# Tree Networks to Assess Financial Contagion

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28 January 2019

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**Abstract**

We propose a two-layered tree network model that decomposes financial contagion into a global component, composed of inter-country contagion effects, and a local component made up of inter-institutional contagion channels. The model is effectively applied to a database containing time series of daily CDS spreads of major European financial institutions (banks and insurance companies), and reveals the importance of monitoring both channels to assess financial contagion. The empirical application revealed evidence of a high inter-country and inter-institutional vulnerability at the onset of the global financial crisis in 2008 and during the sovereign crisis in 2011. The result further identifies Belgium and France as central to the inter-country contagion in the Euro area during the financial crisis, while Italy dominated during the sovereign crisis. The French corporates Groupama, Credit Industriel, and Caisse d'Epargne were central in the inter-institutional contagion in both crises.

*Keywords:* Financial crisis, Graphical Lasso, Inter-country contagion, Inter-institutional contagion, Sovereign crisis, Sparse covariance selection

## 1. Introduction

Over the past two decades, networks models have seen significant applications with various contributions in the fields of computer science, information sciences, neuroscience, bioinformatics, statistics, economics, and finance, etc. Also, over the past decade, especially after the global financial crisis (GFC) in 2008, the study of financial and economic networks have attracted the attention of not only researchers but regulatory institutions like the International Monetary Fund (IMF), the Bank for International Settlements (BIS) and the Financial Stability Board (FSB). From the perspective of regulators, financial networks present a framework to identify systemically important financial institutions (SIFIs) at the global, regional and country levels, as well as providing a scheme to complement micro-prudential supervision with macro-prudential surveillance to ensure financial stability (see Arregui et al., 2013; IMF, 2011; Minoiu and Sharma, 2014; Moghadam and Viñals, 2010; Viñals et al., 2012).

The explosion in the study of financial networks has become vital following the lessons from the global financial crisis. Bernanke (2013) emphasized that the events that led to the GFC can be attributed to two main factors: (i) triggers - the initial losses or shocks that affected many institutions, and (ii) vulnerabilities - the preexisting structural weaknesses of the system that amplifies these initial shocks. The key trigger of the GFC were the losses suffered by many institutions due to subprime mortgages, while the complex interconnectedness

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of institutions created the vulnerabilities for risk transmission (see Ahelegbey et al., 2016a; Battiston et al., 2012; Billio et al., 2012; Diebold and Yilmaz, 2014; Financial Crisis Inquiry Commission, 2011; Hautsch et al., 2015). Acemoglu et al. (2015) showed that when the magnitude of shocks affecting financial institutions are sufficiently small, a highly interconnected system of institutions provides a risk-sharing mechanism which enhances financial stability. However, beyond a certain threshold of connectedness, coupled with a high magnitude of shocks, the densely interconnected system of institutions serves rather as a mechanism for shock propagation and spillovers among markets, leading to the systemic crisis.

Like other living organisms, the interaction among financial institutions can be quite complex and very complicated. This stems from the fact that interactions among institutions emerge through diverse forms. Such interactions can take the form of direct deposits, investments, loans, derivatives, futures contracts etc. Other forms of interactions occur via ownership, partnerships or joint ventures, and through stakeholder relationships in the form of board interlocks, former colleagues or migration of workers from one institution to another. Due to these diverse forms of relationships, analyzing the network among financial institutions can be very tedious. Most existing analytical works therefore focus on either the use of balance sheet and other financial statements to extract such networks (see Cont et al., 2013; Georg, 2013; Georg and Minoiu, 2014; Minoiu and Reyes, 2013), whiles others rely on market data to study the co-movement of the returns/volatilities of security prices (Adrian and Brunnermeier, 2016; Ahelegbey et al., 2016a; Billio et al., 2012; Brownlees and Engle, 2016; Diebold and Yilmaz, 2014; Hautsch et al., 2015; Huang et al., 2011; Segoviano and Goodhart, 2009). There is not much work on the former largely due to lack of transparency in the balance sheet information coupled with the difficulty in obtaining such data and the low frequency of update, which is either annually or at best, quarterly.

It is well known in the finance literature that stock prices reflect new market and firm-level information (Roll, 1988). As a consequence, returns/volatilities of assets can be decomposed into systematic and idiosyncratic components as demonstrated in the arbitrage pricing theory (APT) and the capital asset pricing model (CAPM) (Ross, 1976; Sharpe, 1964). Tang et al. (2010) showed that all financial crises are alike and although the triggers may differ, the vulnerabilities remain predominantly the same across systemic breakdowns. They identified three potential channels for contagion effects: idiosyncratic, market and country channels. Dungey and Gajurel (2015) also identified three channels of contagion in the banking industry, namely, systematic, idiosyncratic and volatility spillover. Their results show that shocks transmitted via idiosyncratic channels are highly likely to destabilize the banking system than through systematic channels.

This paper contributes to the application of networks to model the decomposition of asset returns/volatilities. For related works see Ahelegbey and Giudici (2014); Barigozzi and Brownlees (2016); Diebold and Yilmaz (2014); Dungey and Gajurel (2015); Tang et al. (2010). Following these stream of the literature, we develop a two-layered tree-like model that decomposes financial contagion into a global component, composed of inter-country contagion effects, and a local component made up of inter-institutional contagion channels. The first layer models the inter-institution exposures driven by country-level indicators, and the second layer models the inter-country contagion driven by regional/global market factors. We combined both layers to model the total exposure of institutions as a composition of idiosyncratic inter-institutional shock channels, and a systematic component - composed of institution's sensitivity to regional/global financial market and inter-country risk. We focus on modeling the inter-institution and inter-country exposures via a sparse covariance structure as a network model using the graphical lasso approach (see Dempster, 1972; Friedman et al., 2008; Meinshausen and Bühlmann, 2006).

We assess the efficiency of our model to analyze financial contagion among 50 top European financial institutions, for which corporate default swap spread prices are available, for the period covering 2008–2015. We have a total of 108,316 observations, from 01/01/2008 to 31/12/2015. Each observation describes the daily CDS spread of financial corporations (bank and insurance companies), belonging to 11 different countries. The empirical application revealed a high inter-country and inter-institutional vulnerability at the onset of the global financial crisis in 2008 and the sovereign crisis in 2011.

The remainder of this paper is organized as follows. Section 2 presents the model formulation and a discussion on the inference approach to network extraction from the observed data. Section 3 provides the details of the network analysis methods applied in the empirical analysis. Section 4 presents a discussion of the empirical application and results.

## 2. Econometric Model

In this section, we present the model formulation and inference approach to network extraction from the observed data.

### *2.1. Model Formulation*

We present a two-layer network model in a tree-like configuration. The first layer is an inter-institution model, and the second is an inter-country configuration. Figure 1 illustrates the tree-like structure of the model. The blue rectangle node represents the observed institutional returns, $Y$. The red circled nodes represent a set of inter-institution model latent variables that include the country sector aggregate indicators, $X$, and institution-level shocks, $U$. The green circled nodes are inter-country model latent variables that capture the state of regional/global market factors, $F$, and country-level shocks, $V$. The parameters of the model are $(\Lambda, \Theta, A, B)$. Our main objective is the sparse structure associated with $A$ and $B$.

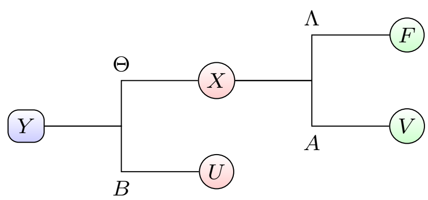


Figure 1: An illustration of the tree-like model configuration.

#### *2.1.1. Inter-Institution Model*

Let $Y_t = \{Y_{i,t}\},\ i = 1, \ldots, n$, be a $n \times 1$ vector of log returns of $n$ institutions observed at time $t$, where $Y_{i,t}$ is the return for institution $i$ at time $t$. Suppose each institution belong to exactly one of $p$-finite number of countries. We denote with $X_t = \{X_{l,t}\},\ l = 1, \ldots, p$, an $p \times 1$ vector of national financial sector indices, where $X_{l,t}$ is country-$l$ financial sector index at time $t$ proxied by averaging the return of institutions in country-$l$. We formulate an inter-institution model where the returns of institution-$i$ depends on the national financial sector index for the country to which institution-$i$ belongs and spillovers from other national financial sectors as well as exposures to shocks from other institutions. Thus, the basic inter-institution model in matrix form is specified as follows

$$Y' \;=\; \Theta X' + \xi_Y' \;=\; \Theta X' + BU' \tag{1}$$

where $Y$ and $X$ are $T \times n$ and $T \times p$ matrix of observations, $\xi_Y$ is $T \times n$ matrix of idiosyncratic terms which can be expressed in terms of $U$ - a $T \times n$ matrix of institution-level shocks, $\Theta$ and $B$ are $n \times p$ and $n \times n$ coefficient matrices, such that $\Theta_{i,l}$ measures the exposure of $Y_i$ to $X_l$, and $B$ has unit diagonal terms, i.e, the magnitude of the exposure of institution $i$ to its own shocks is 1. We assume $X$ and $U$ are uncorrelated, and the elements of $U$ are independent and identically normal with zero mean and diagonal covariance matrix, $\Sigma_U = \mathrm{diag}(\sigma^2_{u_1}, \ldots, \sigma^2_{u_n})$. From these assumptions, the covariance structure of the inter-institution model is given by

$$\begin{aligned}\Sigma_Y \;&=\; \Theta\Sigma_X\Theta' + B\Sigma_U B' \;=\; \Theta\Sigma_X\Theta' + B\Sigma_U^{1/2}(B\Sigma_U^{1/2})' \\ &=\; \Theta\Sigma_X\Theta' + B^*B^{*'} \;=\; \Psi_Y + \Omega_Y\end{aligned} \tag{2}$$

where $B^* = B\Sigma_U^{1/2}$ is a transformation of $B$. Equation (2) shows that total variance of institution returns can be decomposed into a systematic component of country-level indicators, $(\Psi_Y = \Theta\Sigma_X\Theta')$, and an idiosyncratic aspect of inter-institution shock transmissions, $(\Omega_Y = B^*B^{*'})$.

*2.1.2. Inter-Country Model*

We further construct a inter-country model based on the assumption that the observed national financial sector index depends on a small number of common financial market indicators that signal regional/global performance of the financial sector, as well as exposures to inter-national financial sector shocks. We denote with $F$, the regional/global market factors. Thus, we model the inter-country relations as a factor model given by

$$X' \;=\; \Lambda F' + \xi_X' \;=\; \Lambda F' + AV' \tag{3}$$

where $F$ is $T \times r$ matrix $(r < p)$, $\Lambda$ is $p \times r$ matrix of country sensitivity to $F$, $\xi_X$ is $T \times p$ matrix of idiosyncratic terms which can be expressed in terms of $V$ - a $T \times p$ matrix of country-level shocks, $A$ is $p \times p$ matrix of coefficients with unit main diagonal terms such that $A_{k,l}$ measures the impact of a shock of country $X_l$ on country $X_k$. By definition, $A$ has unit diagonal terms, i.e, the magnitude of the exposure of country $k$ to its own shocks is 1. Here, we assume $F$ and $V$ are uncorrelated, and the elements of $V$ are independent and identically normal with zero mean and diagonal covariance matrix, $\Sigma_V = \mathrm{diag}(\sigma^2_{v_1}, \ldots, \sigma^2_{v_p})$. The covariance structure of the inter-country model is given by

$$\begin{aligned}\Sigma_X \;&=\; \Lambda\Sigma_F\Lambda' + A\Sigma_V A' \;=\; \Lambda\Sigma_F\Lambda' + A\Sigma_V^{1/2}(A\Sigma_V^{1/2})' \\ &=\; \Lambda\Sigma_F\Lambda' + A^*A^{*'} \;=\; \Psi_X + \Omega_X\end{aligned} \tag{4}$$

Here, the covariance of $F$ is an identity matrix by normalization, and $A^* = A\Sigma_V^{1/2}$ is a transformation of $A$. From the above equation, the total variance of country-level indicators decomposes into a systematic component composed of country sensitivity to variations in regional/global market factors, $(\Psi_X = \Lambda\Sigma_F\Lambda')$, and an idiosyncratic part composed of inter-country shock transmission, $(\Omega_X = A^*A^{*'})$.

*2.1.3. Nested Inter-Institution and Inter-Country Model*

From equations (1) and (3), we can merge the two models such that the combined model is given by

$$Y' \;=\; (\Theta\Lambda)F' + \Theta\xi_X' + \xi_Y' \;=\; \Phi F' + \Theta(AV') + BU' \tag{5}$$

where $\Phi = \Theta\Lambda$, $(\Theta A)$ and $B$ are coefficient matrices, which capture institution sensitivity to regional/global market factors, inter-country and inter-institution shock transmissions, respectively. Here, we assume $U$ and $V$ are independent and identically normal with zero means and diagonal covariance matrices, $\Sigma_U$ and $\Sigma_V$, $U$ and $V$ are uncorrelated, and $F$ is uncorrelated with $U$ and $V$. The covariance structure of the combined model is given by

$$\Sigma_Y \;=\; \Phi\Sigma_F\Phi' + \Theta\Omega_X\Theta' + \Omega_Y \tag{6}$$

Comparing (6) with (2), the systematic component of the total variance in individual institution returns further decomposes into sensitivity to variation in regional/global market factors, $(\Phi\Sigma_F\Phi')$, and sensitivity to inter-country shock co-movement, $(\Theta\Omega_X\Theta')$. Figure 2 depicts a graphical illustration of the results in (6).

$$\begin{tikzcd}
\Sigma_F \arrow[dr] & \Omega_X \arrow[d] & \Omega_Y \arrow[dl] \\
& \Sigma_Y &
\end{tikzcd}$$

Figure 2: A decomposition of institutional risk as function of regional/global market risk, $\Sigma_F$, inter-country risk, $\Omega_X$, and inter-institution idiosyncratic risk, $\Omega_Y$.

*2.2. Network Models*

From (1) and (5), the simultaneous system of equations can be operationalized as a network model where the coefficient matrix $B$ can be modeled as a sparse matrix encoding the exposures among individual institutions such that

$$B_{i,j} \begin{cases} = 0 & \text{if} \quad Y_i \text{ is not exposed to } U_j \text{ (shocks on } Y_j) \\ \neq 0 & \text{if} \quad Y_i \text{ is exposed to } U_j \text{ (shocks on } Y_j) \end{cases} \tag{7}$$

Likewise, the coefficients matrix $A$ in (3) can be modeled as a sparse matrix encoding the exposures among country sectors such that

$$A_{k,l} \begin{cases} = 0 & \text{if} \quad X_k \text{ is not exposed to } V_l \text{ (shocks on } X_l) \\ \neq 0 & \text{if} \quad X_i \text{ is exposed to } V_l \text{ (shocks on } X_l) \end{cases} \tag{8}$$

Furthermore, the transformations $B^* = B\Sigma_U^{1/2}$ and $A^* = A\Sigma_V^{1/2}$ does not affect the sparsity of $B$ and $A$ respectively. The elements of $B^*$ and $A^*$ are such that $B^*_{ij} = B_{ij}\sigma_{u_j},\ i,j = 1,\ldots,n$ and $A^*_{kl} = A_{kl}\sigma_{v_l},\ k,l = 1,\ldots,p$. Thus, $B^*_{ij} = 0$ if $B_{ij} = 0$, and $A^*_{kl} = 0$ if $A_{kl} = 0$. From (4) and (2), the decomposition of the total variance-covariance between country-$k$ and country-$l$

(or institution-$i$ and institution-$j$) is given by

$$\Sigma_{X,kl} = \begin{cases} \Psi_{X,kl} + \Omega_{X,kl} & \text{if} \quad k \neq l \\ \Psi_{X,kk} + \Omega_{X,kk} & \text{if} \quad k = l \end{cases} \qquad \Sigma_{Y,ij} = \begin{cases} \Psi_{Y,ij} + \Omega_{Y,ij} & \text{if} \quad i \neq j \\ \Psi_{Y,ii} + \Omega_{Y,ii} & \text{if} \quad i = j \end{cases} \tag{9}$$

From the above decomposition, the non-systematic component can be expressed such that

$$\Omega_{X,kl} = \begin{cases} A_k^* \, A_l^{*'} & \text{if} \quad k \neq l \\ A_k^* \, A_k^{*'} & \text{if} \quad k = l \end{cases} \qquad \Omega_{Y,ij} = \begin{cases} B_i^* \, B_j^{*'} & \text{if} \quad i \neq j \\ B_i^* \, B_j^{*'} & \text{if} \quad i = j \end{cases} \tag{10}$$

where $A_k^* = A_k \Sigma_V^{1/2} = (A_{k1}\sigma_{v_1}, \ldots, A_{kp}\sigma_{v_p})$, with $A_{kk} = 1$, where $A_k$ is the $k$-th equation vector of coefficients encoding the exposures among country sectors. Similarly, $B_i^* = B_i \Sigma_U^{1/2} = (B_{i1}\sigma_{u_1}, \ldots, B_{in}\sigma_{u_n})$, and $B_{ii} = 1$, where $B_i$ is the $i$-th equation vector of coefficients encoding the exposures among institutions. We quickly notice that if $A_{ks} = 0, \forall s = 1, \ldots, p,\ s \neq k$, then $\Omega_{X,kk} = \sigma_{v_k}^2$, i.e, the non-systematic variance of country-$k$ will only be composed of only country-$k$'s own risk. Similar argument holds for institution-level non-systematic variance.

Following the literature on graphical models (Ahelegbey et al., 2016a,b; Carvalho and West, 2007; Dahlhaus and Eichler, 2003; Eichler, 2007), we model $\Omega_X$ and $\Omega_Y$ as a undirected sparse covariance structures with a corresponding binary 0/1 matrices, $G_X \in \{0,1\}^{p \times p}$ and $G_Y \in \{0,1\}^{n \times n}$, respectively, such that

$$G_{X,kl} = G_{X,lk} = \begin{cases} 0 & \text{if} \quad \Omega_{X,kl} = 0 \\ 1 & \text{if} \quad \Omega_{X,kl} \neq 0 \end{cases} \qquad G_{Y,ij} = G_{Y,ji} = \begin{cases} 0 & \text{if} \quad \Omega_{Y,ij} = 0 \\ 1 & \text{if} \quad \Omega_{Y,ij} \neq 0 \end{cases} \tag{11}$$

Clearly, by comparing (10) and (11), it can be shown that $\Omega_{X,kl} = 0$ if $A_{kl} = A_{lk} = 0$ and either $A_{kz} = 0$ or $A_{lz} = 0$, where $z = \{1, \ldots, p\} \backslash \{k, l\}$. Thus, shocks on country-$k$ and country-$l$ must be mutually independent, and both countries are not impacted by shocks from country-$z$. Therefore, the country and institution network graphs adopted in this application represent not only marginal independence but conditional independence.

### *2.3. Network Structure Inference*

Given $Y$ (a panel data of returns of institutions from different countries), and $X$ (obtained by averaging elements in $Y$ by countries), our objective is to analyze $G_X$ and $G_Y$, the non-systematic inter-country and inter-institution networks associated with $\Omega_X$ and $\Omega_Y$, respectively, aiming for a more parsimonious and sparse covariance structure. The approach considered in our estimation is as follows:

1. Obtain the factors, $F$, via singular value decomposition (SVD) of $X$, and estimate the residuals of (3), i.e., $\hat{\xi}_X' = X' - \hat{\Lambda}\hat{F}'$
2. Estimate the inter-country model residual covariance matrix, $\hat{\Omega}_X = \text{Cov}(\hat{\xi}_X)$
3. Estimate the inter-country idiosyncratic network $\hat{G}_X$ determined by zeros in $\hat{\Omega}_X$
4. Regress $Y$ on $(\hat{F}, \hat{\xi}_X)$, and estimate the residuals of (5), i.e., $\hat{\xi}_Y' = Y' - (\hat{\Phi}\hat{F}' + \hat{\Theta}\hat{\xi}_X')$
5. Estimate the inter-institution model residual covariance matrix, $\hat{\Omega}_Y = \text{Cov}(\hat{\xi}_Y)$
6. Estimate the inter-institution idiosyncratic network $\hat{G}_Y$ determined by zeros in $\hat{\Omega}_Y$

#### *Determining Number of Factors*

We adopt the singular value decomposition (SVD) of $X$ to obtain the underlying regional/global factors that drive country indicators. We estimate the number of factors via the information criterion (IC) of (Bai and Ng, 2002). The IC specification is given by

$$IC(r) \;=\; \log\left(\frac{1}{pT}\sum_{t=1}^{T}(X_t - \hat{\Lambda}\hat{F}^r)^2\right) \;+\; r\left(\frac{p+T}{pT}\right)\log\left(\frac{pT}{p+T}\right) \tag{12}$$

The number of factors is estimated by minimizing $IC(r)$ for $r = 1, \ldots, r_{\max}$. It well-known in the factor models literature that the Bai and Ng (2002) information criterion tend to overestimate the number of factors. Despite this limitation, the above criterion is considered to be the conventional method in factor model determination. To control the number of factors and avoid over-fitting, we set $r_{\max} = 5$.

*Sparse Covariance Estimation*

There is an extremely large number of methods for sparse covariance estimation that represent conditional independencies. Such network graphs are estimated by setting elements of the inverse covariance matrix to zero (see Dempster, 1972; Friedman et al., 2008; Meinshausen and Bühlmann, 2006). We adopt the graphical lasso approach of Friedman et al. (2008) to estimate the sparse structure associates with the non-systematic variance-covariance matrices. Let $\Omega = \mathrm{Cov}(\xi)$ be the sample covariance matrix of $\xi = \{\xi_X, \xi_Y\}$. The graphical lasso scheme involves minimizing the following function

$$\log(|S|) + \mathrm{trace}(\Omega S^{-1}) + \rho||S||_1 \tag{13}$$

where $\rho$ is the shrinkage parameter, $S$ is a positive-definite and symmetric matrix, $|S|$ is the determinant of $S$, and $||S||_1$ is the element $L_1$ norm of $S$, i.e., the sum of the absolute values of the elements of $S$. In this application, we implement the glasso R-package to estimate the underlying sparse network graph associated with $\Omega = \{\Omega_X, \Omega_Y\}$.

## 3. Descriptive Analysis of Network Graphs

We analyze the estimated network based on network density, maximal community sizes, average path length, node degree, betweenness and eigenvector centrality. We define these measures briefly.

*Density*

The density of a network measures the number of estimated links in the network divided by the total number of possible links. For a $n$ number of institutions and given that out estimate network is an undirected network, there are $n(n-1)/2$ possible links. Standard applications indicate that the higher the network density the higher the degree of interconnectedness of the markets.

*Network Communities*

A network is said to have a community (cohesive) structure if a subset of nodes in the network can be grouped into sets of nodes that has dense connections between its members than to the rest of the network. The higher the maximal community size (number of closely connected nodes), the higher and broader the effect of shock propagation in the community.

*Average Path Length*

The average path length is the average shortest path between two nodes. It represents the average graph-distance between all pair of nodes, where connected nodes have graph distance equals to 1. The higher the graph distance the longer time it takes for a default cascade to cause a systemic breakdown. The average path length for a network with $n$-nodes is given by

$$l_G = \frac{1}{n(n-1)} \sum_{i \neq j} d_{i,j} \tag{14}$$

where $d_{i,j}$ is the shortest path between the nodes $i$ and $j$.

*Degree*

The concept of a degree in network analysis is crucial to understand the most connected institution in terms of shock transmission. It measures the total number of neighbors that are connected to a given institution. The higher the degree the higher the influence (or vulnerability) of an institution in the network.

*Betweenness Centrality*

Betweenness centrality measures the extent to which a institution lies on the path between other institutions. In other words, it quantifies the number of times a institution acts as a bridge to connect other institutions. It is computed as follows:

$$B(i) = \sum_{j \neq i \neq k} \frac{d_{j,k}(i)}{d_{j,k}} \tag{15}$$

where $d_{j,k}(i)$ is the number of shortest paths between node-$j$ and node-$k$ that pass-through node-$i$, and $d_{j,k}$ is the total number of shortest paths between node-$j$ and node-$k$. An node with higher betweenness score can potentially influence the spread of risk through the network.

*Eigenvector Centrality*

Eigenvector centrality assigns a score to each institution in a way that is proportional to the importance scores of its neighbors. Given a graph matrix $G$, eigenvector centrality score involves solving the following problem

$$Gv = \lambda_1 v \tag{16}$$

where $v$ is a vector containing the eigenvectors and $\lambda_1$ is the largest eigenvalue of $G$.

## 4. Empirical Assessment of Financial Contagion

We used the Bloomberg database to retrieve daily time-series data for CDS spread prices of top European financial institutions (bank and insurance companies). The dataset contains 50 institutions from 11 European countries covering 01/01/2008 to 31/12/2015. The countries represented by the different banks include Austria(2), Belgium(2), Finland(1), France(8), Germany(12), Greece(4), Ireland(1), Italy(8), Netherlands(3), Portugal(3), and Spain(5). Table 1 presents a detailed description of the institutions in our dataset classified by countries. Out of the 50 institutions, 42 are banks and 8 are insurance companies.

| No. | Name | Ticker | Type | Country | Country code |
|---|---|---|---|---|---|
| 1 | Erste Group Bank | EBS | Bank | Austria | AT |
| 2 | Raiffeisen Bank International | RBI | Bank | Austria | AT |
| 3 | Dexia | DEXB | Bank | Belgium | BE |
| 4 | KBC Group | KBC | Bank | Belgium | BE |
| 5 | Pohjola Bank Oyj | POHS | Bank | Finland | FI |
| 6 | BNP Paribas | BNP | Bank | France | FR |
| 7 | Caisse d'Epargne | GCE | Bank | France | FR |
| 8 | CIC Credit Mutuel Group | CIC | Bank | France | FR |
| 9 | Credit Agricole | ACA | Bank | France | FR |
| 10 | Groupama | GPA | Insurance | France | FR |
| 11 | Natixis-BPCE Group | BPCE | Bank | France | FR |
| 12 | Score Se | SCR | Insurance | France | FR |
| 13 | Societe Generale | GLE | Bank | France | FR |
| 14 | Allianz | ALV | Insurance | Germany | GE |
| 15 | Commerzbank | CBK | Bank | Germany | GE |
| 16 | Deutsche Bank | DBK | Bank | Germany | GE |
| 17 | DZ Bank | DZB | Bank | Germany | GE |
| 18 | Hannover Ruck. | HNR | Insurance | Germany | GE |
| 19 | Hudson Bay | HBNC | Insurance | Germany | GE |
| 20 | IKB Deutsche Industriebank | IKB | Bank | Germany | GE |
| 21 | Landesbank Baden-W. | LDBW | Bank | Germany | GE |
| 22 | Landesbank Berlin H. | LDBH | Bank | Germany | GE |
| 23 | Landesbank Hessen-T. | LDHT | Bank | Germany | GE |
| 24 | Muenchener Ruck. | MUV | Insurance | Germany | GE |
| 25 | Nord/LB | NLB | Bank | Germany | GE |
| 26 | Alpha Bank | ALPH | Bank | Greece | GR |
| 27 | Eurobank Ergasias | EURB | Bank | Greece | GR |
| 28 | National Bank of Greece | ETE | Bank | Greece | GR |
| 29 | Piraeus Bank | PEIR | Bank | Greece | GR |
| 30 | Permanent TSB | PTSB | Bank | Ireland | IR |
| 31 | Assicurazioni Generali | G | Insurance | Italy | IT |
| 32 | Banca Monte dei Paschi di Siena | BMPS | Bank | Italy | IT |
| 33 | Banca Popolare di Milano | PMI | Bank | Italy | IT |
| 34 | Banca Popolare di Sondrio | BPSO | Bank | Italy | IT |
| 35 | Intesa Sanpaolo | ISP | Bank | Italy | IT |
| 36 | Mediobanca | MB | Bank | Italy | IT |
| 37 | Unione di Banche Italiane | UBI | Bank | Italy | IT |
| 38 | Unipolsai | US | Insurance | Italy | IT |
| 39 | Aegon Bank | AEG | Bank | Netherlands | NL |
| 40 | ING Groep | INGA | Bank | Netherlands | NL |
| 41 | Rabobank | RABO | Bank | Netherlands | NL |
| 42 | SNS Bank | SNS | Bank | Netherlands | NL |
| 43 | Banco BPI | BPI | Bank | Portugal | PT |
| 44 | Banco Comercial Portugues | BCP | Bank | Portugal | PT |
| 45 | Novo Banco | BKES | Bank | Portugal | PT |
| 46 | Banco Bilbao Vizcaya Argentaria | BBVA | Bank | Spain | SP |
| 47 | Banco de Sabadell | SAB | Bank | Spain | SP |
| 48 | Banco Popular Espanol | POP | Bank | Spain | SP |
| 49 | Banco Santander | SAN | Bank | Spain | SP |
| 50 | Bankinter | BKT | Bank | Spain | SP |

Table 1: Description of Banks Classified By Country.

Let $P_{i,t}$ be the daily CDS spread price of institution $i$ at time $t$ and $R_{i,t} = \log P_{i,t} - \log P_{i,t-1}$ be the log-returns. We average the returns of the institutions in the sample for a given country to construct country-level observations. Figure 3 represents the evolution of the 50 considered CDS spreads and spread returns over time. It also reports the evolution of the aggregate country returns. The institutions are grouped according to country blocks: Austria (in red), Belgium (green), Finland (blue), France (violet), Germany (orange), Greece (yellow), Ireland (cyan), Italy (magenta), Netherlands (sky-blue), Portugal (brown), and Spain (coral).

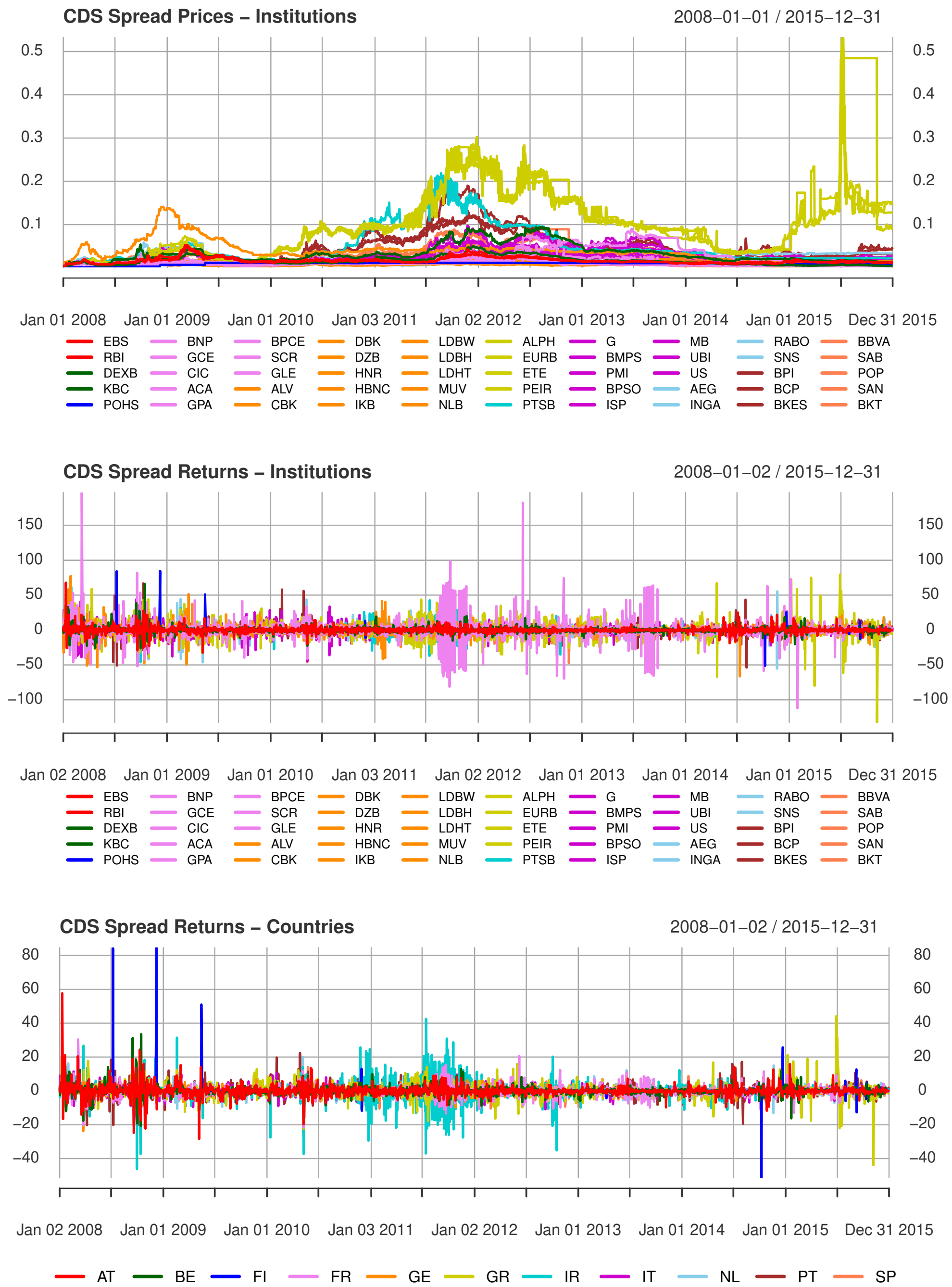


Figure 3: Time series of the corporate default swap spread prices and returns. The institutions represented in the series are colored using country groupings: Austria (AT - red), Belgium ( BG - green), Finland (FI - blue), France (FR - violet), Germany (GE - orange), Greece (GR - yellow), Ireland (IR - cyan), Italy (IT - magenta), Netherlands (NL - sky-blue), Portugal (PT - brown), and Spain (SP - coral).

From the figure, we notice that much volatility in the CDS spreads concentrates during the peak of the financial crisis period, September 2008, in which we observe extreme events for Dutch, French, German, Italian, Portuguese and Spanish institutions. Aggregating over countries, the most volatile ones are Austria, Finland, Greece, and Ireland. Large variations on the observed spreads are also observed during the sovereign crisis, particularly during August and September 2011; but, in this case, events are most concentrated around Greek and some southern European countries (such as Italy and Spain).

Looking at individual dates we notice evidence of "contagion effect", within countries but also between countries. For example, on September 29th, 2008 a 'large shock' affected Credit Industriel. On the same day, large variations were observed not only among other French institutions but also among German, Italian, Spanish and Greek institutions. At the onset of the crisis, on March 7th, 2008, another large spread increase was observed for the French Groupama corporate ($\Delta_{CDS} = 6.15$). The same day, large variations occurred in other institutions in France, Italy, Spain, Greece, and Germany.

We proceed with the application of our model to the data. To better understand the results, we compared the structure and centrality of the idiosyncratic inter-country and inter-financial-institutions connectedness over three different time windows: (a) the financial crisis period (2008-2009), (b) the sovereign crisis period (2010-2012) and (c) the post-crisis period (2013-2015). The application further considered the top four economies in the Euro area over the sup-periods. The analysis finally delves into the yearly connections among the countries and financial institutions over the sample period.

### *4.1. Inter-Country Sector Network*

We start the application of our models considering the inter-country networks that can be obtained in the different time periods. Figure 4 shows the connectedness of the countries in a network format; Table 2 presents the global summary statistics of the network graph, and Table 3 contains the corresponding summary centrality measures.

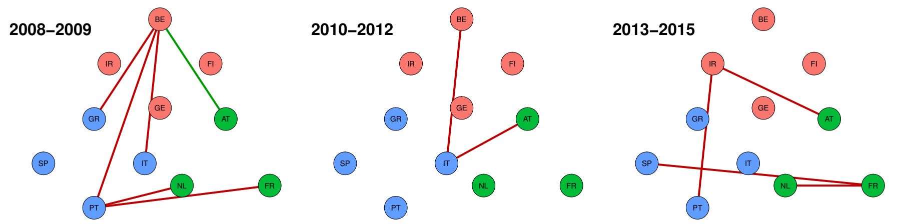


Figure 4: Inter-country Network across sub-periods. The links indicate signs of the correlation coefficients, green indicate positive correlations and red for negative correlations. The nodes are countries categorized into southern Europe (in blue), western Europe (in green), and north-central Europe (in red).

| | Links | Density | Community Size (max.) | Average Path Length |
|---|---|---|---|---|
| 2008-2009 | 6 | 0.11 | 4 | 2.00 |
| 2010-2012 | 2 | 0.04 | 3 | 1.33 |
| 2013-2015 | 4 | 0.07 | 3 | 1.33 |

Table 2: Summary statistics of the inter-country network over the sub-periods.

To aid interpretation, we represent distinguish the links using the signs of the correlation coefficients. Positive correlations are depicted in green and negative correlations are in red. Furthermore, we position the countries based on their regional locations. Southern European countries are in blue, western European countries in green, and northern-central European countries in red. From Figure 4 and Table 2, we notice that the inter-country network is more connected during the financial crisis period: the number of links, the density, and the community size is all at their maxima. This result emphasizes the fact that the crisis affected most European countries. Consistent with the financial network literature, the interconnectedness among the countries increased during the financial crisis. On the other hand, during the sovereign crisis, the network is less connected, indicating that the crisis concentrated on some southern European countries. The post-crisis situation is somewhat in between. In all cases, most correlations are negative and are between "core" countries, indicated in red in the figure, and "peripheral" countries, indicated in blue.

It is important to understand which countries are most central, in the different periods. This may give an indication about which countries are more contagious/subject to contagion (see Table 3). We observe from Table 3 that the smaller countries, such as Belgium, Portugal,

| Criteria | Rank | 2008-2009 | 2010-2012 | 2013-2015 |
|---|---|---|---|---|
| *Degree* | 1 | **BE** - 4 | **IT** - 2 | **FR** - 2 |
| | 2 | PT - 3 | AT - 1 | IR - 2 |
| | 3 | AT - 1 | BE - 1 | AT - 1 |
| | 4 | FR - 1 | FI - 0 | NL - 1 |
| | 5 | GR - 1 | FR - 0 | PT - 1 |
| *Betweenness* | 1 | **BE** - 12 | **IT** - 1 | FR - 1 |
| | 2 | PT - 9 | AT - 0 | IR - 1 |
| | 3 | AT - 0 | BE - 0 | AT - 0 |
| | 4 | FI - 0 | FI - 0 | BE - 0 |
| | 5 | FR - 0 | FR - 0 | FI - 0 |
| *Eigenvector* | 1 | **BE** - 1 | **IT** - 1 | **FR** - 1 |
| | 2 | PT - 0.80 | BE - 0.71 | IR - 1 |
| | 3 | AT - 0.46 | AT - 0.71 | NL - 0.71 |
| | 4 | GR - 0.46 | FI - 0.00 | SP - 0.71 |
| | 5 | IT - 0.46 | FR - 0.00 | AT - 0.71 |

Table 3: Top five countries ranked according to degree, betweenness and eigenvector centrality. The values represent the centrality metrics and bold face variables represent the top rank countries.

and Austria, were more central to the spread of risk during the financial crisis, according to all centrality measures. During the sovereign crisis, Italy was central to the spread of the crisis in the EU. This is consistent with the events between 2010-2012, such that, in mid-2011, the threat to European financial institutions and the global financial system became severe when the crisis of Greece, Ireland, and Portugal began to affect Italy (the third largest Euro zone economy and second biggest debtor to bond investors). With many European institutions heavily exposed to Italy, the sovereign crisis quickly spread within and beyond Europe. The post-crisis period shows France (the third largest Eurozone economy) as the most central country to the spread of risk in the EU. These findings are consistent with the fact that, during crises, contagion effects are higher and shocks are propagated via high order interconnections, which often hit larger banking systems.

### *4.2. Inter-Institution Network*

We now consider inter-institution networks. Figure 5 depicts the sub-period network graphs. The institutions are grouped according to country blocks: Austria (in red), Belgium (green), Finland (blue), France (violet), Germany (orange), Greece (yellow), Ireland (cyan), Italy (magenta), Netherlands (sky-blue), Portugal (brown), and Spain (coral). Tables 4 and 5 contains the results of the summary statistics and centrality measures of the inter-institution sub-period networks, respectively.

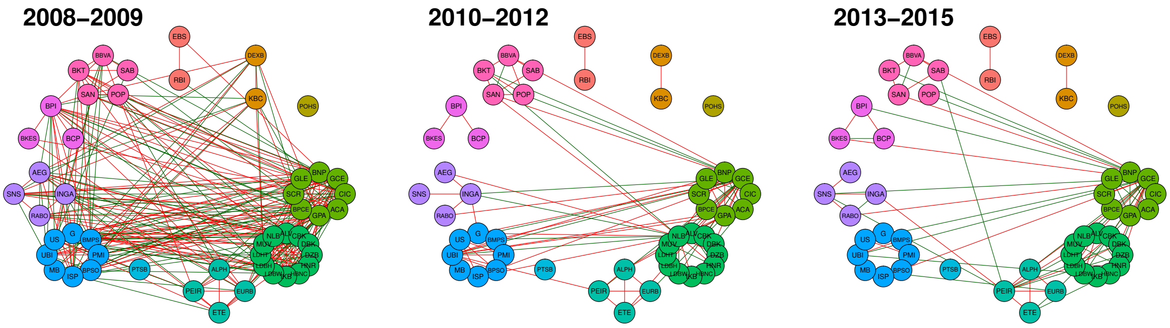


Figure 5: Inter-institutional Network across sub-periods. The institutions are grouped according to country blocks: Austria (in red), Belgium (green), Finland (blue), France (violet), Germany (orange), Greece (yellow), Ireland (cyan), Italy (magenta), Netherlands (sky-blue), Portugal (brown), and Spain (coral).

The institutional idiosyncratic connections in Figure 5 shows that the vulnerability of the European financial system was much higher during the global financial crisis than in the sovereign crisis and post-crisis periods. The total number of links, density and community size as shown in Table 4 emphasizes the above results. Given that the magnitude of shocks

| | Links | Density | Community Size (max.) | Average Path Length |
|---|---|---|---|---|
| 2008-2009 | 307 | 0.25 | 15 | 1.79 |
| 2010-2012 | 104 | 0.08 | 11 | 2.16 |
| 2013-2015 | 81 | 0.07 | 11 | 2.38 |

Table 4: Summary statistics of inter-institution network over the sub-periods.

| Criteria | Rank | 2008-2009 | 2010-2012 | 2013-2015 |
|---|---|---|---|---|
| *Degree* | 1 | **GPA** - 28 | **GCE** - 26 | **GCE** - 27 |
| | 2 | CIC - 26 | NLB - 20 | PEIR - 11 |
| | 3 | US - 25 | GPA - 12 | LDBH - 7 |
| | 4 | LDBH - 23 | UBI - 12 | GPA - 6 |
| | 5 | GCE - 22 | US - 8 | ALV - 6 |
| *Betweenness* | 1 | **CIC** - 156.2 | **GCE** - 332.7 | **GCE** - 586.3 |
| | 2 | GPA - 97.0 | NLB - 215.2 | PEIR - 107.9 |
| | 3 | US - 75.9 | US - 64.1 | SNS - 58.4 |
| | 4 | GCE - 50.2 | UBI - 63.6 | US - 55.5 |
| | 5 | LDBH - 49.7 | GPA - 51.9 | EURB - 45.2 |
| *Eigenvector* | 1 | **GPA** - 1 | **GCE** - 1 | **GCE** - 1 |
| | 2 | US - 0.91 | NLB - 0.79 | ALV - 0.42 |
| | 3 | CIC - 0.91 | GPA - 0.60 | LDBW - 0.40 |
| | 4 | LDBH - 0.88 | UBI - 0.60 | PEIR - 0.39 |
| | 5 | GCE - 0.84 | ACA - 0.44 | HNR - 0.37 |

Table 5: Top five institutions ranked according to degree, betweenness and eigenvector centrality. The values represent the centrality metrics and bold face variables represent the top rank institutions.

affecting financial institutions are sufficiently large at the onset of the crisis, during early-2008, the high vulnerability of the financial system via institutional interconnections served as a mechanism for shock propagation and spillovers among markets, leading to systemic crisis. This corroborates the assertion of (Acemoglu et al., 2015; Elliott et al., 2014; Glasserman and

Young, 2016). In addition to the high interconnectedness, the average path length indicates that the propagation of risk during the financial crisis was much faster than the sovereign crisis and post-crisis period. The sovereign crisis also display a more interconnected system than the post-crisis period. This is consistent with the economic intuition that interconnections are relatively higher during crisis periods.

The centrality measures in Table 5 shows that during the financial crisis, the most central institutions were Groupama (one of the largest European insurance groups) and Credit Industriel (CIC). The importance of Groupama, based on degree and eigenvector centrality, during the crisis, leans toward the interpretation of centrality as a "source of contagion" (hub) rather than "effect". CIC, on the other hand, was influential in terms of intermediating between institutions. These institutions act as "agents of contagion", especially during the financial crisis period. During the sovereign and post-crisis periods, the French Caisse d'Epargne was the most connected and central institution in both periods.

In the next sections, we consider the inter-institution graphs within the top four largest economies of the EU to further establish our conclusions.

### *4.2.1. Germany*

From the estimated networks over the sub-periods, Figure 6 and Tables 6 and 7 show the structure and summary of connections among the German institutions represented in our data. We observe from Figure 6 and Table 6 that the German institutions were much

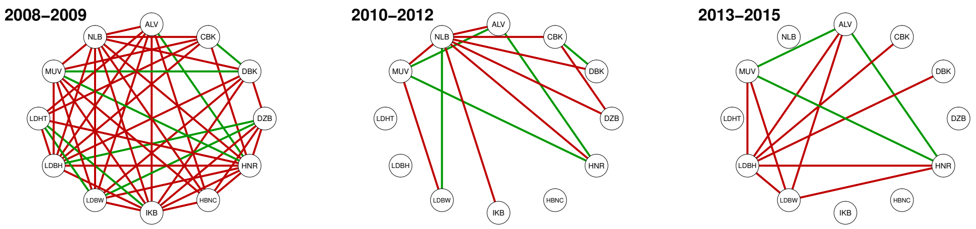


Figure 6: Germany: Within-Country Networks

| | Links | Density | Community Size (max.) | Average Path Length |
|---|---|---|---|---|
| 2008-2009 | 46 | 0.70 | 7 | 1.30 |
| 2010-2012 | 14 | 0.21 | 5 | 1.61 |
| 2013-2015 | 12 | 0.18 | 4 | 1.43 |

Table 6: Germany: Summary statistics of inter-institution network over the sub-periods.

| Rank | 2008-2009 | 2010-2012 | 2013-2015 |
|---|---|---|---|
| 1 | IKB - 1 | NLB - 1 | LDBH - 1 |
| 2 | HNR - 0.99 | MUV - 0.69 | LDBW - 0.9 |
| 3 | NLB - 0.93 | HNR - 0.6 | ALV - 0.9 |
| 4 | LDBH - 0.91 | ALV - 0.6 | HNR - 0.9 |
| 5 | MUV - 0.84 | CBK - 0.46 | MUV - 0.9 |

Table 7: Germany: Institutions ranked by eigenvector centrality

connected during the financial crisis, and less so during the sovereign and post-crisis periods. There were both positive and negative correlations, indicating a diversified "portfolio" of institutions: more risky and more safe. IKB Deutsche Industriebank (IKB) was reported as the most central institution during the financial crisis, Nord/LB (NLB) dominated during the sovereign crisis, and Landesbank, a bank typically controlled the local government, was central during the post-crisis period.

*4.2.2. France*

The network among the French financial institutions over the sub-periods are depicted in Figure 7. Tables 8 and 9 show in more detail the results of the summary statistics of the inter-institution connectedness and the centrality measures, respectively. From the figure, we

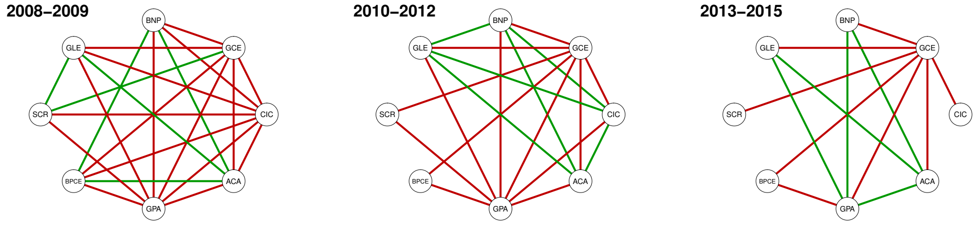


Figure 7: France: Within-Country Networks

| | Links | Density | Community Size (max.) | Average Path Length |
|---|---|---|---|---|
| 2008-2009 | 23 | 0.82 | 5 | 1.18 |
| 2010-2012 | 19 | 0.68 | 4 | 1.32 |
| 2013-2015 | 13 | 0.46 | 5 | 1.54 |

Table 8: France: Summary statistics of inter-institution network over the sub-periods.

| Rank | 2008-2009 | 2010-2012 | 2013-2015 |
|---|---|---|---|
| 1 | CIC - 1 | GPA - 1 | GCE - 1 |
| 2 | GCE - 1 | GCE - 1 | GPA - 0.9 |
| 3 | GPA - 1 | ACA - 0.88 | ACA - 0.81 |
| 4 | ACA - 0.91 | CIC - 0.88 | BNP - 0.67 |
| 5 | BPCE - 0.8 | BNP - 0.88 | GLE - 0.67 |

Table 9: France: Institutions ranked by eigenvector centrality

notice more interconnectedness during the crises periods than in post-crisis period. The total number of links and density was highest during the financial crisis, followed by the sovereign crisis. The average path length indicates that the rate of risk transmission was also higher during the financial crisis than the sovereign crisis period (see Table 8). Both Groupama (GPA) and Caisse d'Epargne (GCE) were central, as we expect, but so are the other large French banks (all large and "too big to fail").

*4.2.3. Italy*

The structure of the Italian institutions over the sub-periods are shown in Figure 8. The results of the networks are similar to that of Germany and France in the sense that there was more interconnectedness during the financial crisis and in the sovereign crisis periods than in post-crisis period.

Table 10 shows that ranking the number of links, density and average path length follow that of the French institutional structure. The only difference is that the maximal number of communities of institutions was highest during the financial crisis, followed by the sovereign

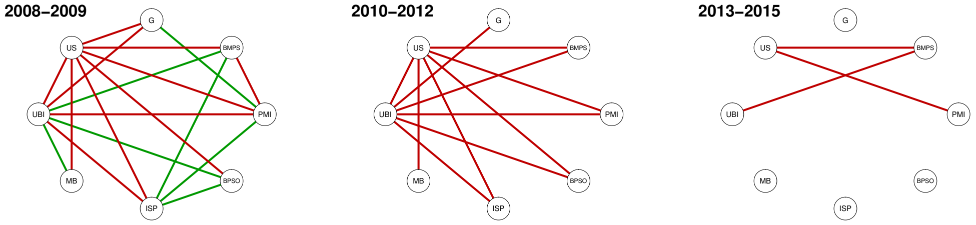


Figure 8: Italy: Within-Country Networks

| | Links | Density | Community Size (max.) | Average Path Length |
|---|---|---|---|---|
| 2008-2009 | 18 | 0.64 | 6 | 1.36 |
| 2010-2012 | 11 | 0.39 | 4 | 1.64 |
| 2013-2015 | 3 | 0.11 | 2 | 1.67 |

Table 10: Italy: Summary statistics of inter-institution network over the sub-periods.

| Rank | 2008-2009 | 2010-2012 | 2013-2015 |
|---|---|---|---|
| 1 | UBI - 1 | UBI - 1 | BMPS - 1 |
| 2 | US - 1 | US - 1 | US - 1 |
| 3 | PMI - 0.84 | PMI - 0.56 | PMI - 0.62 |
| 4 | ISP - 0.84 | BMPS - 0.56 | UBI - 0.62 |
| 5 | BMPS - 0.74 | BPSO - 0.56 | G - 0 |

Table 11: Italy: Institutions ranked by eigenvector centrality

crisis. The post-crisis period, instead, leaves few links and communities among Italian institutions. This is consistent with the fact that the prevailing risk, after the crisis times, is at the country level, rather than at the company level. The most central institutions according to Table 11 are UBI, PMI, BPSO: all large cooperative banks, as well as the troubled Monte dei Paschi di Siena (BMPS), recently nationalized.

#### *4.2.4. Spain*

We now turn our attention on Spain - the fourth largest economy in the EU. Figure 9 and Tables 12 and 13 show in more detail the results for the inter-institutions subgraph that concerns Spain. We notice from these results that the situation in Spain is somewhat intermediate between that of France and Italy, in the sense that there were many connections during the crises periods, and less after crisis, but it remains an institutional diversification, besides the country risk. Over the three sub-periods, the centrality analysis indicates that

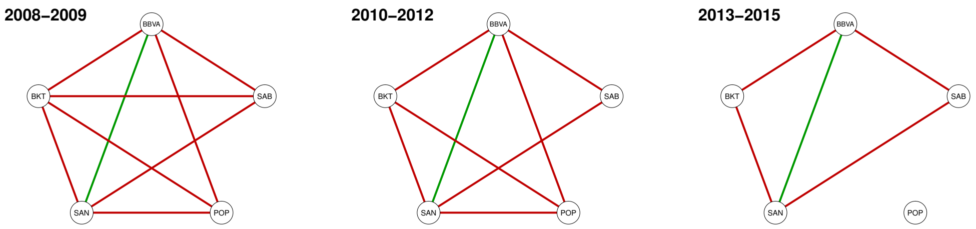


Figure 9: Spain: Within-Country Networks

the most Spanish institutions rotate around two large banks: Santander (SAN) and Banco Bilbao Vizcaya Argentaria (BBVA).

| | Links | Density | Community Size (max.) | Average Path Length |
|---|---|---|---|---|
| 2008-2009 | 9 | 0.90 | 4 | 1.10 |
| 2010-2012 | 8 | 0.80 | 3 | 1.20 |
| 2013-2015 | 5 | 0.50 | 4 | 1.17 |

Table 12: Spain: Summary statistics of inter-institution network over the sub-periods.

| Rank | 2008-2009 | 2010-2012 | 2013-2015 |
|---|---|---|---|
| 1 | BBVA - 1 | SAN - 1 | BBVA - 1 |
| 2 | SAN - 1 | BBVA - 1 | SAN - 1 |
| 3 | BKT - 1 | POP - 0.86 | SAB - 0.78 |
| 4 | POP - 0.82 | BKT - 0.86 | BKT - 0.78 |
| 5 | SAB - 0.82 | SAB - 0.6 | POP - 0 |

Table 13: Spain: Institutions ranked by eigenvector centrality

In the next sections, we consider the yearly inter-country and inter-institution graphs between 2008–2015 to further understand the interconnectedness and centrality within each of the years.

*4.3. Yearly Inter-country Networks*

We show in Figure 10, the yearly inter-country network between 2008–2015. The network structures suggest that the peak of the effect of the financial and sovereign crisis among the EU countries occurred mainly in 2008 and 2011, respectively, with the former interconnectedness much denser than the latter. It can be deduced that 2009 experienced the residual effect of the contagion in 2008. Years 2010 and 2012 can be described as the beginning and end of the sovereign crisis. During the post-crisis period, we notice an increase in the inter-country connections in 2014.

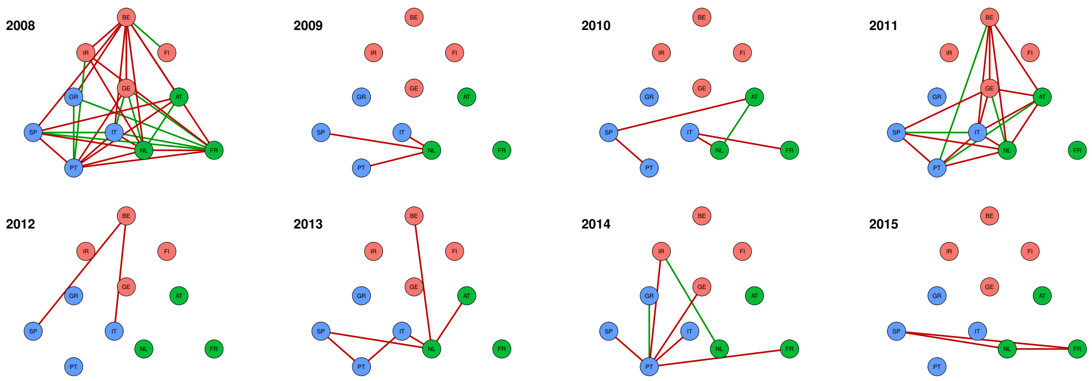

Figure 10: Yearly inter-country network graphs. The links indicate signs of the correlation coefficients, green indicate positive correlations and red for negative correlations.

Table 14, further shows that the maximal community of inter-country connections occurred mainly in 2008 and 2011. Though the links and density of the network seem highest in 2008 than in 2011, the maximal community size and average path length of the latter was much higher than the former. This suggests that the rate of risk transmission among the EU countries was much faster during the sovereign crisis than in the financial crisis. But then again, not many of the countries were as connected as the 2008 financial crisis.

| | Links | Density | Community Size (max.) | Average Path Length |
|---|---|---|---|---|
| 2008 | 31 | 0.56 | 6 | 1.45 |
| 2009 | 3 | 0.05 | 4 | 1.50 |
| 2010 | 5 | 0.09 | 2 | 2.33 |
| 2011 | 18 | 0.33 | 7 | 1.14 |
| 2012 | 2 | 0.04 | 3 | 1.33 |
| 2013 | 6 | 0.11 | 3 | 1.73 |
| 2014 | 7 | 0.13 | 6 | 1.93 |
| 2015 | 3 | 0.05 | 3 | 1.00 |

Table 14: Summary statistics of inter-institution network over the sub-periods.

| Criteria | Rank | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|---|---|---|---|
| *Degree* | 1 | BE | NL | AT | IT | BE | NL | PT | FR |
| | 2 | FR | IT | IT | NL | IT | IT | IR | NL |
| | 3 | NL | PT | NL | AT | SP | PT | FR | SP |
| | 4 | PT | SP | SP | BE | AT | SP | GE | AT |
| | 5 | IT | AT | FR | GE | FI | AT | GR | BE |
| *Betweenness* | 1 | BE | NL | AT | IT | BE | NL | PT | AT |
| | 2 | PT | AT | NL | NL | AT | IT | IR | BE |
| | 3 | FR | BE | IT | GE | FI | SP | AT | FI |
| | 4 | NL | FI | SP | PT | FR | PT | BE | FR |
| | 5 | SP | FR | BE | AT | GE | AT | FI | GE |
| *Eigenvector* | 1 | NL | NL | AT | IT | BE | NL | PT | NL |
| | 2 | FR | IT | NL | NL | SP | IT | IR | FR |
| | 3 | BE | PT | SP | AT | IT | SP | IT | SP |
| | 4 | PT | SP | IT | BE | AT | PT | GE | AT |
| | 5 | IT | AT | PT | GE | FI | AT | GR | BE |

Table 15: Top five countries ranked according to degree, betweenness and eigenvector centrality.

A look at the centrality of the countries over the yearly windows as shown in Table 15 suggests that during the 2008 crisis, Belgium and France were more connected and central to the spread of risk in the Euro area. However, during the 2011 sovereign crisis, Italy and the Netherlands dominated the EU as "sources of contagion".

### *4.4. Yearly Inter-institutional Networks*

The results of the yearly inter-institutional networks and a summary statistics of the structure and centrality measures are presented in Figure 11 and Tables 16 and 17, respectively. Consistent with the yearly inter-country analysis, we find evidence that the interconnectedness among the financial institutions also recorded its peak in 2008-2009 and 2011-2012. This suggests that the vulnerability and rate of risk transmission that led to the financial crisis was much higher in 2008 than the years after 2008.

| | Links | Density | Community Size (max.) | Average Path Length |
|---|---|---|---|---|
| 2008 | 437 | 0.36 | 17 | 1.61 |
| 2009 | 148 | 0.12 | 14 | 2.23 |
| 2010 | 76 | 0.06 | 12 | 2.60 |
| 2011 | 141 | 0.12 | 13 | 2.01 |
| 2012 | 124 | 0.10 | 11 | 2.22 |
| 2013 | 111 | 0.09 | 10 | 2.20 |
| 2014 | 92 | 0.08 | 16 | 2.67 |
| 2015 | 106 | 0.09 | 12 | 2.37 |

Table 16: Summary statistics of inter-institution network over the sub-periods.

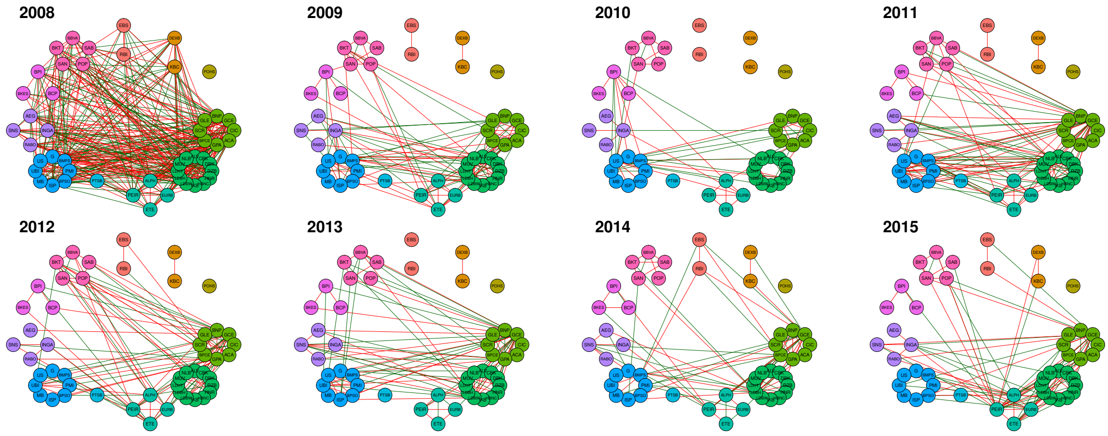

Figure 11: Yearly inter-institutional networks.

| Criteria | Rank | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 |
|---|---|---|---|---|---|---|---|---|---|
| *Degree* | 1 | CIC | LDBH | US | GCE | GCE | GCE | LDBH | GCE |
| | 2 | GPA | CIC | CIC | NLB | GPA | LDBW | GCE | PEIR |
| | 3 | GCE | ALV | GPA | UBI | ACA | GPA | BPCE | ALPH |
| | 4 | US | US | INGA | PEIR | ETE | US | PEIR | EURB |
| | 5 | LDBH | INGA | BPI | US | PEIR | UBI | BMPS | ETE |
| *Betweenness* | 1 | CIC | LDBH | US | GCE | GPA | GCE | LDBH | PEIR |
| | 2 | GPA | CIC | INGA | NLB | GCE | GPA | GCE | GCE |
| | 3 | US | US | CIC | UBI | ETE | US | BPCE | ALPH |
| | 4 | ALPH | BPI | BPI | BPI | ALPH | LDBW | PEIR | EURB |
| | 5 | GCE | BKT | SAN | CBK | PEIR | PEIR | SNS | BPI |
| *Eigenvector* | 1 | CIC | LDBH | US | GCE | GCE | GCE | GCE | PEIR |
| | 2 | GPA | ALV | CIC | NLB | GPA | LDBW | BPCE | GCE |
| | 3 | GCE | CIC | BPI | UBI | BKT | GPA | LDBH | ALPH |
| | 4 | US | G | GCE | US | ACA | US | BNP | EURB |
| | 5 | IKB | INGA | INGA | DZB | PEIR | SNS | GPA | ETE |

Table 17: Top five institutions ranked according to degree, betweennes and eigenvector centrality.

The centrality analysis of the yearly inter-institutional network as shown in Table 17 confirms the initial results that the French institutions (Groupama (GPA), Credit Industriel (CIC) and Caisse d'Epargne (GCE)) were central to the spread of risk during the 2008 financial crisis and the 2011-2012 sovereign crisis.

## 5. Conclusions

The paper has proposed a two-layered tree network model that allows us to decompose financial contagion into a global component, composed of inter-country contagion effects, and a local component made up of inter-institutional contagion effects. The model has been applied to a database containing the time series of daily CDS spreads of the major European financial institutions (banks and insurance companies).

The result revealed a varying structure of interactions among countries and institutions over different periods. More importantly, we find evidence of a high inter-country and inter-institutional vulnerability at the onset of the financial and sovereign crisis. We also found Belgium and France as central to the inter-country contagion in the Euro area during the financial crisis, while Italy dominated the sovereign crisis. The French Groupama, Credit

Industriel, and Caisse d'Epargne were central to the inter-institutional contagion in both crises.

Further application of this work involves considering additional institutions, for which CDS spreads are available, and robustness checks on the model, particularly extending the model to a multilayered context, when more data, besides market prices, are taken into account. An extension of the model formulation includes a dynamic transition in the global market indicators which can be proxied by actual global financial and macroeconomic indicators rather than a factor decomposition of the country-level indicators.

The results show that financial sector policies of major economies and variations in global risk factors play a significant role in the creations of vulnerable financial environments for risk propagation. It is therefore important to focus attention on how the interplay of international and national financial policy initiatives can help ensure and enhance the financial system function as a stable system. This can be achieved by promoting national and international policies that minimize spillovers among inter-country financial systems and institutions.

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