Sovereign, Bank and Insurance Credit Spreads:

Connectedness and System Networks*←

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Abstract

Macrofinancial risk has become increasingly important over time as global markets have become increasingly more connected. We apply several econometric measures of connectedness based on Granger-causality networks to the changes of sovereign risk of European countries and credit risk of major European, U.S., and Japanese banks, brokerages, and insurance companies to investigate the evolution of these connections. Sovereign and credit risk are measured using the Merton Model (Contingent Claims Analysis) applied to risk-adjusted balance sheets, which calculates the sensitivity of the enterprise's assets and liabilities to external "shocks." We highlight connections among countries and institutions to quantifying the effects of asset-liability mismatches within and across countries and financial institutions.

Keywords: Sovereign and Credit Risk; Financial Institutions; Liquidity; Financial Crises; Contingent Pricing

JEL Classification: G13 and G2

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1 Introduction

The risk of the banking and insurance system has become an important element in the determination of sovereign risk and vice-versa. We apply several econometric measures of connectedness based on Granger-causality networks to the changes of sovereign risk of European countries and credit risk of major European, U.S., and Japanese banks, brokerages, and insurance companies. Sovereign risk is measured using Credit Derivative Swaps (CDS) and credit risk is measured using the Merton Model (Contingent Claims Analysis) applied to risk-adjusted balance sheet, which captures the sensitivity of the enterprise's assets and liabilities to external "shocks."

The aim is to highlight connections (explicit and implicit, linear and non-linear) among countries and financial institutions and quantify the effects of asset-liability mismatches between countries and financial institutions.

The recent global financial crisis that began in 2007 reminds us about the importance of including complex interactions, spillovers, and feedback relationships between financial institutions and sovereigns in the analysis and modeling of financial crises and sovereign risk. We examine how vulnerabilities can build up and suddenly erupt in a financial crisis with potentially disastrous feedback effects for sovereign debt and economic growth. Traditional macroeconomic analysis overlooks the importance of financial system risk, which makes it ill-suited to examine interconnectedness and transmission mechanisms in response to common shocks. Using contingent claims analysis (CCA) and network theory, we propose new ways to measure and analyze financial system, sovereign, and credit risks.

So far, however, most policy efforts have not focused in a comprehensive way on assessing network externalities caused by the interconnectedness within financial institutions, financial markets, and sovereign countries and their effect on systemic risk. In this regard, the size, interconnectedness and complexity of individual financial institutions and its interrelationships with sovereign risk create vulnerabilities to systemic risk in the financial sector. There should be more emphasis on the use of system-wide stress-testing approaches to evaluate vulnerabilities and potential impact of "destructive-feedback loops."This paper aims to cover this void and addresses these issues that are important to practitioners, academics, and regulators.

The CCA analysis that delivers the "Fair Value CDS Spread" for banks and insurances is based on balance-sheet, equity, and bond markets data. For the sovereigns, the assets of the sovereign include foreign currency reserves, the net fiscal asset (defined as the present value of taxes and revenues, including seigniorage, minus the present value of government expenditures), and other public assets. The liabilities of the sovereigns include base money and risky local currency and financial guarantees/contingent liabilities.

This paper is related to the growing literature on sovereign risk and in particular to the following recent papers: Degryse, Elahi and Penas (2010), Longstaff, Pan, Pedersen, Singleton (2011), Acharya, Drechsler, and Schnabl (2011), and Kallestrup, Lando, and Murgoci (2012). It is also related to the literature which uses contingent claims analysis to investigate macrofinancial risk such as presented in Merton, Gray, Schweikhard, and Tsesmelidakis (2012). Finally, it is related to the network literature applied to financial markets and macroeconomics: Billio, Getmansky, Lo and Pelizzon (2012), Battiston, Delli Gatti, Gallegati, Greenwald and Stiglitz (2009), Acemoglu, Carvalho, Ozdaglar, Tahbaz-Salehi (2012), and Acemoglu, Ozdaglar, Tahbaz-Salehi (2013).

The key distinguishing features of our paper are: measurement of network of connections among sovereign risk and credit risk in financial and insurance institutions, large sample of entities, and the ability to map the system of connections among all these institutions and sovereigns.

The paper is organized as follows. In Section 2 we present the background that justifies the investigation of interconnections between sovereign risk and financial institutions. In Section 3 we present the Contingent Claims Analysis used to calculate ELR. In Section 4 we propose different network measures. Section 5 presents main results, and Section 6 concludes.

2 Background: Feedback Loops

Existing methods of measuring financial stability have been heavily criticized by Cihak (2007) and Segoviano and Goodhart (2009). These authors suggest that a good measure of systemic stability has to incorporate two fundamental components: (i) the probability of individual financial institution or country default and (ii) the probability and speed of possible shocks spreading throughout the industry and countries. First, with the CCA method we compute the probability of default for financial institutions and countries. Second, using Granger causality network measures we are able to identify the speed of shock propagations and, more importantly, we are able to assess network externalities, interconnectedness between financial institutions, financial markets, and sovereign countries.

The propagation and feedback-loops that we have in mind can be represented by the example reported in Figure (1).

INSERT Figure (1) here

Figure (1) represents a good example of how sovereign and credit risk are intimately related. Consider banks in different countries that often have credit interactions with each other. A particular bank becoming weak has an impact on other banks, and in fact, banks that do not even do business with the weakened bank may have their credit affected. However, it is common for banks in one country to hold the sovereign debt of another country. Figure 1 illustrates that if that foreign country's government debt declines in value, these banks become weaker because they are writing guarantees on that debt. More interesting, however, is the resulting interaction between the two sovereigns. The banks' home country is guaranteeing the banks, which means the decline in the foreign debt indirectly worsens the home country's position. Consequently, the decision to bail out a bank or sovereign affects not only the sovereign and its own banks but also other sovereigns and foreign banks in a significant way.

Moreover, as shown in Figure 1, the mark-to-market fall in the value of sovereign bonds held by banks reduces bank assets. This can increase bank-funding costs, and if the sovereign is distressed enough, the value of official support (guarantees) will be eroded. These have knock-on effects, as shown. An adverse feedback loop ties sovereigns' stresses to banking-sector challenges.

How do we go about measuring this feedback loop effect? We need to examine the impact of a change in credit risk on the interconnectedness and financial strength of different entities. The measure based on CCA and networks proposed in the next sections allow us to investigate and analyze financial system interactions and systemic risk.

2.1 Contingent Claims Analysis

Contingent claims analysis is a proven approach to analyze and manage private-sector risk. A contingent claim is any financial asset whose future payoff depends on the value of another asset. The prototypical contingent claim is an option – the right to buy or sell the underlying asset at a specified exercise price by a certain expiration date. A call is an option to buy; a put is an option to sell. Contingent claims analysis is a generalization of the option pricing theory pioneered by Black-Scholes (1973) and Merton (1973). Option pricing methodology has been applied to a wide variety of contingent claims. When applied to the analysis and measurement of credit risk, contingent claims analysis is commonly called the "Merton Model" (see Merton (1974, 1977, 1992, 1998)). It is based on three principles: (i) the values of liabilities are derived from assets; (ii) assets follow a stochastic process; and, (iii) liabilities have different priority (i.e. senior and junior claims). Equity can be modeled as an implicit call option and risk debt modeled as the default-free value of debt minus an implicit put option. The Merton Model was first adapted and applied commercially by KMV (now Moody's KMV) and is now firmly established as the theoretical basis for several applied models that are widely used in the investment industry to measure and evaluate credit risk for corporate firms and financial institutions. Gray, Merton, and Bodie (2007) adapt the Merton Model and apply it at the aggregate level to the sovereign balance sheet.

Moody's KMV uses equity, equity volatility, and default barrier (from accounting information) to get "distance-to-distress" which it maps to a default probability (EDF) using a pool of 30 years of default information. It then converts the EDF to a risk neutral default probability (using the market price of risk). Using the sector loss given default, we calculate the Expected Loss Ratio (ELR):

$$ELR = RNDP * LGD = \frac{ELV}{B * \exp -rt} \tag{1}$$

where RNDP is risk neutral default probability, LGD is loss given default, ELV is the implicit put option, and B is the value of the default barrier.

Sovereign ELR (S_ELR) can be calculated using sovereign CCA models where the spread is associated with the expected loss value and sovereign default barrier. However, given the limited information available and default ratio etc. for sovereign bonds we prefer to extract the ELR directly from CDS market values using the following formula:

$$S\_ELR = 1 - \exp\left(\left(-\frac{SovereignCDS}{10,000} * T\right)\right) \tag{2}$$

2.2 Measures of Connectedness

In this section we present several measures of connectedness that are designed to capture levels and changes in causality among financial institutions and sovereign countries. To identify connections we use pairwise linear Granger-causality tests to estimate the network of statistically significant relations among financial institutions and countries.

Linear Granger Causality

To investigate the dynamic propagation of shocks to the system, it is important to measure not only the degree of connectedness between financial institutions and sovereigns, but also the directionality of such relationships. To that end, we propose using Granger causality, a statistical notion of causality based on the relative forecast power of two time series. Time series j is said to "Granger-cause" time series i if past values of j contain information that helps predict i above and beyond the information contained in past values of i alone. The mathematical formulation of this test is based on linear regressions of R^i_{t+1} on R^i_t and R^j_t.

Specifically, let R^i_t and R^j_t be two stationary time series, and for simplicity assume they have zero mean. We can represent their linear inter-relationships with the following model:

$$\begin{aligned} R^i_{t+1} &= a^i R^i_t + b^{ij} R^j_t + e^i_{t+1} , \\ R^j_{t+1} &= a^j R^j_t + b^{ji} R^i_t + e^j_{t+1}, \end{aligned} \tag{3}$$

where e^i_{t+1} and e^j_{t+1} are two uncorrelated white noise processes, and a^i, a^j, b^{ij}, b^{ji} are coefficients of the model. Then, j Granger-causes i when b^{ij} is different from zero. Similarly, i Granger-causes j when b^{ji} is different from zero. When both of these statements are true, there is a feedback relationship between the time series.

We consider a Generalized AutoRegressive Conditional Heteroskedasticity (GARCH)(1,1) baseline model of changes in CDS:

$$\begin{aligned} R^i_t &= \mu_i + \sigma_{it}\epsilon^i_t \ , \ \ \epsilon^i_t \sim \mathrm{WN}(0,1) \\ \sigma^2_{it} &= \omega_i + \alpha_i \left(R^i_{t-1} - \mu_i\right)^2 + \beta_i \sigma^2_{it-1} \end{aligned} \tag{4}$$

conditional on the system information:

$$I^S_{t-1} = \mathfrak{S}\left(\left\{\left\{R^i_\tau\right\}_{\tau=-\infty}^{t-1}\right\}_{i=1}^{N}\right), \tag{5}$$

where μ_i, ω_i, α_i, and β_i are coefficients of the model, and $\mathfrak{S}(\cdot)$ represents the sigma algebra. Since our interest is in obtaining a measure of connectedness, we focus on the dynamic propagation of shocks from one entity to others, controlling for changes in CDS autocorrelation for that entity.

A rejection of a linear Granger-causality test as defined in (3) on $\widetilde{R}_t^i = \frac{R_t^i}{\widehat{\sigma}_{it}}$, where $\widehat{\sigma}_{it}$ is estimated with a GARCH(1,1) model to control for heteroskedasticity, is the simplest way to statistically identify the network of Granger-causal relations among entities, as it implies that changes in CDS spread of the i-th entity linearly depend on the past changes of the j-th entity's CDS spread:

$$\mathrm{E}\left[R_t^i \,\middle|\, I_{t-1}^S\right] = \mathrm{E}\left[R_t^i \,\middle|\, \left\{\left(R_\tau^i - \mu_i\right)^2\right\}_{\tau=-\infty}^{t-2}, R_{t-1}^i, R_{t-1}^j, \left\{\left(R_\tau^j - \mu_j\right)^2\right\}_{\tau=-\infty}^{t-2}\right] . \tag{6}$$

Now define the following indicator of causality:

$$(j \to i) = \begin{cases} 1 & \text{if } j \text{ Granger causes } i \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

and define $(j \to j) \equiv 0$. These indicator functions may be used to define the connections of the network of N entities, from which we can then construct the following network-based measures of connectedness.

(i) Degree of Granger causality. Denote by the *degree of Granger causality* (DGC) the fraction of statistically significant Granger-causality relationships among all $N(N-1)$ pairs of N entities:

$$\mathrm{DGC} \equiv \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} (j \to i) . \tag{8}$$

The risk of a systemic event is high when DGC exceeds a threshold K which is well above normal sampling variation as determined by our Monte Carlo simulation procedure.

(ii) Number of connections. To assess the systemic importance of single entities, we define the following simple counting measures, where S represents the system:

$$\begin{array}{llcl} \#Out: & (j \to S)|_{\mathrm{DGC} \geq K} & = & \frac{1}{N-1} \sum_{i \neq j} (j \to i)|_{\mathrm{DGC} \geq K} \\ \#In: & (S \to j)|_{\mathrm{DGC} \geq K} & = & \frac{1}{N-1} \sum_{i \neq j} (i \to j)|_{\mathrm{DGC} \geq K} \\ \#In+Out: & (j \longleftrightarrow S)|_{\mathrm{DGC} \geq K} & = & \frac{1}{2(N-1)} \sum_{i \neq j} (i \to j) + (j \to i)|_{\mathrm{DGC} \geq K} . \end{array} \tag{9}$$

#Out measures the number of entities that are significantly Granger-caused by entity j, *#In* measures the number of entities that significantly Granger-cause entity j, and *#In+Out* is the sum of these two measures.

(iii) Sector-conditional connections. Sector-conditional connections are similar to (9), but they condition on the type of entity. Given M types (that could be: sovereigns, banks, broker dealers, and insurance companies), indexed by $\alpha, \beta = 1, \ldots, M$, we have the following three measures:

$$\#Out - to - Other: \quad \left.\left((j|\alpha) \rightarrow \sum_{\beta \neq \alpha} (S|\beta)\right)\right|_{\text{DGC} \geq K} = \frac{1}{(M-1)N/M} \sum_{\beta \neq \alpha} \sum_{i \neq j} \left.\left((j|\alpha) \rightarrow (i|\beta)\right)\right|_{\text{DGC} \geq K} \tag{10}$$

$$\#In - from - Other: \quad \left.\left(\sum_{\beta \neq \alpha} (S|\beta) \rightarrow (j|\alpha)\right)\right|_{\text{DGC} \geq K} = \frac{1}{(M-1)N/M} \sum_{\beta \neq \alpha} \sum_{i \neq j} \left.\left((i|\beta) \rightarrow (j|\alpha)\right)\right|_{\text{DGC} \geq K} \tag{11}$$

$$\#In + Out - Other: \quad \left.\left((j|\alpha) \longleftrightarrow \sum_{\beta \neq \alpha} (S|\beta)\right)\right|_{\text{DGC} \geq K} = \frac{\sum_{\beta \neq \alpha} \sum_{i \neq j} \left.\left(\left((i|\beta) \rightarrow (j|\alpha)\right) + \left((j|\alpha) \rightarrow (i|\beta)\right)\right)\right|_{\text{DGC} \geq K}}{2(M-1)N/M} \tag{12}$$

where *#Out-to-Other* is the number of other types of entities that are significantly Granger-caused by entity j, *#In-from-Other* is the number of other types of entities that significantly Granger-cause entity j, and *#In+Out-Other* is the sum of the two.

(iv) Closeness. *Closeness* measures the shortest path between an entity and all other entities reachable from it, averaged across all other entities. To construct this measure, we first define j as weakly causally C-connected to i if there exists a causality path of length C between i and j, i.e., there exists a sequence of nodes $k_1, \ldots, k_{C-1}$ such that:

$$(j \rightarrow k_1) \times (k_1 \rightarrow k_2) \cdots \times (k_{C-1} \rightarrow i) \quad \equiv \leftarrow (j \xrightarrow{C} i) \quad = \quad 1 \,.$$

Denote by C_{ji} the length of the shortest C-connection between j to i:

$$C_{ji} \quad \equiv \leftarrow \min_{C} \left\{ \left(C \in [1, N-1] : (j \xrightarrow{C} i) = 1 \right\}, \left(\right. \right. \tag{13}$$

where we set $C_{ji} = N-1$ if $(j \xrightarrow{C} i) = 0$ for all $C \in [1, N-1]$. The closeness measure for entity j is then defined as:

$$C_{jS}|_{\mathrm{DGC} \geq K} = \frac{1}{N-1} \sum_{i \neq j} C_{ji} (j \xrightarrow{C} i) \Big|_{\mathrm{DGC} \geq K} .$$

(v) Eigenvector centrality. The *eigenvector centrality* measures the importance of an entity in a network by assigning relative scores to entities based on how connected they are to the rest of the network. First, define the adjacency matrix A as the matrix with elements:

$$[A]_{ji} \quad = \quad (j \rightarrow i) \ . \tag{14}$$

The eigenvector centrality measure is the eigenvector v of the adjacency matrix associated with eigenvalue 1, i.e., in matrix form:

$$Av = v \ .$$

Equivalently, the eigenvector centrality of j can be written as the sum of the eigenvector centralities of institutions caused by j:

$$v_j|_{\mathrm{DGC} \geq K} = \sum_{i=1}^{N} [A]_{ji} \, v_i|_{\mathrm{DGC} \geq K} \ .$$

If the adjacency matrix has non-negative entries, a unique solution is guaranteed to exist by the Perron-Frobenius theorem.

Network measures described above applied to the "Fair Value CDS" spreads allow us to capture changes in correlation and causality between financial institutions and sovereign countries. Billio, Getmansky, Lo, and Pelizzon (2012) use PCA and linear and non-linear

Granger-causality tests to estimate connectedness measures for banks, insurance companies, hedge funds, and brokers using asset returns. Using contingent claims analysis (CCA) and network theory we propose new ways to measure and analyze the system of connections among sovereigns and credit risks of individual financial institutions.

The new approach that we propose will allow practitioners and policy makers to focus in a comprehensive way on assessing network externalities caused by the interconnectedness between financial institutions, financial markets, and sovereign countries and their effect on systemic risk. Our approach allows us to highlight the size, interconnectedness, and complexity of individual financial institutions and their inter-relationships with sovereign risk, and to access whether this creates vulnerabilities to the system. We also aim to emphasize the importance of the use of system-wide stress-testing approaches to evaluate vulnerabilities and potential impact of "destructive-feedback loops". The issues systemic risk and financial stability are very important to practitioners, academics, and regulators.

3 Data

The pricing data for the sovereign credit default swaps used in this study are obtained from Bloomberg which collects CDS market quotation data from industry sources. We consider the 5-years dollar denominated CDS of European countries, U.S. and Japan. We use 5-year CDS because they are the most liquid. We consider 17 Sovereigns: 10 EMU (Austria, Belgium, Germany, Spain, France, Greece, Ireland, Italy, Netherland, Portugal), 4 EU (Denmark, Sweeden, UK, Norway), Switzerland (CH), U.S. and Japan (JA).

Moody's KMV provided us the ELR for 63 Banks (34 EMU, 11 EU, 2 CH, 12 US, 4 JA) and 39 Insurance Companies (9 EMU, 6 EU, 16 US, 2 CH and 5 CA). The data sample ranges from January 2001 till March 2012.

INSERT Table (1) HERE

Table 1 shows that on average expected losses of sovereigns are lower than those of insurances and banks, however, for most of the peripheral European countries this is not the case. For the sample considered, the variability of the expected losses is quite large and the distribution, as expected is not normal.

We have also investigated correlations between countries and different financial institutions for four different time periods: (July 2004–June 2007 is a period before the global financial crisis), (September 2005–August 2008 encompasses the global financial crisis), (January 2009–December 2011 and April 2009–March 2012 capture the period of the European sovereign crisis). Results are reported in Table 2.

INSERT Table (2) HERE

As Table 2 shows, correlations between banks, insurances, and sovereigns have on average increased a lot from the pre-crisis sample (July 2004–June 2007). It is interesting that during the European Sovereign crisis (period of April 2009–March 2012), the correlation of sovereigns with banks and insurance companies, as well as average correlation between sovereigns is lower compared to the global financial crisis in the period of September 2005–August 2008. This aspect will be investigated more deeply by looking at correlations and relationships between peripheral European countries and the network representation of the system of sovereigns and financial entities.

4 Results

We further calculate network measures developed in Section 2.2. In Table 3 we tabulate the percentage of causal connections between banks, sovereigns, and insurance companies that are significant at 1% for the same time periods as considered in Table 2: (July 2004–June 2007 is a period before the global financial crisis), (September 2005–August 2008 encompasses the global financial crisis), (January 2009–December 2011 and April 2009–March 2012 capture the period of the European sovereign crisis).

INSERT Table (3) HERE

Table 3 shows that the interconnections are not symmetric. Sovereigns on average affect banks, insurance companies, and other sovereigns more than banks and insurance companies affect sovereigns. Specifically given sovereigns experience high expected loss ratio, they are more likely to affect other sovereigns, banks, and insurance companies' expected loss ratio compared to being affected by these entities. This relationship is consistent across different time periods used (Table 3). Moreover, banks are playing a relevant role in affecting other entities mostly during the global financial crisis of 2007–2008, but their role is largely reduced after this period. During the global financial crisis, sovereigns largely Granger cause banks (23.39%), insurance companies (39.21%), with other sovereigns having the largest effect

(45.71%). Even though the percentage of significant connections continued to be large during the European Sovereign crisis, the magnitude changed, now with sovereigns being affected the least by other sovereigns (10.29%), and banks (30.67%) and insurance companies (20.59%) being largely affected by sovereigns. However, not all sovereign behaves in the same way and a more holistic view need to be performed.

Figure 2 illustrates the connectedness between sovereigns, banks, and insurance companies prior to the global financial crisis of 2008–2009 Crisis, July 2004–June 2007. Using Expected Loss Ratio (ELR) of sovereigns, banks, and insurance companies this figures provides a network diagram of linear Granger-causality relationships that are statistically significant at the 1% level. We suggest to the reader to focus on the density of the mass and the colors of the lines in Figure 1, not the detailed print. Banks are depicted in red, insurance companies are in blue, and sovereigns are in black. The density of the lines represents all the connections; thicker lines represent more significant connections among entities. As Figure 2 shows, there are some connections but they are quite sparse and rare.

INSERT Figure (2) HERE

INSERT Figure (3) HERE

Figure 3 illustrates the connectedness of the same set of banks, insurance companies, and sovereigns just after the most intense period of the crisis, April 2009–March 2012. Figure 4 reveals much greater density—connectedness—everywhere. Note that this illustration is not a reflection of how much business or transactions the entities do with each other; rather, it shows connectedness related solely to their impact on the credit of one another. Second, banks (red lines) and sovereigns (black lines) are more noticeable and have a greater reach across the globe than in Figure 1. In short, the post-2008–2009 Crisis environment has a much greater intensity of connectedness in terms of credit sensitivities than beforehand. This is not per se a negative aspect, however it is indicating that ELR and therefore implicitly the probability of defaults of the entities included in our analysis are more connected. Is it indicating the system is more vulnerable? Potentially yes, because it is more connected and therefore could be more fragile. For sure this indicates that these entities are much more connected.

The extent to which sovereign risk is linked to banks and insurances varies through time and across countries. Figure 4 reports the percentage of significant connections at the 1% levels that the Grager causality analysis has highlighted (over a total of 1734 potential connections from sovereign to the financial institutions and the same number from financial institutions to sovereign). In the first part of the sample connections are largely from financial institutions like banks and insurances to sovereigns and in the second part, i.e. form 2009 sovereign stated to play a significant role and the number of connections for sovereign to financial institutions are larger than vice versa. This suggests that risks embedded in Sovereign cannot be readily isolated from the risk of the financial system and that a holistic approach to both sectors is required.

INSERT Figure (4) HERE

We concentrate our analysis on GIIPS countries, i.e. Greece, Ireland, Italy, Portugal and Spain, considered the most problematic countries in the Euro area. Figure 5 reports the measure of eigenvector centrality of these five countries. We could observe that these countries shows a level of eigenvector centrality largely larger of the average of this measure for the 119 entities we considered well before the recent period well recognized as the Euro crisis period starting in 2010. Figure 5 shows also that there has been an attempt to isolate these potential effects of the crises of these countries on the other entities considered but in the initial months of 2012 (before the Greece default) these different countries do started to become largely connected with the other entities considered in our sample.

INSERT Figure (5) HERE

To show the net effect of GIIPS countries we calculate the difference among the number of significant connections from and to these countries. Figure 6 reports this dynamic and shows that in the initial part of the sample considered they are largely receiving risk, so they are affected by the risk of the increase of ELR of the other entities in the sample. In the second part of the sample we have that their ELR is inducing an increase of the ELR of the other entities rather than vice versa.

INSERT Figure (6) HERE

To provide an idea of the level of connections among the different entities, in Figure 7, we represent the network as it appears before the financial crisis of 2007-2009. A first observation is that the three different entities: sovereign (Black), insurances (Blue) are highly interrelated with their own categories. The pictures changes largely already at the beginning of the financial crisis, already in August 2008 (and also before) banks and insurances become to be largely connected among each others and sovereign becomes largely connected and more central than before as Figure 8 shows. This indicates that sovereign risk shows up well before the European Sovereign crisis of 2010-2012 if ELR measures are used. In particular, Figure 8 illustrates the connectedness of Greece in August 2008. Again, these are all the connections with other sovereigns, with insurance companies, and with banks. Clearly, Greece was fairly connected and the other European peripheral countries started to be central.

INSERT Figure (7) HERE

INSERT Figure (8) HERE

INSERT Figure (9) HERE

INSERT Figure (10) HERE

The centrality of the other problematic European countries like Spain and Italy appears to be relevant in 2011. Figure 9 shows the relevant role of Spain as source of risk for the other Sovereign ELR as well as for banks and insurances. Figure 10 shows the centrality of Italy at the time when Greece defaults. Note that the data reveal that in March 2012, the United States had very little connectedness with any of the banks or sovereigns in Europe. So, although the United States is a major player in the financial system, it had very little connectedness, either influencing or being influenced by the credit risk changes in institutions or other sovereigns. In contrast, Italy at that time was highly connected. How does the degree of connectedness between the different types of entities vary over time? Our data suggest that it varies quite substantially over time for the three different network connections (i.e., banks to sovereigns, sovereigns to banks, and sovereigns to sovereigns). As in our earlier demonstration of the nonlinear nature of the risk exposures of credit, these dynamic changes in risk exposures would be expected in response to changing asset values and volatilities, either up or down.

Certainly, one should be cautious in taking these measures of connectedness as actual paths of causality among sovereigns and institutions on which revised investment decisions or corrective policy might be considered. Instead these maps of connectedness should be viewed as raising questions about what is going in the system which might not otherwise be transparent. Subsequent investigation using other information sources and models would then inform what, if any, steps should be taken.

4.0.1 Out-of-Sample Analysis

Our analysis shows that network measures are relevant and provide a different perspective with respect to classical measures of co-movement like correlation and it seems that they may have a certain predictive power. In order to investigate this issue we have calculated the Cumulated Expected Loss as the sum of the EL of entity i and all the expected losses of the institutions that are Granger-caused at time t by entity i, more formally:

$$Cumulated\ Exp.\ Loss_{t+1} \equiv Expected\ Loss_{i,t+1} + \sum_{j=1}^{N} Expected\ losses\ _{i \to j,t+1} \qquad (15)$$

These cumulated losses represents the losses each entity at a certain time could generate considering also its externalities. We have used this value as dependent value and investigate if the level of these cumulated losses is related to the role the entity i where playing one year before in the system network. We have selected the period just before Greece default as the one that well represents a critical time and considered the network measures of the different entities one year before. The results are reported in table 4.

INSERT Table (4) HERE

As Table 4 shows, all the different network measures are largely significant and are able to well explain cumulative losses in the future. Based on the Closeness and Eigenvector centrality measures, entities that are highly connected are the ones that suffered the most later on and are connected with entities that shows large ELR too.

5 Conclusions

This paper proposes a new comprehensive approach to measure, analyze, and manage sovereign and credit risk based on the theory and practice of modern contingent claims analysis (CCA).

Our analysis shows that the system of banks, insurance companies, and countries in our sample is highly dynamically connected, sovereign risk seems became relevant well before the

European Sovereign crisis of 2010–2012 and that network measures allow for early warnings and assessment of the system complexity.

This framework can be used for the analysis of shocks, spillovers, and tradeoffs among policy alternatives. We leave to further researches the investigation of the connections that should be reduced so that the system would be less vulnerable.

6 References

Acemoglu D., V. M. Carvalho, A. Ozdaglar, A. Tahbaz-Salehi (2012), "The Network Origins of Aggregate Fluctuations", Econometrica, 80(5), pp. 1977-2016.

Acemoglu D., A. Ozdaglar, A. Tahbaz-Salehi (2013), Systemic Risk and Stability in Financial Networks, MIT WP

Acharya, V., I. Drechsler, and P. Schnabl, 2011, "A Pyrrhic Victory? Bank Bailouts and Sovereign Credit Risk." NBER Working Paper No. 17136 .

Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B. C., Stiglitz, J.E., 2009. Liasons dangereuses: increasing connectivity, risk sharing, and systemic risk. Unpublished working paper. NBER Working Paper No. 15611.

Billio, M., Getmansky, M., Lo, A.W., and L. Pelizzon, 2012, "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors," *Journal of Financial Economics* 104, 535–559.

Black, F. and M. Scholes, 1973, "The Pricing of Options and Corporate Liabilities," *Journal of Political Economy* 81, May-June, 637–654.

Degryse, H., M. A. Elahi, and M. F. Penas, 2010, "Cross-Border Exposures and Financial Contagion," *International Review of Finance* 10, 2, 209–240.

Gray, D. F., Merton R. C. and Z. Bodie, 2007, "Contingent Claims Approach to Measuring and Managing Sovereign Credit Risk," *Journal of Investment Management* 5, 4, 5–28.

Kallestrup R., D. Lando, and A. Murgoci, 2012, "Financial sector linkages and the dynamics of sovereign and bank credit spreads," Copenhagen WP.

Longstaff, F., J. Pan, L. H. Pedersen, and K. Singleton, 2011, "How Sovereign is Sovereign Credit Risk?" *American Economic Journal: Macroeconomics* 3, 2, 75–103.

KMV Corporation, 1999, "Modeling Default Risk," Moody's KMV.

Merton, R.C., 1973, "Theory of Rational Option Pricing," *Bell Journal of Economics and Management Science* 4, Spring, 141–183.

Merton, R.C., 1974, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," *Journal of Finance* 29, 449–470.

Merton, R.C., 1992, *Continuous-Time Finance.* Oxford, U.K.: Basil Blackwell, (Rev.ed.).

Merton, R.C., 1998, "Applications of Option-Pricing Theory: Twenty-Five Years Later," *American Economic Review* June, 323–349.

Muirhead, R. J., 1982. *Aspects of Multivariate Statistical Theory.* John Wiley & Sons, New York.

Schweikhard, F. A. and Z. Tsesmelidakis, The Impact of Government Interventions on CDS and Equity Markets, 2012 (2010), University of Oxford, the Oxford-Man Institute and Saïd Business School.

Summary statistics

	N Obs	Mean bp	Std	Min	Median	Max	Skewness	Kurtosis
EL_SOV_AT	132	182.62	261.81	7.70	26.91	1122.81	1.49	4.30
EL_SOV_BE	136	226.04	356.81	10.00	28.71	1434.35	1.79	5.14
EL_SOV_CH	59	188.00	171.82	7.20	196.25	813.27	1.39	6.04
EL_SOV_DE	118	106.04	130.73	6.70	31.72	541.82	1.45	4.23
EL_SOV_DK	114	133.83	183.91	6.15	22.80	702.04	1.60	4.45
EL_SOV_ES	135	349.52	547.28	11.74	32.85	2095.28	1.63	4.40
EL_SOV_FR	121	165.99	246.30	7.60	31.75	1016.45	1.85	5.60
EL_SOV_GR	136	1294.16	2568.20	23.62	78.66	9999.91	2.35	7.56
EL_SOV_IE	112	712.40	1056.58	8.85	31.33	3459.26	1.35	3.34
EL_SOV_IT	136	348.88	527.92	23.12	52.61	2151.52	1.97	6.17
EL_SOV_JP	136	163.33	173.24	13.19	87.54	703.67	1.29	3.69
EL_SOV_NL	106	133.93	165.75	5.65	28.01	586.64	1.32	3.66
EL_SOV_NO	103	65.92	69.56	6.40	25.02	272.13	1.07	3.11
EL_SOV_PT	123	703.88	1292.34	19.78	45.10	5582.61	2.10	6.29
EL_SOV_SE	132	98.86	135.71	6.55	26.96	676.90	1.86	6.46
EL_SOV_UK	74	229.75	188.70	6.25	278.11	700.74	0.19	1.92
EL_SOV_US	101	101.03	108.58	4.50	31.70	450.77	0.70	2.36
Sovereigns		306.13	481.48	10.29	62.12	1900.60	1.49	4.63
Insurances		593.51	633.02	46.93	312.13	2638.62	1.70	6.48
Banks		756.52	721.87	50.96	501.50	3350.55	1.61	6.08

Table 1 – This table reports the summary statistics for the Expected Loss Ratio (in bp) of the government debt of different countries and average Expected Loss Ratio statistics for banks and insurance entities. The countries considered are: Austria (AT), Belgium (BE), Germany (DE), Denmark (DK), Spain (ES), France (FR), Greece (GR), Ireland (IE), Italy (IT), Japan (JA), Netherland (NL), Norway, NO), Portugal (PT), Sweeden (SE), Switzerland (CH), United Kingldom (UK) and United States (US).

Correlations

	BAN	SOV	INS
	Jul04-Jun07		
BAN	0.331	0.141	0.289
SOV	0.141	0.518	0.466
INS	0.289	0.466	0.598
	Sep05-Aug08		
BAN	0.918	0.876	0.803
SOV	0.876	0.967	0.816
INS	0.803	0.816	0.785
	Jan09-Dec11		
BAN	0.544	0.378	0.401
SOV	0.378	0.607	0.287
INS	0.401	0.287	0.387
	Apr09-Mar12		
BAN	0.469	0.345	0.308
SOV	0.345	0.676	0.259
INS	0.308	0.259	0.318

Table 2 – This table shows the correlations among Banks (BAN), Sovereigns (SOV), and Insurances (INS) for different sample periods considered. In the primary diagonal, the average correlation among different entities of the same type is reported. In the off-diagonal, the average correlation between the different entities is reported.

Connections

FROM	TO		
	BAN	SOV	INS
Jul04-Jun07			
BAN	5.54%	0.80%	2.13%
SOV	5.17%	9.05%	4.92%
INS	7.76%	6.19%	5.05%
Sep05-Aug08			
BAN	19.86%	8.65%	19.67%
SOV	23.39%	45.71%	39.21%
INS	8.27%	4.44%	14.92%
Jan09-Dec11			
BAN	15.91%	4.10%	11.65%
SOV	30.67%	10.29%	20.59%
INS	14.15%	2.79%	11.79%
Apr09-Mar12			
BAN	13.93%	4.94%	7.46%
SOV	15.34%	8.09%	13.09%
INS	11.79%	1.47%	7.88%

Table 3 – This table shows the percentage of connections that are significant at 1% levels between banks (BAN), insurance companies (INS), and sovereigns (SOV).

Out-of-Sample Analysis

Cumulated Expected Loss Feb 12			
	Coeff	t-stat	
Constant	**7.2**	11.8	
# of in connections	**62.0**	3.5	
# of out connections	**22.8**	3.1	
Closeness	**-1.1**	-7.0	
Eigenvector Centrality	**-108.5**	-4.4	
		R-square	**0.42**

Table 4 - Parameter estimates of a multivariate regression of Expected Loss one step ahead for each entity in February 2012 on Granger-causality-network measures estimated one year before for each entity. Parameter estimates that are significant at the 5% level are shown in bold.

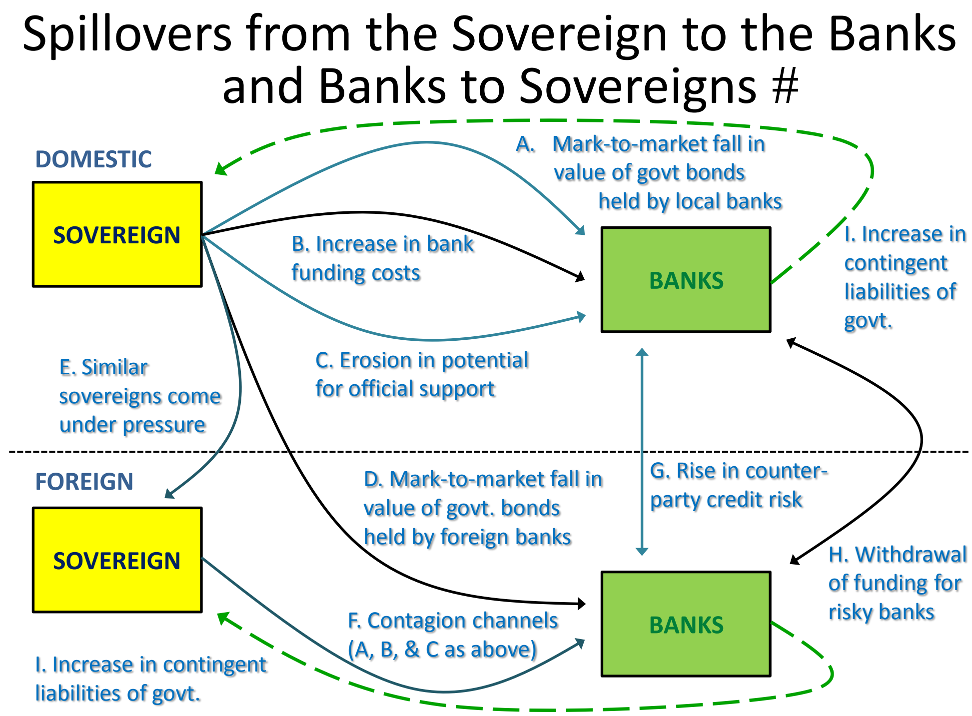

Figure 1 – This figure shows the potential channels of spillovers from Sovereign risk to banks' risk and vice versa.

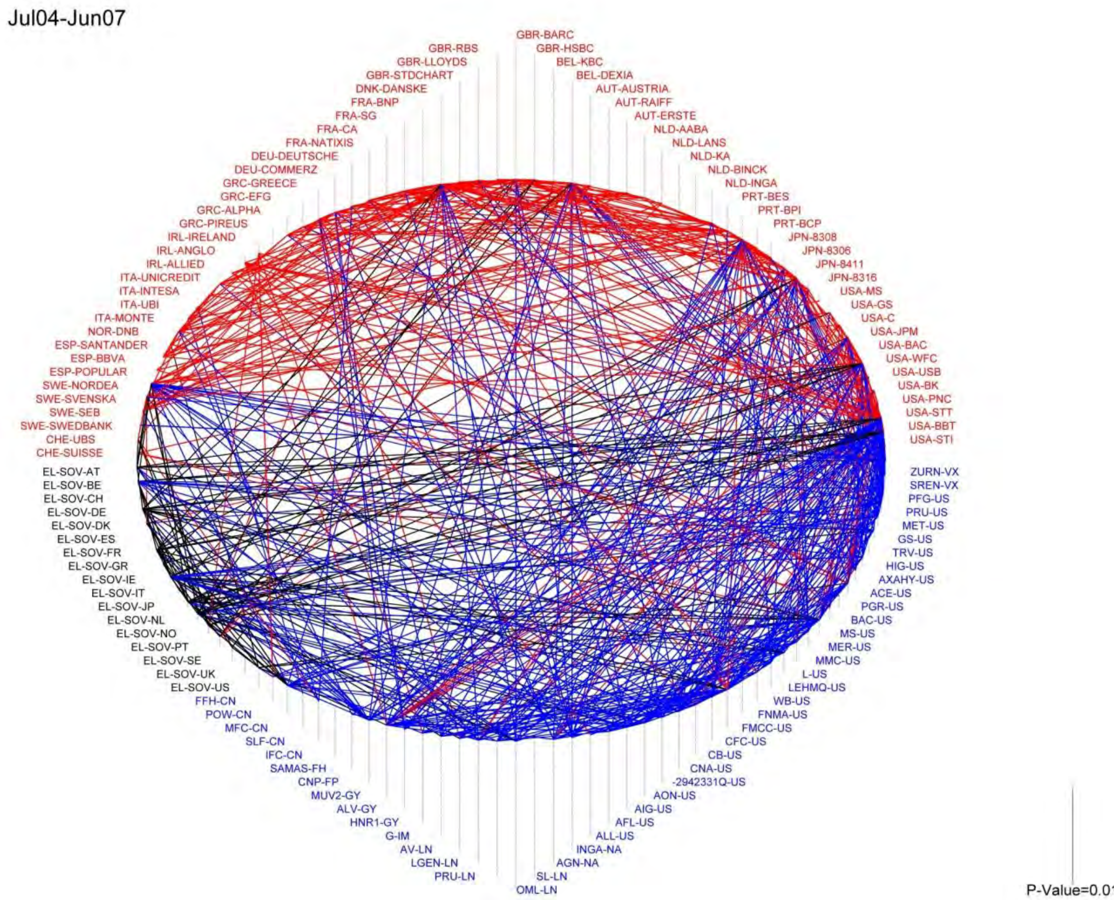

Figure 2 - Network diagram of linear Granger-causality relationships that are statistically significant at the 1% level among the monthly changes of the expected losses of the different entities (Banks, Insurances, and Sovereigns) over July 2004 to June 2007. The type of entities causing the relationship is indicated by color: red for banks, black for insurers, and blue for Sovereigns. Granger-causality relationships are estimated including autoregressive terms and filtering out heteroskedasticity with a GARCH(1,1) model.

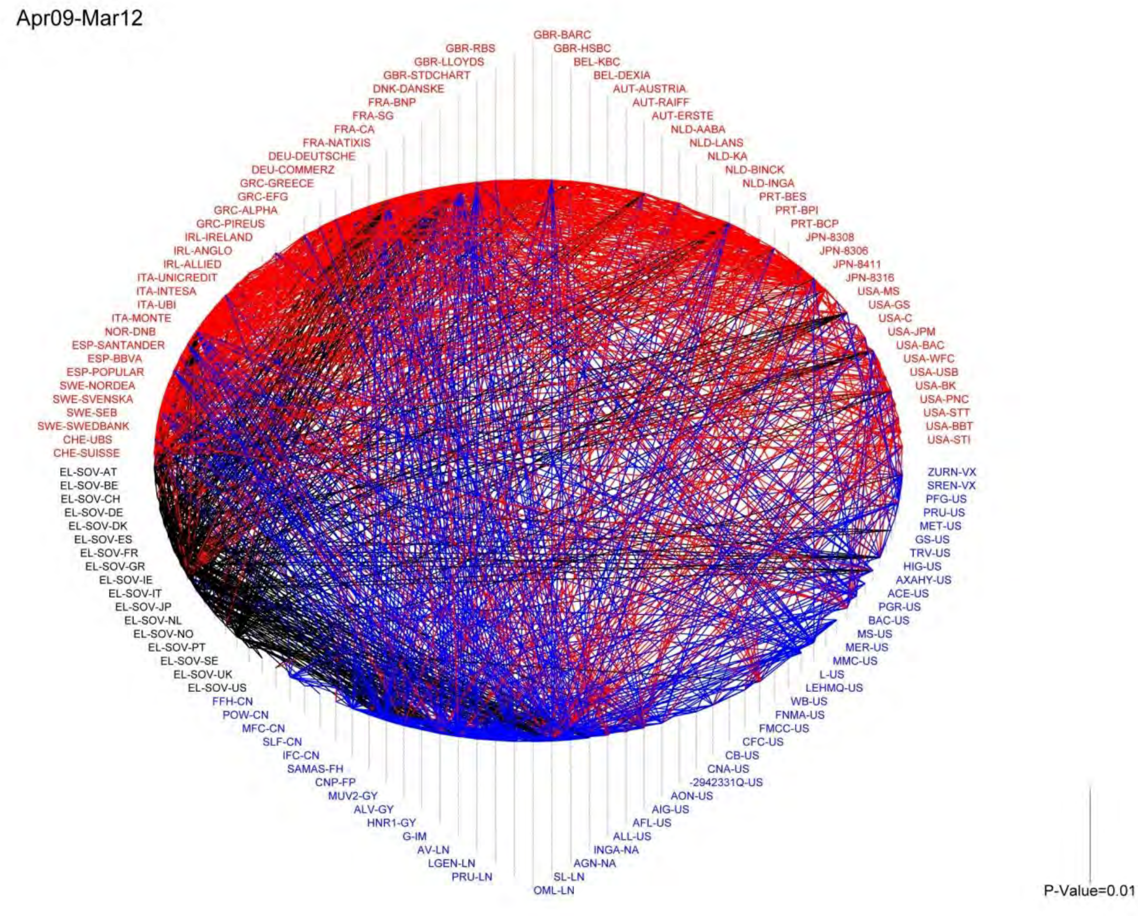

Figure 3 – Network diagram of linear Granger-causality relationships that are statistically significant at the 1% level among the monthly changes of the expected losses of the different entities (Banks, Insurances, and Sovereigns) over April 2009 to March 2012. The type of entities causing the relationship is indicated by color: red for banks, black for insurers, and blue for Sovereigns. Granger-causality relationships are estimated including autoregressive terms and filtering out heteroskedasticity with a GARCH(1,1) model.

Network Measures: FROM and TO Sovereign

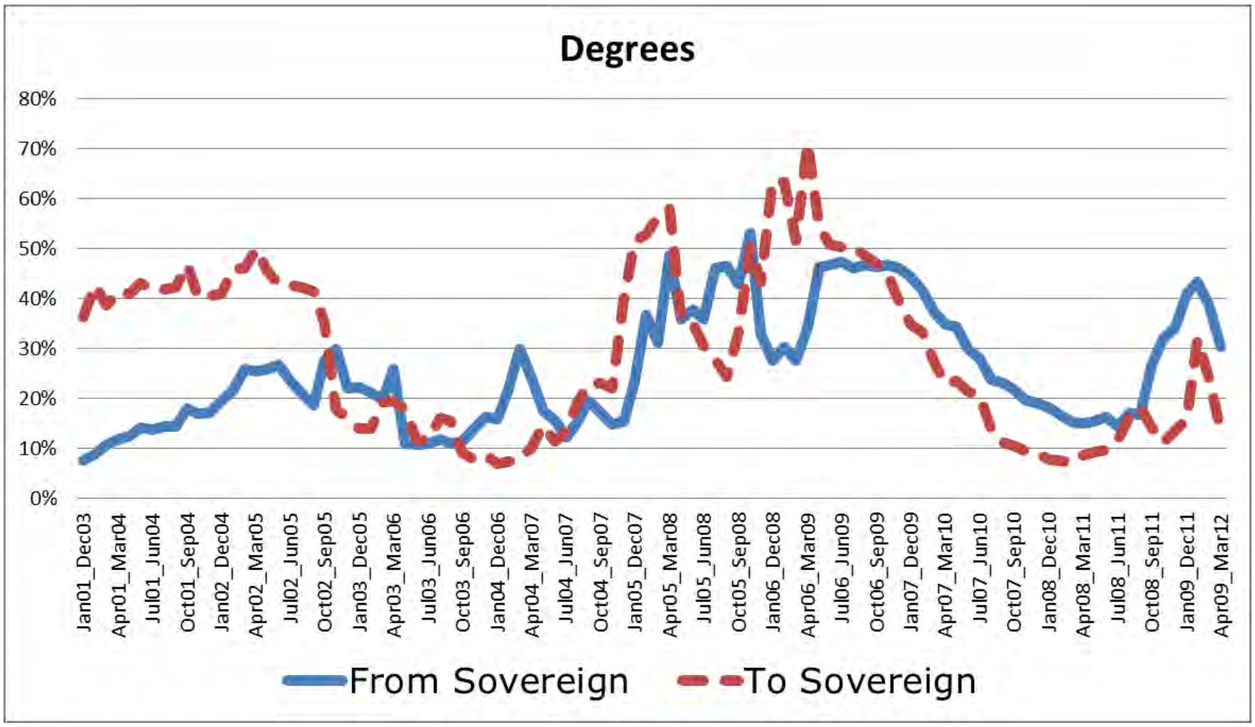

Figure 4 – Interconnectivity measures based on 17 sovereigns, 63 banks, and 39 insurance companies. Percent of significant (at 1%) connections to sovereigns from financial firms (banks and insurances) and from financial firms to sovereigns is depicted from January 2001 through March 2012.

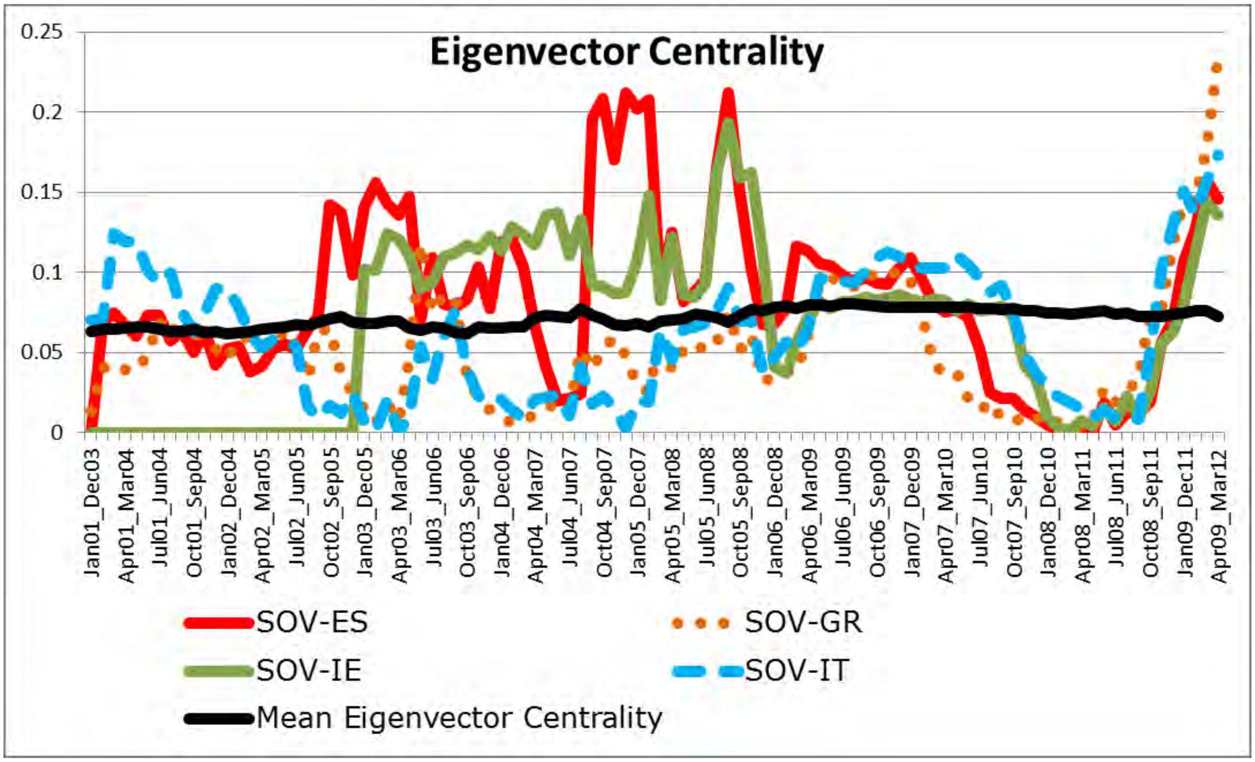

Figure 5 – Eigenvector centrality measures based on 17 sovereigns, 63 banks, and 39 insurance companies for the GIIPS countries: Greece (GR), Ireland (IE), Italy (IT), Portugal (PT), and Spain (ES).

From GIIPS minus TO GIIPS

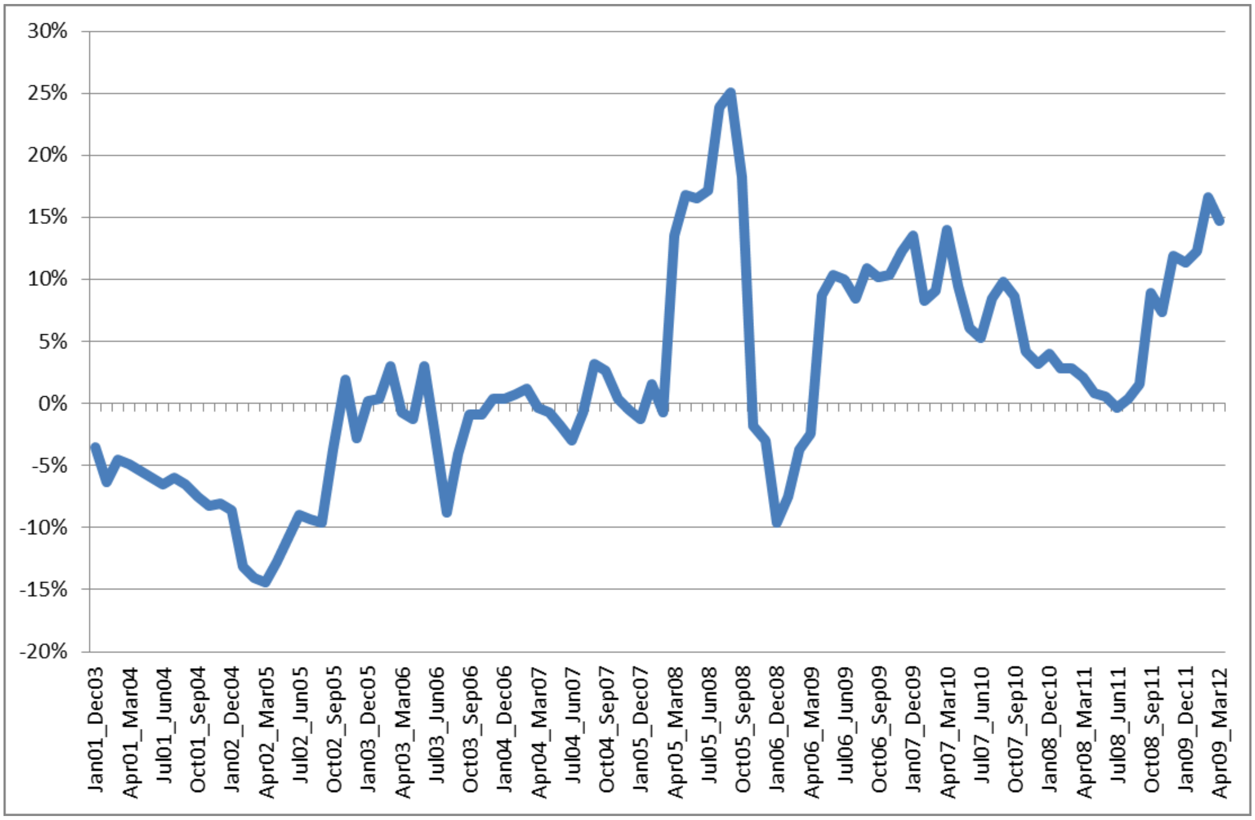

Figure 6 – Difference of the percent of significant connections from GIIPS to GIIPS where GIIPS countries are: Greece (GR), Ireland (IE), Italy (IT), Portugal (PT), and Spain (ES). Interconnectivity measures are based on 17 sovereigns, 63 banks, and 39 insurance companies.

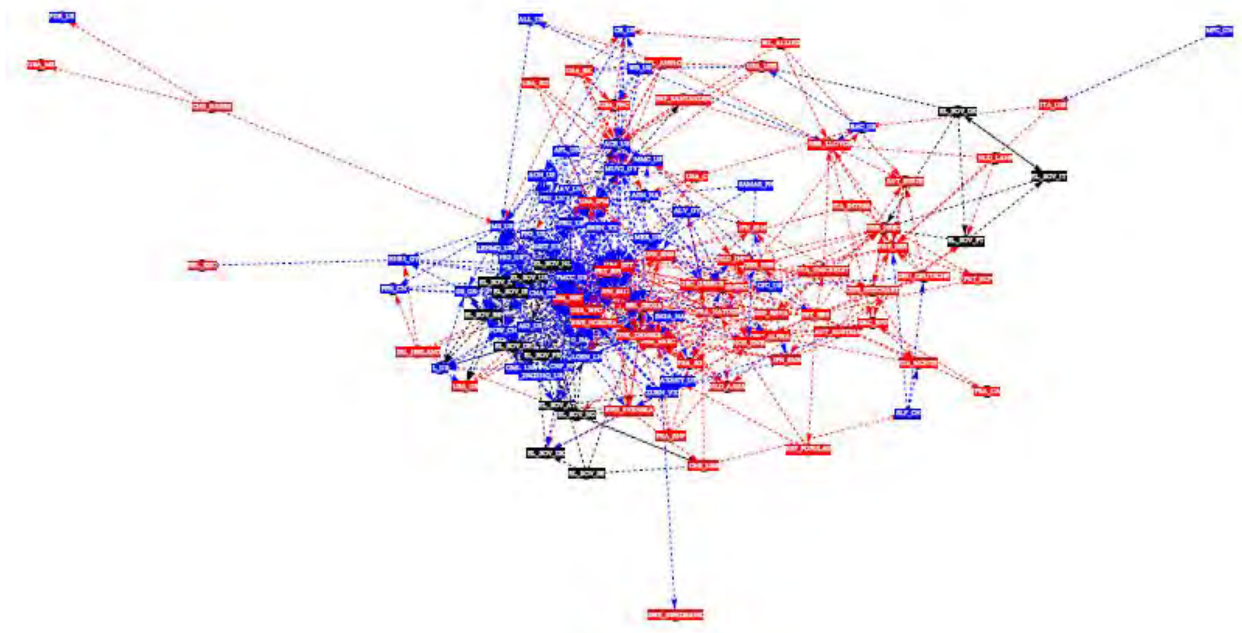

Figure 7 –Network topology diagram of linear Granger-causality relationships that are statistically significant at the 1% level among the monthly changes of the ELR of the different entities (Banks - red, Insurances – blue, and Sovereigns - black) over July 2004 to June 2007. The type of entities causing the relationship is indicated by color: red for banks, black for insurers, and blue for Sovereigns. Granger-causality relationships are estimated including autoregressive terms and filtering out heteroskedasticity with a GARCH(1,1) model.

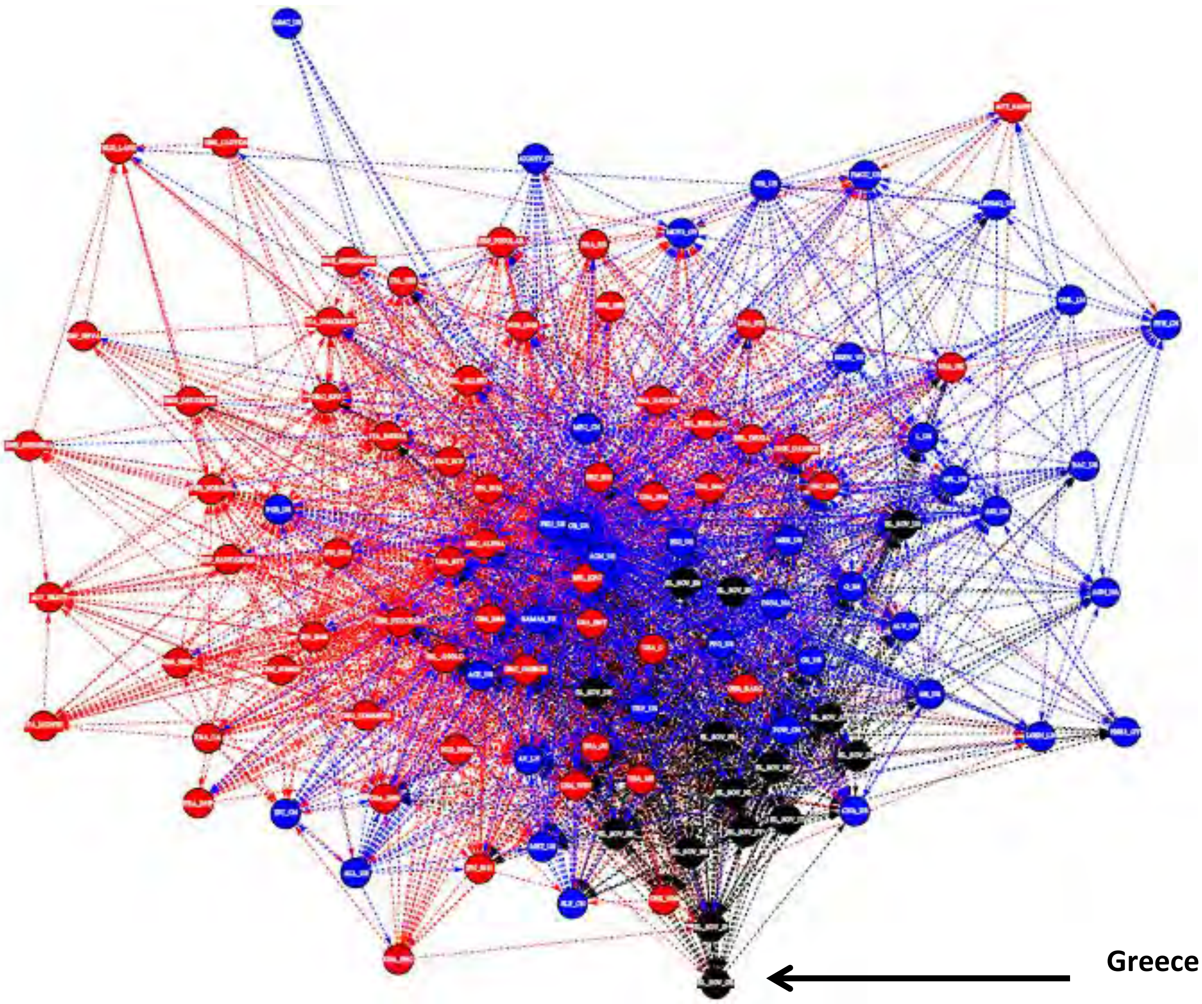

Figure 8 –Network topology diagram of linear Granger-causality relationships that are statistically significant at the 1% level among the changes of the ELR of the different entities (Banks, Insurances, and Sovereigns) over September 2007 to August 2008. The type of entities causing the relationship is indicated by color: red for banks, black for insurers, and blue for sovereigns. Granger-causality relationships are estimated including autoregressive terms and filtering out heteroskedasticity with a GARCH(1,1) model.

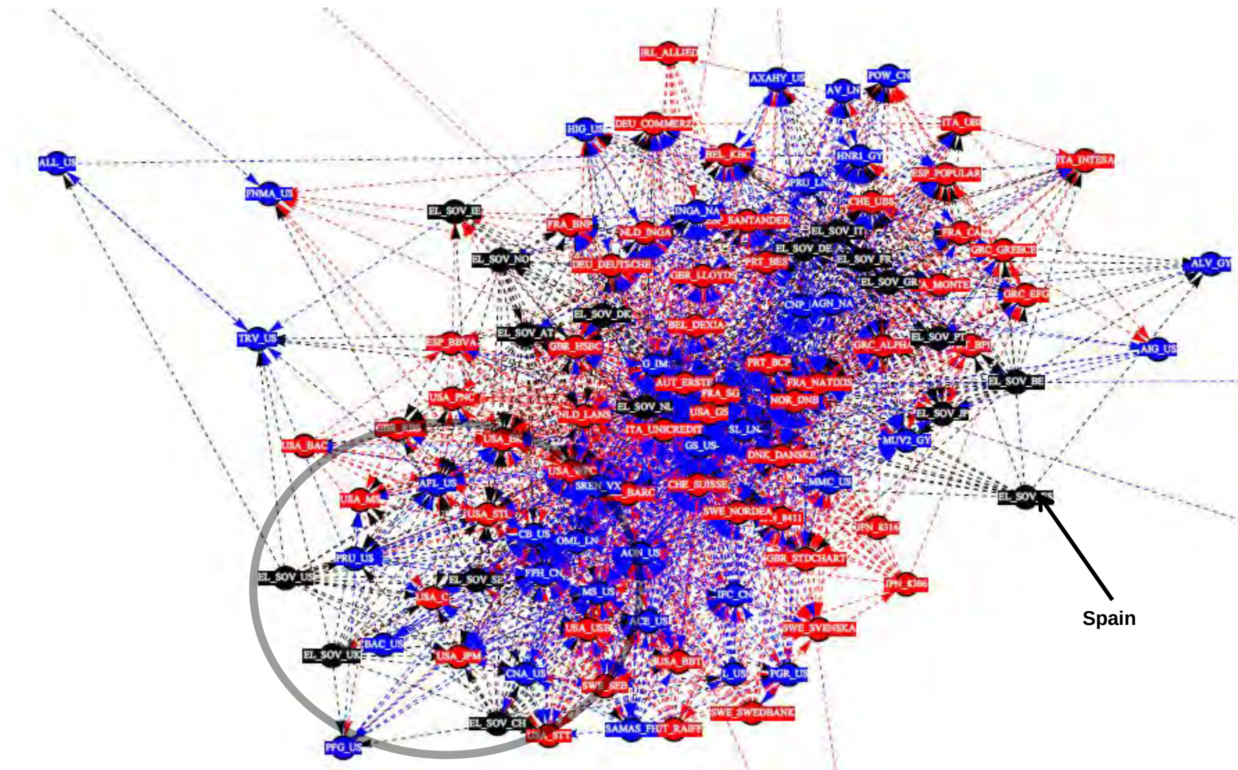

Figure 9 –Network topology diagram of linear Granger-causality relationships that are statistically significant at the 1% level among the monthly changes of the ELR of the different entities (Banks, Insurances, and Sovereigns) over January 2011 to December 2011. The type of entities causing the relationship is indicated by color: red for banks, black for insurers, and blue for sovereigns. Granger-causality relationships are estimated including autoregressive terms and filtering out heteroskedasticity with a GARCH(1,1) model.

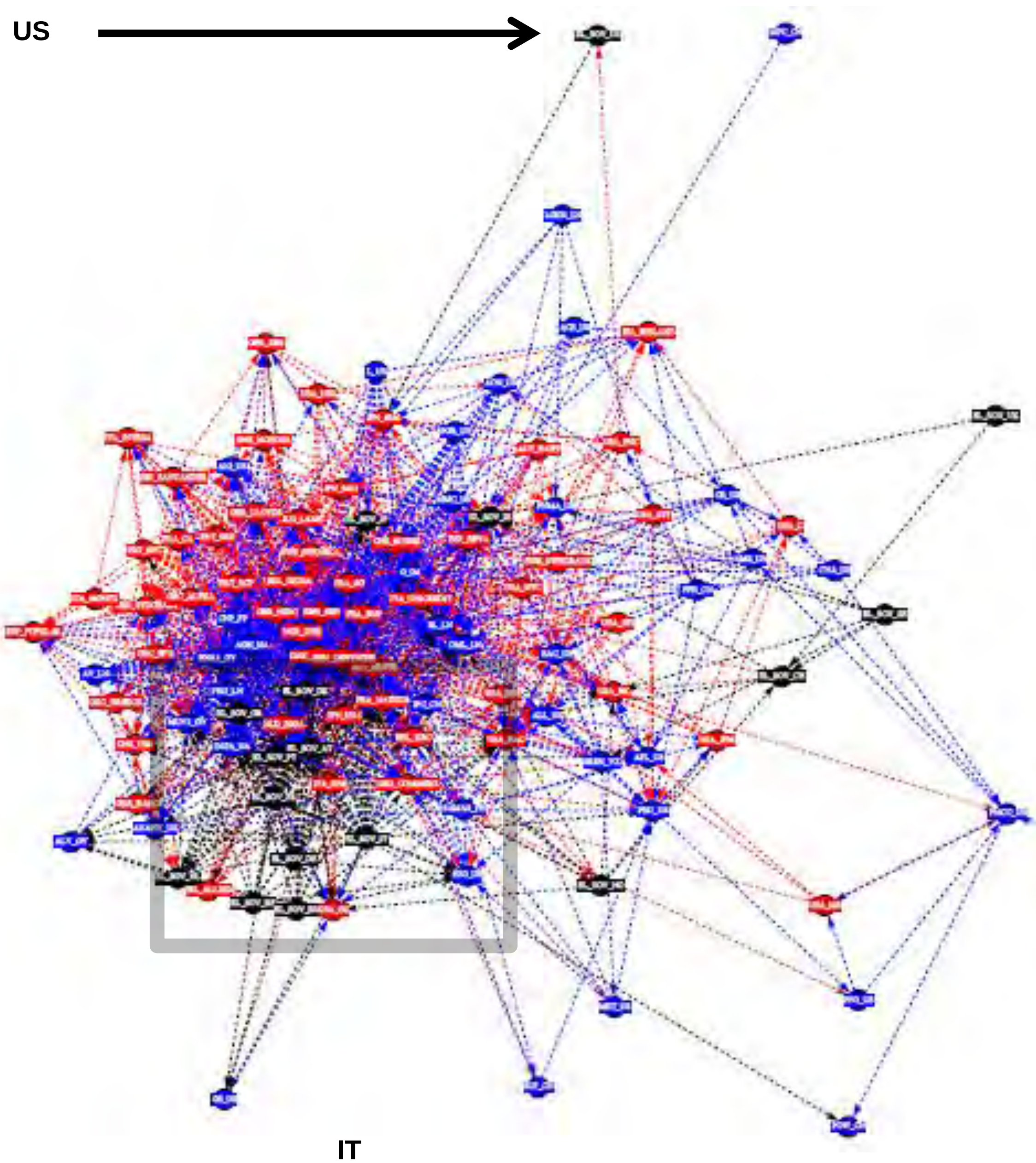

Figure 10 –Network topology diagram of linear Granger-causality relationships that are statistically significant at the 1% level among the monthly changes of the ELR of the different entities (Banks, Insurances, and Sovereigns) over April 2011 to March 2012. The type of entities causing the relationship is indicated by color: red for banks, black for insurers, and blue for sovereigns. Granger-causality relationships are estimated including autoregressive terms and filtering out heteroskedasticity with a GARCH(1,1) model.