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Spatial Dependence and Data-Driven Networks of International Banks

by Ben R. Craig and Martín Saldías

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Spatial Dependence and Data-Driven Networks of International Banks

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Abstract

This paper computes data-driven correlation networks based on the stock returns of international banks and conducts a comprehensive analysis of their topological properties. We first apply spatial-dependence methods to filter the effects of strong common factors and a thresholding procedure to select the significant bilateral correlations. The analysis of topological characteristics of the resulting correlation networks shows many common features that have been documented in the recent literature but were obtained with private information on banks' exposures, including rich and hierarchical structures, based on but not limited to geographical proximity, small world features, regional homophily, and a core-periphery structure.

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I. Introduction

Financial stability research since the global financial crisis has focused on interconnectedness within the financial system. That crisis highlighted the importance of identifying and understanding the role of specific elements within financial networks as well as the channels of risk and stress transmission, including those that are not purely contagion. Ambiguous results of initial theoretical work have emphasized the need to get a clearer understanding of the functioning of financial networks from empirical observation. Such an understanding should provide far more than a measurement of simple terms within a clearly understood model. The theoretical literature needs observation of the actual networks to drive the direction of future investigation. From a macroprudential policy perspective, a clear understanding of networks' structures and functioning in the financial system should provide policymakers with the tools to quickly react to financial shocks, mitigate risks, and take targeted precautionary actions.

While new empirical work is available, and it often makes use of new bilateral data within a network, it is hampered by the fact that those data sets are rare, often highly specific, and usually confidential and hard to access.[2] One possible way to measure an undirected and unweighted network between international financially important institutions is to measure correlation between their equity returns. In correlation networks, common shocks can deliver positive correlations between all of the nodes of the network. The point of departure of this paper is that network connections between international banks are incomplete, and that the incompleteness of these connections is what gives them economic interest. For example, a star network has $N-1$ connections, all between the periphery and the center node, and it is the lack of the other possible $(N-2)(N-1)$ connections that give this network its characteristic properties. Similarly, the sparsity of the network connections in international banking is what gives such properties as who is central in the network, their power, so that some method of filtering out the common shocks is needed.

This paper contributes to the empirical network analysis literature in financial stability by proposing a method to compute undirected and data-driven correlation networks based on daily bank stock returns. Using a sample of 418 banks from around the world between January 1999 and December 2014, we apply recently developed spatial dependence methods that filter the effects of strong common factors in the correlation across banks and apply a thresholding method to obtain a sparse adjacency matrix that can be used for spatio-temporal analysis of shocks across banks in a spatial vector autoregression (SpVAR) or a Global vector autoregression (GVAR) model, as outlined in Bailey et al. (2015b).

In order to assess the soundness and empirical accuracy of this approach, we analyze the topological characteristics of the resulting networks and find a number of interesting common features documented in the recent literature, which were derived from confidential data sources. In particular, the resulting networks show rich and hierarchical structures based on but not limited to geographical proximity, small world features, regional homophily,[3] and

[2] Recent contributions in this area include Peltonen et al. (2014) for CDS markets, Alves et al. (2015) for insurers' balance sheet exposures, Alves et al. (2013) and Langfield et al. (2014) for interbank balance sheet exposures, Minoiu and Reyes (2013) for international cross-border bank lending and Iori et al. (2008) and van Lelyveld and Liedorp (2004) for interbank money markets.

[3] Homophily is the tendency of nodes in a network to associate with similar others in some form. In this particular case, through geographical proximity.

a core-periphery structure. This core-periphery structure is adapted from Craig and von Peter (2014) and applied to a topological structure where domestic (mainly peripheral) linkages coexist with regional and interregional linkages. All these characteristics have relevant implications for the way shocks are diffused in the banking system.

We also demonstrate that our results and the performance of the filtering and thresholding methods are robust to random noise resulting from changes in the structure of the underlying data. Given that our dataset and most others are unbalanced and our filtering and thresholding method does not depend on a balanced panel structure, we show that our network structure does not suffer significant distortions from random noise which would generate spurious correlation. Finally, as a result of the thresholding method, this approach generates sparse networks that are useful in terms of the spatial modeling as a regularization method that clearly distinguishes between neighbors and non-neighbors and allows analysis of large scale datasets.

The rest of the paper is organized as follows. Section II provides a concise review of models of networks based on stock market information in order to provide a context for this research. An empirical application is thoroughly described in Section III. Results are provided in Section IV and conclusions and discussion of future research are summarized in Section V.

II. Empirical Models of Financial Networks

This section first reviews the empirical models of networks that have been developed from stock market information and then describes the general features of the spatial-dependence approach to network analysis that is used in this paper. Among the former models, the most popular ones are grouped into graph theory methods and into multivariate time series models. They differ in terms of the network structure assumed and their use of model shocks within the network.

In particular, graph theory methods have well defined but rigid network structures. Multivariate time series analysis methods allow for flexible network structure, generally producing dense networks, but they put less emphasis on the characteristics and implications of the network's structure on the transmission of shocks across nodes.

In both cases, the presence and importance of common factors are analyzed superficially, which is what takes us to the spatial-dependence approach. This literature belongs to the panel vector autoregression (PVAR) literature and hence, allows us to easily identify and model shocks and their transmission. This approach also allows us to introduce the concept of spatial proximity in order to analyze the extent to which the strength of interdependence is a result of common factors and whether it can be filtered out.

A. Graph Theory Methods

Generally, the methods using graph theory to extract an undirected network of relevant interactions from a complete correlation matrix are based on two graph theory concepts, namely Minimum Spanning Trees (MSTs) and Planar Maximally Filtered Graphs (PMFGs). The application of MSTs is originally outlined in Mantegna (1999) and consists of obtaining a subgraph of $N-1$ links that connect all N nodes of the network by minimizing the sum of the edge distances starting from the possible $N(N-1)/2$ edges of a complete network. The method transforms each element ρ_{ij} of the correlation matrix into a distance metric[4] and applies Kruskal's algorithm or Prim's algorithm to find the MST.

As this method is generally applied to a set of constituents in a stock market index, the resulting MST shows a well-defined topological arrangement that allows to group the network nodes into industries, sectors or even sub-sectors and to establish a hierarchy with an economic meaning.[5] This implies that the MST grouping is consistent with the existence of underlying factors affecting the stock returns such as investors' investment focuses and economic activity. However, MSTs do only allow for single links, and thus the formation of cliques or non-connected components of the network is not possible. As a result, the MST becomes a simple but very restricted topological structure in terms of modeling shock transmission channels among nodes.

Planar Maximally Filtered Graphs (PMFGs) are introduced in Tumminello et al. (2005)[6] and partially address the MST constraints by allowing for slightly richer substructures, including cliques and loops of up to a predefined and small number of nodes. PMFGs produce a network with $3(N-2)$ edges, contain an MST as a subgraph and share its hierarchical organization. They do however keep the completeness of the network and, as in the MST, the resulting dependency structure determines by construction the distribution of centrality or clustering measures across nodes in the network and hence their role as shock transmission channels. Recent developments in this literature include models with network dynamics, more flexible community detection, and the use of partial correlations. These and alternative methods establish a distance metric and hierarchical structure which can explain how shocks are transmitted.

B. Time Series Approach

The contributions from multivariate time series methods to network analysis are even more recent. The resulting networks are mainly directed networks estimated from causality relationships or spillover effects. Regularization methods are often applied in order to deal with large datasets, to induce sparsity and as an econometric identification tool. These models also allow for dynamics in the interdependencies and tend to only include observable factors to control for macrofinancial common factor exposures. Being at an early stage, however, they focus on methodology rather than concentrate on the analysis of the network topology.

For instance, Diebold and Yilmaz (2014) build and analyze static and time-varying directed and complete networks based on variance decompositions from a vector autoregression (VAR) model applied to daily stock returns and realized volatilities of a relatively small

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[4] The distance measure is defined as $d_{i,j} = \sqrt{2(1-\rho_{ij})}$, which fulfills the three axioms of a metric, namely: 1) $d_{i,j} = 0$ if and only if $i = j$ 2) $d_{i,j} = d_{j,i}$ and 3) $d_{i,j} \leq d_{i,k} + d_{j,k}$. Other relevant references along these lines can be found in Bonanno et al. (2004) and Tumminello et al. (2010).

[5] When applied to stock indices and currencies or to stocks in different markets, MST groups nodes according to geography.

[6] See also Aste et al. (2005); Pozzi et al. (2013); Tumminello et al. (2010) and references therein.

number of financial companies.[7] In Billio et al. (2012) network edges are formed by linear and nonlinear Granger-causal relationships between financial institutions, i.e., hedge funds, banks, broker/dealers, and insurance companies, for different sample sub-periods and rolling windows. The authors provide a summary of network measures and show robust results to the inclusion of observed common factors affecting the bilateral relationships. The resulting networks are overall very dense and complete, especially in crisis periods.

Hautsch et al. (2014a,b) model static and time-varying tail risk spillovers between banks and insurance institutions. They use a LASSO-type quantile regression to select the relevant risk drivers across banks and thus define the directed network's edges and gauge their systemic impact and changing roles in time. The authors also control for observable common tail risk drivers and find substantial persistent country-specific risk channels. Also Barigozzi and Brownlees (2013) characterize cross-sectional conditional dependence and define the links of a network using long-run partial correlations. This model is based on a vector autoregressive representation of the data-generating process as in Diebold and Yilmaz (2014) but turns to LASSO to estimate the long-run correlation network. This approach takes into account contemporaneous and dynamic aspects of network connectedness which allows to dealing with large dimensional data. In an empirical application to 41 blue-chip stock returns, the authors control for only observable common factors using a one-factor model but obtain a relatively sparse matrix with interesting features, including unconnected nodes and clustering.

C. Cross-Sectional and Spatial Dependence in Panels

Even though some works mentioned in the previous sections account for observable common factors, empirical models of financial networks have largely overlooked the role of spatial dependence in the data and its implications for interdependence. In this strand of the literature, relationships between spatial units include both purely spatial dependence and the effect of common factors. If common factors are strong, e.g., aggregate shocks or pure contagion, as defined in Chudik et al. (2011) and Bailey et al. (2015a), resulting interdependences are misleading. As a result, strong common factors have to be detected and removed from the data in order to highlight the purely spatial dependence.

Spatial dependence in a broad sense is illustrated in Conley and Topa (2002) and Conley and Dupor (2003); and more recently analyzed in depth in Chudik and Pesaran (2013b). From and economic perspective and applied to the banking sector and its stock market returns, spatial proximity is related to a number of features, including similarity of business lines, common balance-sheet or market exposures, common geographical exposures, accounting practices, or technological linkages. Hence, removing strong common factors from bilateral correlations highlights these features.

Bailey et al. (2015b) extend the cross-sectional dependence analysis from panel data to network analysis by applying a model of spatiotemporal diffusion of shocks to house prices. In this setting, the authors choose a hierarchical model based on geographical areas and introduce a method to filter the strong common factors from the data and establish the significant correlations that create the adjacency matrix (Bailey et al., 2014). The authors compare their results to an exogenously defined adjacency matrix, but the network properties

[7] Diebold and Yilmaz (2015) explain this approach and provides additional applications to macrofinancial data.

become less relevant in their analysis. They do however provide the motivation to apply this method to a different context and to stress its applicability in financial stability analysis.

III. Empirical Application

Following Bailey et al. (2015b), the extraction of the bank network based on correlations comprises two steps, the removal of strong factors from the returns series; and the regularization or thresholding. First, the potential existence of strong factors in the data is evaluated using the cross-section dependence (CD) tests developed in Pesaran (2015) and Bailey et al. (2015a). In case the null of weak dependence is rejected, sequential estimation of common factors is conducted using principal components. Once the CD tests confirm that the strong common factors have been purged, a correlation matrix is computed to apply thresholding.

The thresholding step selects the correlation coefficients, $\hat{\rho}_{ij}$, among weakly-dependent residuals that are statistically different from zero at a given significance level (5 percent) from all possible $N(N-1)/2$ elements of the correlation matrix using the Holm-Bonferroni method. Finally, a data-driven undirected network, W, is obtained which can be analyzed in terms of its topological properties. A detailed description of these steps and the database is presented below.

A. Sample and Preliminary Data Treatment

The sample consists of daily log-returns during the period January 1999–December 2014 (4,173 observations) of 418 banks located across 46 countries from three large geographical regions (Table 1). The sample was selected from the leading country indices and main bank rankings. It is highly representative of the largest traded and highly liquid banks in each country and region, and was subject to a thorough process of filtering by data availability, daily trading liquidity and relevant corporate actions. In the sample, the EMEA (Europe, the Middle East, and Africa) region includes banks from 26 countries, Asia includes banks from 12 and the Americas has 8. Due to the particularities of each country's banking sector and stock market, some countries, such as the United States (U.S.), Japan or India, have many more banks in sample than countries where banks are not as extensively listed, such as Germany or Mexico, or where the banking sector is highly concentrated, like Singapore, Belgium or the Netherlands.

The sample is unbalanced at both ends as it includes delisted, bankrupt, acquired or merged banks, and also newly listed banks. Before the defactoring step, we first transform the log-returns into series with zero means and unit variances to reduce the scale effects in the data. This step is relevant for two reasons. First, it allows us to keep the effect of the stock price movements of new or defunct banks in terms of the common factors filtering and as a possible source of a strong dynamic factor (Chudik and Pesaran, 2013a). Second, it avoids possible significant omissions due to survivorship bias that may affect the resulting structure of the network. For instance, much of the stock market analysis focused on Bear Stearns and (then on Lehman Brothers during 2008) and how their stock price developments were transmitted as global factors to other markets. Similarly, newly listed large Chinese banks have quickly become the largest in the world by market capitalization and in terms of their regional and global relevance.

Then we introduce standard normal random noise into the missing data to obtain a block structure while keeping independence across the draws. This step brings correlations toward zero when a pair of series has a minimum or no overlap, which is equivalent to assuming those correlations are zero. Although Bailey et al. (2015b) do not rely on the block structure of the data or on the length of the time series, some of the features from the asymptotic behavior of eigenvalues rely on the block structure of the data matrix.

As the banks are located all over the world, the sample has to be robust to non-synchronous market trading, which may induce spurious correlations and emphasize the role of the countries where news arrives first and exacerbates regional clustering artificially (Lin et al., 1994). Accordingly, all log-returns from Asian banks were lagged one trading day.

B. Removal of Strong Factors

The presence of strong cross-sectional dependence is modeled using unobserved common factors, i.e., a principal components analysis (PCA), which provides a more flexible approach to capturing the strong common factors. Alternatively, cross-sectional averages at national and regional levels could be used as in Bailey et al. (2015b) and outlined in Pesaran (2006). However, this latter approach embeds hierarchical spatial and temporal relationships, where the hierarchy is exogenously predetermined.

Although a geographical hierarchy is likely to be present in the case of stock returns, the interlinkages in the banking sector go beyond the national and regional boundaries and thus include other forms of spatial dependence across borders. In addition, the definition of regions has some degree of subjectivity that can affect de-factoring and thus the resulting network structure.[8] Finally, the heterogeneous distribution of banks by nationality may also introduce some bias in the defactoring process.

The weakly dependent residuals are obtained from the following regression using robust methods to control for outliers.[9]

$$y_{it} = \hat{\alpha}_i + \hat{\beta}_i' \hat{f}_t + u_{it} \tag{1}$$

where y_{it} is the daily log-return of bank i on trading day t[10]. $\hat{f}_t$ are the principal components extracted through PCA with associated factor loadings $\beta_i = (\beta_{i1}, \beta_{i2}, \dots, \beta_{iN})'$. The de-factored log-returns are then given by the following equation:

$$\hat{u}_{it} = y_{it} - \hat{\alpha}_i - \hat{\beta}_i' \hat{f}_t \tag{2}$$

[8] As a robustness check, de-factoring was also conducted using cross-sectional averages at national, regional and aggregate level. The resulting residuals did not show enough evidence of being stripped from the strong dependence and the networks obtained under different definitions of regions showed unstable topological properties.

[9] The robust estimation method is outlined in Andrews (1974).

[10] Prior to the PCA estimation, the banks' normalized daily log-returns y_{it} were seasonally adjusted using daily dummies and an intercept.

The cross-sectional dependence tests described below set the number of principal components $\hat{f}_t$ to be extracted from the stock returns. In this application, there is no prior regarding the maximum number of factors.

C. Testing Cross-Sectional Dependence

The cross-sectional dependence test, developed in Pesaran (2015), is based on pairwise correlation coefficients, $\hat{\rho}_{ij}$, of regression residuals from equation (2) for a given number of factors.[11]

$$CD_P = \sqrt{\frac{2}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\sqrt{T_{ij}}\hat{\rho}_{ij}\right) \tag{3}$$

Pesaran (2015) shows that the CD_P implicit null depends on the relative rate at which T and N expand. Under an implicit null of weak cross-sectional dependence, $CD_P \to N(0,1)$, and this rate α, defined as the exponent of cross-sectional dependence (Bailey et al., 2015a), is $\alpha < (2-\epsilon)/4$, as $N \to \infty$, such that $T = \kappa N^{\epsilon}$ for some$0 \leq \epsilon \leq 1$, and a finite $\kappa > 0$. In particular, when the null of weak dependence is not rejected, $0 \leq \alpha \leq \frac{1}{2}$. When the null of weak dependence is rejected and $\frac{1}{2} < \alpha < 1$, Bailey et al. (2015a) show that α can be estimated consistently using the variance of cross-sectional averages, and this paper follows this procedure in order to ensure the dataset is stripped from strong common factors.

D. Thresholding and Data-Driven Correlation Network W

Based on the weakly dependent residuals from a subset of the sample,[12] the corresponding correlation matrix turns into a data-driven correlation network, $\widehat{\boldsymbol{W}}$, through a multiple testing of the significant correlation coefficients, $\hat{\rho}_{ij}$. In order to tackle the potential dependence among tests and to control the familywise error rate (FWER), the Holm-Bonferroni multiple comparison test uses the elements of the correlation matrix and corresponding p-values. Holm-Bonferroni is a conservative test and therefore ensures a sparse network, $\widehat{\boldsymbol{W}}$.

In practice, the test consists of sorting the $m = \frac{N(N-1)}{2}$ p-values $P_1, \ldots, P_m$ and associated hypotheses of correlation significance, $H_1, \ldots, H_m$, from smallest to largest. Starting from P_1 and for a significance level of 5 percent, if $P_1 \leq \frac{\alpha}{m}$, the associated correlation is significantly different from zero, and we move to P_2 and compare it with $\frac{\alpha}{m-1}$. The test continues in this fashion until it fails to reject the hypothesis of significance, i.e., $P_k \leq \frac{\alpha}{m-k}$ for $k \leq m$, where k is the stopping index. All elements of the correlation matrix from that point on are set to zero, and the first $k-1$ elements are set to one and form the $\widehat{\boldsymbol{W}}$ matrix.

E. Network Analysis

Based on the $\widehat{\boldsymbol{W}}$ network, we estimate a number of measures that characterize it as an undirected network and describe the properties of its nodes. Then, we construct three sub-networks based on the regions of origin of the banks in the sample and two sub-networks that

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[11] $\hat{\rho}_{ij} = \frac{\sum_{t\in T_i\cap T_j}(\hat{u}_{it}-\bar{\hat{u}}_i)(\hat{u}_{jt}-\bar{\hat{u}}_j)}{\left[\sum_{t\in T_i\cap T_j}(\hat{u}_{it}-\bar{\hat{u}}_i)^2\right]^{\frac{1}{2}}\left[\sum_{t\in T_i\cap T_j}(\hat{u}_{jt}-\bar{\hat{u}}_j)^2\right]^{\frac{1}{2}}}$, where $\hat{u}_{it}$ and $\hat{u}_{jt}$ are residuals from equation (2).

[12] In particular, 31 banks from the initial 418 are excluded from the thresholding step as they were delisted due to bankruptcy, M&A, etc. and their relevance for the network properties is less significant as for the de-factoring. Consequently, the network $\widehat{\boldsymbol{W}}$ analyzes only banks that are listed at the end of the selected time span.

focus on cross-border relationships. In particular, we construct three subnetworks based on the regions of origin of the banks in the sample ($\widehat{\boldsymbol{W}}_{EMEA}$, $\widehat{\boldsymbol{W}}_{Asia}$ and $\widehat{\boldsymbol{W}}_{Americas}$) and two sub-networks that focus on cross-country ($\widehat{\boldsymbol{W}}_{Cross-country}$) and cross-regional relationships ($\widehat{\boldsymbol{W}}_{Cross-region}$).

As for network metrics[13], we compute network density and measures of degree distribution (average degree, maximum degree, average neighbor degree, assortativity and clustering), distance (diameter, average path length) and other complementary metrics.

Finally, a tiering analysis is conducted based on the method outlined in Craig and von Peter (2014) in order to detect whether there is a hierarchical structure in the network that makes transmission channels work through a core-periphery structure. In applications reviewed in Section II, in spite of the fact that networks are very dense, core-periphery structures are quite common. In a sparse network context, this result has important implications in terms of the channels of transmission of shocks, as it identifies those banks that connect countries or regions and highlights their role as central in the network.

IV. Results

A. Aggregate Network $\widehat{\boldsymbol{W}}$

Before turning to the topological properties of network $\widehat{\boldsymbol{W}}$ and in line with the discussions above, we applied CD tests were conducted to the balanced panel of seasonally adjusted and standardized log-returns and sequentially to residuals from equation (2) for an increasing number of factors until strong cross-sectionally was removed. The CD_P statistic for the data without any defactoring (2485.1) clearly rejects the null of cross-sectional weak dependence compared to a critical value of 1.96 at the 5 percent significance level, pointing to the presence of strong common factors. The corresponding bias-free estimate of the exponent of cross-sectional dependence (standard error in parenthesis) from Bailey et al. (2015a) is $\dot{\alpha}$=0.996 (0.022). The sequential inclusion of factors stopped at three, yielding a CD_P statistic of -1.82 (p-value=0.0683), which ensured the weakly cross-section dependence that allows us to proceed to thresholding. The associated bias-free estimate of the exponent of cross-sectional dependence was reduced to $\dot{\alpha}$=0.831 (0.016), still above the borderline value of 0.5 but way below the initial estimate.

The resulting network, $\widehat{\boldsymbol{W}}$, is presented in a sparsity plot in Figure 1, where a square represents the significant correlation coefficient between a given pair of banks. The square colors represent the strength of the relationship[14]. The banks are sorted first by region and then by country in alphabetical order as shown in Table 1. As expected, the Holm-Bonferroni method produced a sparse adjacency matrix with density of 0.0654, which corresponds to 4,885 edges out of a total of 74,691 possible bilateral relationships.[15]

[13] See Boccaletti et al. (2006) and Jackson (2008) for definitions and general interpretation of these measures.

[14] In particular, for both the positive and negative scales, weak, medium strong correlations correspond to correlation coefficients below one third, between one and two thirds, and above two thirds, respectively.

[15] Even after de-factoring, the correlation matrix that generates $\widehat{\boldsymbol{W}}$ shows significant correlation coefficients in the range of -0.22 and 0.76 with a ±0.077 correlation defined by the chosen threshold significance level.

The network is not fully connected, as six banks are isolated from the rest.[16] After removing these nodes, the resulting network diameter is 8, while the average path length is 2.84 and the clustering coefficient is 0.5281, which is much larger than the network density and the clustering coefficient of a random Erdös-Rènyi graph of comparable density[17] (see Table 2).

The degree distribution of the network is heavy tailed. Altogether, this provides evidence of a small world network, which is a common feature found in recent research on networks based on bank exposures (Alves et al., 2013; Peltonen et al., 2014). This result is relevant if this network is used as an adjacency matrix in a spatial model of shock transmission, as it means that second round and feedback effects of a shock to a given bank are likely to propagate quickly to any other bank in the network.

Figure 1 suggests a significant degree of geographic homophily, as most connections seem to exist within regions and in several cases also within countries rather than across borders. Indeed, 26 country subnetworks are fully connected while only 3.7 percent of the edges involve nodes from different regions and mainly involving U.S. banks. Among links within region, almost 50 percent are cross-country and mainly driven by financial integration across EMEA and Asian nodes (69 percent and 65 percent in these sub-networks, respectively).[18] This result suggests that shocks propagate through a small number of hubs across regions, and their scope is determined by the nodes' centrality overall and in their respective regions and countries.

Regional clustering and the hierarchy in $\widehat{\boldsymbol{W}}$ are both consistent with graph theory models and with the spatial dependence approach in Bailey et al. (2015b) even though this approach followed PCA in the defactoring step. In addition, the larger density within country is also consistent with traditional approaches based on vector autoregressive models of shock transmission, given a reasonably small number of banks.

The degree distribution shows an average degree of 25.2, a maximum degree of 93 and a large average neighbor degree of 33.4. The assortativity coefficient, i.e., the tendency of high-degree nodes to be linked to other high-degree nodes, is 0.189, in line with findings in the literature of trade or social networks but at odds with some recent findings in the literature of interbank balance sheet and money market exposures. Key differences in this approach that explain this discrepancy include the fact that these networks are undirected; they have a hierarchical structure based on proximity; and, most important, it is a large-scale network. Litvak and van der Hofstad (2013) show that for scale-free networks, the correlation between pairs of linked nodes tends to become positive as the network size grows.

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[16] The existence of non-connected nodes in filtered correlation networks means that shocks from and to these nodes are not direct but take place through the common factors among stock returns. In this particular case, these are banks from Austria, Switzerland, Finland, and Japan (3) that have a predominantly domestic activity.

[17] For a simulated Erdös-Rènyi graph of size 387 and density of 0.0654, both average path length (2.10) and clustering coefficient (0.069) are smaller.

[18] This feature is however affected by the fact that the U.S. is overrepresented in its region and therefore the number of domestic correlations dominates. In Asia, a similar pattern takes place due to Japan but the effect is corrected by the cross-country linkages from banks in countries such as India, Thailand or Taiwan.

Along these lines, Figure 2 shows the degree and average neighbor degree distribution for the complete network and also for the regional subnetworks, where the corresponding regions are displayed in different colors. Overall, the linear correlation between the nodes' degree and average neighbor degree is positive for both the complete network (0.5988) and the subnetworks. In particular, the correlation coefficients are 0.4733, 0.5396, and 0.6722 for the EMEA region, Asia, and the Americas, respectively. This evidence is consistent with the previous findings on the assortative characteristics of the network, and the differences in association provides some additional insights about the regions.

A large degree concentration among the most connected nodes points to the rich- club phenomenon, i.e. the existence of highly connected and mutually linked nodes, as opposed to a structure comprised of many loosely connected and relatively independent sub-communities, as defined in Colizza et al. (2006). Indeed, the rich-club coefficients[19] for nodes with a degree over 40, 50, and 60 are 0.3370, 0.4273, 0.8693, respectively, which means hubs are tightly connected but also are likely to serve as bridges across borders.

B. Properties of Regional Subnetworks

The regional subnetworks, presented in Figures 3, 4, and 5, show stronger small-world properties due to the higher density across countries, and thus they reinforce those from the $\widehat{\boldsymbol{W}}$ network. Columns 2 to 4 in Table 2 summarize them. Regional subnetworks are at least twice as dense as the aggregate network, $\widehat{\boldsymbol{W}}$. Their diameters are smaller in every case, their average path lengths are shorter, and their clustering coefficients are larger. As a corollary, all regional networks present positive assortativity, especially in the EMEA region, and a rich-club analysis shows coefficients of 0.5654, 0.3951, and 0.5801 for EMEA, Asia, and the Americas for a degree higher than 20.[20]

The sub-network $\widehat{\boldsymbol{W}}_{Cross-country}$ includes all nodes in network $\widehat{\boldsymbol{W}}$ with at least one edge with a bank in a different country and contains subnetwork $\widehat{\boldsymbol{W}}_{Cross-regional}$, which keeps only banks with cross-regional relationships. They are displayed in Figures 6 and 7, as in the regional subnetworks, these networks reinforce the topological properties of the aggregate network $\widehat{\boldsymbol{W}}$. In particular, they exhibit strong evidence of a small-world network, rich-club, and positive assortativity. The sparse distribution of links across regions described above explains the large drop in size from subnetwork, $\widehat{\boldsymbol{W}}_{Cross-country}$ (316) to $\widehat{\boldsymbol{W}}_{Cross-regional}$ (140). As several nodes with only domestic links are excluded in the cross-regional subnetwork $\widehat{\boldsymbol{W}}_{Cross-regional}$, its blocky structure is attenuated and therefore its assortativity coefficient increases significantly compared to the cross-country subnetwork $\widehat{\boldsymbol{W}}_{Cross-country}$.

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[19] In particular, this measure computes the fraction of edges actually connecting those nodes out of the maximum number of edges they might possibly share.

[20] If the higher degree is set to 30, the coefficient reaches 0.5952 in Asia, 0.7058 in the Americas and reaches 0.7749 in the EMEA region.

V. Regions and the International Core

The findings so far suggest a blocky network structure of global banks with low density, low diameter, high degree concentration, positive assortativity but strong regional homophily in $\widehat{\boldsymbol{W}}$, the importance of a small set of nodes in linking countries and regions needs to be analyzed in depth. We turn therefore to a tiering analysis modifying the core-periphery model in Craig and von Peter (2014).[21]

The correlation networks identified in the previous section exhibit key features of the international banking structure, particularly in the structure between a bank with cross-border connections and banks that lie within a particular region or country. By allowing regional cross-sectional strong dependence to persist while estimating interbank linkages, we emphasize links that are created by banks within a region that are tied to a national market, which is indistinguishable from the cross-sectionally weakly dependent ones estimated in the international links.

However, by purging the regions of their regional strong factors, we would eliminate those correlations that are implicit in an extraregional bank with ties to the region, which is crucial to our understanding of international banking networks. This presents a conundrum that is best resolved after the network has been computed, as the network is analyzed.

We demonstrate this with estimates of the core-periphery structure of international banking. Estimating a core using the method proposed in Craig and von Peter (2014) directly from the international correlation networks described above may lead to a misleading core that overemphasizes domestic links. We therefore redefine and reestimate in this section the core-periphery structure with a new measure that correctly allows domestic links to exist within the periphery. This new structure leads to a much more revealing structure that is also consistent with the intuition about money-center banks, R-SIBs, and G-SIBs.

The core-periphery structure of Craig and von Peter (2014) is based upon the adjacency matrix of unweighted links, similar to network $\widehat{\boldsymbol{W}}$, except in that it can be estimated from both directed and undirected networks. The estimated structure depends upon an ideal constrution where within the core, all links are made between the core and periphery, and at least one link occurs between a core bank and a periphery bank, and further, within the periphery, there are no links. An example of an ideal core-periphery structure is illustrated by the matrix in Figure 8, where the top-left *CC* block includes three banks that are fully connected. The off-block-diagonal blocks, *CP* and *PC*, have at least one link from each core bank to the periphery. Finally, and most importantly for our discussion, the *PP* block illustrates no links between the periphery banks.

For this paper we have to modify the setup and redefine the core so that links within a country or region are not penalized and prevented from being in an idealized periphery-to-periphery block. To illustrate, Figure 9 shows an adjacency matrix where several countries are indicated by the labels. In this ideal, the ones in the PP block are not penalized because

[21] Traditional analysis of centrality in this case is misleading as measures such as betweenness, eigenvector or Katz-Bonacich centrality do not have consistency and their ranks are distorted by the structure of the network and regional subnetworks.

they represent domestic or regional links. However, the same ideal is observed in the other blocks: core banks are required to interact tightly with other core banks, and the periphery-to-core and core-to-periphery blocks are required to be column regular and row regular respectively. Deviations from the ideal are penalized according to the same loss function for the *PP*, *CP*, and *PC* blocks as for the standard core-periphery model, while deviations from the ideal in the *PP* block of no links are penalized only if the links are cross-border.

Table 3 reports the results of the estimation of the core structure of Craig and von Peter (2014) (original core) and the alternative structure (new core) on the $\widehat{\boldsymbol{W}}$ network and the three regional subnetworks. The core banks are then split (in columns) by communities, as defined by the Louvain algorithm (Blondel et al., 2008), in order to add additional information about the interconnectedness among core banks.

For the complete network $\widehat{\boldsymbol{W}}$, the original core comprises 49 banks from the three regions that also make up the three communities found by the Louvain algorithm. As the original core-periphery algorithm does penalize periphery-to-periphery connections, the number of core banks is larger and several Asian banks[22] are included in because they have simultaneously high domestic density and significant links to other international banks, mainly American SIFIs. Core banks are therefore not a complete subnetwork and shows some sparsity among detected communities (see Figure 10). American banks stand out as the hubs linking not only core banks from EMEA and Asia but also linking regions. In addition, 11 out of the 17 identifies American core banks are SIFIs as listed by the FSB.[23]

We computed two sets of new core banks for the $\widehat{W}$ network. The first set does not penalize the periphery-to-periphery links if they belong to the same country. This new core is displayed in Figure 11. It is a subset of the former and includes 39 banks. In contrast to the original core, no U.S. banks are represented as the strong domestic density and large domestic subnetwork exclude them from the core. However, several features stand out. First, the core is more densely connected and positive correlations dominate. Second, a more preeminent role is given to EMEA banks while new players emerge in the Asian region, including Australian banks. Third, the Asian banks are divided into two tightly connected communities that go beyond national borders.

Finally, the third definition of core allows does not penalize links if they belong to the same region. The resulting new core, displayed in Figure 12, is therefore much smaller and comprises only 25 American banks. The loss function in this case is very small, which is not surprising because all periphery intraregional links contribute marginally to the loss function. This suggests that the U.S. banks have a key role in intermediating across the globe between regions, especially given that they still tend to rely on domestic funding for their intermediation. As in the previous case, this set of core banks are largely a subset of the former and mainly includes SIFIs. This core is almost a complete subnetwork although there is no dominance of negative or positive correlations.

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[22] These core banks are mainly Thai and Indian banks that are however considered systemically important institutions domestically.

[23] See details at http://www.fsb.org/wp-content/uploads/r_141106b.pdf

As in the case of the complete network, core composition applied to regional sub-networks does not change significantly across models, especially because the countries' networks sizes are less heterogeneous. There is only an alternative definition of cores that does not penalize intra-country links to take place in the periphery. Well known SIFIs and R-SIBs link countries within regions and show their importance as channels of transmission regionally. These findings confirm their systemic importance both globally and regionally and provide support to our findings as a method to identify SIFIs using correlation networks and tiering analysis.

VI. ROBUSTNESS CHECKS: INTERCONNECTEDNESS DRIVEN BY RANDOM NOISE

This robustness check applies the theory of random networks to analyze whether some links in our network from weak cross-sectional dependent data could have been generated by random noise. The methodology described in Section III is based on the successive removal of factors that create strong cross-sectional dependence and that are often associated with the largest principal components of the variance-covariance matrix, until our tests indicate that weak cross-sectional variation is sufficient to be detected. However, this procedure does not remove noise, which can generate links randomly, nor detect their presence and importance.

The theory of random networks has a rich literature on noise reduction, where the noise appears in independent observations that indicate correlations randomly. This literature is based on Edelman (1988), Bowick and Brézin (1991), Litvak and van der Hofstad (2013) and Sengupta and Mitra (1999) and applied to finance by Laloux et al. (2000), whose notation we follow.

If we have N banks with T observations of independent normalized returns with mean zero and variance one, stacked into an NxT matrix M, then the estimated correlation matrix is $C = \frac{1}{T}MM'$, where the prime notation just denotes the transpose. The estimated correlation matrix C has some very useful properties when N and T both get large. If $Q = \frac{T}{N} \geq 1$ is fixed, then as $N \to \infty,\ T \to \infty$ the density of the probability of eigenvalues, $f(\lambda)$, goes to the following function:

$$f(\lambda) = \frac{Q\sqrt{(\lambda_{max}-\lambda)(\lambda-\lambda_{min})}}{2\pi\lambda} \quad (4)$$

, where:

$$\lambda_{min}^{max} = \frac{Q+1}{Q} \pm 2\sqrt{\frac{1}{Q}} \quad (5)$$

This structure suggests that we look at and identify those nodes which depend on variation that is only present in the range of those eigenvalues where random noise could have produced it. Our experiment consists of identifying a critical eigenvalue such that random matrices with uncorrelated noise will generate eigenvalues lower than this level, λ_{max}, and then of obtaining the links that are generated by the variation entirely in this region.

This ideal result differs from our matrix of correlations because we have a finite sample size, which can be analyzed using the results of random matrices that calculate the rate of convergence to the limiting density, as presented in Bowick and Brézin (1991). The second difference we analyze using Monte-Carlo methods to see by how much a matrix with a similar structure to ours differs from the limiting distribution implied by equation (4).

The Monte-Carlo experiments are reported in Figure 13 where the maximum eigenvalue distribution is shown. The eigenvalue distribution is very tightly distributed around 2.03. Any bandwidth that deletes all eigenvalues less than 2.2 will throw out noise in all but a small fraction of the cases. Second, this represents a sample size value of Q that is much smaller than our actual set of observations. To be more precise, if we were to calculate Q naively from the size of our block, then $Q = \frac{4123}{387}$=10.65, which the theory of random matrices would imply a maximum λ sharply distributed at 1.707. If, instead, Q is calculated at the average value of T for our sample, which accounts for the missing values, then $Q = \frac{3781}{387}$=9.77, which our theory would imply a maximum λ sharply distributed at 1.742. Instead, our observed maximum has a distribution that is only somewhat sharply focused on 2.03, which is what the theory would predict for a sample T in a block sample of around 2,150 implied by a $Q =$ 5.56. Thus, by losing only 10 percent of our observations, we are gaining noise that is equivalent to a reduction of 43 percent of our sample if this reduction had been in block format. Going to an unbalanced sample is costly in terms of random noise.

Our results were similar whether we used the cutoff points implied by either the balanced or unbalanced panel. When we remove the information of the lower eigenvalues from the sample our estimates of the correlation coefficients are much more tightly focused. This implies is that the upper eigenvalues alone given correlation coefficients that reject the value of zero given our significance level of 0.05 for very many of the correlations. The implied networks have a density of nearly 0.5, because by assuming that the lower eigenvalues contain only noise, we essentially assume that all correlation measured in the upper eigenvalues is significant because it is lacking in this noise. The resulting network is so dense as to be meaningless. As with the work cited above for random matrices as applied to the case of portfolio analysis, the information included in the lower eigenvalues contains both noise and meaningful information that should not be removed.

Instead, we ask a different question in exploring the information contained in the lower eigenvalues, i.e., those eigenvalues that are less than the cutoff for the balanced panel design. We ask which links in our network could be generated only by that information contained in the set of eigenvalues that could be random noise. In other words, if A is the set of links generated by the information in these eigenvalues (given the information that could be generated by noise alone, which of the links are significant by our test) and B is the set of links implied by our sample, what is the set $A \cap B$. These are the links in our networks that could have been generated solely by noise. We ask the question of whether these are key links in our networks. We find that the number of these links is small, and we also find that they are not important for any of our findings. In fact, these links are scattered randomly across our networks with no clusters, with the small exception of a cluster of seven links that correspond to Middle Eastern banks. These links do not affect any of our reported results. Noise alone is not driving our conclusions.

VII. CONCLUDING REMARKS

This paper proposes a method to compute undirected data-driven networks based on bank stock returns of 418 banks from around the world during the period January 1999–December 2014. We use spatial-dependence methods that filter the effect of strong common factors and obtain a large network and three regional subnetworks. The resulting networks show a number of interesting topological properties when compared to other emerging approaches in the literature and serve as a market-based adjacency matrix for a panel-data type of analysis of shocks across banks in a SpVAR or a GVAR model. Our results provide valuable input into the analysis of contagion from a financial stability perspective. Networks embed a number of characteristics that are important drivers in the recent financial stability literature, and our construction relies on public information rather than on confidential sources.

In particular, the networks and subnetworks show rich and hierarchical structures, including geographical clustering, nonconnected nodes, sparsity, or large cliques. In general, their sparsity or low density is a result of the Holm-Bonferroni method of thresholding, a method that proves useful in terms of the spatial modeling as a regularization that clearly distinguishes between neighbors and non-neighbors. The regularization technique is also robust to other regularization methods. The network and subnetworks also have a very clear hierarchical structure based on but not limited to geographical proximity.

All networks show small world properties, which situates this method in line with findings in recent research on networks based on actual banks' exposures to different asset classes. This feature means that second-round and feedback effects of a shock to a given bank are likely to propagate quickly and to reach any other bank in the network. We also find a significant degree of regional homophily, as most connections seem to be established within regions and intensively within countries. There is also evidence of a rich-club phenomenon, where highly connected nodes are also mutually linked.

Finally, a joint centrality and tiering analysis of the networks shows evidence of a core-periphery structure, also in line with recent empirical findings. In particular, a relatively small number of banks serve as bridges for connections between banks in their regions and between banks across regions.

Table 1. Sample—Countries and Number of Banks

EMEA				ASIA		AMERICAS	
Austria (AT)	3	Ireland (IE)	3	Australia (AU)	6	Argentina (AR)	4
Belgium (BE)	3	Italy (IT)	18	China (CN)	13	Brazil (BR)	6
Switzerland (CH)	8	Netherlands (NL)	2	Hong Kong (HK)	4	Chile (CL)	6
Cyprus (CY)	1	Norway (NO)	3	India (IN)	22	Colombia (CL)	2
Czech Republic (CZ)	1	Poland (PL)	4	Japan (JP)	80	Peru (PE)	1
Germany (DE)	6	Portugal (PT)	3	Korea (KR)	6	Mexico (MX)	2
Denmark (DK)	5	Russia (RU)	2	Sri Lanka (LK)	7	Canada (CA)	10
Spain (ES)	8	Sweden (SE)	4	Malaysia (MY)	10	United States (US)	82
Finland (FI)	2	Turkey (TR)	16	Philippines (PH)	6		
France (FR)	4	Israel (IL)	5	Singapore (SG)	3		
United Kingdom (UK)	9	South Africa (ZA)	6	Thailand (TH)	7		
Greece (GR)	6	Egypt (EG)	3	Taiwan (TW)	8		
Hungary (HU)	1	Qatar (QA)	7				

Source: Author's calculations.

Table 2. Network Measures

	$\widehat{W}$	$\widehat{W}_{EMEA}$	$\widehat{W}_{Asia}$	$\widehat{W}_{Americas}$	$\widehat{W}_{Cross-country}$	$\widehat{W}_{Cross-regional}$
Size	387	116	166	105	316	140
Density	0.0654	0.146	0.172	0.253	0.0871	0.1524
Diameter /1	8	6	5	6	6	5
Average path length /1	2.84	2.3	2.07	2.3	2.61	2.21
Average degree	25.2	16.8	28.3	26.3	27.4	21.2
Max degree	93	50	87	56	93	44
Average neighbor degree	33.4	22.9	37.9	31.2	36.9	26
Assortativity	0.189	0.1	0.083	0.297	0.122	0.235
Power-law coefficient	5.9688	3.8553	4.5407	3.679	3.3947	5.678
Clustering	0.5281	0.5345	0.5501	0.5858	0.5409	0.5304
Core banks	49	27	42	33		
New core banks	39	25	37	21		

Source: Author's calculations.

1/ Calculation of diameter and average path length is applied to the giant components for al networks. Core and new core banks are obtained using the modified methodology from Craig and von Peter (2004) and that described in section V. New core banks for the $\widehat{\mathbf{W}}$ network refers to the case where intra-country links are allowed to be part of the periphery.

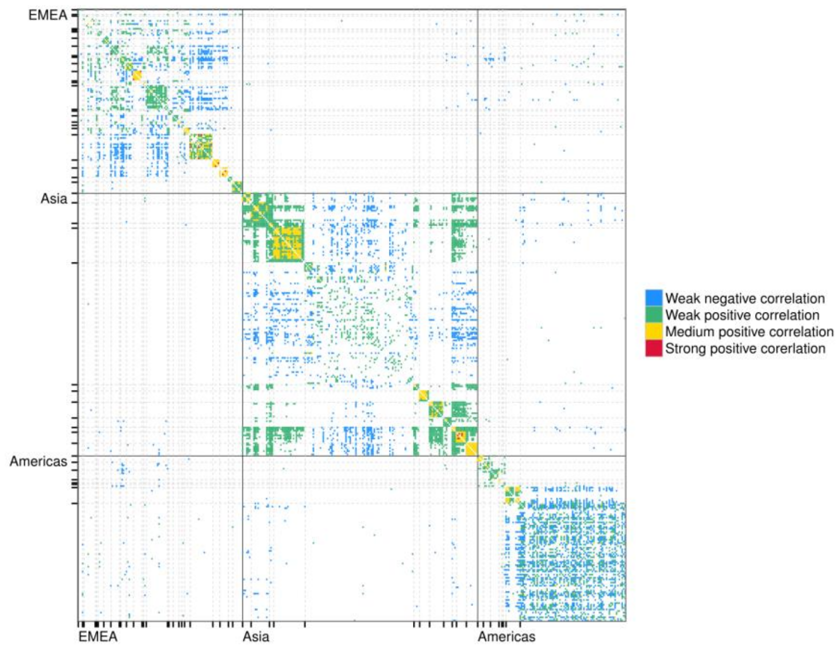
Table 3. Core Banks

Network	Core	Community	Core Banks									
$\widehat{\boldsymbol{W}}$	Original	1	FR2	FR3	IT11	IT12						
		2	CN12	CN13	CN3	CN4	CN5	CN6	HK1	HK2	HK3	IN10
			IN11	IN17	IN2	IN9	JP21	JP38	JP49	SG1	SG2	SG3
			TH1	TH2	TH3	TH5	TW2	TW4	TW5	TW6		
		3	US12	US13	US15	US18	US21	US26	US4	US40	US41	US43
			US48	US5	US54	US6	US63	US73	US80			
	New Core (Cross-country)	1	ES1	FR2	FR3	IT11	IT12					
		2	AU4	AU5	CN13	CN4	CN5	CN6	HK1	HK2	KR4	TW1
			TW2	TW4	TW5	TW6	TW7	TW8				
		3	AU1	CN12	CN3	HK3	IN10	IN11	IN9	JP38	JP49	SG1
			SG2	SG3	TH1	TH2	TH3	TH4	TH5	TH6		
	New Core (Cross-region)	1	US15	US17	US18	US21	US27	US28	US37	US41	US48	US5
			US53	US56	US58	US62	US63					
		2	US10	US12	US24	US26	US4	US54	US65	US70	US73	US80
$\widehat{\boldsymbol{W}}_{EMEA}$	Original	1	ES6	IT10	IT11	IT12	IT14	IT17	IT18	IT2	IT4	IT5
			IT8	TR9								
		2	CH6	DE2	ES1	ES8	FR2	FR3	GB2	NL1	TR1	TR12
			TR13	TR14	TR15	TR16	TR7					
	New Core	1	ES6	ES7	IT11	IT12	IT14	IT18	IT2	IT4	IT5	TR1
			TR9									
		2	CH6	DE2	ES1	ES8	FR2	FR3	GB2	NL1	TR12	TR13
			TR14	TR15	TR16	TR7						
$\widehat{\boldsymbol{W}}_{Asia}$	Original	1	IN11	IN12	IN13	IN15	IN17	IN2	IN3	IN4	IN9	JP38
			JP64	SG1	SG2	SG3						
		2	AU1	AU5	CN13	CN4	CN5	CN6	HK2	HK3	JP21	JP47
			KR4	TW2	TW4	TW5	TW6	TW8				
		3	CN12	CN3	HK1	IN10	JP49	MY2	TH1	TH2	TH3	TH4
			TH5	TH6								
	New Core	1	AU1	CN13	CN3	CN4	CN5	CN6	HK2	HK3	IN10	IN11
			IN12	IN17	IN2	IN9	JP21					
		2	CN12	HK1	MY2	TH1	TH2	TH3	TH4	TH5	TH6	
		3	AU5	JP38	KR4	SG1	SG2	SG3	TW1	TW2	TW4	TW5
			TW6	TW7	TW8							
$\widehat{\boldsymbol{W}}_{Americas}$	Original	1	US13	US15	US21	US29	US40	US43	US45	US48	US49	US51
			US53	US6	US64							
		2	US12	US18	US19	US24	US25	US26	US28	US36	US37	US41
			US54	US58	US62	US63	US65	US70	US71	US73	US80	US82
	New Core	1	CA1	CA10	CA2	CA3	CA9	US26	US32	US71		
			US12	US15	US19	US25	US39	US40	US43	US51	US54	US6
			US62	US64	US73							

Source: Author's calculations.

Note: Original core uses the methodology described in Craig and von Peter (2014). The new cores used the modified methodology as described in Section V. Each core is split into communities using the Louvain algorithm from Blondel et al. (2008).

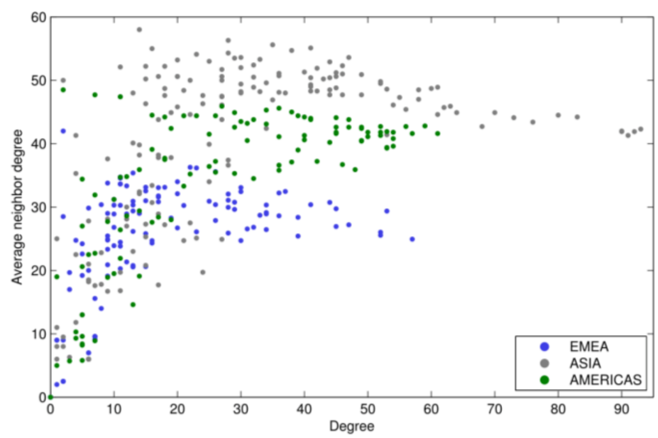
Figure 1. Data-Driven Banking Network



Source. Authors' calculations and Bloomberg.

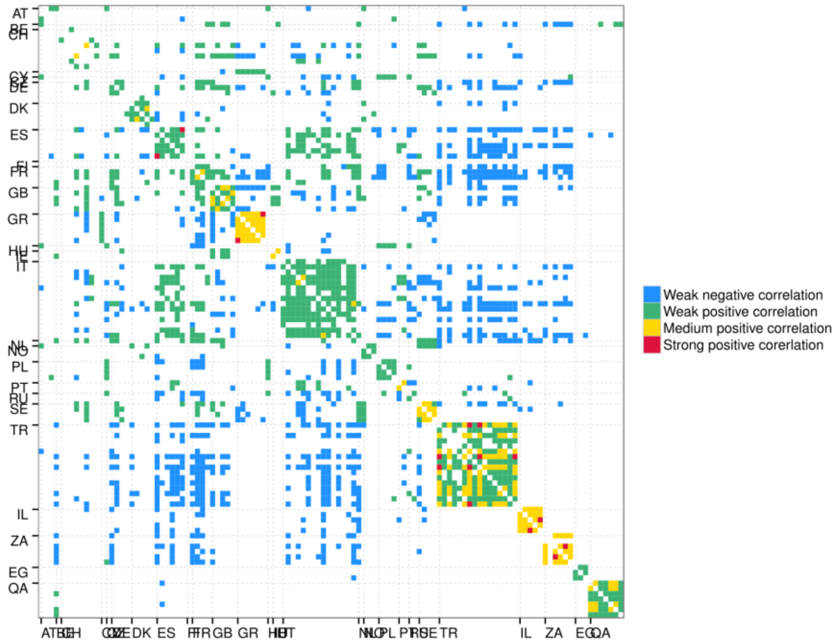
Note: Each colored square represents the significant correlation coefficient between a given pair of banks. For both the positive and negative scales, weak, medium strong correlations correspond to correlation coefficients below one third, between one and two thirds, and above two thirds, respectively.

Figure 2. Degree and Average Neighbor Degree Distribution



Source. Authors' calculations and Bloomberg.

Figure 3. Data-Driven Banking Sub-Network—EMEA



Source. Authors' calculations and Bloomberg.

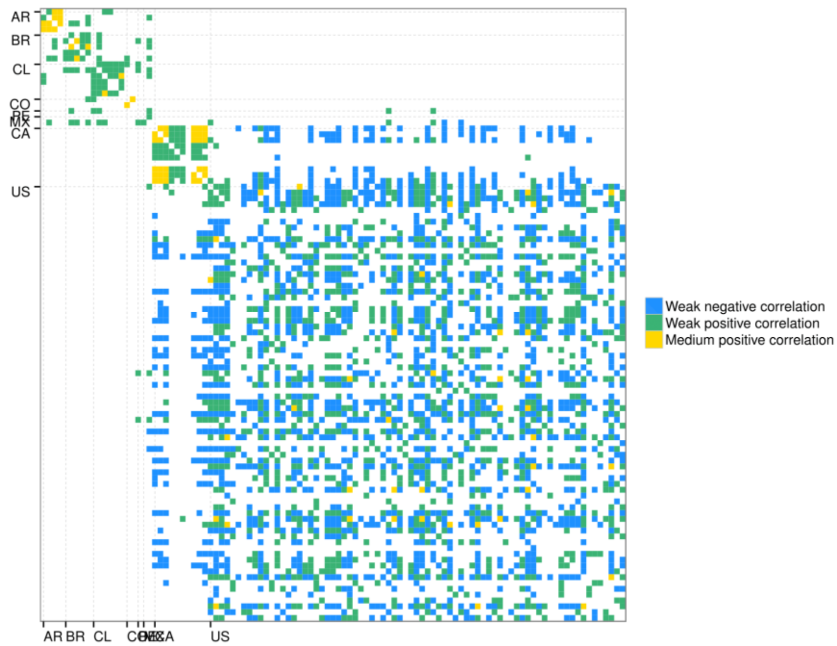
Note: Each colored square represents the significant correlation coefficient between a given pair of banks. For both the positive and negative scales, weak, medium strong correlations correspond to correlation coefficients below one third, between one and two thirds, and above two thirds, respectively.

Figure 4. Data-Driven Banking Sub-Network—Asia

Source. Authors' calculations and Bloomberg.

Note: Each colored square represents the significant correlation coefficient between a given pair of banks. For both the positive and negative scales, weak, medium strong correlations correspond to correlation coefficients below one third, between one and two thirds, and above two thirds, respectively.

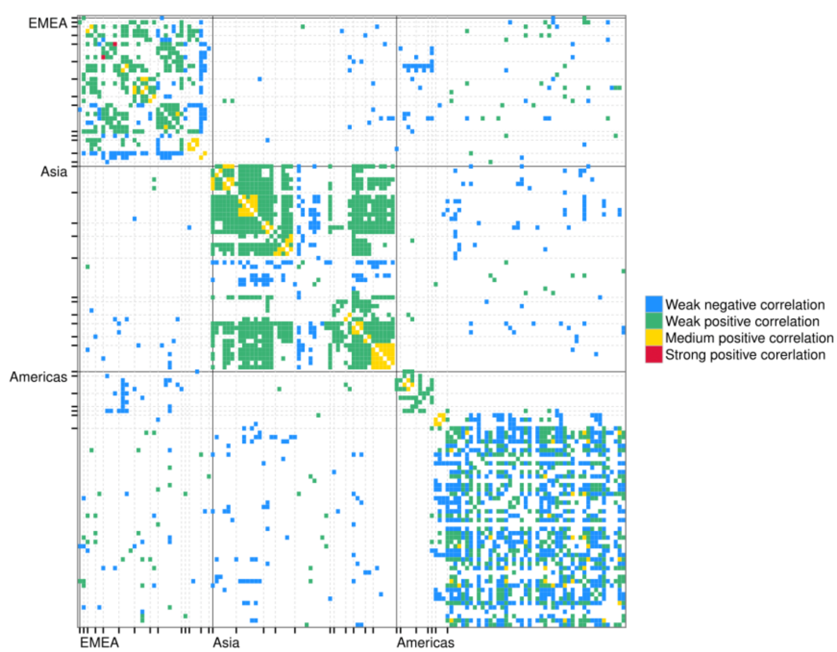
Figure 5. Data-Driven Banking Sub-Network—Americas



Source. Authors' calculations and Bloomberg.

Note: Each colored square represents the significant correlation coefficient between a given pair of banks. For both the positive and negative scales, weak, medium strong correlations correspond to correlation coefficients below one third, between one and two thirds, and above two thirds, respectively.

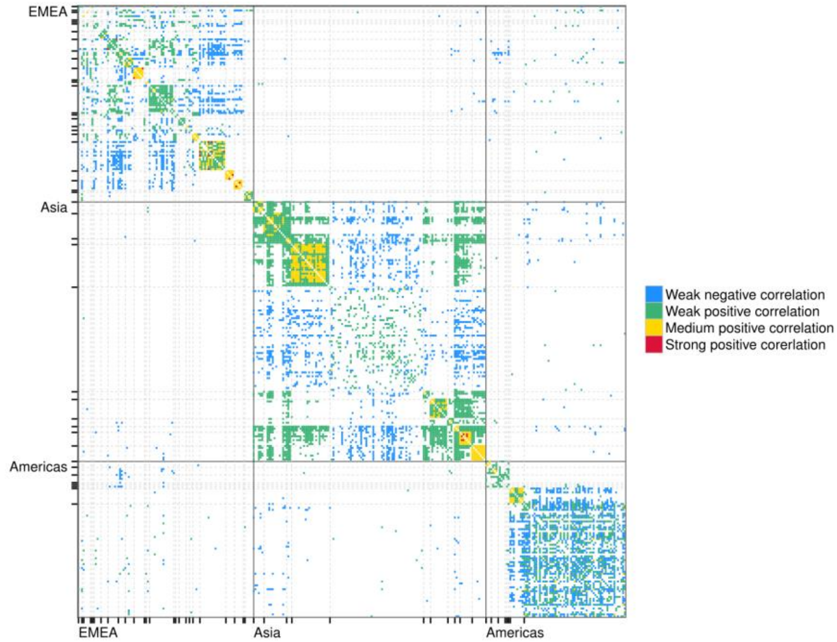
Figure 6. Data-Driven Banking Sub-Network—Cross-Regional Relationships



Source. Authors' calculations and Bloomberg.

Note: Each colored square represents the significant correlation coefficient between a given pair of banks. For both the positive and negative scales, weak, medium strong correlations correspond to correlation coefficients below one third, between one and two thirds, and above two thirds, respectively.

Figure 7. Data-Driven Banking Sub-Network—Cross-Country Relationships



Source. Authors' calculations and Bloomberg.

Note: Each colored square represents the significant correlation coefficient between a given pair of banks. For both the positive and negative scales, weak, medium strong correlations correspond to correlation coefficients below one third, between one and two thirds, and above two thirds, respectively.

Figure 8. Network Model of Tiering

- A network exhibiting tiering should have this block-model form:

$$M = \begin{pmatrix} CC & CP \\ PC & PP \end{pmatrix} = \begin{pmatrix} \mathbf{1} & \mathbf{RR} \\ \mathbf{CR} & \mathbf{0} \end{pmatrix} = \left(\begin{array}{ccc|ccccc} 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ \hline 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{array}\right)$$

- Special kind of core-periphery model: emphasis on relation *between* core and periphery
- Tight on core, lax on periphery, makes sense for interbank market.

Source. Authors' calculations.

Figure 9. Network Model of Tiering—No Penalty in PP

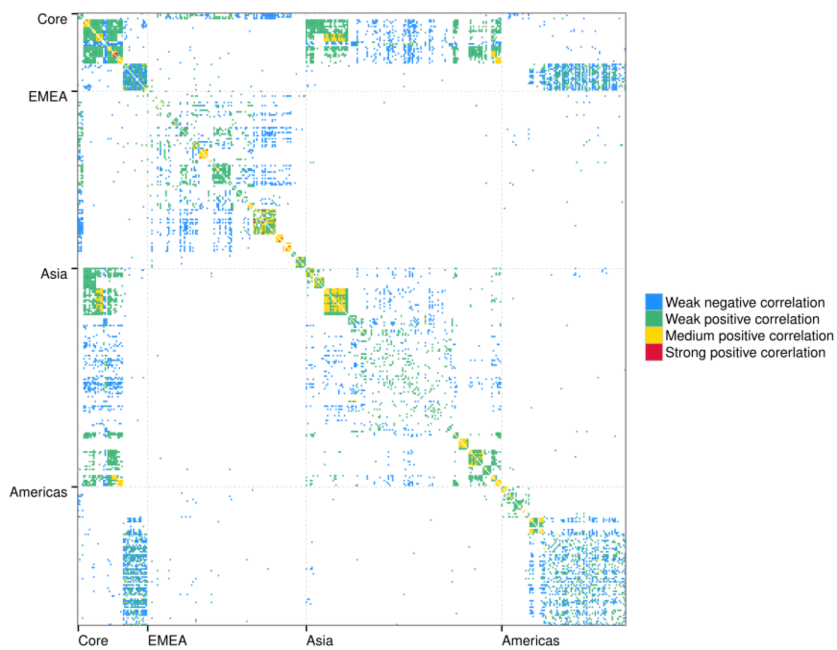
- A network exhibiting tiering should have this block-model form:

$$M = \begin{pmatrix} CC & CP \\ PC & PP \end{pmatrix} = \begin{pmatrix} \mathbf{1} & \mathbf{RR} \\ \mathbf{CR} & \mathbf{0} \end{pmatrix} = \left(\begin{array}{ccc|ccccc} 0 & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ \hline 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 0 \end{array}\right)$$

- If the ones in the periphery are due to regional factors, then these connections should not be penalized in the PP portion.

Source. Authors' calculations.

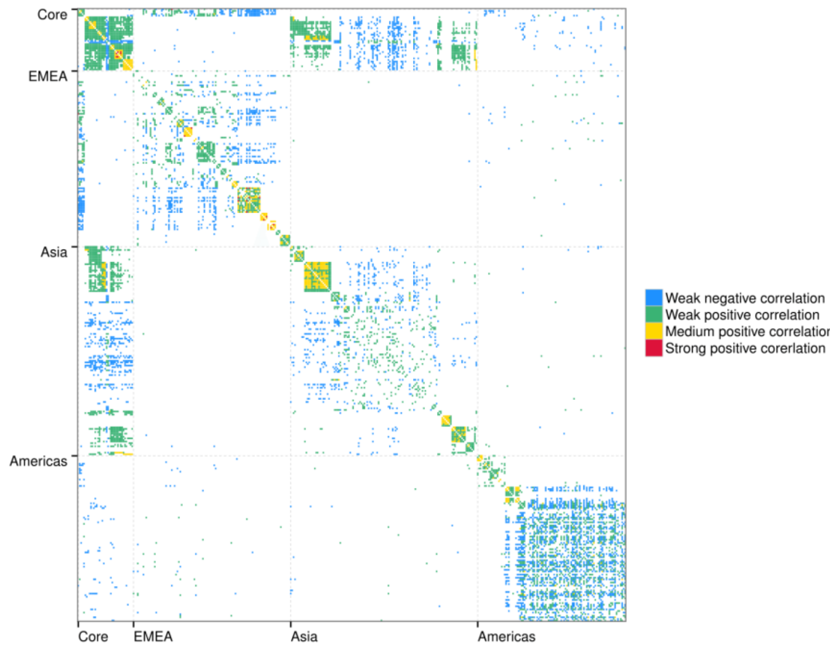
Figure 10. Core-Periphery Structure



Source. Authors' calculations and Bloomberg.

Note: Each colored square represents the significant correlation coefficient between a given pair of banks. For both the positive and negative scales, weak, medium strong correlations correspond to correlation coefficients below one third, between one and two thirds, and above two thirds, respectively.

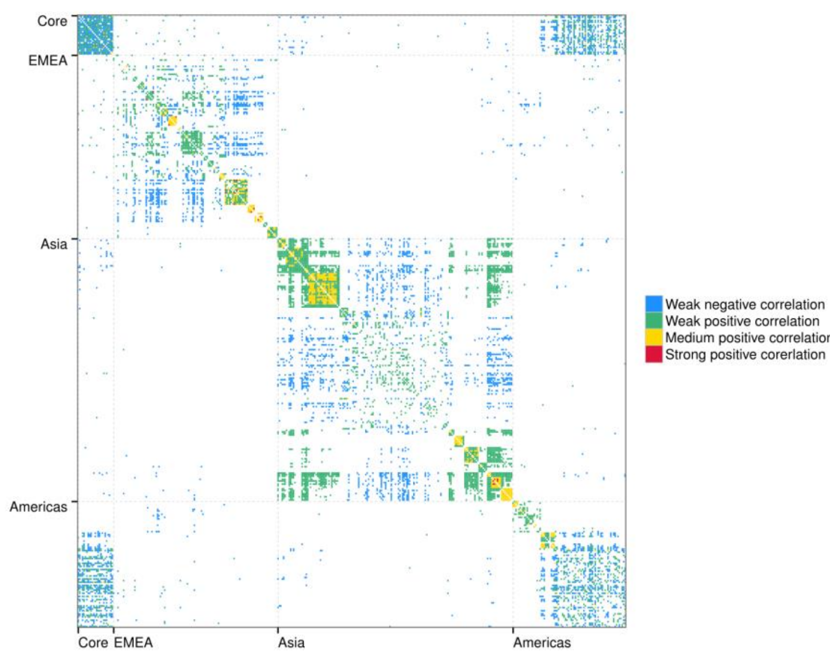
Figure 11. Core-Periphery Structure—Cross-Country Adjustment



Source. Authors' calculations and Bloomberg.

Note: Each colored square represents the significant correlation coefficient between a given pair of banks. For both the positive and negative scales, weak, medium strong correlations correspond to correlation coefficients below one third, between one and two thirds, and above two thirds, respectively.

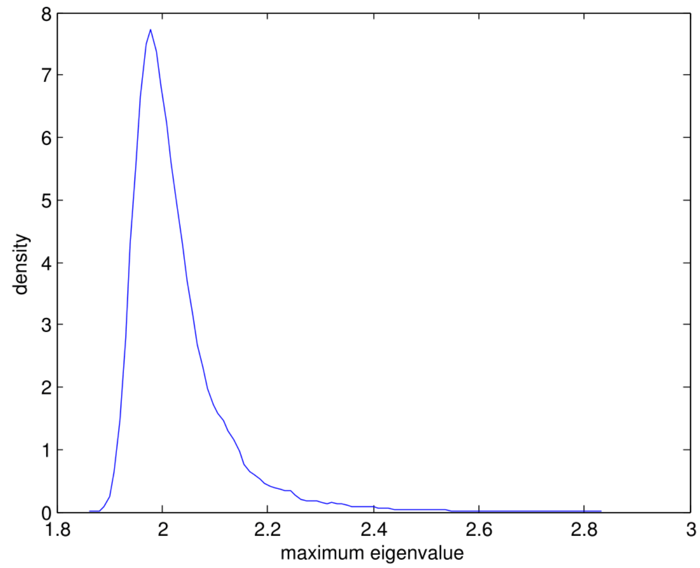
Figure 12. Core-Periphery Structure—Cross-Region Adjustment



Source. Authors' calculations and Bloomberg.

Note: Each colored square represents the significant correlation coefficient between a given pair of banks. For both the positive and negative scales, weak, medium strong correlations correspond to correlation coefficients below one third, between one and two thirds, and above two thirds, respectively.

Figure 13. Random Matrices Eigenvalues



Source. Authors' calculations.

APPENDIX I. SAMPLE OF BANKS

Appendix Table 1. Banks List

AT	Erste Group Bank
	Oberbank
	Raiffeisen Bank International
BE	Dexia
	Fortis
	KBC
CH	Bank Coop
	Banque Cantonale Vaudoise
	Basler Kantonalbank
	Credit Suisse
	EFG International
	UBS
	Valiant
	Vontobel Holding
CY	Hellenic Bank Public
CZ	Komerční banka
DE	Commerzbank
	Deutsche Bank
	Deutsche Postbank
	Hypo Real Estate
	Unicredit
	IKB
DK	Danske Bank
	Jyske Bank
	Spar Nord Bank
	Sydbank
	Vestjysk Bank
ES	BBVA
	Bankinter
	Banco de Valencia
	Caixabank
	Banco Pastor
	Banco Popular Español
	Banco de Sabadell
	Santander
FI	Aktia Bank
	Pohjola Bank
FR	Crédit Agricole
	BNP Paribas
	Société Générale
FR	Natixis
GB	Alliance & Leicester
	Barclays
	Bradford & Bingley
	HBOS
	HSBC
	Lloyds Banking Group
	Northern Rock
	Royal Bank of Scotland
	Standard Chartered
GR	Alpha Bank
	National Bank of Greece
	Eurobank Ergasias
	Attica Bank
	Bank of Greece
	Piraeus Bank
HU	OTP Bank
IE	Allied Irish Banks
	Anglo Irish Bank
	Bank of Ireland
IT	Banco di Desio e della Brianza
	Banca Monte dei Paschi di Siena
	Banco Popolare
	BP dell'Emilia Romagna
	Banca Popolare di Sondrio
	Capitalia
	Credito Bergamasco
	Credito Emiliano
	Banca Carige
	Credito Valtellinese
	Intesa Sanpaolo
	Mediobanca
	Banca Etruria
	Banca Popolare di Milano
	Banca Profilo
	Sanpaolo Imi
	UBI Banca
	Unicredit
NL	ING Group
	SNS Reaal
NO	DNB ASA
	SpareBank 1 SMN
	SpareBank 1 SR-Bank
PL	ING Bank Slaski
	Bank Millennium
	Bank Pekao
	PKO Bank Polski
PT	Banco Comercial Português
	Banco Espírito Santo
	BPI
RU	Sberbank
	VTB Bank
SE	Nordea Bank
	Skandinaviska Enskilda Banken
	Svenska Handelsbanken
	Swedbank
TR	Akbank
	Albaraka Turk Katilim Bankasi
	Alternatifbank
	Asya Katilim Bankasi
	DenizBank
	Finansbank
	Garanti Bank
	Halk Bankasi
	Turkiye Is Bankasi
	Turkiye Kalkinma Bankasi
	Sekerbank
	Turk Ekonomi Bankasi
	Tekstilbank
	TSKB
	VakifBank
	Yapi Kredi
IL	Israel Discount Bank
	First International Bank of Israel
	Bank Leumi Le-Israel
	Mizrahi Tefahot Bank
	Bank Hapoalim
ZA	Barclays Africa Group
	Capitec Bank
	FirstRand

Appendix Table 1. Sample of Banks (continued)

ZA	Nedbank	IN	Canara Bank	JP	Toho Bank Ltd
	RMB		Central Bank of India		Tohoku Bank Ltd
	Standard Bank Group		Corporation Bank		Michinoku Bank Ltd
EG	Abu Dhabi Islamic Bank/Egypt		Federal Bank Ltd		Fukuoka Financial Group Inc
	Suez Canal Bank		Hdfc Bank Limited		Shizuoka Bank Ltd
	Commercial International Bank		ICICI Bank		Juroku Bank Ltd
QA	Commercial Bank of Qatar Qsc		Idbi Bank Ltd		Suruga Bank Ltd
	Doha Bank Qsc		Indusind Bank Ltd		Hachijuni Bank Ltd
	Al Khaliji Bank		Indian Overseas Bank		Yamanashi Chuo Bank Ltd
	Masraf Al Rayan		Jammu and Kashmir Bank		Ogaki Kyoritsu Bank Ltd
	Qatar Islamic Bank		Oriental Bank of Commerce		Fukui Bank Ltd
	Qatar International Islamic		Punjab National Bank		Hokkoku Bank Ltd
	Qatar National Bank		State Bank of India		Shimizu Bank Ltd
AU	ANZ Banking Group		Syndicate Bank		Shiga Bank Ltd
	Bendigo And Adelaide Bank		Uco Bank		Nanto Bank Ltd
	Bank of Queensland		Union Bank of India		Hyakugo Bank Ltd
	Commonwealth Bank of Austral		Ing Vysya Bank Ltd		Bank of Kyoto Ltd
	National Australia Bank		Yes Bank Ltd		Mie Bank Ltd
	Westpac Banking Corp	JP	Shinsei Bank Ltd		Hokuhoku Financial Group Inc
CN	Ping An Bank		Aozora Bank Ltd		Hiroshima Bank Ltd
	Bank of Ningbo Co Ltd -A		Mitsubishi Ufj Financial Gro		San-In Godo Bank Ltd
	ICBC		Resona Holdings Inc		Chugoku Bank Ltd
	Bank of Communications Co-H		Sumitomo Mitsui Trust Holdin		Tottori Bank Ltd
	China Merchants Bank-H		Sumitomo Mitsui Financial Gr		Iyo Bank Ltd
	Bank of China Ltd-H		Daishi Bank Ltd		Hyakujushi Bank Ltd
	Huaxia Bank Co Ltd-A		Hokuetsu Bank Ltd		Shikoku Bank Ltd
	China Minsheng Banking-A		Nishi-Nippon City Bank Ltd		Awa Bank Ltd
	Bank of Nanjing Co Ltd -A		Chiba Bank Ltd		Kagoshima Bank Ltd
	Industrial Bank Co Ltd -A		Bank of Yokohama Ltd		Oita Bank Ltd
	Bank of Beijing Co Ltd -A		Joyo Bank Ltd		Miyazaki Bank Ltd
	China Construction Bank-H		Gunma Bank Ltd		Higo Bank Ltd
	China Citic Bank Corp Ltd-H		Musashino Bank Ltd		Bank of Saga Ltd
HK	Hang Seng Bank Ltd		Chiba Kogyo Bank Ltd		Eighteenth Bank Ltd
	Bank of East Asia		Tsukuba Bank Ltd		Bank of Okinawa Ltd
	Boc Hong Kong Holdings Ltd		Tokyo Tomin Bank Ltd		Bank of The Ryukyus Ltd
	Wing Hang Bank Ltd		77 Bank Ltd		Yachiyo Bank Ltd
IN	Allahabad Bank		Aomori Bank Ltd		Seven Bank Ltd
	Axis Bank Ltd		Akita Bank Ltd		Mizuho Financial Group Inc
	Bank of Baroda		Yamagata Bank Ltd		Kiyo Holdings Inc
	Bank of India		Bank of Iwate Ltd		Yamaguchi Financial Group In

Appendix Table 1. Sample of Banks (continued)

JP	Nagano Bank Ltd
	Bank of Nagoya Ltd
	Aichi Bank Ltd
	Daisan Bank Ltd
	Chukyo Bank Ltd
	Higashi-Nippon Bank Ltd
	Taiko Bank Ltd
	Ehime Bank Ltd
	Tomato Bank Ltd
	Minato Bank Ltd
	Keiyo Bank Ltd
	Kansai Urban Banking Corp
	Tochigi Bank Ltd
	Kita-Nippon Bank Ltd
	Towa Bank Ltd
	Fukushima Bank Ltd
	Daito Bank Ltd
	Nomura Holdings Inc
KR	Jeonbuk Bank
	Industrial Bank of Korea
	Woori Finance Holdings Co
	Shinhan Financial Group Ltd
	Hana Financial Group
	Kb Financial Group Inc
LK	Commercial Bank of Ceylon Pl
	Dfcc Bank
	Hatton National Bank Plc
	National Development Bank Pl
	Nations Trust Bank Plc
	Sampath Bank Plc
	Seylan Bank Plc
MY	Alliance Financial Group Bhd
	Affin Holdings Berhad
	Ammb Holdings Bhd
	Bimb Holdings Bhd
	Cimb Group Holdings Bhd
	Hong Leong Bank Berhad
	Hong Leong Financial Group
	Malayan Banking Bhd
	Public Bank Berhad
MY	Rhb Capital Bhd
PH	Bdo Unibank Inc
	Bank of The Philippine Islan
	Metropolitan Bank & Trust
	Philippine National Bank
	Security Bank Corp
	Union Bank of Philippines
SG	Dbs Group Holdings Ltd
	Oversea-Chinese Banking Corp
	United Overseas Bank Ltd
TH	Bank of Ayudhya Pcl
	Bangkok Bank Public Co Ltd
	Kasikornbank Pcl
	Krung Thai Bank Pub Co Ltd
	Siam Commercial Bank Pub Co
	Thanachart Capital Pcl
	Tmb Bank Pcl
TW	Chang Hwa Commercial Bank
	Hua Nan Financial Holdings C
	E.Sun Financial Holding Co
	Mega Financial Holding Co Lt
	Taishin Financial Holding
	Sinopac Financial Holdings
	Ctbc Financial Holding Co Lt
	First Financial Holding
AR	Banco Hipotecario Sa-D Shs
	Banco Macro Sa-B
	Bbva Banco Frances Sa
	Grupo Financiero Galicia-B
BR	Banco ABC Brasil
	Banco do Brasil
	Banco Bradesco
	Banco Panamericano
	Banrisul
	Itau Unibanco Holding Sa
CL	Banco De Credito E Inversion
	Banco Santander Chile
	Banco De Chile
	Corpbanca
	A.F.P. Provida S.A.
CL	Sm-Chile Sa-B
CO	Bancolombia Sa
	Banco De Bogota
PE	Bbva Banco Continental Sa-Co
MX	Grupo Financiero Inbursa-O
	Grupo Financiero Banorte-O
CA	Bank of Montreal
	Bank of Nova Scotia
	Can Imperial Bk of Commerce
	Canadian Western Bank
	Home Capital Group Inc
	Laurentian Bank of Canada
	Genworth Mi Canada Inc
	National Bank of Canada
	Royal Bank of Canada
	Toronto-Dominion Bank
US	Bear Stearns Cos Llc
	Associated Banc-Corp
	American Express Co
	Bank of America Corp
	BB&T Corp
	Bank of New York Mellon Corp
	Bank of Hawaii Corp
	Bok Financial Corporation
	Boston Private Finl Holding
	Brookline Bancorp Inc
	Bancorpsouth Inc
	Citigroup Inc
	Cathay General Bancorp
	Commerce Bancshares Inc
	Community Bank System Inc
	Cullen/Frost Bankers Inc
	City Holding Co
	Comerica Inc
	Capital One Financial Corp
	Columbia Banking System Inc
	Cvb Financial Corp
	City National Corp
	East West Bancorp Inc
	First Commonwealth Finl Corp

Appendix Table 1. Sample of Banks (concluded)

US	First Financial Bancorp	US	Susquehanna Bancshares Inc
	First Finl Bankshares Inc		Tcf Financial Corp
	First Horizon National Corp		Texas Capital Bancshares Inc
	Fifth Third Bancorp		Tfs Financial Corp
	First Midwest Bancorp Inc/Il		Trustmark Corp
	Firstmerit Corp		United Bankshares Inc
	Fnb Corp		Umb Financial Corp
	First Niagara Financial Grp		Umpqua Holdings Corp
	Fulton Financial Corp		Us Bancorp
	Glacier Bancorp Inc		Valley National Bancorp
	Goldman Sachs Group Inc		Westamerica Bancorporation
	Huntington Bancshares Inc		Washington Federal Inc
	Hancock Holding Co		Washington Mutual Inc
	Hudson City Bancorp Inc		Wachovia Corp
	Iberiabank Corp		Webster Financial Corp
	JPMorgan Chase		Wells Fargo
	Keycorp		Wintrust Financial Corp
	Lehman Brothers Holdings Inc		Zions Bancorporation
	Mb Financial Inc		
	Mellon Financial Corp		
	Morgan Stanley		
	M&T Bank Corp		
	National City Corp		
	Natl Penn Bcshs Inc		
	Northern Trust Corp		
	New York Community Bancorp		
	Pacwest Bancorp		
	People's United Financial		
	Provident Financial Services		
	Pnc Financial Services Group		
	Pinnacle Financial Partners		
	Park National Corp		
	Privatebancorp Inc		
	Regions Financial Corp		
	Signature Bank		
	Svb Financial Group		
	Synovus Financial Corp		
	S&T Bancorp		
	Suntrust Banks Inc		
	State Street Corp		

Source. Bloomberg, The Banker.

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