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““Estimating Global Bank Network Connectedness”

by

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Estimating Global Bank Network Connectedness

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Abstract: We use lasso methods to shrink, select and estimate the network linking the publicly-traded subset of the world's top 150 banks, 2003-2014. We characterize static network connectedness using full-sample estimation and dynamic network connectedness using rolling-window estimation. Statistically, we find that global banking connectedness is clearly linked to bank location, not bank assets. Dynamically, we find that global banking connectedness displays both secular and cyclical variation. The secular variation corresponds to gradual increases/decreases during episodes of gradual increases/decreases in global market integration. The cyclical variation corresponds to sharp increases during crises, involving mostly cross-country, as opposed to within-country, bank linkages.

Key Words: Systemic risk, connectedness, systemically important financial institutions, vector autoregression, variance decomposition, lasso, elastic net, adaptive lasso, adaptive elastic net

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Contents

1 Introduction

Network connectedness is central to modern financial risk measurement and management. It features prominently in key aspects of market risk (return connectedness and portfolio concentration), credit risk (default connectedness), counter-party and gridlock risk (bilateral and multilateral contractual connectedness), and not least, systemic risk (system-wide connectedness). It is also central to understanding underlying fundamental macroeconomic risks, in particular business cycle risk (e.g., intra- and inter-country real activity connectedness).

Recent theoretical work has therefore emphasized network connectedness and formation in financial and industry contexts, as in Jackson (2008), Easley and Kleinberg (2010), Acemoglu et al. (2012), and Babus (2013). Related empirical work, which sometimes includes banking contexts, has begun to appear; see for example, Adrian and Brunnermeier (2008), Diebold and Yilmaz (2009), Acharya et al. (2010), Billio et al. (2012), Allen et al. (2012), Acharya et al. (2012), Barigozzi and Brownlees (2013), Diebold and Yilmaz (2014), Brownlees and Engle (2015), Giglio et al. (2015), and Bianchi et al. (2015).

There is, however, little empirical research on *global* bank connectedness. This is particularly unfortunate given the role of financial institutions in the Great Recession of 2007-2009, and given the many channels that produce linkages among banks, such as counter-party linkages associated with positions in various assets and recorded in balance sheets, and contractual linkages associated with services provided to clients and other institutions.

A key reason for the lack of empirical work on global bank connectedness is the high dimensionality of bank networks. There are simply very many important banks globally, which renders unrestricted vector-autoregressive (VAR) network approximations intractable. Hence, for example, Diebold and Yilmaz (2014) were forced to limit their analysis to U.S. institutions. Although a useful first step, such an analysis is clearly incomplete, given the global nature of the financial services industry.

In this paper we progress on both the methodological and substantive fronts. On the methodological side, we overcome the dimensionality problem while nevertheless remaining squarely in the Diebold-Yilmaz network connectedness measurement tradition, which is intimately related to the key centrality measure in the modern network literature, the mean node degree. We do so by estimating the network using lasso methods, which select and shrink in optimal ways.

On the substantive side, no longer constrained by the dimensionality problem, we perform a truly global bank connectedness analysis. In particular, we characterize the static and dynamic high-frequency stock-return volatility connectedness of all banks among the world's top 150 globally, 2004-2014.

We proceed as follows. In section 2, we briefly summarize the Diebold-Yilmaz connectedness-measurement framework. In section 3, we introduce "lassoed" large VAR's as empirical approximating models in the Diebold-Yiamaz framework. In sections 4 and 5, respectively, we provide static and dynamic characterizations of the global bank network. We conclude in section 6.

2 Population Network Connectedness

All network connectivity analyses require *approximating models.* Here we use vector autoregressions, with network connectedness measures based on variance decompositions, as proposed and developed in a series of papers that includes Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), and Diebold and Yilmaz (2014).

Such connectedness measures are appealing for several reasons. First, they make obvious intuitive sense, answering a key question, which at the most granular pairwise level is "How much of entity i's future uncertainty (at horizon H) is due to shocks arising *not* with entity i, but rather with entity j?"

Second, connectedness measures based on variance decompositions allow connectedness to differ across horizons, facilitating examination of a variety of horizons and selection of a preferred horizon if desired. This is important because, for example, 1-day connectedness may be very different from 10- or 30 day connectedness.[1]

Third, Diebold and Yilmaz (2014) show that connectedness measures based on variance decompositions are closely linked to modern network theory, in particular the degree distribution and mean degree, and that they are also closely linked to recently-proposed measures of systemic risk, such as marginal expected shortfall (Acharya et al. (2010)) and CoVaR (Adrian and Brunnermeier (2008)).

2.1 Variance Decompositions in Approximating VAR's

As an approximating model we use an N-variable VAR(p), $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim (0, \Sigma)$. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the NxN coefficient

[1]Alternative frameworks that attempt to characterize network connectedness directly from a fitted sparse VAR(1) coefficient matrix (e.g., Bonaldi et al. (2013)) are unfortunately limited to assessment of connectedness at a fixed horizon, by construction.

matrices A_i obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 an NxN identity matrix and $A_i = 0$ for $i < 0$.

Standard variance decompositions based on Cholesky factorization depend on the ordering of the variables, significantly complicating the study of directional connectedness. Hence Diebold and Yilmaz (2012) suggest exploiting the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998), which produces variance decompositions invariant to ordering. Instead of attempting to orthogonalize shocks, the generalized approach allows for correlated shocks but accounts for them appropriately.

2.2 Pairwise Directional Connectedness

Firm j's contribution to firm i's H-step-ahead generalized forecast error variance, $\theta_{ij}^g(H)$, is

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \quad H = 1, 2, ..., \tag{1}$$

where Σ is the covariance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the j^{th} equation and e_i is the selection vector with one as the i^{th} element and zeros otherwise.

Because we work in the Koop-Pesaran-Potter-Shin generalized VAR framework, the variance shares do not necessarily add to 1; that is, in general $\sum_{j=1}^N \theta_{ij}^g(H) \neq 1$. Hence we normalize each entry of the generalized variance decomposition matrix (1) by the row sum:

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)}. \tag{2}$$

Now by construction $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$.

2.3 Total Directional Connectedness, "To" and "From"

Now we get less granular, moving from pairwise directional connectedness to total directional connectedness. Total directional connectedness to firm i from all other firms j is:

$$C_{i \leftarrow \bullet} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^N \tilde{\theta}_{ij}^g(H)}{N} \times 100. \tag{3}$$

Similarly, total directional connectedness from firm i to all other firms j is

$$C_{\bullet \leftarrow i} = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \times 100. \tag{4}$$

2.4 System-Wide Connectedness

Now we get still less granular, proceeding to a system-wide level. Using the normalized entries of the generalized variance decomposition matrix (2), we measure total connectedness as

$$C(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N}. \tag{5}$$

We call this total connectedness *system-wide* connectedness. It is simply the sum of total directional connectedness whether "to" or "from." (It doesn't matter which way, because "exports" must equal "imports" at the "global" level.)

3 Sample Bank Network Connectedness

Thus far we have discussed population network connectedness measurement in general. Now we discuss *sample* connectedness measurement, specialized, moreover, to our context of global banking. We first introduce our banks and sample period, and then our preferred connectedness object (volatility), and finally, lasso methods for estimating the requisite high-dimensional approximating models.

3.1 Banks and Sample Period

We study 96 banks from 29 developed and emerging economies, downloaded from Thomson-Reuters, from September 12, 2003 through February 7, 2014. Our 96 banks are those in the world's top 150 (by assets) that were publicly traded throughout our sample. They are largely banks from developed countries: 82 of the banks are from 23 developed economies, and the remaining 14 banks are from 6 emerging economies.[2]

[2]See Appendix A for details as regards market capitalization, assets, bank codes, and Reuters tickers. Our bank codes are easier to interpret than the Reuters tickers, particularly as regards identifying banks' countries, so we use them in our empirical work.

3.2 Volatility

For the most part we study the global bank stock return volatility network.

3.2.1 Background

Cyclical financial volatility connectedness is of direct interest. If volatility tracks investor fear (e.g., the VIX is often touted as an "investor fear gauge"), then volatility connectedness is fear connectedness. How connected is fear? How does it spread and cluster? Volatility connectedness is also of special interest from the perspective of real-time crisis monitoring, as volatilities tend to lurch and move together only in crises, whereas returns often move closely together in both crises *and* upswings.

Secular volatility connectedness in financial contexts extends beyond risk considerations, at least as traditionally conceptualized, and certain types of connectedness may be directly desirable. For example, connectedness can arise from and vary with risk sharing via insurance, links between sources and uses of funds as savings are channeled into investments, patterns of comparative advantage that generate international trade, regional and global capital market integration, and enhanced coordination of global financial regulation and accounting standards.

Note that increases in secular volatility conectedness as described above are associated with something "good," whereas cyclical volatility conectedness as described above are associated with something "bad". Hence connectedness is neither intrinsically good nor intrinsically bad; instead, it depends on the situation and context.[3] In any event connectedness is *important*, and the ability to measure it accurately is therefore useful.

3.2.2 Data Requirements

It is fortunate that we do not require high-frequency balance sheet and related information, which is unavailable in real time. Instead we need only high-frequency stock return data, which are readily available. Stock market valuations are of course imperfect – like all valuations – but thousands of smart analysts devote massive time and resources to uncovering and interpreting information relevant for valuation.

[3]We will have more to say about this when we discuss our dynamic empirical results for the global bank network in section 5.3.

3.2.3 Estimation

Volatility is latent and must be estimated. Many approaches to volatility estimation have received attention, including observation-driven GARCH-type models, parameter-driven stochastic volatility models, realized volatility, and implied volatility.[4] Volatilities tend to be strongly serially correlated, particularly when observed at relatively high frequency. They also tend to be distributed asymmetrically, with a right skew, and taking natural logarithms produces approximate normality.

We construct daily stock return volatilities using daily stock price data (high, low, open, close). We assume that volatility is fixed within a day but variable across days. Then, following Garman and Klass (1980) and Alizadeh et al. (2002), we use the log of daily high, low, opening and closing prices to estimate daily bank stock return volatility:

$$\begin{aligned}\tilde{\sigma}^2_{4,it} &= 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ &\quad -2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2, \qquad (6)\end{aligned}$$

where H_{it}, L_{it}, O_{it} and C_{it} are, respectively, the logs of daily high, low, opening and closing prices for bank stock i on day t.

3.3 Selecting and Shrinking the Approximating Model

In applications we base connectedness assessment on an estimated approximating VAR. For compelling applications, we need the approximating VAR to be estimable in very high dimensions, somehow recovering degrees of freedom.[5] One can do so by pure shrinkage (as with traditional informative-prior Bayesian analyses, or ridge regression) or pure selection (as with traditional criteria like AIC and SIC), but *blending* shrinkage and selection, using variants of the lasso, proves particularly appealing.

3.3.1 Lasso

Consider the least-squares estimator,

$$\hat{\beta} = \arg\min_{\beta} \sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2,$$

[4] For a survey see Andersen et al. (2013).

[5] In what follows we refer to estimators that achieve this as "regularized," and associated environments as involving "regularization."

subject to the constraint:

$$\sum_{i=1}^{K} |\beta_i|^q \leq c.$$

Equivalently, consider the penalized estimation problem:

$$\hat{\beta} = \arg\min_{\beta} \left(\sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} |\beta_i|^q \right).$$

Concave penalty functions non-differentiable at the origin produce subset selection (e.g., $q \to 0$) , whereas smooth convex penalties produce shrinkage (e.g., $q = 2$). Hence penalized estimation nests and can blend selection and shrinkage. The case of $q = 1$, to which we now turn, is of special interest.

The lasso (short for "least absolute shrinkage and selection operator"), introduced in the seminal work of Tibshirani (1996), solves the L_1-penalized regression problem:

$$\hat{\beta}_{Lasso} = \arg\min_{\beta} \left(\sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} |\beta_i| \right).$$

Lasso shrinks *and* selects. It uses the smallest q for which the minimization problem is convex, which is valuable computationally.

Note that although we want to impose (or at least encourage) sparsity in our approximating model, we do not necessarily want to impose sparsity in the implied bank network. Our approach of shrinking and selecting on the approximating VAR, as opposed to shrinking and selecting on the variance decomposition network directly, achieves that goal. The approximating VAR is intentionally shrunken and made sparse by the lasso, but the variance decomposition matrix that drives our connectedness measures is a non-linear transformation of the VAR coefficients and is therefore generally not sparse.[6]

Lasso has some undesirable properties, however, not least of which is that the oracle property does not obtain. Hence we now proceed to consider lasso extensions with better properties.

[6] Alternative frameworks that attempt to characterize network connectedness directly from a fitted sparse VAR(1) coefficient matrix (e.g., Bonaldi et al. (2013)) force sparse networks, by construction. Moreover, they also provide incomplete connectedness characterizations, because VAR connectedness arises not only through cross-lag linkages, but also through the disturbance covariance matrix. Network connectedness measures based on Granger-causal patterns (e.g. Billio et al. (2012)) also ignore the disturbance covariance matrix and hence are similarly incomplete.

3.3.2 Extensions

The adaptive lasso estimator (Zou (2006)) solves

$$\hat{\beta}_{ALasso} = \arg\min_{\beta} \left(\sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} w_i |\beta_i| \right),$$

where $w_i = 1/|\hat{\beta}|_i^{\nu}$ with $\hat{\beta}_i$ the OLS estimate (or ridge if regularization is needed), and $\nu > 0$. Every parameter in the penalty function is weighted differently, in contrast to the "regular" lasso. In particular, the weighting by inverse parameter estimates shrinks "small" coefficients most heavily. The oracle property obtains.

The elastic net estimator (Zou and Hastie (2005)) solves

$$\hat{\beta}_{Enet} = \arg\min_{\beta} \left(\sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} \left(\alpha |\beta_i| + (1-\alpha) \beta_i^2 \right) \right).$$

Elastic net blends lasso and Ridge regression; that is, it combines a lasso L_1 penalty and a ridge L_2 penalty. There are two tuning parameters, λ and $\alpha \in [0, 1]$. Obviously elastic net is lasso when $\alpha = 1$ and ridge when $\alpha = 0$. Unlike lasso, elastic net moves strongly-correlated predictors in or out of the model together.

The adaptive elastic net estimator (Zou and Zhang (2009)) solves

$$\hat{\beta}_{AEnet} = \arg\min_{\beta} \left(\sum_{t=1}^{T} \left(y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} w_i \left(\alpha |\beta_i| + (1-\alpha) \beta_i^2 \right) \right),$$

where $w_i = 1/|\hat{\beta}_i|^{\nu}$ with $\hat{\beta}_i$ the OLS estimate (or ridge if regularization is needed), and $\nu > 0$. Adaptive elastic net blends adaptive lasso and elastic net and inherits good properties from each: it has the oracle property like adaptive lasso and displays improved predictor handling like elastic net.

In the empirical work to which we soon turn, we focus on estimation using the elastic net and adaptive elastic net.

Figure 1: Network Graph Color Spectrum

3.4 Graphical Display

The issue of how best to display results takes on great importance in high-dimensional network modeling. In our subsequent empirical work, for example, we will estimate networks with approximately 100 nodes, and presenting and examining $100 \times 100 = 10,000$ estimated pairwise variance decompositions would be thoroughly uninformative. Hence we follow the huge network literature in using graphical depictions, using node and link colors, thicknesses, etc., to convey information about estimated network characteristics.

We study complete, weighted, directed networks, which we characterize using five aspects of network graphs: node size, node location, node color, edge thickness and color, and edge arrow sizes (two per edge, because the network is directed).[7]

Node Size Indicates Asset Size

We make node size a linear function of bank asset size.[8] We assign the sizes of the largest and smallest nodes, and then assign the rest linearly. We emphasize assets rather than market capitalization for two reasons. First, market capitalization is subject to abrupt changes due to fluctuations in stock price. Second, cross-country differences in financial system characteristics and ownership structure of publicly traded companies have direct effects on market capitalization levels, thereby producing persistent differences in cross-country market capitalizations.

Node Color Indicates Total Directional Connectedness "To Others"

The node color indicates total directional connectedness "to others," ranging from 3DRA02 (bright green), to E6DF22 (luminous vivid yellow), to CF9C5B (whiskey sour), to FC1C0D (bright red), to B81113 (dark red; close to scarlet). We show the color range in Figure 1.

Node Location Indicates Average Pairwise Directional Connectedness

We determine node location using the ForceAtlas2 algorithm of Jacomy et al. (2014) as implemented in Gephi. The algorithm finds a steady state in which repelling and attracting

[7] We use the open-source Gephi (`https://gephi.github.io/`) software to visualize large network graphs.

[8] Note well that we make node size and asset size linearly related, but not directly proportional. Huge asset-size differences between the largest and smallest banks in our sample make directly-proportional representation impossible.

forces exactly balance, where (1) nodes repel each other, but (2) edges attract the nodes they connect according to average pairwise directional connectedness "to" and "from." The steady state node locations depend on initial node locations and hence are not unique. This is largely irrelevant, however, as we are interested in relative, not absolute, node locations in equilibrium.

Edge Thickness Also Indicates Average Pairwise Directional Connectedness
Note that edge color indicates nothing; it never changes.

Edge Arrow Sizes Indicate Pairwise Directional Connectedness "To" and "From"
Note that because the full set of edge arrow sizes reveals the full set of pairwise directional connectednesses, from which all else can be derived (with the exception of asset size), the various additional devices employed as described (node color, node location, and edge thickness) are in principle redundant and therefore unnecessary. In practice, however, they are helpful for examining large networks in which, for example, the thousands of arrows can be largely impossible to see. They are therefore invaluable supplements to examination of "edge arrows" alone.

Trimming Improves Interpretabilty
We trim the less important half of estimated links. This dramatically improves interpretability of the network graphs while simultaneously discarding almost no information, as the trimmed links are responsible for only a negligible fraction of system-wide connectedness.

4 Static Estimation of the Global Bank Network

We estimate logarithmic volatility VAR's using the adaptive elastic net as described above. Then we compute variance decompositions and corresponding connectedness measures, using the estimated VAR parameters.

4.1 The Individual Bank Network

We show the full-sample global bank network graph in Figure 2. A striking result is immediately apparent: the graph shows clear bank clustering, both within and across countries.

The within-country bank clustering is ubiquitous, ranging from countries with many banks in our sample (e.g., U.S., Canada, Australia, China, Japan) to those with only two or three (e.g., Korea, Singapore, India, Malaysia).

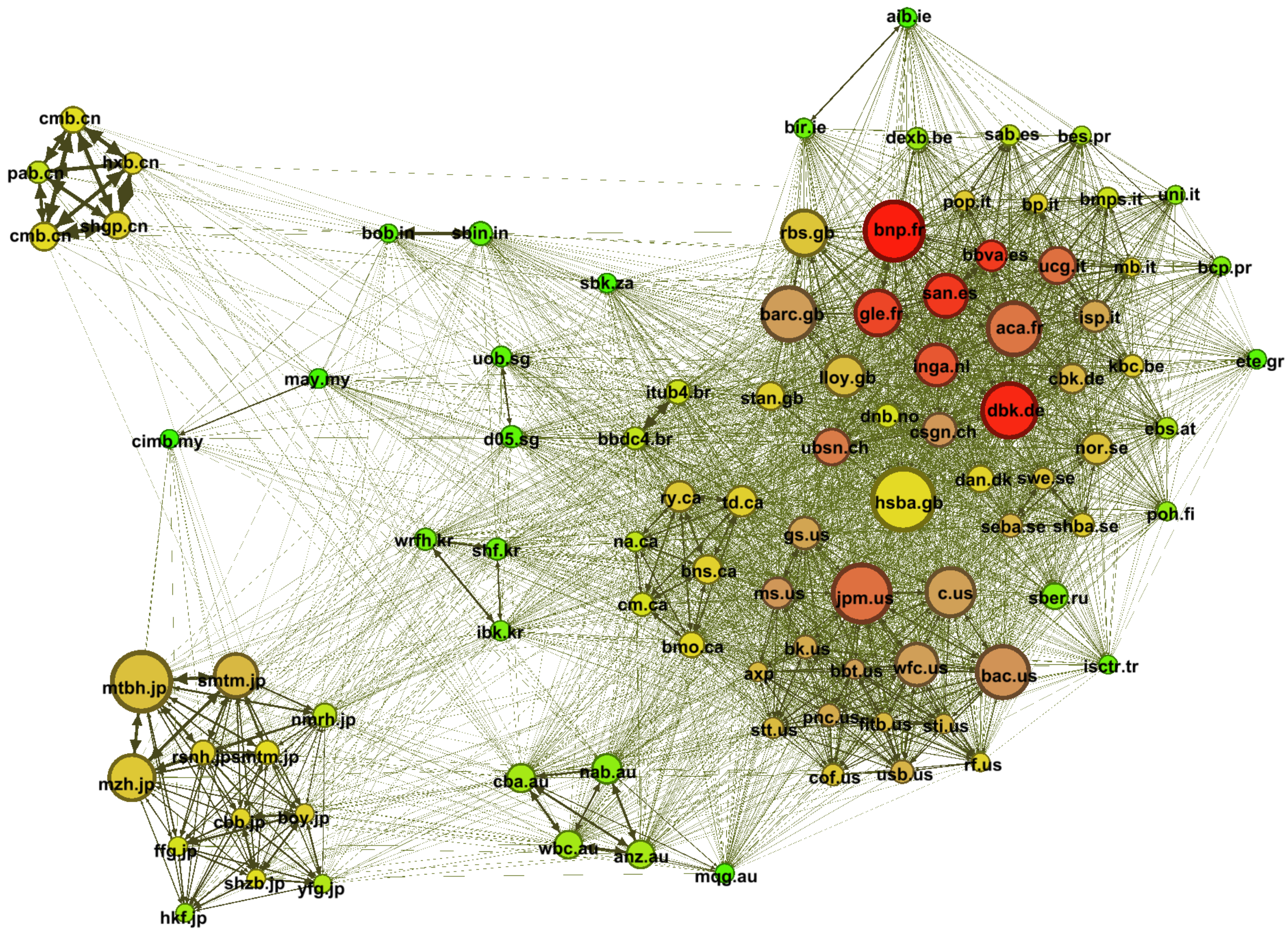


Figure 2: Global Individual Bank Network, 2003-2014

The cross-country clustering is also obvious throughout the graph, whose left side clearly tends to contain banks if eastern countries, and whose right side clearly tends to contain banks of western countries. Moreover, the western side clearly breaks into a large Anglo / European bank cluster and a smaller American / Canadian cluster, each of which contains sub-clusters.

It is not obvious that country of origin would be the dominant factor driving network connectedness. One might have thought, for example, that other factors, such as bank size, might dominate, but such is not the case. Japan illustrates this clearly. Although the majority of very large banks are located in the Anglo / American / European cluster, the three very large Japanese banks (Mitsubishi UFJ, Mizuho Financial, and Sumitomo Mitsui Financial) are located not in the Anglo / American / European cluster, but rather in the Japanese cluster.

4.1.1 Including Sovereign Bonds

Above we analyzed the global network of bank equity return volatilities, but we can also include other important financial asset volatilities. This is potentially interesting because, although the U.S. financial crisis did not have a sovereign debt component, the ensuing European crisis did.

Against this background, we now include sovereign bond yield volatilities in the analysis, in addition to bank stock volatilities. We include 10-year G-7 sovereigns (United States, Germany, France, Japan, United Kingdom, Canada, and Italy), as well as those of Spain, Greece and Australia. We plot the estimated individual bank / sovereign bond network in Figure 3. The sovereigns appear in the upper left of the graph, which is otherwise similar to Figure 2.[9]

Figure 3 delivers several related insights. First, the bonds cluster strongly. Second, European bond nodes are nevertheless closer to European bank nodes, U.S. and Canadian bond nodes are closer to U.S. and Canadian bank nodes, and Japanese and Australian bond nodes are closer to Japanese and Australian bank nodes. Third, although the bond nodes are pulled toward their respective country bank nodes, they remain completely distinct and never appear inside their national/regional banking clusters: bank stocks form regional/national clusters, and sovereign bonds are not part of those clusters.

[9]We denote bonds by the suffix "b" added to country acronyms.

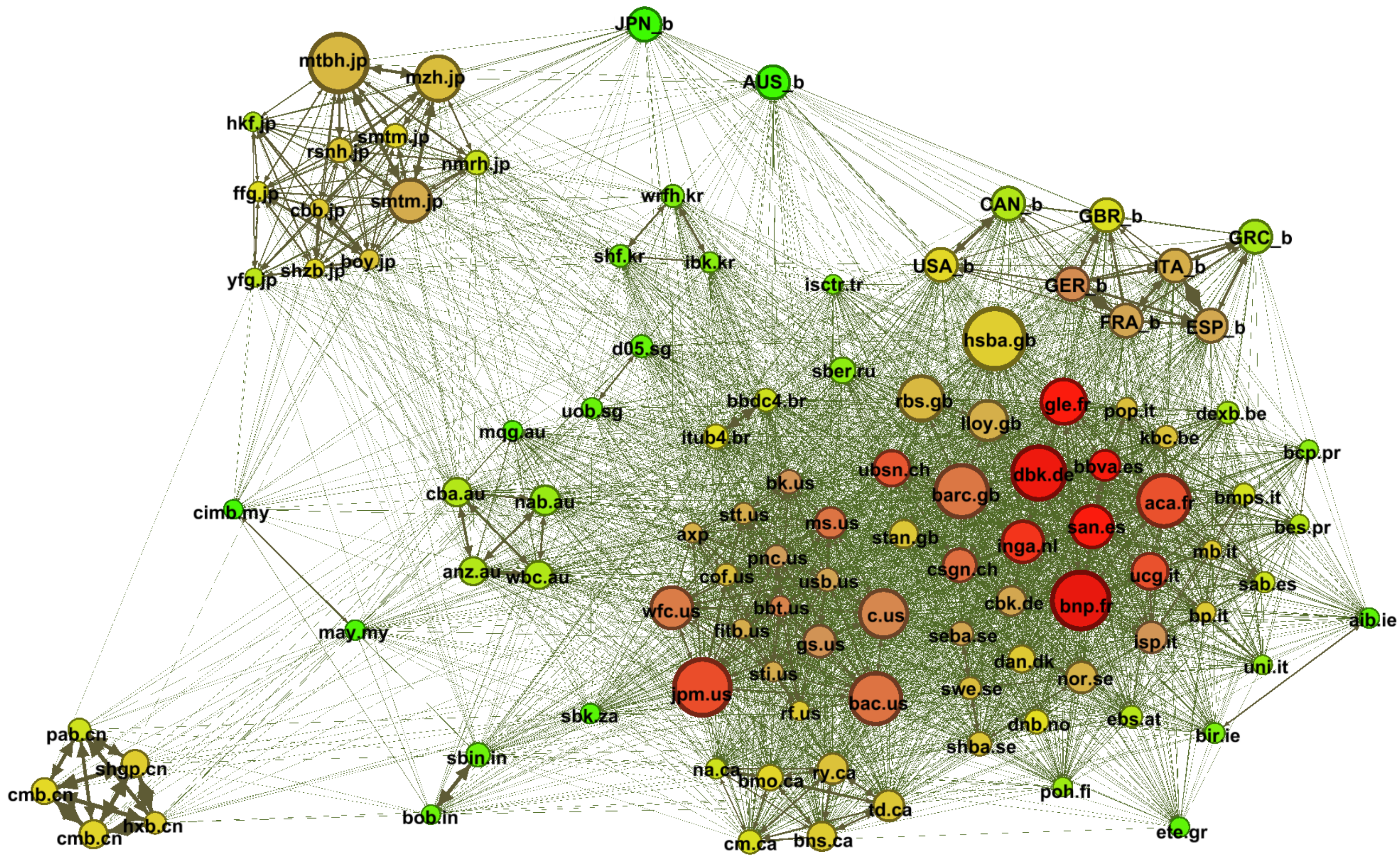


Figure 3: Individual Bank / Sovereign Bond Network, 2003-2014

4.2 The Country Bank Network

In Figure 4 we aggregate the individual bank network graph to obtain the country bank network graph.[10] This serves two useful and distinct purposes.

First, examination of the country bank network is intrinsically interesting and a logical next step. Our individual-bank analysis showed strong connectedness of banks both within and across countries, so we now proceed to dig more deeply into the cross-country links. Examination of the country bank network allows us to distinguish the relative strengths of directional "to" and "from" connectedness of the most-connected country banking systems.

Second, the smaller number of edges in the country bank network makes visual interpretation of connectedness simpler and more revealing. (29 countries produce only $29^2 = 841$ edges in the country network, whereas 96 banks produce $96^2 = 9216$ edges in the bank network.)

The U.S. is clearly massively connected; its strongest links are with Canada, Great Britain, and Australia. It is not always visible, but the arrows indicate greater connectedness from the U.S. to Canada, Australia and Great Britain than conversely.

The Anglo / European countries form a cluster just above the U.S. Of the Anglo / European countries, Britain has the strongest links to and from the U.S. The northern European countries are to the south-east of the cluster; Sweden has the strongest connectedness with the U.S. Ireland, Portugal, Greece, Finland and Austria are located on the perimeter of the cluster.

Other countries are scattered farther away from the European cluster. As noted previously for individual banks, moving leftward on the graph generally takes one from western to eastern countries.

We can also include sovereign bonds. In Figure 5 we show the estimated country bank / sovereign bond network.

5 Dynamic Estimation of the Global Bank Network

We now characterize the global banking network dynamically. We use rolling estimation with a 150-day window, with repeated cross validation of the penalty parameter λ in each window.[11] We start with comparisons of estimated network graphs "before and after" major

[10] We place country nodes at the centers of gravity of the corresponding country banks.

[11] We switch from adaptive elastic net to elastic net dynamic estimation, as the latter produces less noisy estimates under rolling estimation.

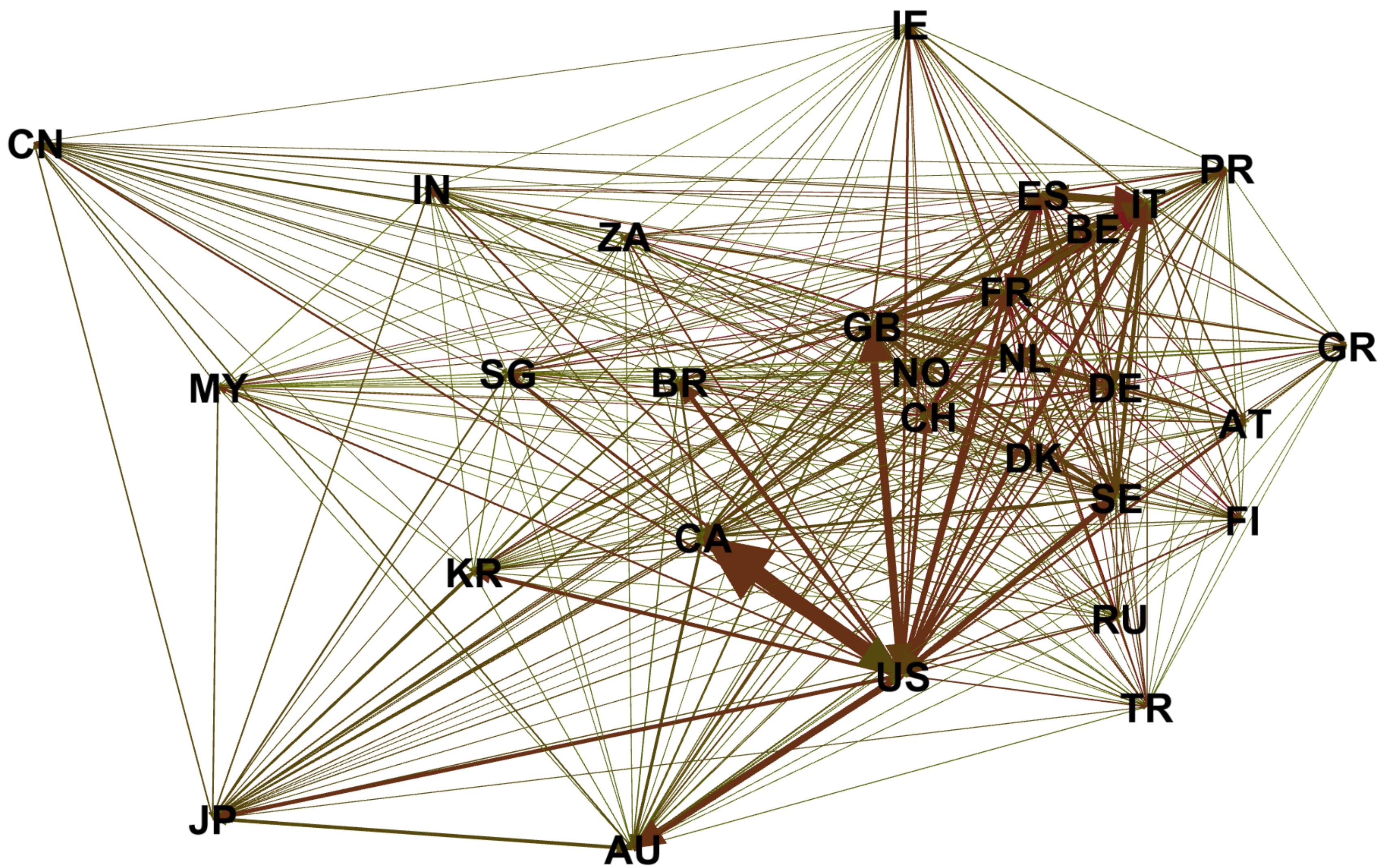


Figure 4: Country Bank Network, 2003-2014

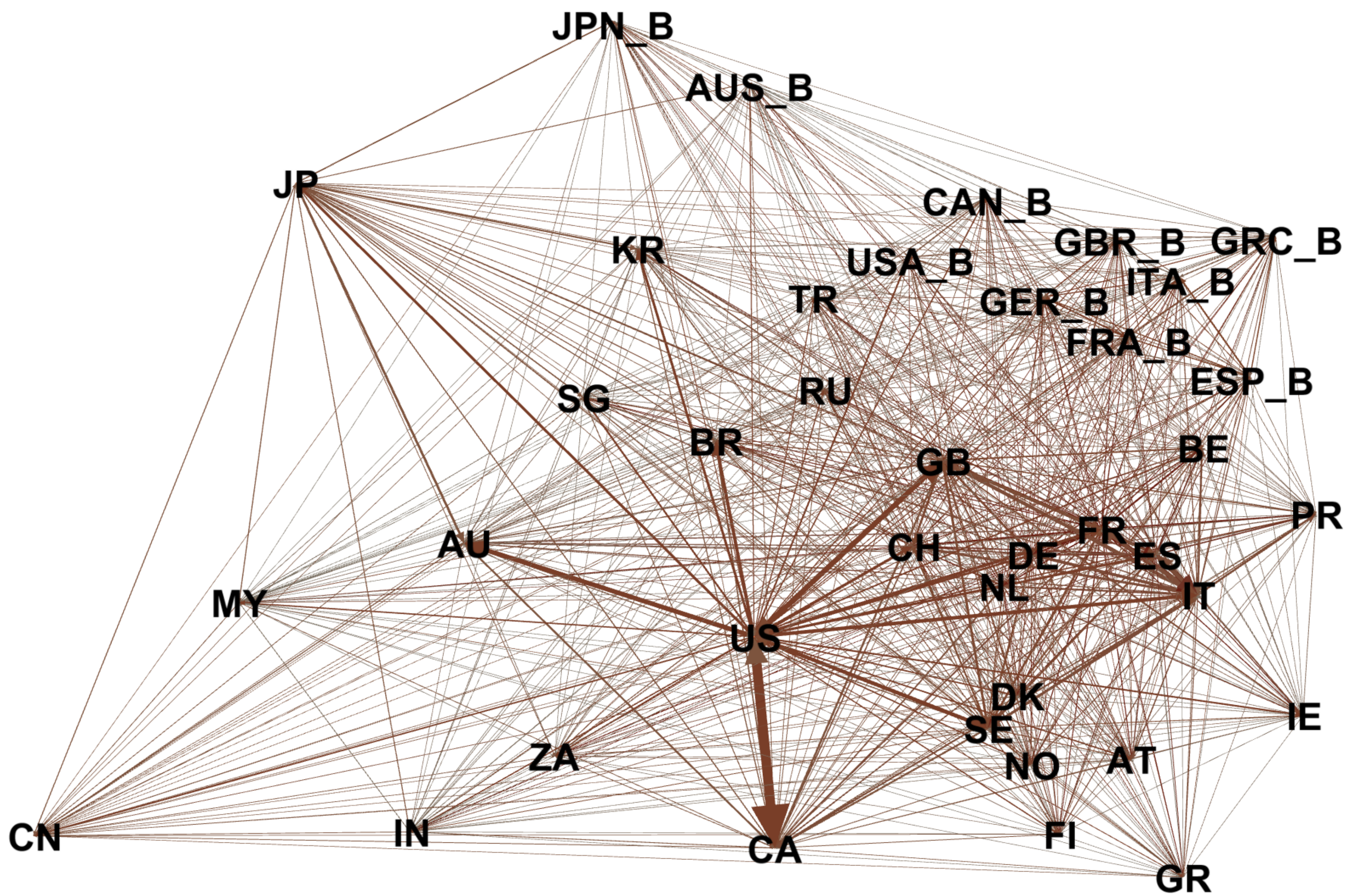


Figure 5: Country Bank / Sovereign Bond Network, 2003-2014

crisis episodes, and then we proceed to examine the continuous real-time evolution of system-wide connectedness.

5.1 Banks Pre- and Post-Lehman

The critical point in the financial crisis was Lehman's bankruptcy, which was announced on September 15, 2008. In Figure 6 we show the 96-bank network graphs on September 1, 2008 and on November 21, 2008. There is a clear difference between the individual bank network graphs on the two dates.

In particular, connectedness of U.S. banks with others increased sharply after Lehman's collapse and the transformation of the U.S. financial crisis into a global one. Before the Lehman collapse, the U.S. and European banks stood far apart around the Anglo / American / European cluster, with was visible gap in the network graph between the U.S. and European banks. The Japanese and Chinese banks also stood apart. Once the Lehman shock hit global markets, the entire individual bank network, perhaps with the exception of Chinese banks, moved closer together, indicating the spread of volatility across bank stocks and countries.

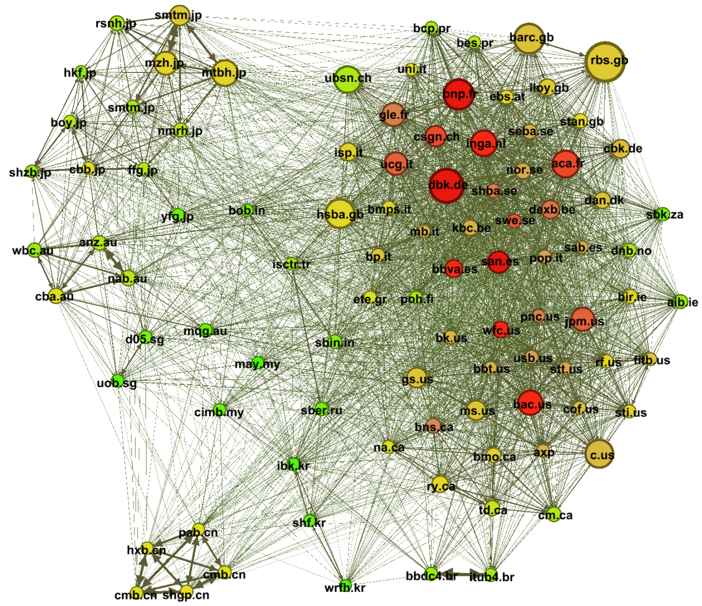
A similar picture arises when we analyze the country bank network before and after Lehman's collapse. We show the country bank network graphs in Figure 7. Connectedness was comparatively weak before the collapse, and much stronger afterward. Moreover, the directional volatility connectedness from the U.S. to others increased substantially.

5.2 Banks, Bonds, and the European Debt Crisis

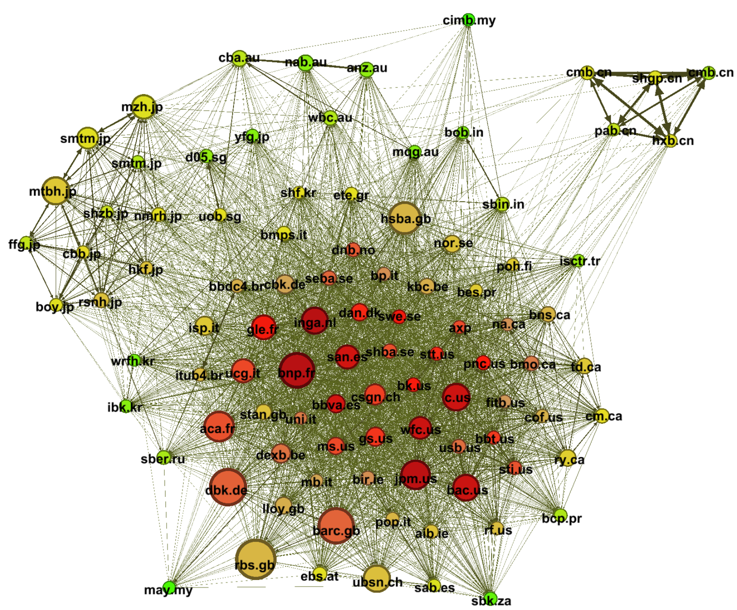
To see how the individual bank / sovereign bond network was transformed following the European banking and sovereign bond crisis, we analyze the network graph once the European sovereign debt and banking crisis spread throughout the continent, affecting mostly the periphery countries such as Greece, Portugal, Ireland, Italy and Spain. However, sovereign bonds of the center countries such as Germany, France and the Great Britain could not be isolated from the events unfolding in the periphery. As a result, by the end of the summer 2011 connectedness reached one of its high points on October 7, 2011.

In Figure 8(a) we show the individual bank / sovereign bond network on October 7, 2011, when the volatility connectedness of the banks and bonds reached its local maximum. In Figure 8(b), we once again show the full-sample graph, for comparison. The graphs are quite different.

On Oct. 7, 2011, bond yield volatilities are no longer on the outskirts of the regional /

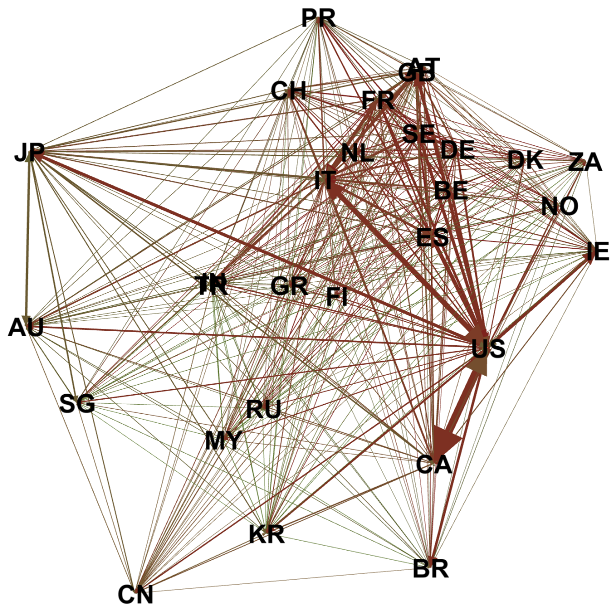


(a) September 1, 2008

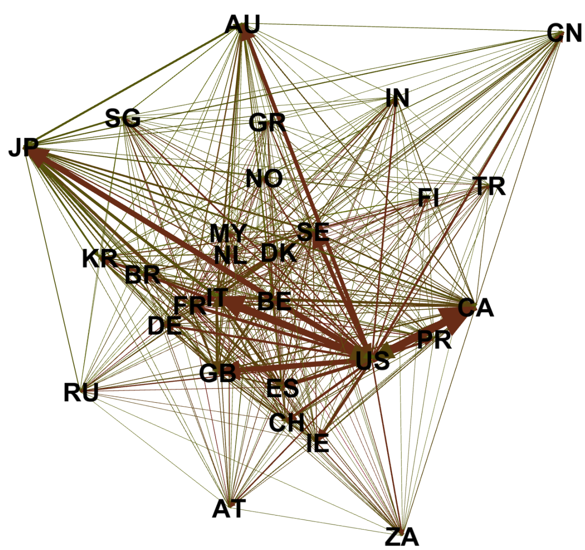


(b) November 21, 2008

Figure 6: Individual Bank Network Pre- and Post-Lehman

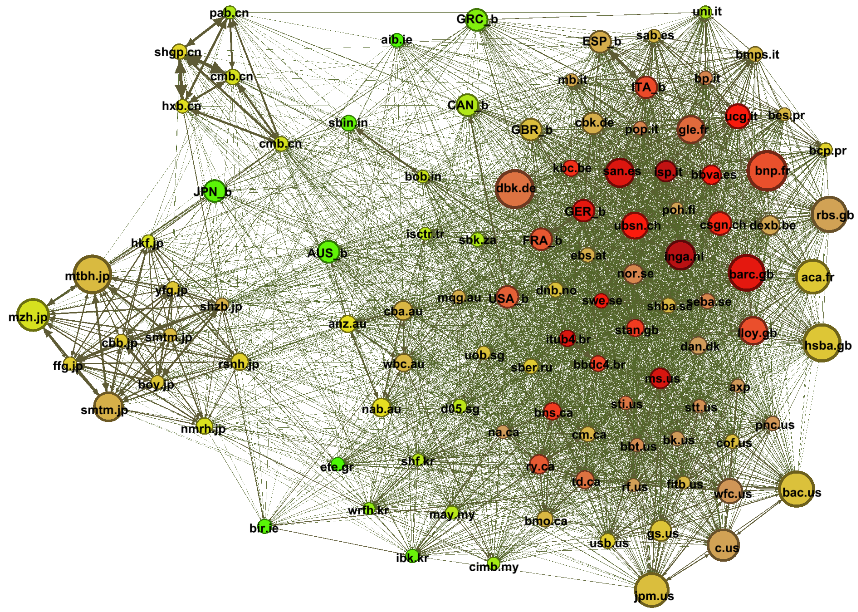


(a) September 1, 2008

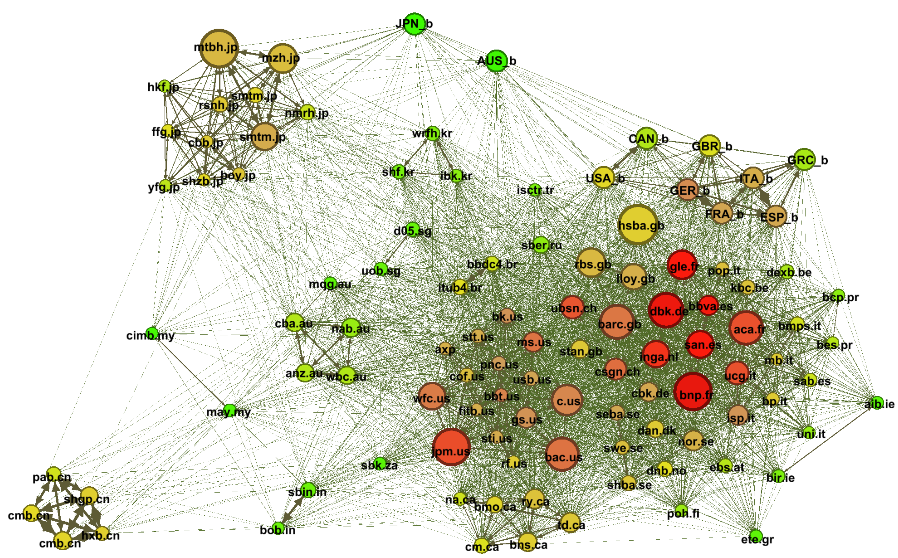


(b) November 21, 2008

Figure 7: Country Bank Network Pre- and Post-Lehman



(a) Rolling Estimation, 150-Day Window Ending October 7, 2011



(b) Full-Sample Estimation

Figure 8: Individual Bank / Sovereign Bond Network, Full-Sample vs. After the European Crisis

national banking clusters. Indeed, bond yield volatilities for the U.S., the UK, Germany and France moved toward the center of the European / North American banking cluster. Italy and Spain did not move to the center of the cluster, but they are still closer to the center of Anglo / American / European cluster than they were in the full sample. Greek bonds, on the other hand, are separated from other European bonds. Australian bonds moved closer to the Japanese bonds. Furthermore, the nodes for the Japanese and Chinese banks, as well as the ones from other countries, moved closer to the Anglo / American / European cluster, indicating stronger volatility connectedness in October 2011 compared to the full sample.

All told, Figure 8 clearly shows how the European banking and sovereign debt crises had become intertwined as of October 2011. The U.S. banks are farther away from the center of the Anglo / American / European cluster, and the European banks are at the center, close to the government bond markets of the U.S., France Germany, and the U.K.

5.3 System-Wide Connectedness

Now we consider system-wide connectedness. There are two interesting ways to display and decompose it.

5.3.1 Trend and Cycle

The first involves distinguishing between secular (trend) and cyclical variation, as shown in Figure 10. As indicated by the superimposed piece-wise linear trend, total system-wide connectedness broadly increased for roughly the first half of our sample, peaking with the Lehman bankruptcy. It then decreased gradually, albeit with some major bumps associated with the European debt crisis, falling by almost twenty percentage points relative to its peak by the end of the sample. The pre-Lehman upward connectedness trend is "good," corresponding to increased financial market integration, and the post-Lehman connectedness trend is evidently similarly "bad," presumably corresponding to decreased financial market integration. Bursts of cyclical connectedness around trend, in contrast, are always "bad," corresponding to crises.

Let us first discuss aspects of the pre-Lehman episode. First, the connectedness of major global bank stocks increased following the Fed's unexpected decision to tighten monetary policy in May and June 2006. However, there was no other major volatility shock across the global banking system in 2006, so that estimated connectedness subsides as the observations for May-June 2006 vanish from the rolling-window. Volatility connectedness was low in

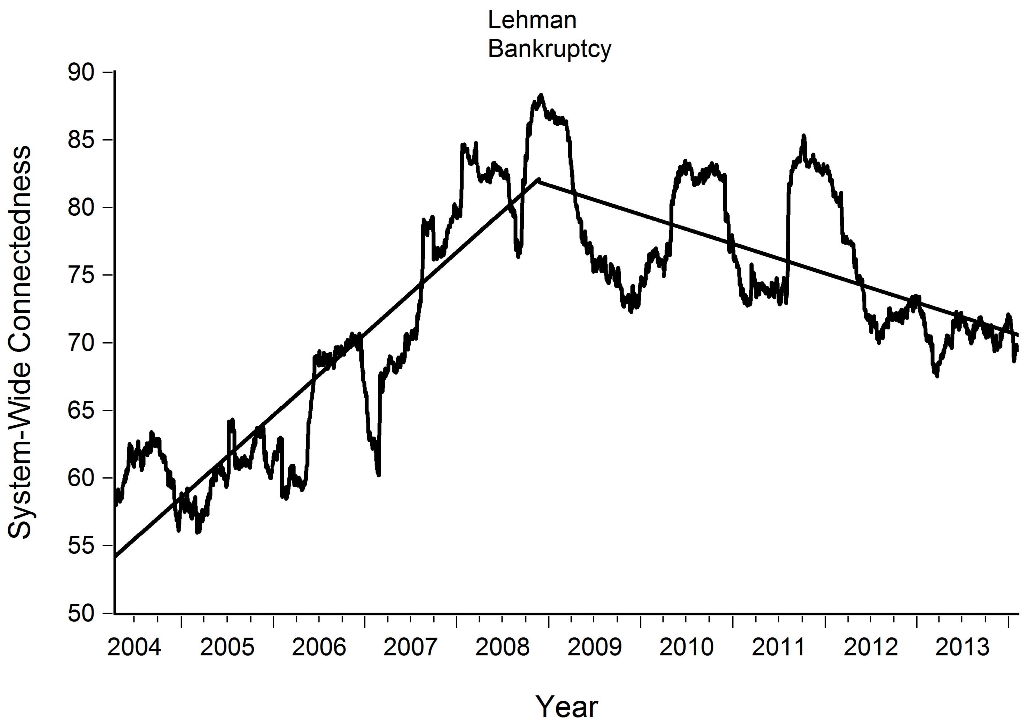


Figure 9: System-Wide Connectedness, With Superimposed Trend

early 2007. However, following the collapse of several mortgage originators in the U.S., connectedness increased sharply. This jump was followed by an even greater jump during the liquidity crisis of August 2007, when it became apparent that along with the U.S. banks the European banks also had to write off billions of dollars of losses due to their investments in mortgage backed securities. By the end of 2007, it became apparent that the major U.S. banks would end up writing of tens of billions of dollars in losses. Then in March 2008, Bear Stearns, one of the top U.S. investment banks, was acquired by J.P. Morgan to avoid bankruptcy.

Now consider the post-Lehman episode. Total system-wide connectedness reached its peak following the Lehman bankruptcy on September 15, 2008, at which time the U.S. government introduced a huge package of direct capital injection in major U.S. banks. As months passed, the U.S. markets calmed, and total system-wide connectedness started to trend downward. However, in 2009 and 2010 the EU member countries were shocked by developments in the banking and sovereign debt markets of some of its peripheral member

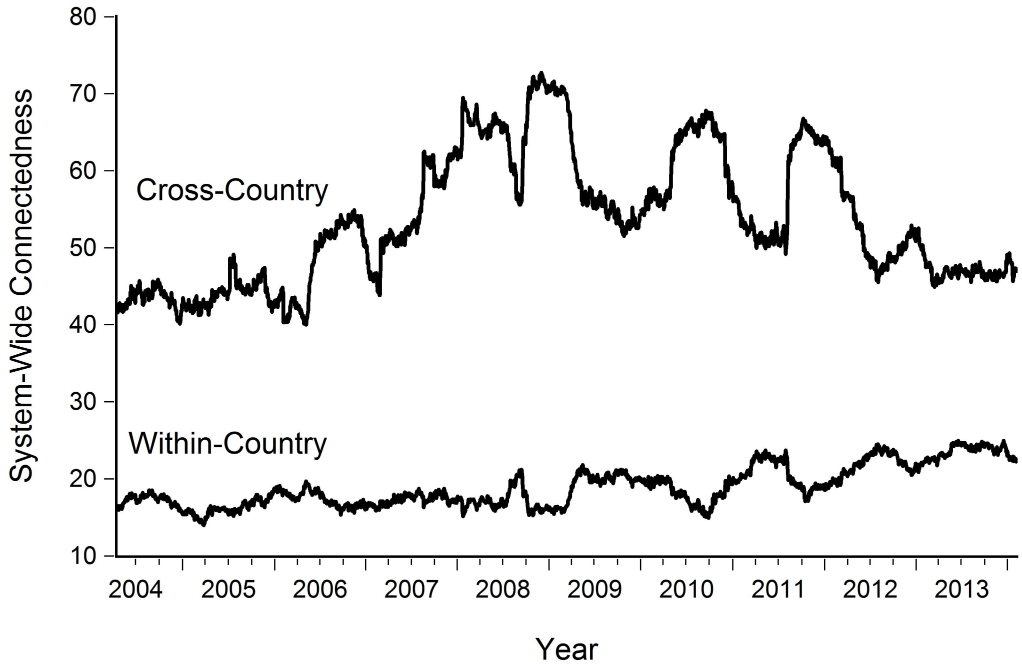


Figure 10: System-Wide Connectedness, Cross-Country and Within-Country

countries, including Greece, Ireland and Portugal. Then in 2011, Italy and Spain joined the countries with stressed banking systems and sovereign bond markets. As a result, total system-wide connectedness experienced two more significant jumps in May 2010 (due to delay in the rescue package for Greece) and in July-August 2011 (due to spread of sovereign debt and banking sector worries to Spain and Italy).

5.3.2 Cross-Country and Within-Country

The second way to display and decompose dynamic system-wide connectedness involves decomposing it into two parts: cross-country and within-country, as in Figure 10. Cross-country system-wide connectedness is the sum of all pairwise connectedness across banks located in different countries. Within-country system-wide connectedness is the sum of pairwise connectedness across banks in the same country. By construction cross-country and within-country system-wide connectedness must sum to total system-wide connectedness.

The decomposition is of interest because exploring the country origins of volatility shocks and their temporal evolution may help us better understand the dynamics of the global bank connectedness. Although we are interested in global banking network and global banking connectedness, there are many banks in our sample located in the same country. Moreover, the banks with the same country of origin tend to be more connected to each other as they are exposed to the same country-level shocks.

The decomposition shows that most movements in total system-wide connectedness are due to movements in cross-country system-wide connectedness. Cross-country system-wide connectedness is around 40% from 2004 to May 2006, but it then begins to fluctuate significantly. Following the Fed's unexpected decision to further tighten U.S. monetary policy, cross-country system-wide connectedness increases by around 15% in May-December 2006. Following this episode, cross-country connectedness continues to vary throughout the sample.

5.4 Size and Eigenvalue Centrality

One of the primary goal of the network analysis is to evaluate the relative importance of each individual member in the network. This is also relevant for the global banking network, because, as shown during the recent global financial crisis, an individual bank may be the source of financial stress that can be transmitted to the whole system. Furthermore, from the policymakers point of view, detecting the systemically important financial institutions carries enormous importance in preventing future crises. In order to shed some light on this issue, we calculate the eigenvalue centrality of each bank in our sample using our estimated network measures with the following formula.

$$S_t = C_t.S_t \tag{7}$$

where S_t is Nx1 vector of centrality of the banks and C_t is NxN connectedness (adjacency) matrix of the network at time t. So the eigenvalue centrality for a bank is equal to the sum of the centralities of the connected banks weighted by the size of the respective edge. The solution for S_t in the above equation corresponds to eigenvector associated with the largest eigenvalue of connectedness matrix C_t.

As we've already obtained the dynamic volatility connectedness measures, we can also calculate the dynamic centrality measures evolving over time. The dynamic analysis therefore allows us to investigate the interaction between bank market capitalization and centrality measures over time.

Toward that objective, we estimate the cross-section rank regression between bank eigenvalue centrality and bank market capitalization for each sub-sample window. Figure 11 presents the rank regression coefficient, its p-value and the R^2 of the rank regression over the rolling windows. In line with the expectation, the bank eigenvalue centrality is highly correlated with the bank size, with the correlation coefficient fluctuating between 0.4 and 0.6 in 2004 and 2005. More importantly, however, the correlation between the centrality rank and the size rank weakened during the global financial crisis of late 2008 and early 2009. It even disappeared completely during the second phase of the European debt crisis in the summer of 2011 and in the second half of 2012. Over these episodes the p-value of the correlation coefficient moved well above the 5% level.

On the basis of this evidence we can conclude that, whereas the largest banks are more likely to be central in the global financial system in good times, smaller banks can also become central during bad times and generate volatility connectedness that will have systemic implications.

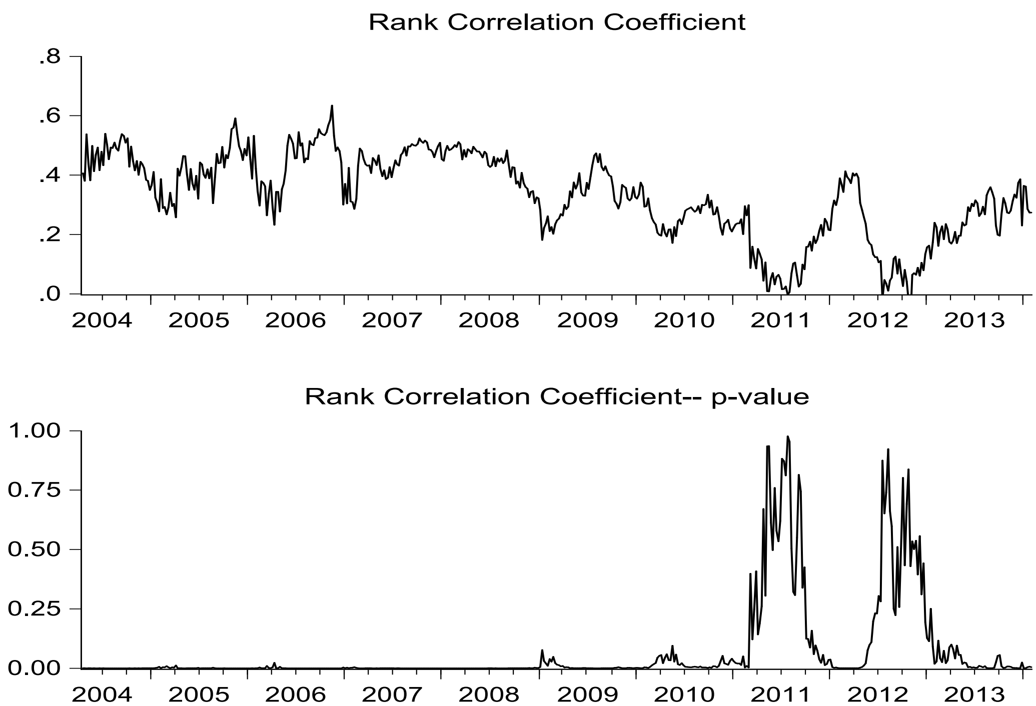


Figure 11: Market Capitalization and Eigenvalue Centrality: Rank Regression Results

6 Conclusion

We have used lasso methods to shrink, select and estimate the network linking the publicly-traded subset of the world's top 150 banks, 2003-2014. We characterize static network connectedness using full-sample estimation and dynamic network connectedness using rolling-window estimation. Statically, we find that global banking connectedness is clearly linked to bank location, not bank assets. Dynamically, we find that global banking connectedness displays both secular and cyclical variation. The secular variation corresponds to gradual increases/decreases during episodes of gradual increases/decreases in global market integration. The cyclical variation corresponds to sharp increases during crises, involving mostly cross-country, as opposed to within-country, bank linkages.

Appendices

A Global Bank Detail, by Assets

Here we provide detail on our sample of all 96 publicly-traded banks in the world's top 150 (by assets). In Table 1 we show the banks ordered by assets, and we provide market capitalizations and assets (both in billions of U.S. dollars), our bank codes (which shows country), and Reuters tickers. The bank codes are easier to understand than the Reuters ticker, particularly as regards identifying banks' countries, so we use them in our empirical work.

Table 1: Global Bank Detail (Ordered by Assets)

Bank Name	**Country**	**Mcap**	**Asset**	**Bank Code**	**Reuters Ticker**
HSBC Holdings	UK	2010	2.671	hsba.gb	hsba.ln
Mitsubishi UFJ Financial Group	Japan	822	2.504	mtbh.jp	X8306.to
BNP Paribas	France	1000	2.482	bnp.fr	bnp.fr
JPMorgan Chase & Co	US	2180	2.416	jpm.us	jpm
Deutsche Bank	Germany	498	2.224	dbk.de	dbk.xe
Barclays	UK	682	2.174	barc.gb	barc.ln
Credit Agricole	France	367	2.119	aca.fr	aca.fr
Bank of America	US	1770	2.102	bac.us	bac
Citigroup	US	1500	1.880	c.us	c
Mizuho Financial Group	Japan	497	1.706	mzh.jp	8411.to
Societe Generale	France	516	1.703	gle.fr	gle.fr
Royal Bank of Scotland Group	UK	356	1.703	rbs.gb	rbs.ln
Sumitomo Mitsui Financial Group	Japan	643	1.567	smtm.jp	8316.to
Banco Santander	Spain	1030	1.538	san.es	san.mc
Wells Fargo	US	2430	1.527	wfc.us	wfc
ING Groep	Netherland	557	1.490	inga.nl	inga.ae
Lloyds Banking Group	UK	961	1.403	lloy.gb	lloy.ln
Unicredit	Italy	477	1.166	ucg.it	ucg.mi
UBS	Switzerland	802	1.138	ubsn.ch	ubsn.vx
Credit Suisse Group	Switzerland	503	983	csgn.ch	csgn.vx
Goldman Sachs Group	US	742	912	gs.us	gs
Nordea Bank	Sweden	556	870	nor.se	ndasek.sk
Intesa Sanpaolo	Italy	458	864	isp.it	isp.mi
Morgan Stanley	US	577	833	ms.us	ms
Toronto-Dominion Bank	Canada	827	827	td.ca	td.t
Royal Bank of Canada	Canada	935	825	ry.ca	ry.t
Banco Bilbao Vizcaya Argentaria	Spain	708	803	bbva.es	bbva.mc
Commerzbank	Germany	206	759	cbk.de	cbk.xe

Continued on next page

Table 1 – *Continued from previous page*

Bank Name	Country	Mcap	Asset	Bank Code	Reuters Ticker
National Australia Bank	Australia	724	755	nab.au	nab.au
Bank of Nova Scotia	Canada	698	713	bns.ca	bns.t
Commonwealth Bank of Australia	Australia	1100	688	cba.au	cba.au
Standard Chartered	UK	524	674	stan.gb	stan.ln
China Merchants Bank	China	358	664	cmb.cn	600036.sh
Australia and New Zealand Banking Group	Australia	776	656	anz.au	anz.au
Westpac Banking	Australia	918	650	wbc.au	wbc.au
Shanghai Pudong Development Bank	China	295	608	shgp.cn	600000.sh
Danske Bank	Denmark	256	597	dan.dk	danske.ko
Sberbank Rossii	Russia	594	552	sber.ru	sber.mz
China Minsheng Banking Corp	China	297	533	cmb.cn	600016.sh
Bank of Montreal	Canada	419	515	bmo.ca	bmo.t
Itau Unibanco Holding	Brazil	332	435	itub4.br	itub4.br
Resona Holdings	Japan	122	434	rsnh.jp	8308.to
Nomura Holdings	Japan	256	422	nmrh.jp	8604.to
Sumitomo Mitsui Trust Holdings	Japan	184	406	smtm.jp	8309.to
State Bank of India	India	165	400	sbin.in	sbin.in
DNB ASA	Norway	289	396	dnb.no	dnb.os
Svenska Handelsbanken	Sweden	309	388	shba.se	shba.sk
Skandinaviska Enskilda Banken	Sweden	291	387	seba.se	seba.sk
Canadian Bank of Commerce	Canada	324	382	cm.ca	cm.t
Bank of New York Mellon	US	363	374	bk.us	bk.us
U.S. Bancorp	US	745	364	usb.us	usb
Banco Bradesco	Brazil	235	355	bbdc4.br	bbdc4.br
KBC Groupe	Belgium	260	333	kbc.be	kbc.bt
PNC Financial Services Group	US	435	320	pnc.us	pnc.us
DBS Group Holdings	Singapore	320	318	d05.sg	d05.sg
Ping An Bank	China	190	313	pab.cn	000001.sz
Woori Finance Holdings	Korea	84	309	wrfh.kr	053000.se
Dexia	Belgium	1	307	dexb.be	dexb.bt
Capital One Financial	US	415	297	cof.us	cof
Shinhan Financial Group	Korea	188	295	shf.kr	055550.se
Swedbank	Sweden	308	284	swe.se	sweda.sk
Hua Xia Bank	China	124	276	hxb.cn	600015.sh
Erste Group Bank	Austria	168	276	ebs.at	ebs.vi
Banca Monte dei Paschi di Siena	Italy	29	275	bmps.it	bmps.mi
State Street Corporation	US	30	243	stt.us	stt.us
Banco de Sabadell	Spain	131	225	sab.es	sab.mc
United Overseas Bank	Singapore	251	225	uob.sg	u11.sg
Banco Popular Espanol	Spain	13	204	pop.es	pop.mc
Industrial Bank of Korea	Korea	66	193	ibk.kr	024110.se
BB&T Corp	US	266	183	bbt.us	bbt
Bank of Ireland	Ireland	146	182	bir.ie	bir.db
National Bank of Canada	Canada	131	180	na.ca	na.t
SunTrust Banks	US	203	175	sti.us	sti.us
Banco Popolare	Italy	36	174	bp.it	bp.mi
Malayan Banking Berhad	Malaysia	263	171	may.my	maybank.ku

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Table 1 – *Continued from previous page*

Bank Name	**Country**	**Mcap**	**Asset**	**Bank Code**	**Reuters Ticker**
Allied Irish Banks	Ireland	999	162	aib.ie	aib.db
Standard Bank Group	South Africa	177	161	sbk.za	sbk.jo
American Express	US	947	153	axp	axp
National Bank of Greece	Greece	121	153	ete.gr	ete.at
Macquarie Group	Australia	160	143	mqg.au	mqg.au
Fukuoka Financial Group	Japan	33	137	ffg.jp	8354.to
Bank Of Yokohama	Japan	63	134	boy.jp	8332.to
Pohjola Bank	Finland	58	132	poh.fi	poh1s.he
Fifth Third Bancorp	US	185	130	fitb.us	fitb.us
Regions Financial	US	143	117	rf.us	rf.us
Chiba Bank	Japan	52	117	cbb.jp	8331.to
Unipol Gruppo Finanziario	Italy	28	116	uni.it	uni.mi
Banco Comercial Portugues	Portugal	51	113	bcp.pr	bcp.lb
CIMB Group Holdings	Malaysia	163	113	cimb.my	cimb.ku
Bank of Baroda	India	37	113	bob.in	bankbaroda.in
Turkiye Is Bankasi	Turkey	89	112	isctr.tr	isctr.is
Banco Espirito Santo	Portugal	71	111	bes.pr	bes.lb
Hokuhoku Financial Group	Japan	25	108	hkf.jp	8377.to
Shizuoka Bank	Japan	61	104	shzb.jp	8355.to
Mediobanca Banca di Credito Finanziario	Italy	85	95	mb.it	mb.mi
Yamaguchi Financial Group	Japan	23	93	yfg.jp	8418.to

B Global Bank Detail, by Country

In Table 2 we show the same banks by country, starting with those countries with the most banks, and proceeding through those countries with fewer banks.

Table 2: Global Bank Detail (Ordered by Country)

Bank Name	**Country**	**Mcap**	**Asset**	**Bank Code**	**Reuters Ticker**
JPMorgan Chase & Co	US	2180	2.416	jpm.us	jpm
Bank of America	US	1770	2.102	bac.us	bac
Citigroup	US	1500	1.880	c.us	c
Wells Fargo	US	2430	1.527	wfc.us	wfc
Goldman Sachs Group	US	742	912	gs.us	gs
Morgan Stanley	US	577	833	ms.us	ms
Bank of New York Mellon	US	363	374	bk.us	bk.us
U.S. Bancorp	US	745	364	usb.us	usb
PNC Financial Services Group	US	435	320	pnc.us	pnc.us
Capital One Financial	US	415	297	cof.us	cof

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Table 2 – *Continued from previous page*

Bank Name	**Country**	**Mcap**	**Asset**	**Bank Code**	**Reuters Ticker**
State Street Corporation	US	30	243	stt.us	stt.us
BB&T Corp	US	266	183	bbt.us	BBT
SunTrust Banks	US	203	175	sti.us	sti.us
American Express	US	947	153	axp	axp
Fifth Third Bancorp	US	185	130	fitb.us	fitb.us
Regions Financial	US	143	117	rf.us	rf.us
Mitsubishi UFJ Financial Group	Japan	822	2.504	mtbh.jp	X8306.to
Mizuho Financial Group	Japan	497	1.706	mzh.jp	8411.to
Sumitomo Mitsui Financial Group	Japan	643	1.567	smtm.jp	8316.to
Resona Holdings	Japan	122	434	rsnh.jp	8308.to
Nomura Holdings	Japan	256	422	nmrh.jp	8604.to
Sumitomo Mitsui Trust Holdings	Japan	184	406	smtm.jp	8309.to
Fukuoka Financial Group	Japan	33	137	ffg.jp	8354.to
Bank Of Yokohama	Japan	63	134	boy.jp	8332.to
Chiba Bank	Japan	52	117	cbb.jp	8331.to
Hokuhoku Financial Group	Japan	25	108	hkf.jp	8377.to
Shizuoka Bank	Japan	61	104	shzb.jp	8355.to
Yamaguchi Financial Group	Japan	23	93	yfg.jp	8418.to
Toronto-Dominion Bank	Canada	827	827	td.ca	td.t
Royal Bank of Canada	Canada	935	825	ry.ca	ry.t
Bank of Nova Scotia	Canada	698	713	bns.ca	bns.t
Bank of Montreal	Canada	419	515	bmo.ca	bmo.t
Canadian Bank of Commerce	Canada	324	382	cm.ca	cm.t
National Bank of Canada	Canada	131	180	na.ca	na.t
Unicredit	Italy	477	1.166	ucg.it	ucg.mi
Intesa Sanpaolo	Italy	458	864	isp.it	isp.mi
Banca Monte dei Paschi di Siena	Italy	29	275	bmps.it	bmps.mi
Banco Popolare	Italy	36	174	bp.it	bp.mi
Unipol Gruppo Finanziario	Italy	28	116	uni.it	uni.mi
Mediobanca Banca di Credito Finanziario	Italy	85	95	mb.it	mb.mi
National Australia Bank	Australia	724	755	nab.au	nab.au
Commonwealth Bank of Australia	Australia	1100	688	cba.au	cba.au
Australia and New Zealand Banking Group	Australia	776	656	anz.au	anz.au
Westpac Banking	Australia	918	650	wbc.au	wbc.au
Macquarie Group	Australia	160	143	mqg.au	mqg.au
China Merchants Bank	China	358	664	cmb.cn	600036.sh
Shanghai Pudong Development Bank	China	295	608	shgp.cn	600000.sh
China Minsheng Banking Corp	China	297	533	cmb.cn	600016.sh
Ping An Bank	China	190	313	pab.cn	000001.sz
Hua Xia Bank	China	124	276	hxb.cn	600015.sh
HSBC Holdings	UK	2010	2.671	hsba.gb	hsba.ln
Barclays	UK	682	2.174	barc.gb	barc.ln
Royal Bank of Scotland Group	UK	356	1.703	rbs.gb	rbs.ln
Lloyds Banking Group	UK	961	1.403	lloy.gb	lloy.ln
Standard Chartered	UK	524	674	stan.gb	stan.ln
Banco Santander	Spain	1030	1.538	san.es	san.mc
Banco Bilbao Vizcaya Argentaria	Spain	708	803	bbva.es	bbva.mc

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Table 2 – *Continued from previous page*

Bank Name	**Country**	**Mcap**	**Asset**	**Bank Code**	**Reuters Ticker**
Banco de Sabadell	Spain	131	225	sab.es	sab.mc
Banco Popular Espanol	Spain	13	204	pop.es	pop.mc
Nordea Bank	Sweden	556	870	nor.se	ndasek.sk
Svenska Handelsbanken	Sweden	309	388	shba.se	shba.sk
Skandinaviska Enskilda Banken	Sweden	291	387	seba.se	seba.sk
Swedbank	Sweden	308	284	swe.se	sweda.sk
BNP Paribas	France	1000	2.482	bnp.fr	bnp.fr
Credit Agricole	France	367	2.119	aca.fr	aca.fr
Societe Generale	France	516	1.703	gle.fr	gle.fr
Woori Finance Holdings	Korea	84	309	wrfh.kr	053000.se
Shinhan Financial Group	Korea	188	295	shf.kr	055550.se
Industrial Bank of Korea	Korea	66	193	ibk.kr	024110.se
UBS	Switzerland	802	1.138	ubsn.ch	ubsn.vx
Credit Suisse Group	Switzerland	503	983	csgn.ch	csgn.vx
KBC Groupe	Belgium	260	333	kbc.be	kbc.bt
Dexia	Belgium	1	307	dexb.be	dexb.bt
Itau Unibanco Holding	Brazil	332	435	itub4.br	itub4.br
Banco Bradesco	Brazil	235	355	bbdc4.br	bbdc4.br
Deutsche Bank	Germany	498	2.224	dbk.de	dbk.xe
Commerzbank	Germany	206	759	cbk.de	cbk.xe
Bank of Ireland	Ireland	146	182	bir.ie	bir.db
Allied Irish Banks	Ireland	999	162	aib.ie	aib.db
State Bank of India	India	165	400	sbin.in	sbin.in
Bank of Baroda	India	37	113	bob.in	bankbaroda.in
Malayan Banking Berhad	Malaysia	263	171	may.my	maybank.ku
CIMB Group Holdings	Malaysia	163	113	cimb.my	cimb.ku
Banco Comercial Portugues	Portugal	51	113	bcp.pr	bcp.lb
Banco Espirito Santo	Portugal	71	111	bes.pr	bes.lb
DBS Group Holdings	Singapore	320	318	d05.sg	d05.sg
United Overseas Bank	Singapore	251	225	uob.sg	u11.sg
Erste Group Bank	Austria	168	276	ebs.at	ebs.vi
Danske Bank	Denmark	256	597	dan.dk	danske.ko
Pohjola Bank	Finland	58	132	poh.fi	poh1s.he
National Bank of Greece	Greece	121	153	ete.gr	ete.at
ING Groep	Netherlands	557	1.490	inga.nl	inga.ae
DNB ASA	Norway	289	396	dnb.no	dnb.os
Sberbank Rossii	Russia	594	552	sber.ru	sber.mz
Turkiye Is Bankasi	Turkey	89	112	isctr.tr	isctr.is
Standard Bank Group	South Africa	177	161	sbk.za	sbk.jo

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