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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. Our empirical application reveals 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 results identify France as central to the inter-country contagion in the Euro area during the financial crisis, while Italy dominates during the sovereign crisis. The application of the model to detect contagion between sectors of the European economy reveals similar findings, and identifies the manufacturing sector as the most central, while, at the company level, financial institutions dominate during the 2008 crisis.

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

1. Introduction

Over the past two decades, network models have seen significant applications with various contributions in the fields of computer science, information sciences, neuroscience, bioinformatics, statistics, economics, finance, and so on. Also, over the past decade, especially after the global financial crisis (GFC) in 2008, the study of financial and economic networks has attracted the attention of not only researchers but also 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 GFC. Bernanke (2013) emphasized that the events that led to the GFC can be

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attributed to two main factors: (i) triggers - the initial losses or shocks that affected many institutions, and (ii) vulnerabilities - the pre-existing structural weaknesses of the system that amplified the initial shocks. The key trigger of the GFC were the losses suffered by many institutions due to subprime mortgages, while the complex interconnectedness of institutions created the vulnerabilities for risk transmission (see Ahelegbey et al., 2016a; Billio et al., 2012; Diebold and Yilmaz, 2014; MacDonald et al., 2015; Mezei and Sarlin, 2018; Pourkhanali et al., 2016). Acemoglu et al. (2015) showed that, when the magnitude of shocks affecting financial institutions is 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 systemic crisis.

Like other living organisms, the interaction among financial institutions can be quite complex and very complicated. This stems from the fact that the linkages 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 various 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), while others rely on market data to study the co-movement of measurement of security prices (Adrian and Brunnermeier, 2016; Ahelegbey et al., 2016a; Billio et al., 2012; Brownlees and Engle, 2016; Diebold and Yilmaz, 2014; Pourkhanali et al., 2016; 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 spillovers. Their results show that shocks transmitted via idiosyncratic channels are highly more likely to destabilize the banking system than systematic channels are.

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 (2019); Diebold and Yilmaz (2014); Dungey and Gajurel (2015); Tang et al. (2010). Following this stream of the literature, we develop a two-layered tree-like model that decomposes financial contagion into a global component, composed of inter-country (or inter-sector) 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 market factors. We combine 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 inter-country risk. We focus on modelling 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).

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 reveals a high inter-country and inter-institutional vulnerability at the onset of the global financial crisis in 2008 and the sovereign crisis in 2011.

To robustify our analysis we also consider daily CDS data of both financial and non-financial European companies from Bloomberg. The dataset consists of 30 companies and covers the period between 31 December 2004 to 19 December 2018. The results reveal a high inter-sector and inter-institutional contagion in 2008 and 2011. They also show that, as expected, the manufacturing sector is overall the most central, while the financial sector dominates during the financial crisis.

The rest of the paper is organized as follows. Section 2 presents the model formulation and the network inference methodology. Section 3 presents the analysis and results for the financial sector application. Section 4 presents the empirical findings for the all sectors application. Finally, Section 5 presents some concluding remarks.

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 measures (returns, change in CDS spread), 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 (Λ, Θ, A, B). Our main objective is the sparse structure associated with A and B.

2.1.1. Inter-Institution Model

Let $Y_t = \{Y_{i,t}\},\ i = 1, \dots, n$, be a $n \times 1$ vector of CDS spread returns of n institutions observed at time t, where $Y_{i,t}$ is the return for institution i at time t. Suppose each institution belongs to exactly one of p-finite number of countries. We denote with $X_t = \{X_{l,t}\},\ l = 1, \dots, p$ a $p \times 1$ vector of CDS spread returns of the financial sector, where $X_{l,t}$ is country l financial sector index at time t proxied by averaging the CDS spread returns of major financial institutions in country-l. We formulate an inter-institution model under the assumption that the CDS spread returns of institution i depend on the financial sector index for the country

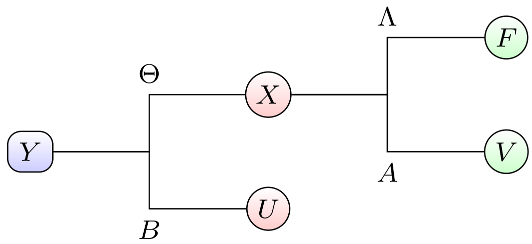

Figure 1: An illustration of the tree-like model configuration.

to which institution i belongs and spillovers from other financial sectors of other countries 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 $T \times p$ matrices of observations, ξ_Y is a $T \times n$ matrix of idiosyncratic terms which can be expressed in terms of U - a $T \times n$ matrix of institution-level shocks, Θ 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 financial sector index of a given country depends on a small number of common financial market indicators that signal regional/global performance of the financial sector, as well as exposures to international 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 a $T \times r$ matrix ($r < p$), Λ is a $p \times r$ matrix of country sensitivity to F, ξ_X is a $T \times p$ matrix of idiosyncratic terms which can be expressed in terms of V - a $T \times p$ matrix of country-level shocks, A is a $p \times p$ 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 $\Phi = \Theta\Lambda$, (ΘA) 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, Σ_U and Σ_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, Σ_F, inter-country risk, Ω_X, and inter-institution idiosyncratic risk, Ω_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

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

Likewise, the coefficients matrix A in (3) can be modelled 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 $A^* = A\Sigma_V^{1/2}$ do 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

$$\Omega_{X,kl} = \begin{cases} A^*_k\ A^{*\prime}_l & \text{if} \quad k \neq l \\ A^*_k\ A^{*\prime}_k & \text{if} \quad k = l \end{cases} \qquad \Omega_{Y,ij} = \begin{cases} B^*_i\ B^{*\prime}_j & \text{if} \quad i \neq j \\ B^*_i\ B^{*\prime}_j & \text{if} \quad i = j \end{cases} \tag{10}$$

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 $\Omega_{X,kk} = \sigma^2_{v_k}$, 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; Eichler, 2007), we model Ω_X and Ω_Y as undirected sparse covariance structures with corresponding binary 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 also 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 Ω_X and Ω_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 the 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 is well-known in the factor models literature that the Bai and Ng (2002) information criterion tends 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 to 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). We adopt the graphical lasso approach of Friedman et al. (2008) to estimate the sparse structure associated with the non-systematic variance-covariance matrices. Let $\Omega = \text{Cov}(\xi)$ be the sample covariance matrix of $\xi = \{\xi_X, \xi_Y\}$. The graphical lasso scheme involves minimizing the following function

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

where ρ 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. Applications to Financial Corporates

Description of Data

In this application we use 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 from 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. Out of the 50 institutions, 42 are banks and 8 are insurance companies.

Table 1: Description of Banks Classified By Country.

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

Each institution is assigned to a single country depending on the headquarter location. Although many companies in the dataset operate in several European countries, it seems indeed reasonable that the riskiness of financial institutions is strongly connected with that of the country they are established in. First, banks usually own a high portion of sovereign debt of their country. Furthermore, in case of a corporate crisis, individual States play a decisive role, being actually the last-resort guarantors. However, the presence of large banking and/or insurance groups throughout Europe could partly explain spillovers at the country level. In particular, it is worth mentioning that in 2015, the final year of our sample, eight among the analyzed financial institutions were included in the list of "globally systemically important institutions" published by the Financial Stability Board and the Basel Committee on Banking Supervision. For each of these companies, Table 2 reports the percentage contribution of the considered countries to the total revenues. Though foreign activities are overall relevant, the national business prevails in most cases. Two exceptions - with a contribution of domestic market lower than 30% - are Santander, whose activity is highly geographically diversified with a strong presence in South America, and Allianz, which has indeed the legal form of "European company" since 2006.

Company	Country	Percentage of consolidated revenues
Societe Generale	France	44.9%
	Germany	3.2%
	Italy	2.6%
Allianz	Germany	25.8%
	Italy	14.1%
	France	10.4%
Deutsche Bank	Germany	31.3%
	Italy	3.1%
	Spain	1.6%
BNP Paribas	France	41.7%
	Belgium	22.3%
	Italy	19.6%
Banco Santander	Spain	11.2%
	Portugal	2.2%
Credit Agricole	France	50.9%
	Italy	15.7%
	Germany	2.0%
Natixis - BPCE Group	France	80.1%
	Germany	0.9%
	Italy	0.7%
ING Groep	Netherlands	31.7%
	Belgium	18.3%
	Germany	11.9%

Table 2: Contribution to total revenues of the three (or two) most relevant countries of activity - among the 11 considered - for each of the globally systemically important institutions included in the sample (according to annual reports as of 31 December 2015).

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-return. 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). 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 in the

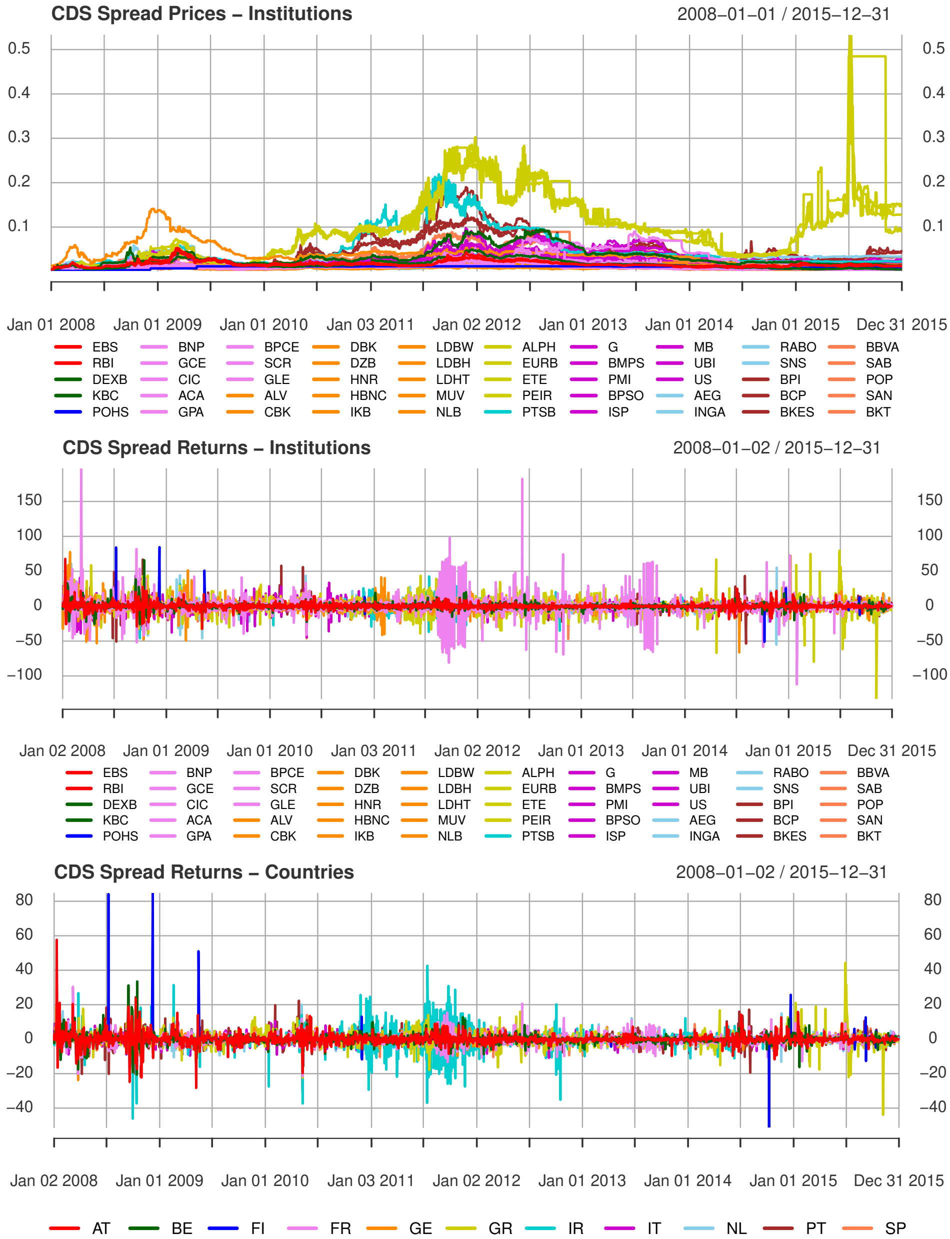

Figure 3: Time series of the corporate default swap spread prices and returns. The institutions represented in the series are coloured using country groupings: Austria (AT - red), Belgium (BG - green), Finland (FI - blue), France (FR - violet), Germany (GE - orange), Greece (GR - yellow), Ireland (IR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

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 compare 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 considers 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.

3.1. Inter-Country Sector Network

We begin our analysis by considering the inter-country networks that can be obtained in the different time periods. We analyze the estimated network based on network density, maximal community sizes, average path length, node degree, betweenness and eigenvector centrality. These measures are briefly defined in Appendix A. Figure 4 shows the connectedness of the countries in a network format; Table 3 presents the global summary statistics of the network graph, and Table 4 contains the corresponding summary centrality measures.

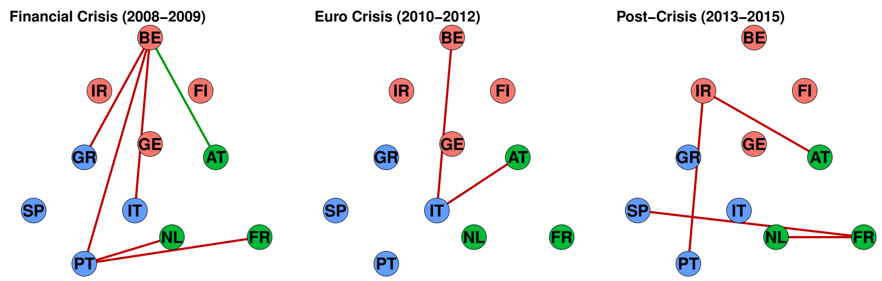

Figure 4: Inter-country Network across sub-periods. The links indicate signs of the correlation coefficients, green indicate positive correlations and red for negative correlations. The nodes are countries categorized into southern Europe (in blue), western Europe (in green), and north-central Europe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

	Links	Density	Community Size	Ave. 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 3: Summary statistics of the inter-country network over the sub-periods.

To aid interpretation, we 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 3, 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 are 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 increases during the financial crisis. On the other hand, during the sovereign crisis, the network is less connected, indicating that the crisis concentrates 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 4). We observe from Table 4 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 4: 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.

3.2. Inter-Institution Network

We present in Figure 5 the inter-institutional sub-period network with institutions color-coded according to countries: 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 5 and 6 contains the summary statistics and centrality measures of the inter-institution sub-period networks, respectively.

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

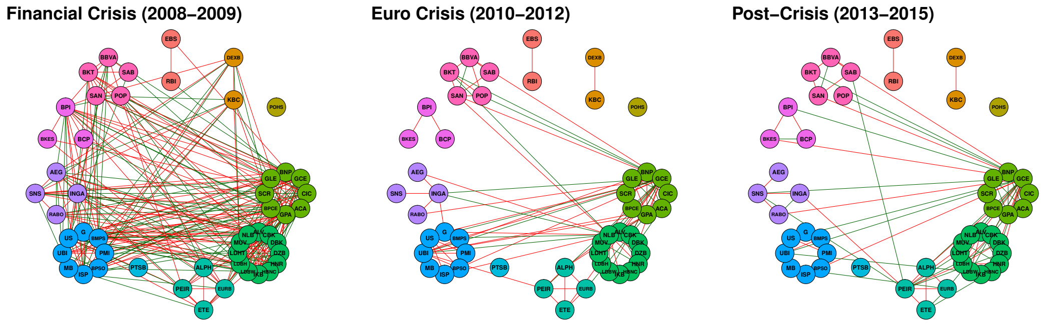

Figure 5: Inter-institutional Network across sub-periods. The institutions are grouped according to country blocks: Austria (in red), Belgium (green), Finland (blue), France (violet), Germany (orange), Greece (yellow), Ireland (cyan), Italy (magenta), Netherlands (sky-blue), Portugal (brown), and Spain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

	Links	Density	Community Size	Ave. 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 5: 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 6: 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.

size as shown in Table 5 emphasize the above results. Given that the magnitude of shocks affecting financial institutions was 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 in the sovereign crisis and post-crisis period. The sovereign crisis also displays 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 6 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.

3.2.1. Germany

From the estimated networks over the sub-periods, Figure 6 and Tables 7 and 8 show the structure and summary of connections among the German institutions represented in our data. We observe from Figure 6 and Table 7 that the German institutions were much

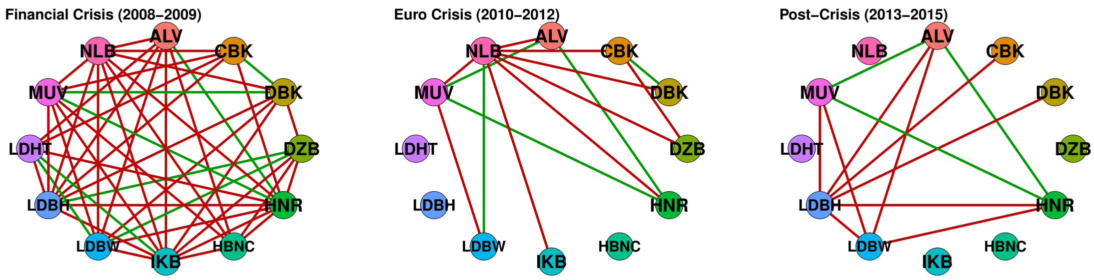

Figure 6: Germany: Within-Country Networks

	Links	Density	Community Size	Ave. 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 7: 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
Eigenvector	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 8: 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.

3.2.2. France

The networks among the French financial institutions over the sub-periods are depicted in Figure 7. Tables 9 and 10 show in more detail the results of the summary statistics of the inter-institution connectedness and the centrality measures, respectively. From the figure, we

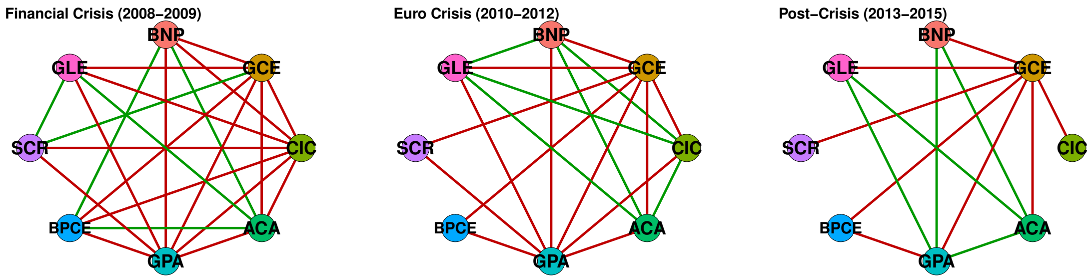

Figure 7: France: Within-Country Networks

	Links	Density	Community Size	Ave. 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 9: 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
Eigenvector	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 10: 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 in the sovereign crisis period (see Table 9). 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").

3.2.3. Italy

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

Table 11 shows that the ranking of the number of links, density and average path length follows 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 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

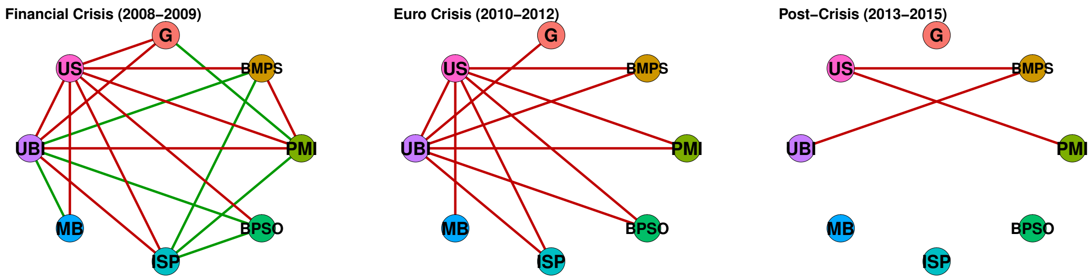

Figure 8: Italy: Within-Country Networks

	Links	Density	Community Size	Ave. 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 11: 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
Eigenvector	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 12: Italy: Institutions ranked by eigenvector centrality

times, is at the country level, rather than at the company level. The most central institutions according to Table 12 are UBI, PMI, BPSO: all large cooperative banks, as well as the troubled Monte dei Paschi di Siena (BMPS), recently nationalized.

3.2.4. Spain

We now turn our attention on Spain - the fourth largest economy in the EU. Figure 9 and Tables 13 and 14 show the network metrics among Spanish institutions. We notice that the dependence structure estimated for 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 there remains an institutional diversification, besides the country risk.

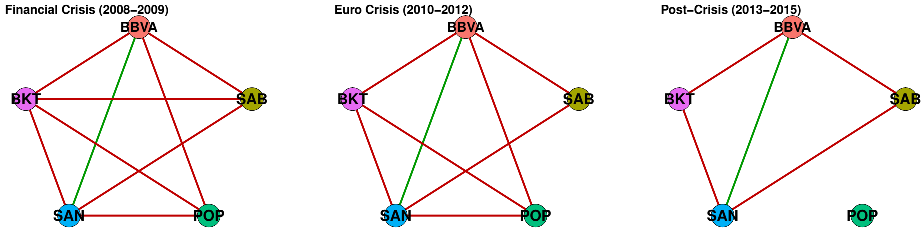

Figure 9: Spain: Within-Country Networks

Over the three sub-periods, the centrality indicates that the most Spanish institutions rotate around two large banks: Santander (SAN) and Banco Bilbao Vizcaya Argentaria (BBVA).

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

	Links	Density	Community Size	Ave. 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 13: 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
Eigenvector	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 14: Spain: Institutions ranked by eigenvector centrality

3.3. Yearly Inter-country Networks

We show in Figure 10, the yearly inter-country network between 2008–2015. The structures suggest that the effect of the financial and sovereign crisis among the EU countries peaked 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.

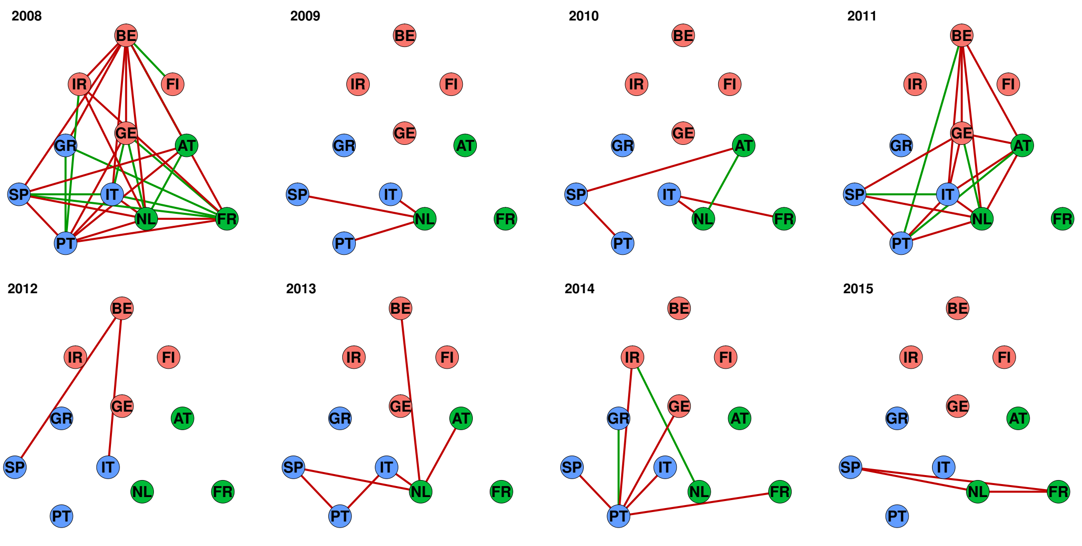

Figure 10: Yearly inter-country network graphs. The links indicate signs of the correlation coefficients, green indicate positive correlations and red for negative correlations.

Table 15 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 higher 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	Ave. 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 15: Summary statistics of inter-institution network over the sub-periods.

Criteria	Rank	2008	2009	2010	2011	2012	2013	2014	2015
	1	BE	NL	AT	IT	BE	NL	PT	FR
	2	FR	IT	IT	NL	IT	IT	IR	NL
Degree	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
	1	BE	NL	AT	IT	BE	NL	PT	AT
	2	PT	AT	NL	NL	AT	IT	IR	BE
Betweenness	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
	1	NL	NL	AT	IT	BE	NL	PT	NL
	2	FR	IT	NL	NL	SP	IT	IR	FR
Eigenvector	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 16: 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 16 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".

3.4. Yearly Inter-institutional Networks

The estimated yearly inter-institutional networks and summary statistics of the structure and centrality measures are presented in Figure 11 and Tables 17 and 18, 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 in the years after.

The centrality analysis of the yearly inter-institutional network as shown in Table 18 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.

As a robustness check of our study, we conduct an analysis to assess the sensitivity of the results when individual country's financial sector risk is proxied by sovereign CDS spreads (see Appendix B).

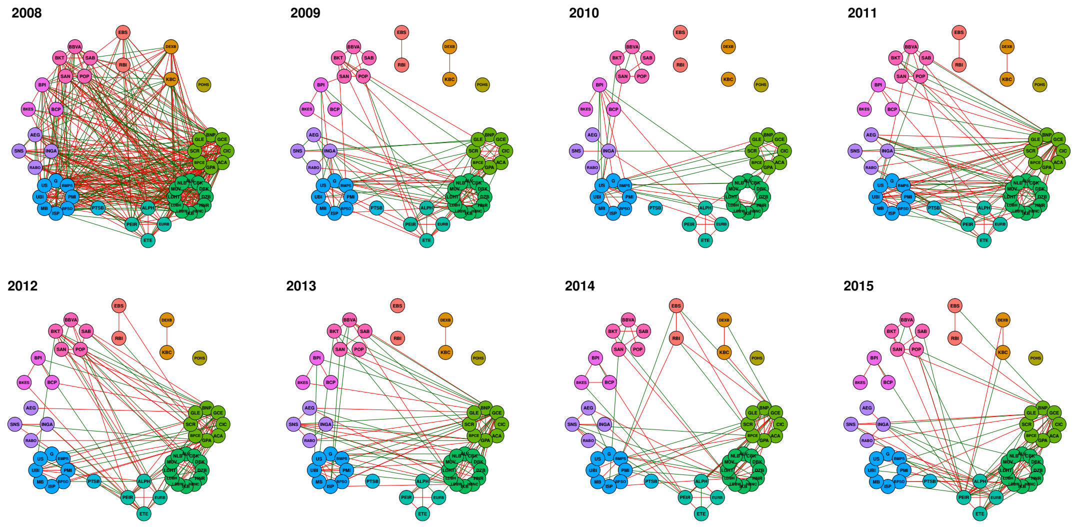

Figure 11: Yearly inter-institutional networks.

	Links	Density	Community Size	Ave. 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 17: Summary statistics of inter-institution network over the sub-periods.

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 18: Top five institutions ranked according to degree, betweenness and eigenvector centrality.

4. Applications to All Corporates

To further illustrate the effectiveness of the application of the tree network methodology, in this application we consider a sample of European corporates, from all sectors, and not only from the financial one, and we focus on the modelling of the inter-sectorial contagion, rather than on the inter-country one. This is in line with the assumption that, while the financial sector is highly regulated and, for this reason, presents a still high institutional difference between countries, the other sectors are more globalised so that we can assume the systematic component be embedded in a sector rather than in a country effect.

We focus on companies belonging to the Euro Stoxx 50 index. The corresponding daily CDS data are extracted from the Bloomberg database. We pre-process the data as follows: i) remove variables with more than 500 missing observations, ii) remove dates with more than half missing observations, and iii) replace missing observations with monthly averages of each series. The final dataset considered for our empirical analysis consists of 30 companies covering the period between 31 December 2004 to 19 December 2018.

We begin by first considering the connectivity over the full sample (2005-2018). We then partition the sample period into five sub-periods, to assess the interconnectedness among the companies and the sectors. The partition includes: 1) Pre-crisis period (2005 - 2007), 2) Financial crisis period (2008 - 2009), 3) Euro crisis period (2010 - 2012), 4) Post-crisis period (2013 - 2015), and 5) Most recent period (2016-2018).

No.	Name	Ticker	Sector	Abbv.
1	Vinci	VNC	Real Estate	RE
2	BBVA	BBV	Financial	FIN
3	Santander	BSH	Financial	FIN
4	Koninklijke Philips	KPN	Manufacturing	MFG
5	Telefonica	TLF	ICT	ICT
6	FP Total	FPT	Energy	NRG
7	AXA	AXA	Financial	FIN
8	BNP	BNP	Financial	FIN
9	Danone	DN	Manufacturing	MFG
10	Vivendi	VVU	Financial	FIN
11	Louis V	LV	Manufacturing	MFG
12	Kering	KRN	Trade	TRD
13	Koninklijke Ahold	AHD	Trade	TRD
14	Unilever	ULV	Trade	TRD
15	Iberdrola	IBD	Energy	NRG
16	ING	ING	Financial	FIN
17	Intesa	ISP	Financial	FIN
18	ENI	ENI	Energy	NRG
19	ENGI	ENG	Energy	NRG
20	Orange	FTE	ICT	ICT
21	Societe Generale	SGE	Financial	FIN
22	ENEL	ENL	Energy	NRG
23	Nokia	NOL	ICT	ICT
24	Allianz	ALZ	Financial	FIN
25	BMW	BMW	Manufacturing	MFG
26	SIEMENS	SMN	Manufacturing	MFG
27	Volkswagen	VW	Manufacturing	MFG
28	Munich RE	MRE	Financial	FIN
29	Deutsche Telekom	DT	ICT	ICT
30	Daimler	DCX	Manufacturing	MFG

Table 19: Description of Companies.

We report the time series plots of the CDS of the series over the sample period in Figure 12. The series are grouped in terms of sectors. The top left depict the series for Financial institutions, ICT institutions are on the top middle, Manufacturing companies on the top right, Energy companies on bottom left, Real Estates on bottom middle, and Trade companies on bottom right.

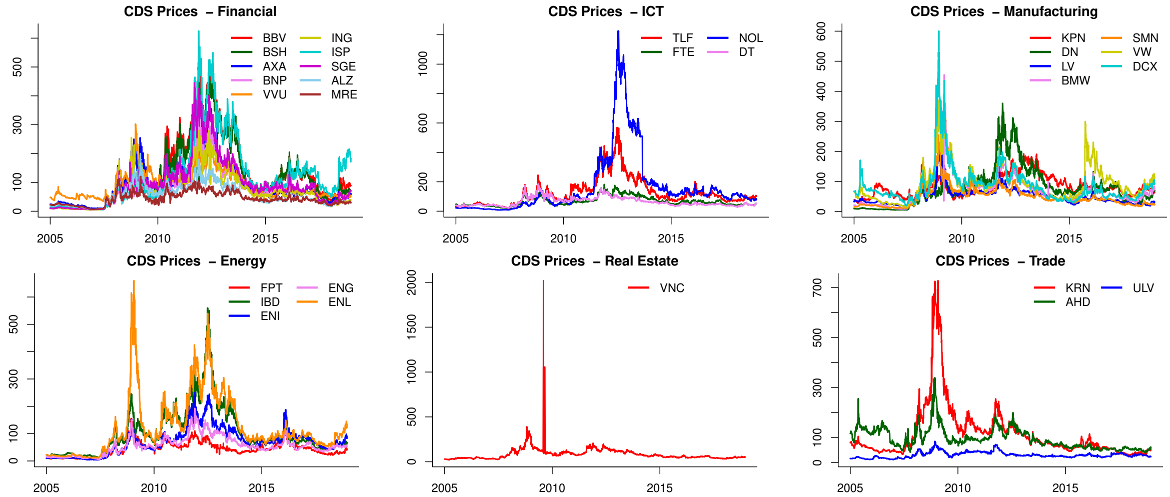

Figure 12: Time series of the CDS prices of companies, grouped by sectors

	Mean	Std.Dev	Min	Max	Skew	Kurt.
VNC	0.0160	9.0901	-243.9981	243.9981	-1.5653	527.5318
BBV	0.0623	5.3649	-43.3636	40.3746	0.0008	9.0640
BSH	0.0535	7.9581	-144.8170	132.4556	-0.7938	107.4124
KPN	0.0151	3.4182	-29.5845	28.4026	0.1232	10.9825
TLF	0.0339	4.3357	-38.3582	33.4293	-0.1053	10.5686
FPT	0.0430	6.9465	-150.7528	133.7949	-0.8382	113.1470
AXA	0.0242	5.2906	-37.1905	38.5363	0.1127	8.8941
BNP	0.0556	5.6912	-42.6743	47.7573	0.1573	9.0108
DN	0.0556	5.6912	-42.6743	47.7573	0.1573	9.0108
VVU	0.0019	3.5483	-44.2698	45.6303	0.3599	20.6901
LV	-0.0006	4.4128	-41.8424	40.7139	0.3303	17.7021
KRN	-0.0117	3.8021	-39.3653	33.2041	0.2955	14.3945
AHD	-0.0197	4.4363	-71.8168	72.0309	0.0591	73.8029
ULV	0.0111	4.2817	-34.0727	43.7622	1.0218	17.3766
IBD	0.0314	4.4392	-43.9815	43.9815	0.2657	13.0559
ING	0.0388	7.9199	-91.2283	90.5480	-0.3407	51.1723
ISP	0.0714	6.3912	-50.1976	52.8293	0.2903	12.4295
ENI	0.0628	5.0878	-53.6629	50.1684	0.4478	16.3808
ENG	0.0375	4.6659	-46.2949	45.8399	0.3912	18.7434
FTE	0.0040	3.5378	-29.2259	26.5108	0.2337	9.2723
SGE	0.0545	5.7967	-56.4314	58.2891	0.1153	14.0115
ENL	0.0500	4.7381	-46.6177	57.8851	0.3083	16.0391
NOL	0.0371	4.2641	-84.9031	33.5830	-1.9002	52.3938
ALZ	0.0101	6.1989	-93.4808	65.1474	-0.4407	26.5832
BMW	0.0365	7.3700	-231.6770	241.0799	1.3213	616.4756
SMN	0.0140	4.1359	-40.3081	38.7398	0.3635	12.3673
VW	0.0154	4.5624	-33.3144	58.7787	1.2195	19.9078
MRE	0.0078	6.9962	-68.2218	65.9995	0.4971	23.3466
DT	0.0087	3.9271	-35.9615	36.6734	0.2083	13.8593
DCX	0.0093	4.6595	-31.1646	46.3452	0.4895	11.6841

Table 20: Descriptive statistics of the daily log returns of companies in terms of mean, standard deviation, minimum, maximum, skewness, and kurtosis.

Descriptive statistics about the log returns of the series are reported in Table 20. On the average, the daily log returns of all the companies are not significantly different from zero. The statistics show that Vinci, Santander, FP Total, ING and BMW exhibit highly volatile returns with standard deviations greater than 7. The skewness statistics indicate that Vinci, Unilever, Nokia, BMW and Volkswagen are highly skewed, and the rest are approximately symmetric. The tail distribution shows high likelihood of extreme values for all the series, with Vinci and BMW reporting the highest excess kurtosis. Although the properties of skewness and kurtosis strongly indicate that the the daily log returns are non-normal, this does not affect the application since the assumption of multivariate normality is not generally required for factor analysis (see Tabachnick et al., 2007).

4.1. Inter-Sectorial Connectedness

Figure 13 reports the inter-sectorial networks, obtained from the application of the proposed model, for the six considered sub-periods. According to the results, the financial crisis period is the one showing the greatest network connectedness. After the financial crisis and even during the sovereign crisis, the network density is close to the pre-crisis level. This supports the idea that disruptive market dynamics during the 2008 - 2009 crisis period created inter-sector connections which are not significant in non-crisis times.

Looking at Figure 13 in more detail, the manufacturing sector turns out to be the most central and persistently linked to the ICT and financial sector over the sub-periods. In particular, out of the financial crisis period, manufacturing is the only sector with a direct connection to the financial one. It is interesting to note that the link between trade and manufacturing sector emerges during the crisis and post-crisis periods. This could be due to the decrease in private consumptions, which first affects trade corporates, then spreads its effect on the producers.

Table 21 reports the main statistics corresponding to the networks in Figure 13 and, in particular: the number of links, the density, the community size and the average path length of each network, as well as the most central sectors, according to degree, betweenness and eigenvector centrality, respectively. The table confirms the above findings, with manufacturing the most central sector, followed by the financial and the ICT sectors. During the financial crisis period, the manufacturing and the ICT sectors are equally central.

4.2. Inter-Company Connectedness

We now show the results obtained at the company level. Figure 14 reports the inter-company networks, obtained from the application of the proposed model, for the six considered sub-periods. Table 22 reports the main network statistics corresponding to the networks in Figure 14. The results of the figure and table show that, similar to what we found for the inter-sectorial layer, the financial crisis period recorded the highest interconnectedness, followed by the Euro-crisis. While in other periods connections are present mainly between companies belonging to the same sector, with contagion effects spreading through commercial and financial relationships, during crisis times connections across different sectors become relevant, due to the emergence of underlying common risk factors.

Looking at the average path length in Table 22, financial crisis was also the period in which risk propagated fastest. The calculated centrality measures also show that the most central companies are financial institutions, such as BNP, SGE, along with companies from the manufacturing sector, such as DN and NOL, and the energy company FP Total. During the financial crisis, most central companies are mainly financials.

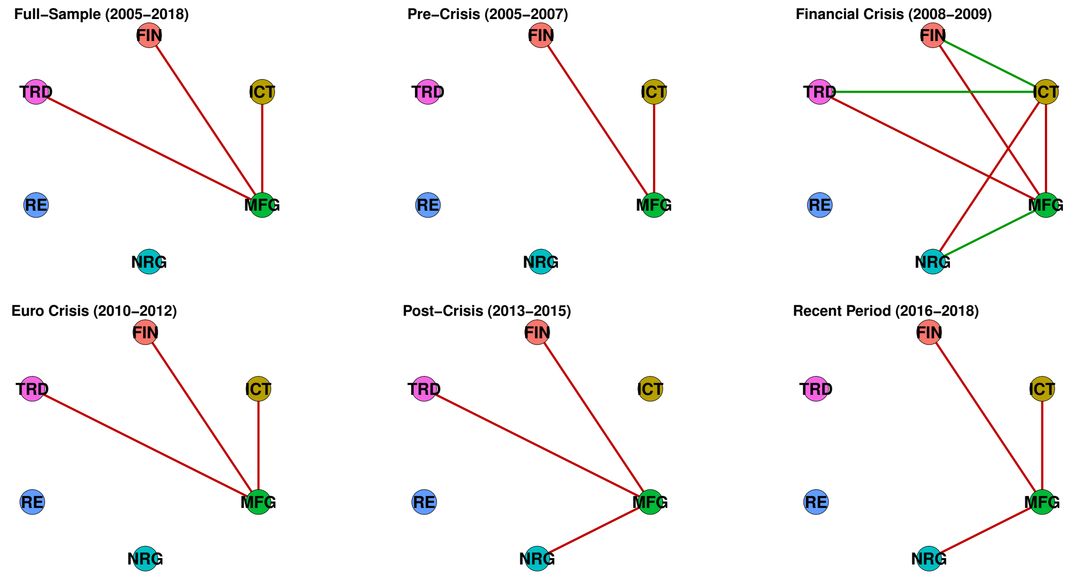

Figure 13: Inter-Sectorial Network across sub-periods. The red-color node represent the Financial sector, brown for ICT, green for Manufacturing, cyan for Energy, blue for Real Estate and pink for Trade.

	Full-Sample (2005-2018)	Pre-Crisis (2005 - 2007)	Fin.-Crisis (2008 - 2009)	Euro-Crisis (2010 - 2012)	Post-Crisis (2013 - 2015)	Recent (2016-2018)
Links	3	2	7	3	3	3
Density	0.20	0.13	0.47	0.20	0.20	0.20
Comm.Size	4	3	5	4	4	4
Ave.Path.L	1.50	1.33	1.30	1.50	1.50	1.50
Degree				:		
1	MFG	MFG	ICT	MFG	MFG	MFG
2	FIN	FIN	MFG	FIN	FIN	FIN
3	ICT	ICT	FIN	ICT	NRG	ICT
Betweenness				:		
1	MFG	MFG	ICT	MFG	MFG	MFG
2	FIN	FIN	MFG	FIN	FIN	FIN
3	ICT	ICT	FIN	ICT	ICT	ICT
Eigenvector				:		
1	MFG	MFG	ICT	MFG	MFG	MFG
2	ICT	FIN	MFG	FIN	NRG	ICT
3	TRD	ICT	FIN	TRD	FIN	NRG

Table 21: Summary statistics of inter-sectorial network over the sub-periods.

5. Conclusions

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

The results reveal a varying structure of interactions among countries and institutions over different time 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

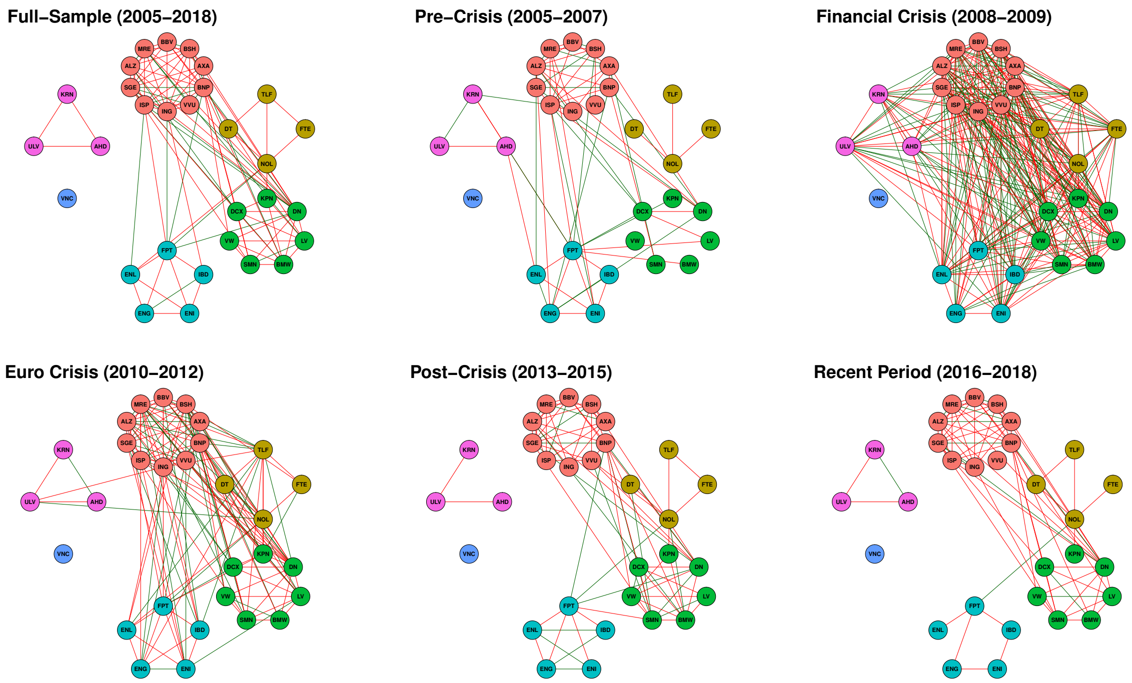

Figure 14: Inter-Company Network across sub-periods. The red-color nodes represent the Financial companies, brown for ICT, green for Manufacturing, cyan for Energy, blue for Real Estate and pink for Trade.

	Full-Sample (2005-2018)	Pre-Crisis (2005 - 2007)	Fin.-Crisis (2008 - 2009)	Euro-Crisis (2010 - 2012)	Post-Crisis (2013 - 2015)	Recent (2016-2018)
Links	103	68	314	148	81	76
Density	0.24	0.16	0.72	0.34	0.19	0.17
Comm.Size	9	11	15	12	9	10
Ave.Path.L	2.10	2.04	1.23	1.81	2.24	1.65
Degree						
1	BNP	FPT	ING	BSH	BNP	BNP
2	DN	ISP	BBV	MRE	DN	DN
3	SGE	ALZ	LV	BNP	SMN	SGE
Betweenness						
1	FPT	FPT	ING	ING	FPT	NOL
2	NOL	ISP	BBV	ULV	NOL	FPT
3	BNP	BSH	ENL	BSH	SMN	BNP
Eigenvector						
1	DN	ISP	ING	MRE	BNP	BNP
2	BNP	ALZ	BBV	DN	DN	DN
3	SGE	AXA	LV	BNP	SGE	SGE

Table 22: Summary statistics of inter-company network over the sub-periods.

find 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 application to all sectors reveals the manufacturing sector as the most central overall, while the financial sector becomes central during the financial crisis.

Further application of the work involves considering additional institutions and robustness checks on the model, particularly extending it to a multilayered context, when more data, besides market prices, are taken into account. From a methodological point of view, a first

possible extension of our model formulation includes global macroeconomic factors, interpolated at the daily level, rather than a factor decomposition of the country-level indicators. This specification would allow changes in macroeconomic and financial variables to affect individual firms' credit risk and shock propagation, thus making our model not only descriptive, but also predictive. Furthermore, the inclusion of exogenous variables would make possible to assess the contribution of single macroeconomic and financial factors to the contagion process. Second, the presented methodology could be extended in a Bayesian framework, following the work of Ahelegbey et al. (2016a), that allows to measure directed influences both within time and across time. Building a directed network would ease the interpretation of our results in terms of causality in the contagion mechanism.
Another relevant issue which is left to further research is the definition of a dynamic tree network specification. The dynamic extension can be pursued either by incorporating the serial correlated behaviour of asset returns or a time varying parameter model to investigate the dynamic dependencies among the global and local components.

Overall, our empirical findings show that country and sector effects play a significant role in the creations of vulnerable environments for financial risk propagation. It is therefore important to focus attention on how the interplay of national financial policy initiatives can help ensure and enhance the financial system function as a stable system. Spillovers between countries can be removed, for example, by fostering convergence between the different economies participating in some form of political cooperation (as the European Union). Common fiscal policies at the supranational level can induce such convergence, and the desired degree of harmonisation could be calibrated using the spillovers resulting from the application of a tree network model. On the other hand, spillovers between sectors could be reduced developing structural policies that avoid excessive dependence between them. For example, the dependence of the manufacturing sector on the financial one could be limited by encouraging forms of corporate funding less dependent on the banking system, such as peer to peer lending, equity crowdfunding and access to capital markets.

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Appendix A. Metrics for Network Analysis

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 our estimated network is an undirected network, there are $n(n-1)/2$ possible links.

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 have denser 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

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

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 neighbours 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: This 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:

$$B(i) = \sum_{j \neq i \neq k} \frac{d_{j,k}(i)}{d_{j,k}} \tag{A.2}$$

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

$$Gv = \lambda_1 v \tag{A.3}$$

where v is a vector containing the eigenvectors and λ_1 is the largest eigenvalue of G.

Appendix B. Supplementary: Application to Financial Corporates

This section presents the result of the sensitivity analysis when individual country's financial sector risk is proxied by sovereign CDS spreads.

Appendix B.1. Inter-Country Sector Network Analysis

We present in Figure B.15 the result of the inter-country network structures for the sub-sample analysis. Compared to Figure 4, we notice that there are more links in Figure B.15 than the former. This shows that the choice of proxy for the country-level financial sector risk can strongly affect the results. However, we must bear in mind that the sovereign CDS spreads measure the health of a country, rather than corporates, hence, the networks shown in Figure B.15 actually depicts the sovereign risk exposures rather than financial sector exposures among countries.

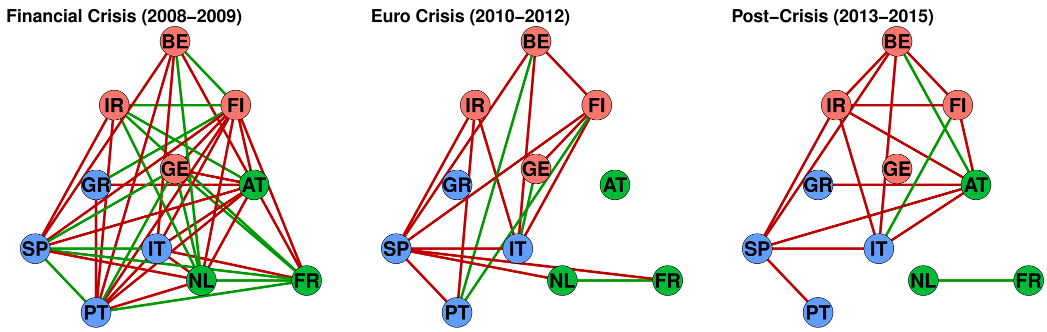

Figure B.15: Inter-country Network across sub-periods. The links indicate signs of the correlation coefficients, green indicate positive correlations and red for negative correlations. The nodes are countries categorized into southern Europe (in blue), western Europe (in green), and north-central Europe (in red).

	Links	Density	Community Size	Ave. Path Length
2008 - 2009	42	0.76	7	1.24
2010 - 2012	17	0.31	4	1.58
2013 - 2015	17	0.31	6	1.48

Table B.23: Summary statistics of the inter-country network over the sub-periods.

Table B.23 presents the network summary statistics of the sovereign risk exposures. The result partly confirm the findings in Table 3 in the sense that the financial crisis period recorded the highest density and number of communities with the shortest average path length for risk propagation. The Euro crisis and post-crisis periods, however, recorded the same density but different community size and average path length.

Appendix B.2. Inter-Institutional Network Analysis

Figure B.16 the result of the inter-institution network structures for the sub-sample analysis. Again we notice that the networks in the figure have more links than those in Figure 5. This can be seen clearly by looking at the network summary statistics in Table B.24. The results partly confirms our findings that the interconnectedness and vulnerability among the European financial institutions was higher in 2008-2009 than the subsequent periods.

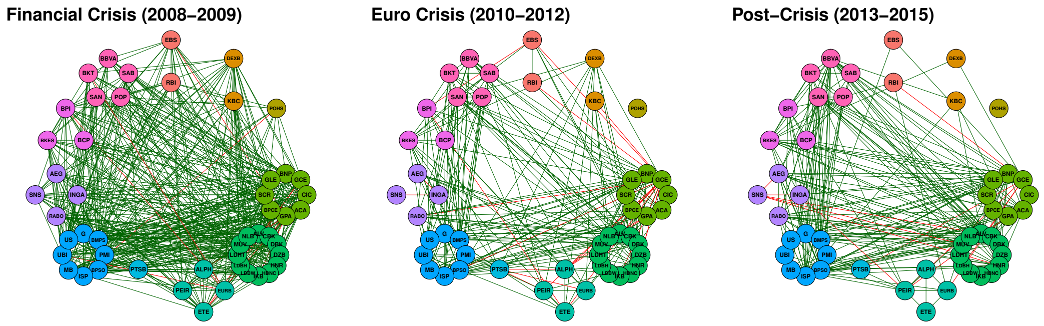

Figure B.16: Inter-institutional Network across sub-periods. The institutions are grouped according to country blocks: Austria (in red), Belgium (green), Finland (blue), France (violet), Germany (orange), Greece (yellow), Ireland (cyan), Italy (magenta), Netherlands (sky-blue), Portugal (brown), and Spain (coral).

	Links	Density	Community Size	Ave. Path Length
2008 - 2009	512	0.42	24	1.58
2010 - 2012	246	0.20	20	2.07
2013 - 2015	242	0.20	18	1.95

Table B.24: Summary statistics of inter-institution network over the sub-periods.