect is discussed by Diebold and Yilmaz (2015, pp. 7-8). The observation that spillovers intensify over time suggests that the international transmission of shocks occurs gradually. Second, outward (to) spillovers arising from the dominant units in the global system — notably the US, the Eurozone and the oil price — tend to strengthen over the forecast horizon. This increase is rapid in the case of the US, with its to contribution rising from 5.99% at $h = 1$ to 12.83% at $h = 8$. Meanwhile, outward spillovers from the Eurozone increase gradually over the forecast horizon, from 4.86% at $h = 1$ to 7.77% at $h = 12$. In most cases, however, the connectedness measures plotted in Figure 1 converge to their long-run value after 3–5 quarters. In light of these considerations, we elect to focus henceforth on the four-quarters-ahead forecasting horizon.
Table 2 records the within, from, to and net connectedness among countries in the system at the four-quarters-ahead horizon measured as a percentage of the systemwide FEV. The two rightmost columns of Table 2 report the dependence and influence indices, respectively. To further test the robustness of our results to alternative choices of the forecast horizon, Table 3 records the range of values that are obtained for each of the connectedness measures reported in Table 2 using forecast horizons in the interval $h = 1, 2, \ldots, 12$. In the large majority of cases, the range of possible values is rather narrow, confirming that our results do not depend crucially on the selection of $h = 4$. Furthermore, the connectedness measures evaluated at $h = 4$ typically lie toward the centre of the interval reported in Table 3, indicating that results based on $h = 4$ are representative of the general pattern of connectedness across horizons.

— Insert Tables 2 and 3 about here —

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

The dependence index 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). The resulting ranking derived from our model is generally consistent with established beliefs about economic openness. Since our network-based dependence index is considerably more general than standard measures of trade openness, we evaluate it relative to one of the broadest measures of economic freedom to be found in the literature. Gwartney et al. (2013) compute a ranking of economic freedom which encompasses the size of government, the legal sys-

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10 Saudi Arabia records the lowest within-country effect in our sample as well as the fourth highest dependence index. However, these results are likely to overstate the external dependence of the Saudi economy as its dominant role within OPEC is not fully reflected within our model because the oil price is modelled separately as a global common factor.
tem and property rights, measures relating to inflation and the exchange rate, trade freedom and various aspects of regulation. We conjecture that the extent to which an economy integrates within the global economic system is likely to be positively related to the quality of its institutions and the degree to which it protects the rights of its citizens and firms. This appears to be the case, as the correlation between our dependence index and Gwartney et al.’s summary index of economic freedom is strongly positive, at 0.52.11

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

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

The influence index is recorded in the rightmost column of Table 2, and is mapped onto the globe in Figure 2(b). Economic influence measured in this way aligns closely with common perceptions of geo-political influence and with economic mass in particular. Figure 2(b) also provides a simple means of assessing the risks to the global economy posed by shocks 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.19 Similarly, shocks to the Eurozone and to the market for oil will have considerable

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11 We compare our dependence index against the mean value of Gwartney et al.’s summary index in the years 1990, 1995, 2000, 2005 and 2010. Note that we use Gwartney et al.’s reported values for Germany to proxy for the Eurozone as a region but only for its constituent states. Furthermore, for Saudi Arabia we use the value of Gwartney et al.’s overall freedom index for 2010 since this is the earliest period for which they provide data.
global impact. This is also becoming increasingly true of the BRICs, particularly China which has emerged as a major global power during our sample period. The figure also offers an explanation of why some regional crises have not translated into global crises. For example, Japan does not exhibit strong external spillover effects and thus the Japanese real-estate and stock-market collapse was not strongly felt outside Asia. Likewise, Black Wednesday in the UK and the 1997 Asian financial crisis were not strongly propagated beyond their respective regions.

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

--- Insert Figure 3 about here ---

4.2 Economic Connectedness and the GFC

It has been argued in the global business cycle literature that a sufficiently large shock hitting one economy is likely to spillover to others, resulting in increased business cycle correlation across countries [Doyle and Faust 2005]. Therefore, a large shock — such as the GFC — is likely to influence the observed pattern of macroeconomic connectedness in our framework. By observing the evolution of our GCMs in the wake of the GFC we can analyse how the crisis propagated through the global economy. To this end, we re-estimate the model recursively using 30 samples starting in 1980q2 and ending in 2005q2,...,2012q3.\footnote{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 \( \Sigma_u \) where the null hypothesis of cross section independence cannot be rejected, as described in Section 3. We then retain this pattern of restrictions when estimating the 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 $169 \times 169$ connectedness matrix; (ii) aggregation into 25 countries/regions as in the preceding section; and (iii) aggregation into 8 groups of common variables, such that the 25 GDP series are gathered into one group, the 25 export series into another group and so on, with the oil price being treated separately as a global common factor. 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.

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

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

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13 The figures also report intervals which record the range of values that the spillover index takes in each recursive sample over horizons 1 to 12. As in the reference sample 1980q2–2007q2, in each case the range of possible values is relatively narrow and our results using $h = 4$ lie toward its center.
Given our definition of dependence, the massive increase in spillovers from the world’s dominant economy is reflected in increased dependence of most other countries. The average dependence index increases from 0.58 prior to the GFC to 0.67, indicating much greater sensitivity to external conditions during the crisis than in previous periods. This is a natural result in the context of contagion where shocks spread forcefully across national borders. This effect can be seen very clearly in Figure 3(b) which reproduces the analysis in Figure 3(a) for selected major economies. As the source of the shock, the US behaves quite differently than any other economy, being the only country to record a significant increase in influence while all others record a marked increase in dependence, often coupled with reduced influence.

As a final exercise, we switch our frame of reference away from geographical units and focus instead on spillovers among different classes of variables in the system. As with the rightmost panel of Figure 4, Figure 6 is computed by aggregating the connectedness matrix $C^{(h)}$ 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 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. This illustrates the widespread flight-to-quality instigated by the
GFC, in which investors rebalanced their portfolios to favour the safer investment opportunities offered by fixed income markets over the riskier environment afforded by a volatile stock market in the early days of the crisis (Caballero and Krishnamurthy 2008). The resulting money flows have been identified as a key factor driving significant exchange rate movements, particularly the strong appreciation of high yielding currencies including the Australian Dollar. This provides an excellent illustration of the value of studying global macroeconomic connectedness. An improved ability to model and potentially to predict such spillover effects would have been invaluable during the GFC, where many countries including Switzerland and Japan were obliged to intervene in foreign exchange markets in an effort to control the value of their currencies and, thereby, to mitigate the real impact of the crisis.

5 Concluding Remarks

We develop a technique to measure macroeconomic connectedness in the global economy. Our framework is a generalisation of that developed by Diebold and Yilmaz (2009; 2014) for the study of financial connectedness. Our principal innovation is to introduce a new stratum between the level of individual variables and the level of systemwide aggregates which allows us to measure connectedness between countries, regions or any arbitrary group of variables within the model. Our approach is therefore well suited to the analysis of sophisticated global models, where multiple variables for each of a potentially large number of countries are modelled simultaneously. In addition, our method is accessible to non-specialists as it provides a stylised representation of macroeconomic connectedness, the interpretation of which is intuitive and does not require advanced knowledge of economic modelling techniques.

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

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

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

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


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Note: r denotes the numbers of cointegrating vectors in the country-specific models. (●) is our chosen break point. Note that the oil price is included among the set of endogenous variables for the US CVARX model for estimation purposes following the precedent of [Dees et al., 2007].

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

Table 1: Specification Details for the GNS25 Model
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Average: 1.63 | 2.21 | 2.21 | 0.00 | 0.57 | -0.11
Average (excl. oil): 1.68 | 2.29 | 2.16 | -0.13 | 0.58 | -0.14

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

Table 2: Connectedness Among Countries, Four-Quarters Ahead
<table>
<thead>
<tr>
<th>Within Min</th>
<th>From Min</th>
<th>To Min</th>
<th>Net Min</th>
<th>Dependence Min</th>
<th>Influence Min</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil 0.29</td>
<td>0.25</td>
<td>1.85</td>
<td>1.58</td>
<td>0.42</td>
<td>0.75</td>
</tr>
<tr>
<td>United States 1.85</td>
<td>1.45</td>
<td>5.99</td>
<td>4.54</td>
<td>0.41</td>
<td>0.61</td>
</tr>
<tr>
<td>Eurozone 1.50</td>
<td>2.43</td>
<td>4.86</td>
<td>2.43</td>
<td>0.59</td>
<td>0.33</td>
</tr>
<tr>
<td>Japan 0.54</td>
<td>2.29</td>
<td>1.85</td>
<td>1.95</td>
<td>-1.64</td>
<td>0.45</td>
</tr>
<tr>
<td>United Kingdom 1.46</td>
<td>2.20</td>
<td>1.58</td>
<td>-0.63</td>
<td>0.53</td>
<td>-0.16</td>
</tr>
<tr>
<td>Norway 1.40</td>
<td>2.46</td>
<td>1.20</td>
<td>-1.54</td>
<td>0.59</td>
<td>-0.39</td>
</tr>
<tr>
<td>Sweden 1.20</td>
<td>2.49</td>
<td>2.14</td>
<td>-0.79</td>
<td>0.60</td>
<td>-0.16</td>
</tr>
<tr>
<td>Switzerland 0.59</td>
<td>1.27</td>
<td>2.34</td>
<td>-1.21</td>
<td>0.66</td>
<td>-0.21</td>
</tr>
<tr>
<td>Canada 1.02</td>
<td>2.12</td>
<td>1.11</td>
<td>-1.72</td>
<td>0.51</td>
<td>-0.40</td>
</tr>
<tr>
<td>Australia 1.64</td>
<td>1.87</td>
<td>1.01</td>
<td>-1.49</td>
<td>0.45</td>
<td>-0.43</td>
</tr>
<tr>
<td>New Zealand 1.62</td>
<td>1.76</td>
<td>0.41</td>
<td>-2.11</td>
<td>0.43</td>
<td>-0.72</td>
</tr>
<tr>
<td>South Africa 1.98</td>
<td>1.94</td>
<td>1.52</td>
<td>-0.43</td>
<td>0.47</td>
<td>-0.12</td>
</tr>
<tr>
<td>Brazil 2.01</td>
<td>1.49</td>
<td>1.93</td>
<td>0.44</td>
<td>0.36</td>
<td>0.13</td>
</tr>
<tr>
<td>Chile 1.92</td>
<td>1.55</td>
<td>1.07</td>
<td>-1.15</td>
<td>0.37</td>
<td>-0.35</td>
</tr>
<tr>
<td>Mexico 1.70</td>
<td>1.79</td>
<td>1.34</td>
<td>-0.98</td>
<td>0.43</td>
<td>-0.26</td>
</tr>
<tr>
<td>India 1.85</td>
<td>1.75</td>
<td>0.69</td>
<td>-1.60</td>
<td>0.42</td>
<td>-0.54</td>
</tr>
<tr>
<td>South Korea 1.15</td>
<td>2.02</td>
<td>1.19</td>
<td>-1.01</td>
<td>0.49</td>
<td>-0.26</td>
</tr>
<tr>
<td>Malaysia 0.90</td>
<td>2.14</td>
<td>1.31</td>
<td>-1.55</td>
<td>0.52</td>
<td>-0.32</td>
</tr>
<tr>
<td>Philippines 1.89</td>
<td>1.82</td>
<td>1.32</td>
<td>-0.56</td>
<td>0.44</td>
<td>-0.16</td>
</tr>
<tr>
<td>Singapore 1.09</td>
<td>2.32</td>
<td>1.36</td>
<td>-0.96</td>
<td>0.56</td>
<td>-0.26</td>
</tr>
<tr>
<td>Thailand 1.64</td>
<td>1.94</td>
<td>1.24</td>
<td>-1.16</td>
<td>0.47</td>
<td>-0.31</td>
</tr>
<tr>
<td>China 2.05</td>
<td>1.16</td>
<td>1.76</td>
<td>0.60</td>
<td>0.33</td>
<td>0.21</td>
</tr>
<tr>
<td>Indonesia 0.95</td>
<td>1.71</td>
<td>1.58</td>
<td>-1.01</td>
<td>0.48</td>
<td>-0.24</td>
</tr>
<tr>
<td>Peru 1.04</td>
<td>1.18</td>
<td>0.73</td>
<td>-1.77</td>
<td>0.33</td>
<td>-0.54</td>
</tr>
<tr>
<td>Turkey 1.94</td>
<td>1.17</td>
<td>0.54</td>
<td>-1.06</td>
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<td>-0.49</td>
</tr>
<tr>
<td>Saudi Arabia 0.56</td>
<td>1.80</td>
<td>1.55</td>
<td>-0.81</td>
<td>0.61</td>
<td>-0.20</td>
</tr>
</tbody>
</table>

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

Table 3: Robustness to the Choice of Forecast Horizon
<table>
<thead>
<tr>
<th>Country</th>
<th>Within</th>
<th>From</th>
<th>To</th>
<th>Net</th>
<th>Dep.</th>
<th>Infl.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oil</td>
<td>0.13</td>
<td>0.46</td>
<td>2.89</td>
<td>2.43</td>
<td>0.77</td>
<td>0.73</td>
</tr>
<tr>
<td>United States</td>
<td>1.65</td>
<td>1.90</td>
<td>17.27</td>
<td>15.37</td>
<td>0.54</td>
<td>0.80</td>
</tr>
<tr>
<td>Eurozone</td>
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<td>3.06</td>
<td>6.44</td>
<td>3.38</td>
<td>0.74</td>
<td>0.36</td>
</tr>
<tr>
<td>Japan</td>
<td>0.64</td>
<td>3.50</td>
<td>2.98</td>
<td>-0.52</td>
<td>0.85</td>
<td>-0.08</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>1.55</td>
<td>2.59</td>
<td>2.00</td>
<td>-0.59</td>
<td>0.63</td>
<td>-0.13</td>
</tr>
<tr>
<td>Norway</td>
<td>1.21</td>
<td>2.93</td>
<td>1.60</td>
<td>-1.34</td>
<td>0.71</td>
<td>-0.30</td>
</tr>
<tr>
<td>Sweden</td>
<td>1.00</td>
<td>3.14</td>
<td>1.83</td>
<td>-1.31</td>
<td>0.76</td>
<td>-0.26</td>
</tr>
<tr>
<td>Switzerland</td>
<td>0.66</td>
<td>3.48</td>
<td>2.67</td>
<td>-0.81</td>
<td>0.84</td>
<td>-0.13</td>
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<tr>
<td>Canada</td>
<td>0.92</td>
<td>3.22</td>
<td>1.34</td>
<td>-1.88</td>
<td>0.78</td>
<td>-0.41</td>
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<td>Australia</td>
<td>1.64</td>
<td>2.51</td>
<td>1.11</td>
<td>-1.40</td>
<td>0.61</td>
<td>-0.39</td>
</tr>
<tr>
<td>New Zealand</td>
<td>1.51</td>
<td>2.63</td>
<td>0.45</td>
<td>-2.18</td>
<td>0.64</td>
<td>-0.71</td>
</tr>
<tr>
<td>South Africa</td>
<td>1.71</td>
<td>2.43</td>
<td>2.25</td>
<td>-0.19</td>
<td>0.59</td>
<td>-0.04</td>
</tr>
<tr>
<td>Brazil</td>
<td>2.13</td>
<td>2.02</td>
<td>3.17</td>
<td>1.15</td>
<td>0.49</td>
<td>0.22</td>
</tr>
<tr>
<td>Chile</td>
<td>1.67</td>
<td>2.47</td>
<td>1.03</td>
<td>-1.44</td>
<td>0.60</td>
<td>-0.41</td>
</tr>
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<td>Mexico</td>
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<td>2.73</td>
<td>1.58</td>
<td>-1.15</td>
<td>0.66</td>
<td>-0.27</td>
</tr>
<tr>
<td>India</td>
<td>1.59</td>
<td>2.55</td>
<td>0.76</td>
<td>-1.79</td>
<td>0.62</td>
<td>-0.54</td>
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<tr>
<td>South Korea</td>
<td>1.53</td>
<td>2.61</td>
<td>2.17</td>
<td>-0.43</td>
<td>0.63</td>
<td>-0.09</td>
</tr>
<tr>
<td>Malaysia</td>
<td>0.82</td>
<td>3.32</td>
<td>1.75</td>
<td>-1.57</td>
<td>0.80</td>
<td>-0.31</td>
</tr>
<tr>
<td>Philippines</td>
<td>1.51</td>
<td>2.63</td>
<td>1.65</td>
<td>-0.98</td>
<td>0.64</td>
<td>-0.23</td>
</tr>
<tr>
<td>Singapore</td>
<td>0.78</td>
<td>3.37</td>
<td>3.17</td>
<td>-0.19</td>
<td>0.81</td>
<td>-0.03</td>
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<tr>
<td>Thailand</td>
<td>1.02</td>
<td>3.12</td>
<td>1.84</td>
<td>-1.29</td>
<td>0.75</td>
<td>-0.26</td>
</tr>
<tr>
<td>China</td>
<td>1.87</td>
<td>1.68</td>
<td>2.30</td>
<td>0.62</td>
<td>0.47</td>
<td>0.16</td>
</tr>
<tr>
<td>Indonesia</td>
<td>1.16</td>
<td>2.39</td>
<td>1.87</td>
<td>-0.52</td>
<td>0.67</td>
<td>-0.12</td>
</tr>
<tr>
<td>Peru</td>
<td>1.25</td>
<td>2.30</td>
<td>0.68</td>
<td>-1.61</td>
<td>0.65</td>
<td>-0.54</td>
</tr>
<tr>
<td>Turkey</td>
<td>1.58</td>
<td>1.97</td>
<td>0.49</td>
<td>-1.48</td>
<td>0.55</td>
<td>-0.60</td>
</tr>
<tr>
<td>Saudi Arabia</td>
<td>0.80</td>
<td>2.16</td>
<td>1.88</td>
<td>-0.27</td>
<td>0.73</td>
<td>-0.07</td>
</tr>
<tr>
<td>Average</td>
<td>1.26</td>
<td>2.58</td>
<td>2.58</td>
<td>0.00</td>
<td>0.67</td>
<td>-0.14</td>
</tr>
<tr>
<td>Average (excl. oil)</td>
<td>1.31</td>
<td>2.67</td>
<td>2.57</td>
<td>-0.10</td>
<td>0.67</td>
<td>-0.18</td>
</tr>
</tbody>
</table>

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

Table 4: Connectedness Among Countries, Four-Quarters Ahead (1980q2–2008q4)
Note: The values of within, from, to and net are computed following equations (15) and (19). In all cases, the unit of measurement is the percentage of the total h-step ahead forecast error variance of the system. Note the difference in the scaling of the vertical axes for the US and the Eurozone relative to the other cases.

Figure 1: Connectedness Among Countries over the Reference Sample, 1980q2–2007q2
Note: The dependence index, \( O_k^h \), is computed following equation (21). Recall that \( 0 \leq O_k^h \leq 1 \) and that a higher value indicates greater dependence on external conditions. The influence index, \( I_k^h \), is computed following equation (22). Country \( k \) is a net recipient at horizon \( h \) if \( -1 \leq I_k^h < 0 \) and a net shock transmitter if \( 0 < I_k^h \leq 1 \). 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
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

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 $B^{(h)}$. In each case, the interval reports the range of values taken by the spillover index over horizons 1 to 12 in a similar manner to the values reported in Table 3. Note that the time axis records the end of the recursive sample period so that values shown at 2008q4, for example, are derived from the estimation sample 1980q2–2008q4. In all cases, the unit of measurement is the percentage of the total $h$-step ahead forecast error variance of the system.

Figure 4: Time-Varying Aggregate Spillover Indices, Four-Quarters Ahead
Note: The values of from, to and net are computed following equation (19). In all cases, the unit of measurement is the percentage of the total four-quarters-ahead forecast error variance of the system. Note the difference in the scaling of the vertical axes for the US and the Eurozone relative to the other cases.

Figure 5: Time-Varying Connectedness Among Countries, Four-Quarters-Ahead
Note: The values of from, to and net are computed following equation [19]. In all cases, the unit of measurement is the percentage of the total four-quarters-ahead FEV of the system.

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

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