Sovereign, Bank and Insurance Credit Spreads: Connectedness and System Networks*

Monica Billio†, Mila Getmansky‡, Dale Gray§, Andrew W. Lo¶,

Robert C. Merton‖ and Loriana Pelizzon**

This Draft: February 18, 2014

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 and insurers to investigate the evolution of these connections. Credit risk for banks and insurers is measured using a version of the Merton Model (Contingent Claims Analysis) applied to risk-adjusted balance sheets. We highlight connections among banks, insurers, and sovereigns by quantifying the effects of risk transmission within and across countries and financial institutions.

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

JEL Classification: G13 and G2

---

*We thank Giulio Girardi, PK Jain and seminar participants at Consortium for Systemic Risk Analytics, Goethe University, MIT, Princeton University, Scuola Normale di Pisa, University of Orleans, and the U.S. Securities and Exchange Commission (SEC). We also thank Lorenzo Frattarolo and Roberto Panzica for excellent research assistance. We thank Inquire Europe and the MIT Laboratory for Financial Engineering for their financial support.

†Ca' Foscari University of Venice, Department of Economics, Fondamenta San Giobbe 873, 30100 Venice, (39) 041 234–9170 (voice), (39) 041 234–9176 (fax), billio@unive.it (email).

‡Isenberg School of Management, University of Massachusetts, 121 Presidents Drive, Room 308C, Amherst, MA 01003, (413) 577–3308 (voice), (413) 545–3858 (fax), msherman@isenberg.umass.edu (email).

§International Monetary Fund, 700 19th Street, N.W., Washington, D.C. 20431, (202) 623–6858 (voice), dgray@imf.org (e-mail).

¶Charles E. & Susan T. Harris Professor, MIT Sloan School of Management, and Chief Investment Strategist, AlphaSimplex Group, LLC, 100 Main Street, E62–618, Cambridge, MA 02142–1347, (617) 253–0920 (voice), alo@mit.edu (email).

‖MIT Sloan School of Management, 100 Main Street, E62–618, Cambridge, MA, 02142, (617) 258–6855 (voice), rmerton@mit.edu (email).

**Ca' Foscari University of Venice, Department of Economics, Fondamenta San Giobbe 873, 30100 Venice, (39) 041 234–9164 (voice), (39) 041 234–9176 (fax), pelizzon@unive.it (email).

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, broker-dealers, and insurers. Sovereign risk is measured using Credit Derivative Swaps (CDS) and credit risk is measured using a version of the Merton Model (Contingent Claims Analysis, CCA) 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 financial institutions and sovereigns.

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 modeling and analysis of financial crises and sovereign risk. We examine how vulnerabilities can build up and suddenly results 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 sovereigns and their effect on systemic risk. In this regard, the size, interconnectedness and complexity of individual financial institutions and their inter-relationships with sovereign risk create vulnerabilities to systemic risk. 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.

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 Schweikhard, and Tsesmelidakis (2012). Finally, it is related to the network literature applied to financial markets and macroeconomics: Battiston, Delli Gatti, Gallegati, Greenwald and Stiglitz (2009), Billio, Getmansky, Lo and Pelizzon (2012), Acemoglu, Carvalho, Ozdaglar, Tahbaz-Salehi (2012), Acemoglu, Ozdaglar, Tahbaz-Salehi (2013), and Diebold and Yilmaz (2013).

The key distinguishing features of our paper are: measurement of network of connections of credit risk between a large sample of banks, insurers, and sovereigns, and the ability to map the system of connections among all these financial 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 credit risk indicators, including fair-value spreads and expected loss ratios. 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, using the CCA we compute forward-looking credit risk indicators for banks and insurers as well as sovereign credit risk indicators. 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 risk transmission and feedback-loops between sovereigns and financial institutions are shown in Figure (1).

INSERT Figure (1) here

Figure (1) represents a good example of how sovereign and credit risk are intimately related. Distressed banks transmit risk to their sovereign via explicit and implicit government guarantees. Increased sovereign risk lowers the value of sovereign debt held by banks and increases bank funding costs which increases bank distress that, in turn, increases government guarantees. If the sovereign is distressed enough, the value of official support (guarantees) will be eroded. These have knock-on effects, as shown. Therefore, an adverse feedback loop ties sovereigns' stresses to banking-sector challenges.

Also banks in different countries 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. Banks in one country may hold the sovereign debt of another country and if that foreign country's government debt declines in value, these banks become weaker. 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.

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 measures 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 measure, 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). For banks and insurers assets equal equity plus risky debt. Risky debt is default-free value of debt minus the expected loss due to default. In CCA, equity can be modeled as an implicit call option and risky debt modeled as the default-free value of debt minus an implicit put option. CCA 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.

Equity values are consensus views of market participants and thus provide forward-looking information. The value of assets is not directly observable, but it can be implied using CCA. The calibration of the model for banks and corporates uses the value of equity, the volatility of equity, the distress barrier as inputs in order to calculate the implied asset value and implied asset volatility. The implied asset value and volatility can then be used with the other parameters to calculate risk indicators such as the fair-value credit spreads, the expected loss value (implicit put option), default probabilities, expected loss ratio, and other risk indicators.

Strong evidence supports the claim that implicit and explicit government backing for banks depresses bank CDS spreads to levels below where they would be in the absence of government support. Bank creditors are the beneficiaries of implicit and explicit government guarantees, but equity holders are not. Contingent claims analysis (CCA), which uses bank equity market information together with balance sheet data, can estimate credit risk indicators and infer a fair value CDS spread (FVCDS) for financial institutions. The FVCDS is an estimate of the spread without implicit or explicit government support, thus disentangling its effect. Several studies have shown that for banks during the crisis in 2008-2009 the CCA-based fair value spreads are higher than the observed market CDS spreads in many cases (see Gray, Merton, and Bodie (2008), Moody's Analytics (2010), Gray and Jobst (2011), and Schweikhard and Tsemelidakis (2012)). The observed CDS spreads of banks are lower than fair value spreads because of the effect of implicit and explicit government guarantees on observed CDS, especially in times of crisis, and thus the bank CDS is distorted. Also, it is observed that for banks in countries with very high sovereign spreads, the observed CDS is frequently higher than the fair value spreads.

Moody's CreditEdge is a commercial application of CCA that provides a long time series of risk indicators, calculated in a consistent manner, which can be used to calculate what Moody's CreditEdge refers to as the Fair Value CDS spread (FVCDS). This FVCDS is a good proxy for the fair value spread we need, so we can use it to obtain the individual bank expected and insurer expected loss ratios. These expected loss ratios have a five year horizon, monthly frequency, and are reported in basis points.

Moody's CreditEdge 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.

For the sovereigns, we do not have equity values, like for banks and insurers. We extract the sovereign ELR directly from sovereign CDS market values using the following formula.[1]

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

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:

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

[1]If the European Stability Mechanism (ESM) or another entity outside of certain country were to explicitly guarantee sovereign debt then it might be possible to measure the effect on the sovereign CDS.

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:

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

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 $\widetilde{R}^i_t = \frac{R^i_t}{\widehat{\sigma}_{it}}$, 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:

$$\mathrm{E}\left[R^i_t \middle| I^S_{t-1}\right] = \mathrm{E}\left[R^i_t \middle| \left\{\left(R^i_\tau - \mu_i\right)^2\right\}^{t-2}_{\tau=-\infty}, R^i_{t-1}, R^j_{t-1}, \left\{\left(R^j_\tau - \mu_j\right)^2\right\}^{t-2}_{\tau=-\infty}\right] \ . \tag{6}$$

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:

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

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:

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

#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 insurers), indexed by $\alpha, \beta = 1, \ldots, M$, we have the following three measures:

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

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

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

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:

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

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

$$C_{ji} \equiv \min_C \left\{ C \in [1, N-1] : (j \overset{C}{\rightarrow} i) = 1 \right\}, \tag{13}$$

where we set $C_{ji} = N-1$ if $(j \overset{C}{\rightarrow} i) = 0$ 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:

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

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, insurers, 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 monthly data for the 5-year dollar denominated CDS of European, U.S. and Japanese sovereigns. We use 5-year CDS because they are the most liquid compared to other maturities. We consider 17 Sovereigns: 10 EMU (Austria (AT), Belgium (BE), Germany (DE), Spain (ES), France (FR), Greece (GR), Ireland (IE), Italy (IT), Netherland (NL), Portugal (PT)), 4 EU (Denmark (DK), Sweden (SE), United Kingdom (UK), Norway (NO)), Switzerland (CH), U.S. and Japan (JA).

Expected Loss Ratios (ELR) for banks and insurers are obtained from Moody's CreditEdge with a monthly frequency as reported at the end of March, 2012. Specifically, ELR for 59 Banks (31 EMU, 10 EU, 2 CH, 12 US, 4 JA) and 43 insurers (9 EMU, 6 EU, 21 US, 2 CH and 5 CA) are used in the analysis. The data sample ranges from January 2001 to March 2012. Analysis is conducted on 36-month rolling window intervals.

INSERT Table (1) HERE

Table 1 reports Expected Loss Ratios (in basis points) for sovereigns, banks, and insurers. Table 1 shows that on average Expected Loss Ratios (ELR) of sovereigns are lower than those of insurers and banks, however, for most of the peripheral European countries (GIIPS) this is not the case. We further narrow down our analysis of sovereign risk and concentrate on GIIPS countries, i.e., Greece, Ireland, Italy, Portugal, and Spain. GIIPS countries were highly affected by the recent European sovereign debt crisis and as a result are a focal point of the analysis. For GIIPS countries the average ELR was 6.82% compared to ELR of non-GIIPS countries of 1.50%. For the sample considered, the variability of the Expected Loss Ratios is quite large and the distribution, as expected is not normal. Given that Greece defaulted on its debt in March, 2012, the maximum for ELR for Greece was 100% as expected.

We investigate correlations between countries and different financial institutions using rolling windows of 36 months from January 2001 till March 2012. We present results for four different time periods spanning crisis and tranquil time intervals: July 2004–June 2007, September 2005–August 2008, January 2009–December 2011, and April 2009–March 2012.[2] The July 2004–June 2007 period is a period before the global financial crisis; the September 2005–August 2008 period encompasses the global financial crisis just before the Lehman Brothers default. We selected this period to show that the connections between sovereigns and financial institutions were already very large even before the Lehman Brothers default happened. January 2009–December 2011 contains the most severe part of the European sovereign debt crisis period just before the intervention of ECB with the LTRO (Long-Term Refinancing Operation by the European Central Bank) program, and April 2009–March 2012 period contains LTRO and Greek sovereign default. Results are reported in Table 2.

INSERT Table (2) HERE

As Table 2 shows, correlations between banks, insurers, and sovereigns (GIIPS and NO-GIIPS) have on average increased a lot from the pre-crisis sample (July 2004–June 2007). During the global financial pre-Lehman crisis period of September 2005–August 2008 correlations are very large, with almost no distinction among GIIPS and NO-GIIPS countries. However, during the European sovereign debt crisis there is more heterogeneity in the correlations with a strong correlation among sovereign GIIPS (0.914) and a much lower average correlation among non-GIIPS countries (0.682). However, all other correlations between sovereigns, banks, and insurers are on average lower compared to correlations between the same groupings during 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 (GIIPS) and the network representation of the system of sovereigns and financial entities.[3]

[2]Analysis was conducted for all 36 months rolling windows from January 2001 till March 2012 and results for these time periods are available upon request.

[3]GIIPS is the acronym for Greece, Ireland, Italy, Portugal, and Spain.

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 insurers that are significant at 1% for the same time periods as considered in Table 2.

The July 2004–June 2007 period is a period before the global financial crisis; the September 2005–August 2008 period encompasses the global financial crisis just before the Lehman Brothers default, January 2009–December 2011 is the European sovereign debt crisis period, and April 2009–March 2012 period captures LTRO (Long-Term Refinancing Operation by the European Central Bank) and Greek sovereign default.

INSERT Table (3) HERE

Table 3 shows that the interconnections are not symmetric. Sovereigns on average affect banks, insurers, and other sovereigns more than banks and insurers affect sovereigns. Specifically, larger Expected Loss Ratios (ELR) of sovereigns are more likely to affect other sovereigns, banks, and insurers' Expected Loss Ratios, compared to being affected by these entities. This relationship is consistent across different time periods (Table 3).

Moreover, banks are strongly affecting other entities during the global financial crisis before Lehman Brothers default, but their impact is largely reduced after this period. Specifically, degree of Granger causality (DGC) for banks affecting insurers is 19.67% (i.e., 471 causal connections between banks and insurers out of 2,436 (58 banks X 42 insurers)[4] possible connections are significant at 1% level) during the September 2005–August 2008 period. The DGC for banks affecting sovereigns is 7.63% (i.e. 74 causal connections between banks and sovereigns out of 986 (58 banks X 17 sovereigns) possible connections are significant at 1% level) during the same time period.[5] We further separate sovereign debt into sovereign debt for GIIPS countries and for non-GIIPS countries. Even before the European sovereign debt crisis, the impact of ELR for GIIPS countries on banks and insurers were much larger compared to the impact of ELR for non-GIIPS countries. However, banks and insurers had a higher degree of Granger causality (DGC) for non-GIIPS countries compared to GIIPS countries for first three periods (June 04–June 07, September 2005-August 2008, and January 2009-December 2011). During both the global financial crisis pre-Lehman (September

[4]One bank and one insurer are not included in the sample because the data for these companies were missing during this time period.

[5]Results are provided upon request.

2005–August 2008) and the European sovereign debt crisis, April 2009–March 2012 banks and insurers became much more affected by credit risk of sovereigns in general. In the last sample considered, April 2009–March 2012, sovereign GIIPS play a relevant role in largely increasing connections with other entities rather than among themselves.[6]

Figure 2 illustrates the connectedness between sovereigns, banks, and insurers prior to the global financial crisis of 2007–2009, represented by a July 2004–June 2007 period. Using Expected Loss Ratio (ELR) for sovereigns, banks, and insurers this figure provides a network diagram of linear Granger-causality relationships that are statistically significant at the 1% level. Granger-causality relationships are drawn as straight lines connecting two entities, color-coded by the type of entity that is "causing" the relationship, i.e., the entity at date-t which Granger-causes the ELR of another entity at date $t+1$. Banks are depicted in red, insurers are in blue, and sovereigns are in black. The lines represents significant connections at 1% level; a larger number of lines represent more connections among entities. As Figure 2 illustrates, there are several connections between banks, insurers, and sovereigns, but they are quite sparse.

INSERT Figure (2) HERE

Figure 3 illustrates the connectedness of the same set of banks, insurers, and sovereigns during the time period that includes the LTRO and Greek debt default, April 2009–March 2012. Figure 3 reveals much greater density and connectedness between all types of financial institutions and sovereigns compared to Figure 2. 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 each other's credit. Moreover, banks (red lines) and sovereigns (black lines) are more noticeable and thus are a greater source of interconnectedness compared to the network topology described in Figure 2. Therefore, banks, insurers, and sovereigns are much more connected after the global financial crisis and during the period of the European Sovereign debt crisis and Greek bond default compared to the period before the global financial and European Sovereign debt crises.

INSERT Figure (3) HERE

Higher connectedness is not necessarily a negative attribute of a system; however, it is indicating that ELR, and therefore implicitly the probability of defaults of the entities are

[6]Not all sovereigns behave the same and a country specific analysis was performed to separate effect of each country. Results are provided upon request.

more connected. Is it indicating the system is more vulnerable? Potentially yes, because the system is more connected and therefore could be more fragile.

The extent to which sovereign risk is linked to banks and insurers varies through time and across countries. Figure 4 shows the degrees of Granger causality (DGC) measuring connectedness from sovereigns to financial institutions (Out degrees) and to sovereigns from financial institutions(In degrees). Degrees are defined as the percentage of significant connections at the 1% level using a Granger causality analysis (i.e., the number of significant connections out of a total of 1,717 (17 sovereigns X (59 banks + 42 insurers)) potential connections between sovereigns and financial institutions). We find that during the period from 2001 to mid-2005 connections are largely from banks and insurers to sovereigns, and in the period from mid-2009 to early 2012 there are more connections from sovereigns to banks and insurers. In this later period the results show that sovereign credit risk can spill over to the financial sector.

INSERT Figure (4) HERE

We further narrow down our analysis of sovereign risk and concentrate on GIIPS countries, i.e., Greece, Ireland, Italy, Portugal, and Spain. GIIPS countries were highly affected by the recent European sovereign debt crisis and as a result are a focal point of the analysis. Based on our network of 17 sovereigns, 59 banks, and 42 insurers, we calculate mean eigenvector centrality for all entities and eigenvector centrality for each of the GIIPS countries. Figure 5 plots the eigenvector centrality of GIIPS countries and the mean eigenvector centrality of all 118 entities for 36-month rolling windows from January 2001 to the end of the sample, March 2012. We observe that the eigenvector centrality of GIIPS countries is larger than average during the period of the European sovereign debt crisis (January 2009 through September 2010), it then decreases, and becomes severe in the last part of the sample, starting December 2011.

INSERT Figure (5) HERE

Based on the above analysis we find that GIIPS countries are eigenvector central, especially at the end of the sample. This is consistent with our previous results that showed that GIIPS countries became an important source of causal connections starting in the January 2009–December 2011 time period. The next step is to determine whether these peripheral countries are the source of causal connections or are merely affected by other entities. To capture the net impact of GIIPS countries we calculate the difference between the number of significant connections from and to these countries. Figure 6 depicts the number of out degrees minus the number of in degrees for GIIPS countries. Out degrees capture the number of entities that are significantly Granger-caused by GIIPS countries, and in degrees capture the number of Granger-causal connections from other entities to GIIPS countries. Since the net value is mostly below zero in the 2001 to 2007 period, this shows that GIIPS are largely receivers of risk, i.e., they are affected by the credit risk from the increase of ELR of other entities in the sample. In the second part of the sample, after 2008, the GIIPS are transferring risk to other entities in the sample. As a result, in the second part of the sample GIIPS became sources of credit risk.

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 global financial crisis of 2007-2009, analyzed during the July 2004–June 2007 time period. These results show three different groups of entities: sovereigns (black), insurers (blue), and banks (red) are highly connected with other entities in their respective groups, i.e, banks with other banks, insurers with other insurers, and sovereigns with other sovereigns. In Figure 8 the network diagram for the same entities is depicted during the global financial crisis period September 2005–August 2008. We find that in comparison to the earlier time period, different types of entities became more interrelated. Banks and insurers became more interconnected, and sovereigns became more interconnected with financial institutions. Using our analysis on ELR measures we find that sovereign credit risk became important even before the European sovereign debt crisis of 2010-2012. Figure 8 also illustrates a high interconnectedness of Greece to other financial institutions and sovereigns in August 2008, way before other GIIPS countries started to become more network central and before the Greek default.

INSERT Figure (7) HERE

INSERT Figure (8) HERE

INSERT Figure (9) HERE

INSERT Figure (10) HERE

The centrality of Spain and Italy appears to be relevant in 2011 as shown by Figure 9 for the part of the European sovereign debt crisis, January 2011–December 2011 period. Figure 9 shows Spain as source of risk for other sovereigns as well as for banks and insurers. Figure 10 shows the centrality of Italy at the time of Greek default, April 2011–March 2012. Note that we find 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, neither influencing or being influenced by the credit risk changes in other non-US banks, insurers, or sovereigns. In contrast, Italy 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 three different network channels (i.e., financial institutions to sovereigns, sovereigns to financial institutions, and sovereigns to sovereigns). Our results for eigenvector centrality and degrees illustrate the nonlinear nature of credit risk transmission.

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 happening in the system that might not otherwise be transparent. Subsequent investigation using other information sources and models would then inform what, if any, risk mitigation measures might be taken.

4.0.1 Out-of-Sample Analysis

One important application of any systemic risk measure is to provide early warning signals to regulators and the public. We follow Billio, Getmansky, Lo, and Pelizzon (2012) to specify the importance of Granger-casuality measures for out-of-sample analysis. To this end, we explore the out-of-sample performance of our Granger-causality measures in Section 2. For each entity i, we calculate the Cumulated Expected Loss Ratio as the sum of the ELR of entity i at time t and all the expected losses of the institutions that are Granger-caused at time t by entity i, multiplied by $\beta^{i,j}$, more formally[7]:

$$Cumulated\ ELR_{i,t} \equiv ELR_{i,t} + \sum_{j=1}^{N} \beta^{i,j} ELR_{\ i \to j,t} \tag{15}$$

[7]We only consider $\beta^{i,j}$ that are significant at 1%, otherwise $\beta^{i,j}$ is zero.

These cumulated losses represent the losses each entity can generate at a certain time considering its own externalities. Following Billio, Getmansky, Lo, and Pelizzon (2012), we use this value as a dependent value and regress it on past year's network measures: # of in connections, # of out connections, Closeness, and Eigenvector centrality. For this analysis, we consider the period of February 2012, right before March 2012 - Greek default and consider network measures a year before. The results are reported in table 4.

INSERT Table (4) HERE

As Table 4 shows, network measures (# of out connections and Closeness) 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 central and highly connected through their ELR measures, are more likely to suffer larger expected loss ratios (ELR) in the future. In conclusion, our analysis shows that network measures are relevant and provide a different perspective with respect to classical measures of co-movement like correlations and it seems that they have a certain predictive power.

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, insurers, and countries in our sample is highly dynamically connected. Sovereign risk became relevant well before the European sovereign debt crisis of 2010–2012. We propose financial network measures that 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 research stress-testing of interconnections and specific analysis and proposal of risk mitigation actions that might help to reduce systemic risk.

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 Working Paper

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.

Cihak M., 2007, Systemic Loss: A Measure of Financial Stability, Czech Journal of Economics and Finance, 57(1-2)

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

Diebold, F.X. and K. Yilmaz, 2013, "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms," *Journal of Econometrics*, Forthcoming.

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.

Gray, D. F., Merton R. C. and Z. Bodie, 2008, "A New Framework for Measuring and Managing Macrofinancial Risk and Financial Stability," Harvard Business School Working Paper No. 09-015.

Gray, D. F. and A. Jobst, 2011, "Modeling Systemic Financial Sector and Sovereign Risk," Sveriges Riksbank Economic Review, September.

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.

Moody's Analytics, 2011, "Quantifying the Value of Implicit Government Guarantees for Large Financial Institutions," Moody's Analytics Quantitative Research Group, January.

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

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

Segoviano, M. and C. Goodhart, 2009, "Banking Stability Measures", IMF Working Paper 09/04

Summary Statistics

	N Obs	Mean	Std	Min	Median	Max	Excess Skewness	Kurtosis
EL_SOV_AT	132	182.62	261.81	7.7	26.91	1122.81	1.49	4.3
EL_SOV_BE	136	226.04	356.81	10	28.71	1434.35	1.79	5.14
EL_SOV_CH	59	188	171.82	7.2	196.25	813.27	1.39	6.04
EL_SOV_DE	118	106.04	130.73	6.7	31.72	541.82	1.45	4.23
EL_SOV_DK	114	133.83	183.91	6.15	22.8	702.04	1.6	4.45
EL_SOV_ES	135	349.52	547.28	11.74	32.85	2095.28	1.63	4.4
EL_SOV_FR	121	165.99	246.3	7.6	31.75	1016.45	1.85	5.6
EL_SOV_GR	136	1294.16	2568.2	23.62	78.66	9999.91	2.35	7.56
EL_SOV_IE	112	712.4	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	6.4	25.02	272.13	1.07	3.11
EL_SOV_PT	123	703.88	1292.34	19.78	45.1	5582.61	2.1	6.29
EL_SOV_SE	132	98.86	135.71	6.55	26.96	676.9	1.86	6.46
EL_SOV_UK	74	229.75	188.7	6.25	278.11	700.74	0.19	1.92
EL_SOV_US	101	101.03	108.58	4.5	31.7	450.77	0.7	2.36
Sovereigns		306.13	481.48	10.29	62.12	1900.6	1.49	4.63
GIIPS		681.76	1198.46	17.42	48.11	4657.71	1.88	5.55
Non-GIIPS		149.61	182.74	7.32	67.96	751.80	1.33	4.25
Insurers		593.51	633.02	46.93	312.13	2638.62	1.7	6.48
Banks		756.52	721.87	50.96	501.5	3350.55	1.61	6.08

Table 1 – This table reports summary statistics for Expected Loss Ratios (in bp) for the government debt of different countries and average Expected Loss Ratio statistics for banks and insurers. 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), Sweden (SE), Switzerland (CH), United Kingdom (UK), and United States (US). GIIPS is the acronym for Greece, Ireland, Italy, Portugal, and Spain. Time period is from January 2001 through March 2012.

Correlations

	BAN	SOV-NON-GIIPS	SOV-GIIPS	INS
		Jul04-Jun07		
BAN	0.331	0.197	0.029	0.289
SOV-NG	0.197	0.710	0.330	0.583
SOV-G	0.029	0.330	0.503	0.231
INS	0.289	0.583	0.231	0.598
		Sep05-Aug08		
BAN	0.918	0.877	0.876	0.803
SOV-NG	0.877	0.964	0.965	0.817
SOV-G	0.876	0.965	0.986	0.814
INS	0.803	0.817	0.814	0.785
		Jan09-Dec11		
BAN	0.544	0.485	0.121	0.401
SOV-NG	0.485	0.682	0.454	0.367
SOV-G	0.121	0.454	0.914	0.094
INS	0.401	0.367	0.094	0.387
		Apr09-Mar12		
BAN	0.469	0.368	0.290	0.308
SOV-NG	0.368	0.669	0.633	0.297
SOV-G	0.290	0.633	0.913	0.168
INS	0.308	0.297	0.168	0.318

Table 2 – This table shows the correlations among Banks (BAN), sovereigns (SOV-GIIPS and SOV-NON-GIIPS) and Insurers (INS) for different sample periods considered. GIIPS is the acronym for Greece, Ireland, Italy, Portugal, and Spain. In the primary diagonal, the average correlation among different entities of the same type is reported. In the off-diagonal, the average correlation between different entities is reported.

Connections

FROM		TO			
		BAN	SOV-NON-GIIPS	SOV-GIIPS	INS
			Jul04-Jun07		
	BAN	5.54%	0.69%	1.03%	2.13%
	SOV-NG	6.72%	10.00%	8.00%	5.71%
	SOV-G	2.07%	4.00%	20.00%	3.33%
	INS	7.76%	6.90%	4.76%	5.05%
			Sep05-Aug08		
	BAN	19.86%	10.70%	4.56%	19.67%
	SOV-NG	20.00%	50.00%	28.00%	37.14%
	SOV-G	30.18%	52.00%	55.00%	43.33%
	INS	8.27%	6.43%	0.48%	14.92%
			Jan09-Dec11		
	BAN	15.91%	5.06%	1.79%	11.65%
	SOV-NG	29.91%	8.33%	3.33%	23.33%
	SOV-G	32.50%	23.33%	5.00%	14.00%
	INS	14.15%	3.96%	0.00%	11.79%
			Apr09-Mar12		
	BAN	13.93%	3.27%	8.93%	7.46%
	SOV-NG	11.31%	6.82%	8.33%	9.58%
	SOV-G	25.00%	13.33%	0.00%	21.50%
	INS	11.79%	1.04%	2.50%	7.88%

Table 3 – This table shows the percentage of connections that are significant at 1% level between banks (BAN), insurers (INS), and sovereigns (SOV-GIIPS and SOV-NON-GIIPS). GIIPS is the acronym for Greece, Ireland, Italy, Portugal, and Spain.

Out-of-Sample Analysis

Cumulative Expected loss Ratios				
	Mar-09		Feb-12	
	Coeff	t-stat	Coeff	t-stat
# of out lines	0.42	2.92		
Closeness Centrality	-0.63	-2.5	-0.96	-6.4
R-Square		0.17		0.24

Table 4 - Parameter estimates of a multivariate regression of Expected Loss Ratios (ELRs) as of February 2012 for 17 sovereigns, 59 banks, and 43 insurers 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.

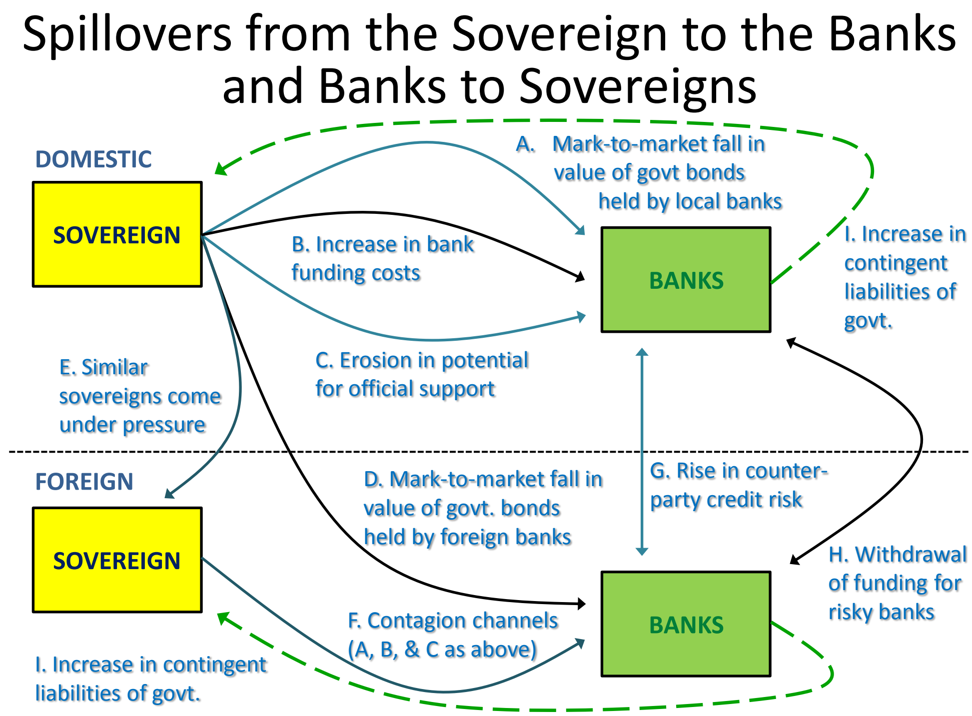

Figure 1 – This figure shows the potential channels of spillovers from Sovereign risk to banks' risk and vice versa.

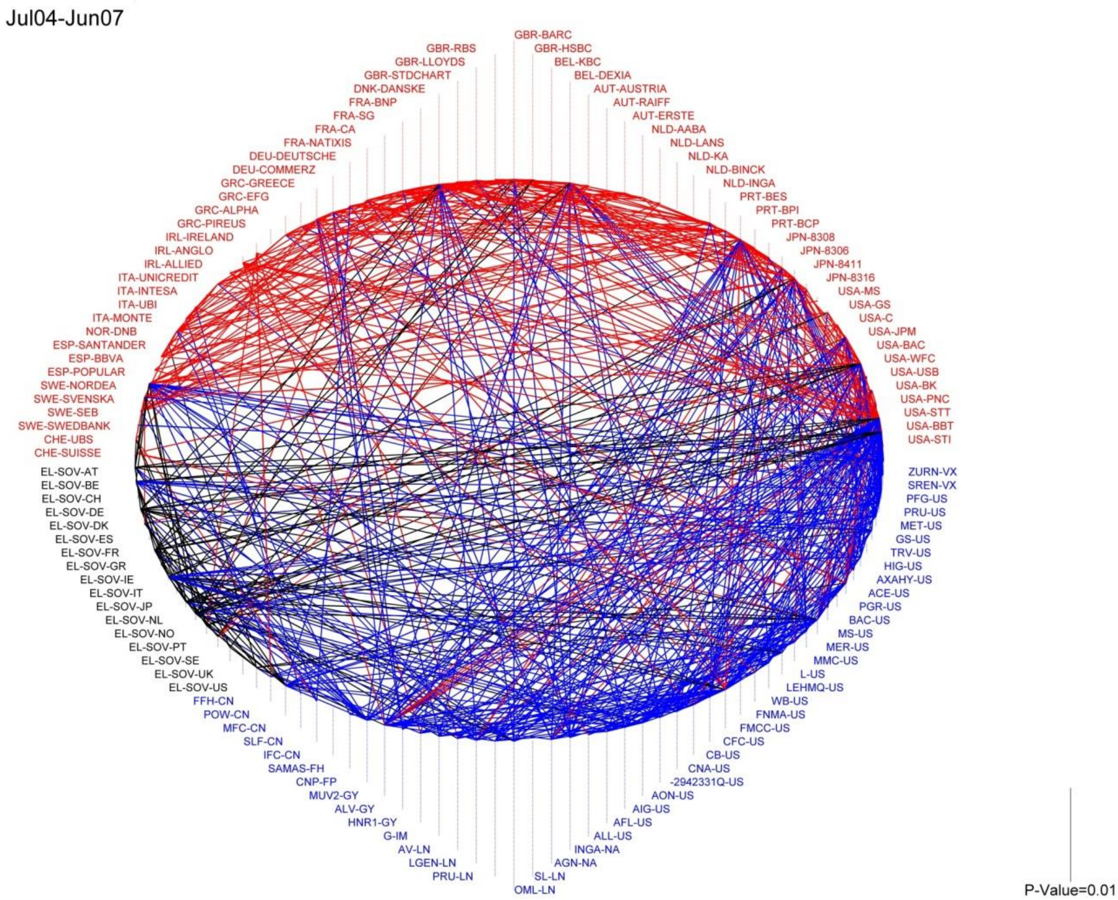

Figure 2 - Network diagram of linear Granger-causality relationships that are statistically significant at the 1% level among the monthly changes of the expected losses of the different entities (Banks, Insurances, and Sovereigns) over July 2004 to June 2007. The type of entities causing the relationship 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.

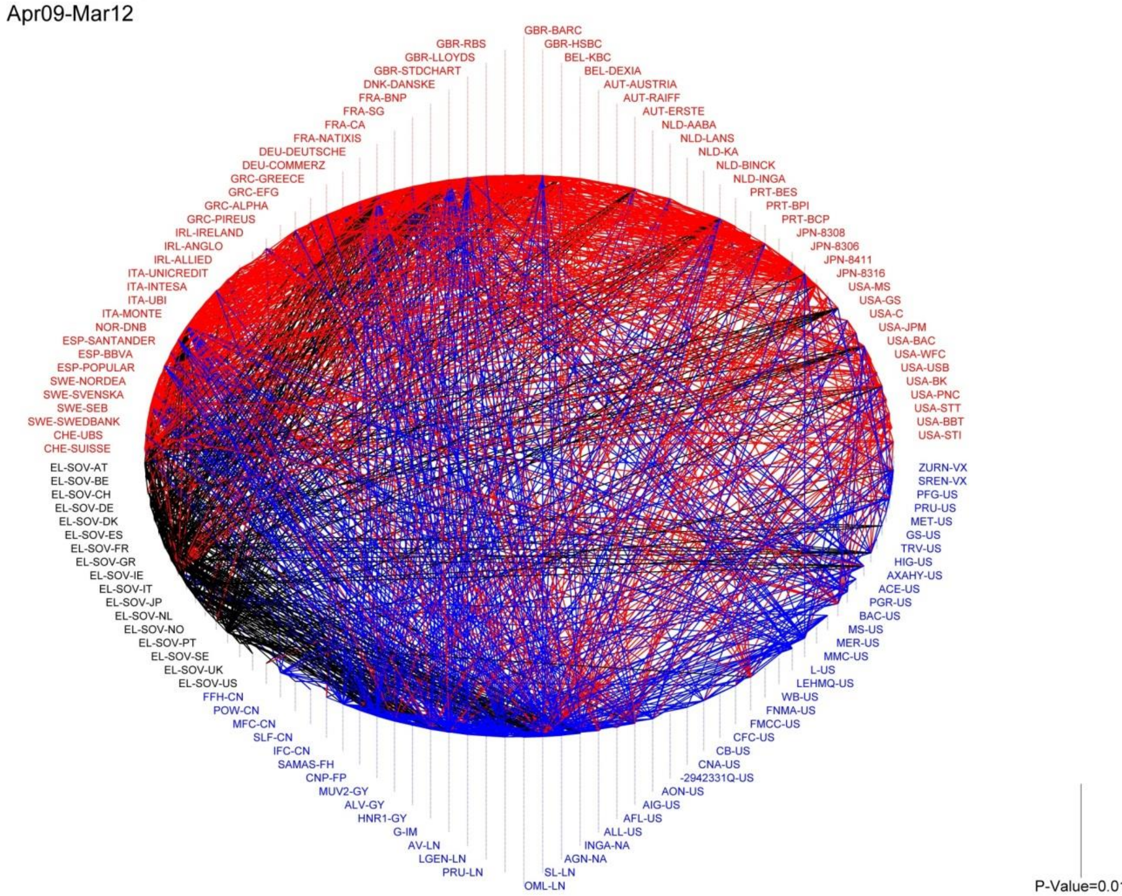

Figure 3 – Network diagram of linear Granger-causality relationships that are statistically significant at the 1% level among the monthly changes of the expected losses of the different entities (Banks, Insurances, and Sovereigns) over April 2009 to March 2012. The type of entities causing the relationship 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: Degrees FROM and TO Sovereign

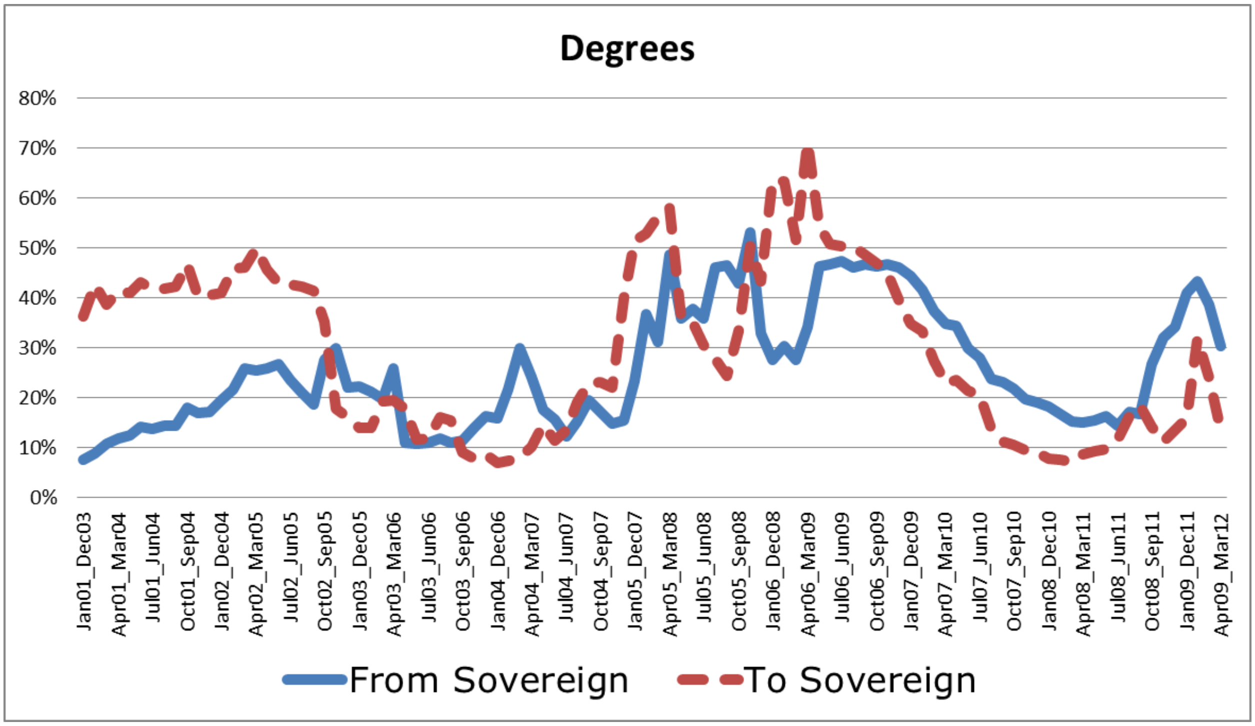

Figure 4 – Interconnectivity measures based on 17 sovereigns, 59 banks, and 43 insurers. Percent of significant (at 1%) connections to sovereigns from financial firms (banks and insurers) and from financial firms to sovereigns is depicted from January 2001 through March 2012. The x-axis captures 36-month rolling windows from January 2001 through March 2012.

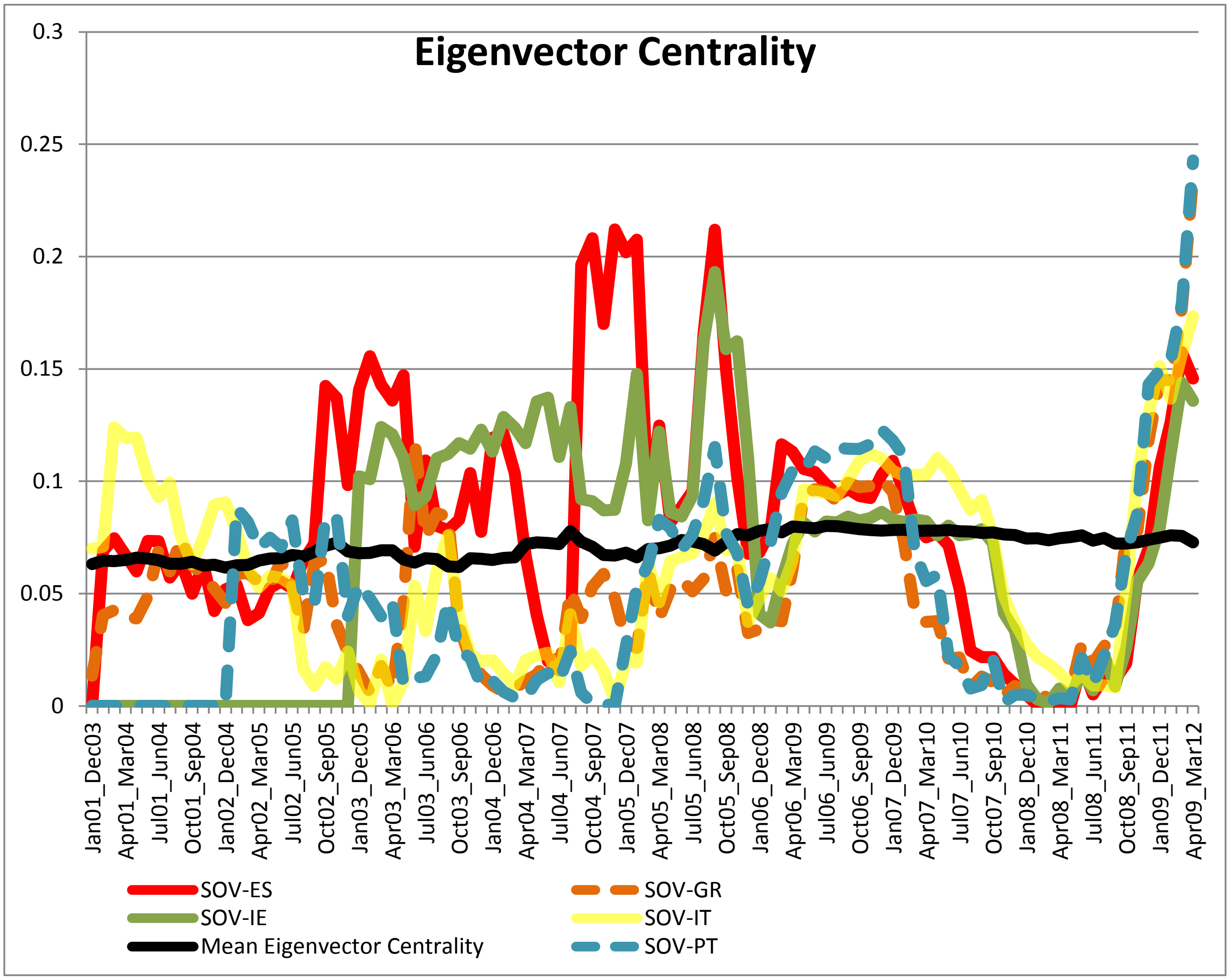

Figure 5 – Eigenvector centrality measures based on 17 sovereigns, 59 banks, and 43 insurers for the GIIPS countries: Greece (GR), Ireland (IE), Italy (IT), Portugal (PT), and Spain (ES). The x-axis captures 36-month rolling windows from January 2001 through March 2012. Mean eigenvector centrality for all entities is depicted for comparison.

Number of Out Degrees Minus Number of In Degrees for GIIPS Countries

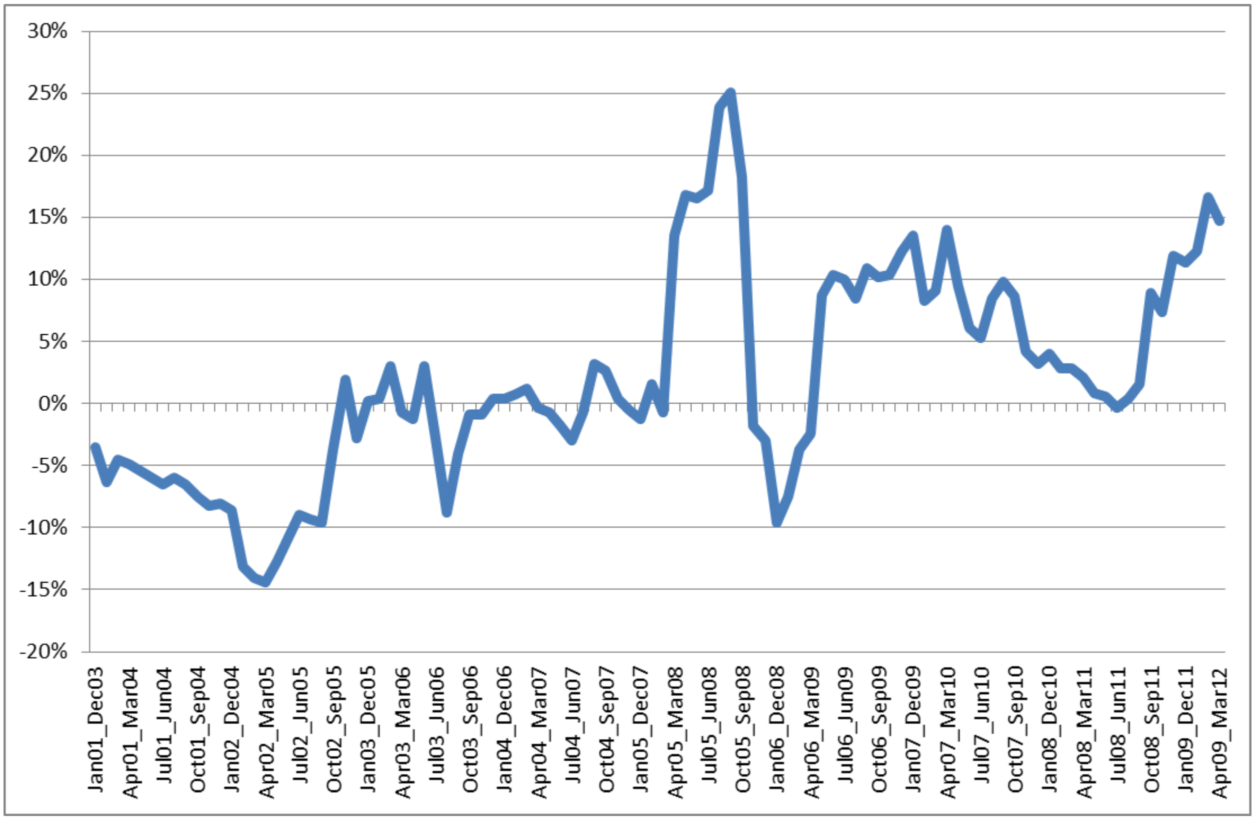

Figure 6 – Number of out degrees minus number of in degrees for GIIPS countries: Greece (GR), Ireland (IE), Italy (IT), Portugal (PT), and Spain (ES). Interconnectivity measures are based on 17 sovereigns, 59 banks, and 43 insurers. The x-axis captures 36-month rolling windows from January 2001 through March 2012.

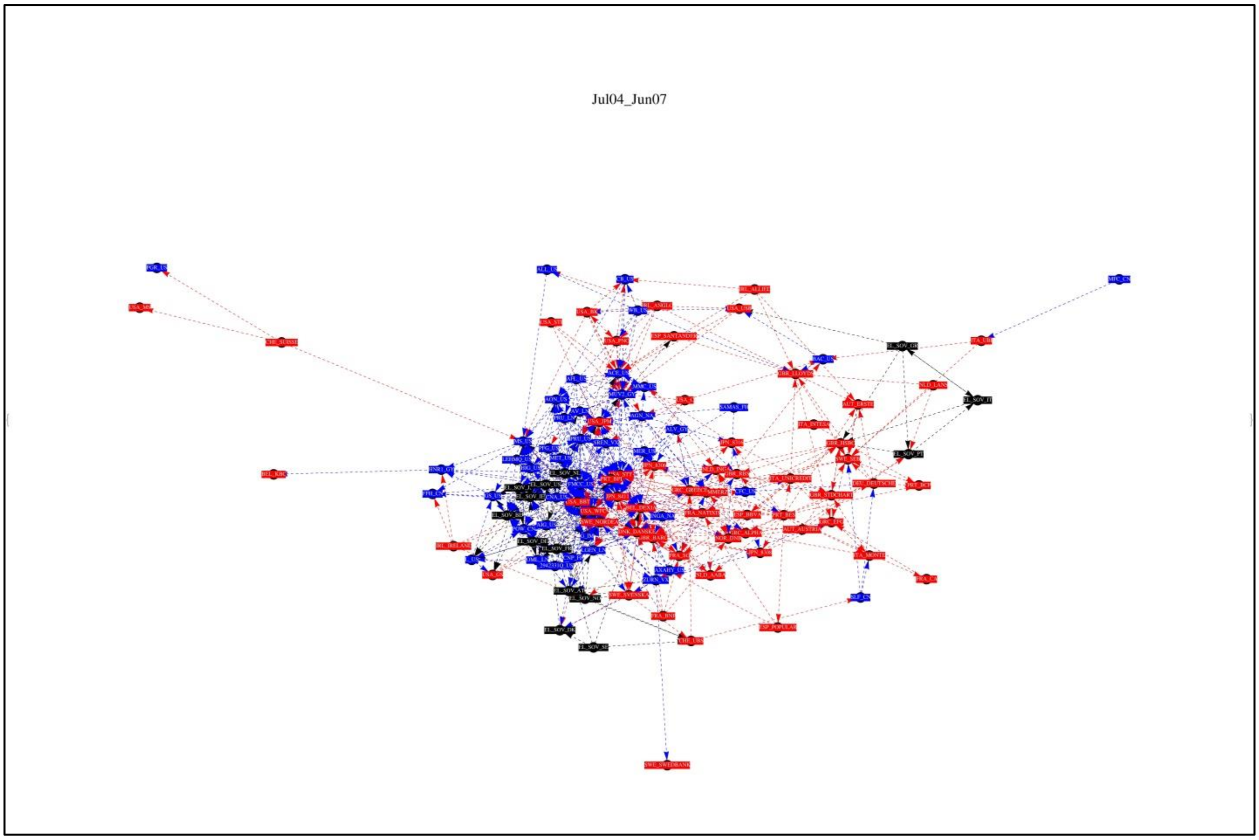

Figure 7 –Network topology diagram of linear Granger-causality relationships between ELR of banks, insurers, and sovereigns that are statistically significant at the 1% over July 2004 to June 2007. The type of entities causing the relationship is indicated by color: red for banks, blue for insurers,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

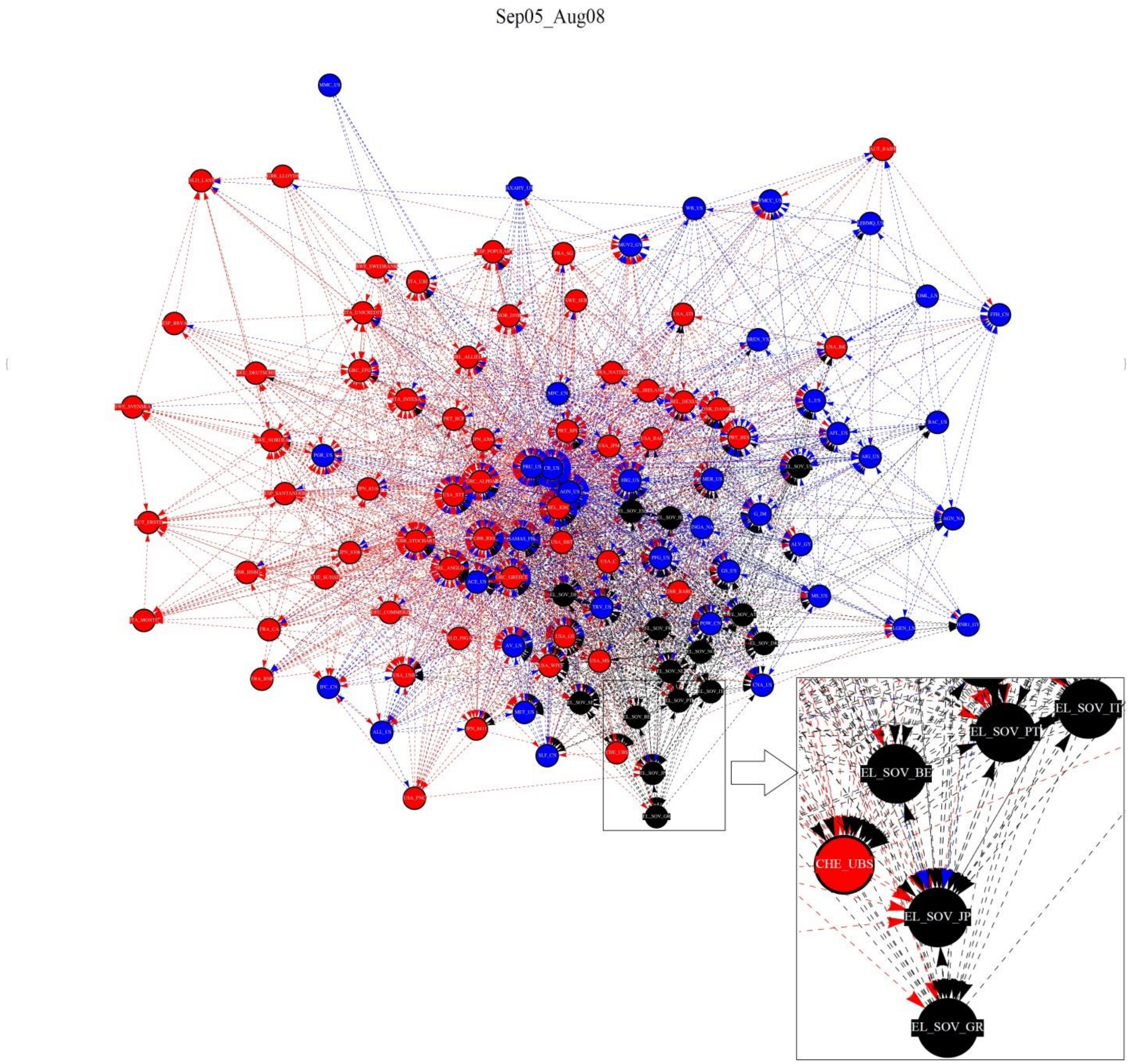

Figure 8 – Network topology diagram of linear Granger-causality relationships between ELR of banks, insurers, and sovereigns that are statistically significant at the 1% over September 2005 to August 2008. The type of entities causing the relationship is indicated by color: red for banks, blue for insurers, and black for Sovereigns. Granger-causality relationships are estimated including autoregressive terms and filtering out heteroskedasticity with a GARCH(1,1) model.

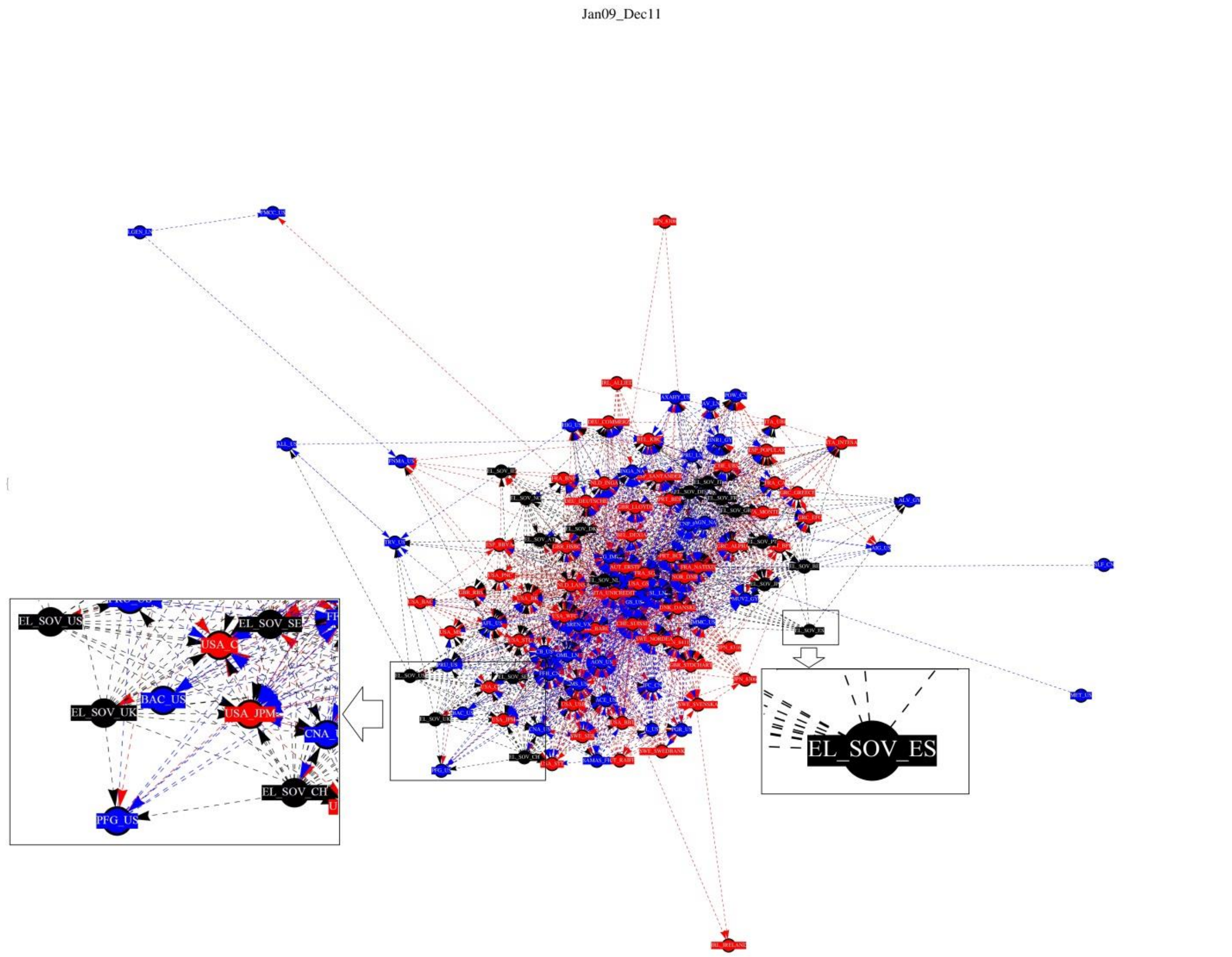

Figure 9 –Network topology diagram of linear Granger-causality relationships between ELR of banks, insurers, and sovereigns that are statistically significant at the 1% over January 2011 to December 2011. The type of entities causing the relationship is indicated by color: red for banks, blue for insurers,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

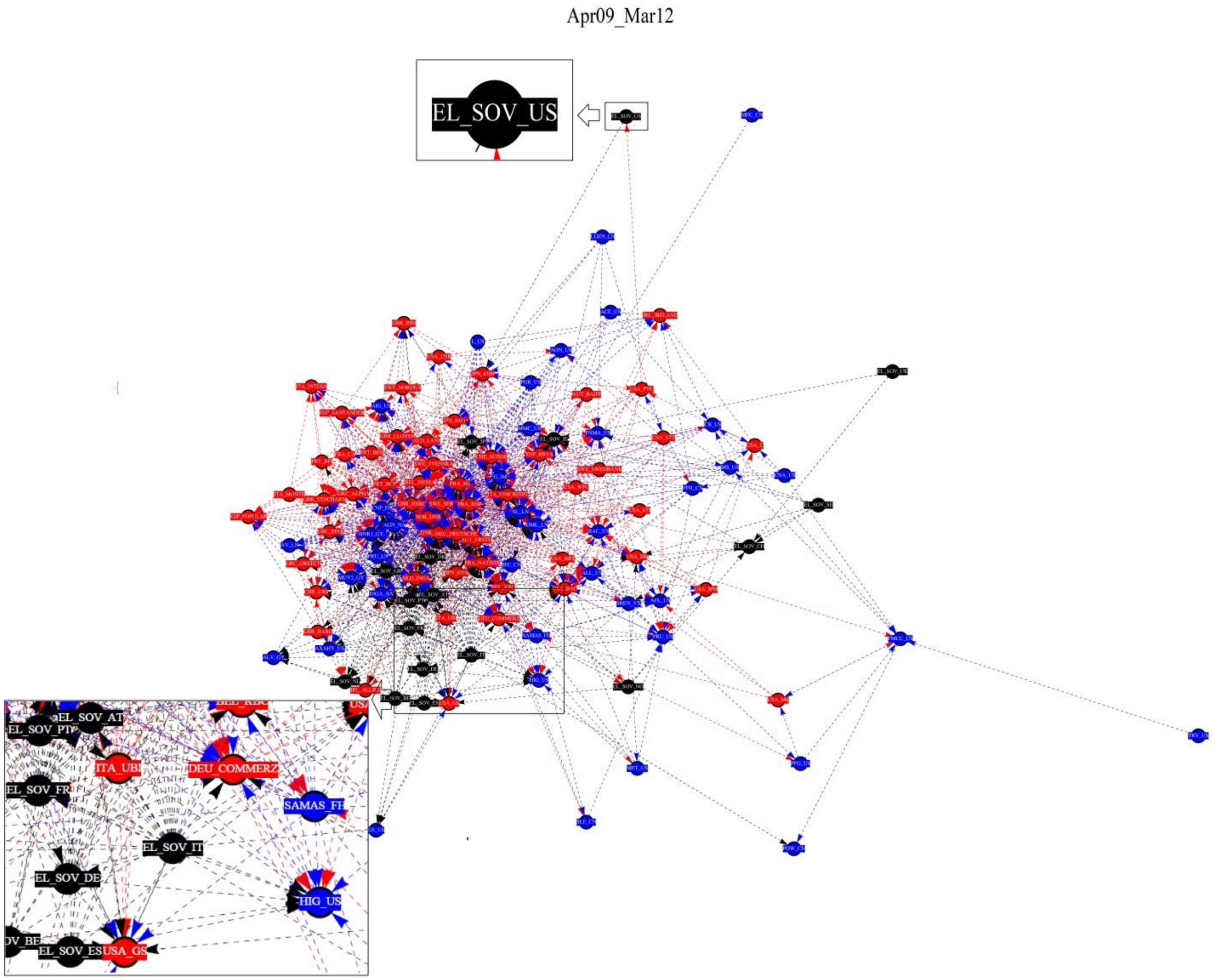

Figure 10 –Network topology diagram of linear Granger-causality relationships between ELR of banks, insurers, and sovereigns that are statistically significant at the 1% over April 2011 to March 2012. The type of entities causing the relationship is indicated by color: red for banks, blue for insurers,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