**Financial Crises and Connectedness of European Banks**

by

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**Abstract**

The literature on financial connectedness has expended significantly since the last financial crisis. While there is a voluminous literature on financial linkages, mostly due to lack of empirical work these studies fail to provide conclusive policy recommendation. Complementary to this literature, my study focuses on all aspects of the linkages among the large banks of the EU member countries. My thesis identifies how financial shocks propagate during crisis times and which banks become main transmitters of these shocks. In empirical analysis, I use Diebold and Yilmaz connectedness measurement to calculate the reciprocal effects of each banks. The data set includes daily stock market return volatilities for 45 European banks over the period 1998-2014. The resulting connectedness matrix serves as my main data in full sample and dynamic analysis.

**Keywords:** Connectedness, Eurozone Crisis, European Banks, Diebold and Yilmaz Connectedness Measurement

**Özet**

Son ekonomik krizden sonra finansal ağlar üzerine yapılan çalışmalar artmıştır. Finansal bağlantılarla ilgili geniş bir literatür olmasına rağmen, ilgili bilimsel çalışmaların kısıtlılığı bu konuda net bir sonuca varılamamasına sebep olmaktadır. Var olan literatürü tamamlayıcı nitelikte olan araştırmam, Avrupa Birliği üyesi ülkelerin büyük bankaları arasındaki bağlantılara odaklanmaktadır. Bu çalışma, kriz döneminde finansal şokların nasıl yayıldığını ve hangi bankaların bu şokların yayılmasında etkin bir rol oynadığını analiz etmektedir. Bilimsel analiz bölümünde, her bankanın ağ üzerindeki çift taraflı etkisini hesaplamak için Diebold-Yılmaz'ın bağlanmışlık ölçümü kullanılmaktadır. Veri seti, 45 Avrupa bankasının 1998-2014 yılları arasında, hisse senedi getiri oynaklığı değerlerini içermektedir. Bu değerler sonucunda ortaya çıkan bağlanmışlık matrisi, tam örneklem analizi ve dinamik analiz için ana veri setini oluşturmaktadır.

**Anahtar Kelimeler:** Anahtar kelimeler: Euro Krizi, Avrupa Bankaları, Diebold ve Ylmaz, Bağlanmışlık Ölçümü

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# 1 Introduction

The global financial crisis of 2007-2009 encourages economists to venture into the new research areas to understand interconnections between financial institutions. Until recently, the effects of small banks or firms on the whole system were slightly ignored and underestimated. In the early months of 2007, sub-prime mortgage lenders started to declare bankruptcies in US. Though there had been more than 50 bankruptcies occurred until May 2007, most academic economists, even Federal Reserve Board Chairman Ben Bernanke, pointed out that they did not expect to see any significant spillovers from the subprime market to whole economy. However, the inexorable force of connectedness resulted with a strong domino effect and economists are convinced the importance of channels for the spread of shock.

After understanding the importance of contagion channels, economists had begun to seek various methods to calculate financial connectedness or to understand contagion across banks. The strong presumption was that if we could observe direct channels across banks such as assets and liabilities, we would find true approaches and models to observe links. There are two main difficulties lie in this idea: the existence of indirect channels and hardship of finding daily data on balance sheets.

To deal with these drawbacks, in this thesis, I use financial connectedness calculation methods of Diebold and Yilmaz (2010). The main idea is to do time series analysis by using daily stock market returns of banks, which can easily be obtained in local stock markets. This connectedness measurement gave us directional connectedness index across banks, which are called "from" and "to" connectedness. In a contagion channel analogy, connectedness and directions can be considered as the thickness of channel and the direction of flow respectively. In the light of both financial connectedness and contagion, representing my findings in a well-defined plot is a simple but effective way to have a comprehensive perspective. Graph topology would enable to see how connectedness evolves during a span of time or who is responsible for contagion of shocks. Realizing high volatile distribution of "to" connectedness , by comparing with "from" connectedness and total connectedness, is another corner-stone of my analysis. Ranking banks according to their "to" connectedness helps to have a clear plot, which eventually provides a better ground to analyse how bank attributions are changing in tranquil times and crisis periods.

While there is a voluminous literature on financial connectedness, lack of empirical work fails to provide a clear conclusion in most papers. Demirer, Diebold and Yilmaz(2014) study on the connectedness of the global banks. They use elegant framework of Diebold and Yilmaz (2014) that obtain high frequency measures of connectedness. My empirical objective in this paper is to apply Diebold and Yilmaz framework to the European banks.

There are three main underlying reasons behind choosing European banks for my empirical study. First, the recent era of regionalization impairs the effectiveness of globalization in different areas, notably in banking sector, and as a result financial flows begin to be fuelled by regional factors. For instance, inter-regional fiscal transfers change circular symmetry of EU. Through these types of spillover effects, observing the effects of endogenous shocks becomes much more straightforward like in EU interventions in Greece. Furthermore, sovereignty causes country-wise effect against exogenous shocks instead of system-wide changes. I have found that UK can be considered as a part of Atlantic power because a financial shock in US has a direct impact on UK banks; whereas, German banks are less responsive to these shocks.

Second, existence of the common currency is another key factor leading me to study on European banks, which elegantly captures the relation between currency zone core and the other countries. Vast empirical studies on connectedness literature concentrate on US stock markets while European research are limited in financial sector analysis. The explanatory power of these studies is not able to cover the effects of having a common currency and common central bank. In my analysis, it can be seen how Eurozone crisis has a negative impact on Eurozone countries, but not on other European countries in crisis times. Even, banking regulations of European Central Bank (ECB) cause similar influence on the banks of Eurozone countries. Third, dense yet clear structure of Europe, where core countries and periphery countries are not so much disintegrated, can still be observed clearly. In most cases, adding new banks to a financial measurement increases the number of outliers, or even more dramatically exercises pervasive influence on graph positioning. This situation held also for my research; for example, adding Japanese and US banks to the connectedness measurement increases the average country connectedness, which eventually creates "island of Japan" and "island of US " in the graph visualization. These islands are not affected crucially during crises time but unfortunately lessen the effectiveness of my study to make a clear observation on Europe. As a result of these points elaborated upon this section, I have decided to focus on European banks in my empirical analysis.

The remainder sections of the thesis are constructed in five sections. In section 2, I present my detailed study on prevailing approaches in both theoretical and empirical studies. Methodology that used in connectedness analysis is introduced in section 3. In section 4, I introduce my empirical data and justify the reasons of excluding some banks from the analysis. Section 5 discusses the effects of shocks on the graph topology, which also compares changes in the graph structure during crisis periods and tranquil times. Finally, section 6 concludes the thesis with its contributions and further research directions.

# 2 Literature Review

Throughout this section, my main aim is to review both empirical and theoretical researches focusing on connectedness literature. It begins with the evaluation of connectedness studies in literature. After that, I present recent studies on graph theory.

The last economic crises and globalization encourage economists to examine connectedness between firms and countries. The main difficulty lies in the measurement of connectedness. Until recently, linear Gaussian thinking and correlation-based methods have been used for measuring connectedness in the vast majority of papers. These techniques serve a useful but limited purpose for empirically measuring connectedness; hence, economists must, inescapably, pursue new methodologies to make measure of connectedness more tractable and comprehensible. Engle & Kelly (2012) apply dynamic equi-correlation approach, whose idea is simple in terms of using average correlations across pairs yet still obscure. In systemic risk analysis, connectedness is used in risk calculation methods such as Value at Risk (VaR) and more elaborately CoVaR. Adrian & Brunnermeier (2011) define the contribution of an institution to the system by using linear Gaussian methods. Diebold & Yilmaz (2009) introduce a unified framework to measure connectedness by applying VAR framework and forecasting error variance decomposition. Their main aim is to find H-step forecast error variance of a variable due to shocks in another variable. They use daily stock range volatility data of major US banks to measure connectedness. In my analysis, I have applied the elegant framework of Diebold-Yilmaz to obtain pairwise volatility connectedness of European banks.

Graph visualization studies have a quite old history by comparing with the financial connectedness literature, which have became popular after the last financial downturn. Most studies on graph theory had focused on social relations until the beginning of 90s. Simple graph properties was adequate for the needs of social analysts. For example, centrality concept has been widely used to sort elements according to their importance. Freeman (1979) analyzes structural centrality concepts by focusing on social relations. He mainly concentrates on point and graph centralities for binary graphs. His paper also figures out the strong relation between centrality and perceived leadership. His result still can be applied in financial connectedness, where focal and central banks play a crucial role in crises according to my analysis.

Freeman et al. (1991) introduce a new centrality measure, $C_F$, that is applicable for weighted graphs. His new approach aims to assign capacities for each link to calculate contagion flow. However, his both papers do not provide any research ground for directed mesh graphs.

Allen & Gale (2000) discuss the fragility, decentralization, robustness and containment of incomplete and complete interbank market under a financial shock by observing different states for four regions. Exposures between banks are main channels and it is used as weighted link parameter in interbank market. Their paper reveals the strong relation between completeness and resilience of an interbank market. Complete market structures prevent the threat of fragility and the effects of crisis abate through banks in long term. Channels between firms are served as runaway track ramp. However, incomplete market structures lack in financial channels. The empirical approach of their model cannot be easily constructed due to the hardship of finding exact exposures in interbank market unfortunately.

As a latter approach, Allen & Babus (2009) suggest that financial systems can be evaluated using graph topology and market structures can be represented as points and links. They argue that assets and liabilities of banks are the main source of links such as holding similar portfolios or exposures. Their results indicate that complete mesh graphs are better in absorbing risks of contagion by comparing with incomplete market structures, which is consistent with their earlier studies. Their latter paper also applies graph topology into the last financial crisis and explains freezes in interbank markets. Gai & Kapadia (2010) concentrated on the relation between the probability of contagion and its effects during crisis times. Their paper presents why each shock has different impacts on the financial systems depending on the source points of shocks. Their theoretical model covers in-degree and out-degree definitions which is a good way to introduce weighted directed graphs into the financial system. Incoming link weights are associated with interbank exposures where interbank liabilities are proxies for outgoing link weights.

# 3 Methodology

## 3.1 Connectedness Measurement

To analyse connectedness of European bank, I apply Diebold & Yilmaz connectedness methodology. Diebold & Yilmaz connectedness measurement is based on the variance composition associated with N variable vector autoregression. Consider a covariance stationary $N$-variable VAR($p$), $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim (0, \Sigma)$. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the $N$x$N$, coefficient matrices $A_i$ p order autoregressive process $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with $A_0$ an $N$x$N$ identity matrix and $A_i = 0$ for $i < 0$. The MA representation of VAR is used to estimate the effects of shocks to variable $x_i$ to the forecast of variable $x_j$ for $i, j = 1, 2, .., N$. From this representation, own variance shares is defined as the fraction of H-step-ahead error variances in forecasting $x_i$ due to $x_i$, and connectedness is defined as fraction of H-step-ahead error variances in forecasting $x_i$ due to shocks $x_j$ for all i, j.

This representation of connectedness requires the derivation of the impulse response function of VAR(p) process which is obtained a la Pesaran & Shin (1998). They show that when the error term $\varepsilon_t$ has a multivariate normal distribution, the $H$-step generalized impulse response function scaled by the variance of the variable is given by:

$$\gamma_j^g(h) = \frac{1}{\sqrt{\sigma_{jj}}} A_h \Sigma e_j, \qquad h = 0, 1, 2, ... \tag{1}$$

where $\Sigma$ is the variance matrix for the error vector $\varepsilon$, $\sigma_{jj}$ is the standard deviation of the error term for the $j^{th}$ equation, and $e_i$ is the selection vector with one as the $i^{th}$ element and zeros otherwise.

The last step to obtain the connectedness index is to calculate each variable's contribution to each other's $H$-step-ahead generalized forecast error variance. This is calculated by the following formula:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{2}$$

Since the sum of each row of the variance decomposition matrix is not necessarily equal to one, we normalize each entry of the decomposition matrix to obtain the index from variance decomposition. This is performed by dividing each entry by row sum,

$$\tilde{\theta}^g_{ij}(H) = \frac{\theta^g_{ij}(H)}{\sum_{j=1}^{N} \theta^g_{ij}(H)} \tag{3}$$

Finally, using the normalized entries of the variance decomposition matrices Diebold & Yilmaz define four different connectedness measures: the total connectedness $C(H)$ , the gross directional connectedness received by variable $i$ from all other variables $j$ $C_{i\leftarrow\bullet}$ (from connectedness), the gross directional volatility connectedness transmitted by variables i to all other variables j $C_{\bullet\leftarrow i}$ (to connectedness), and finally, the net directional connectedness transmitted from variable $i$ to all other variables $C_i(H)$ (net connectedness):

$$C(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}^g_{ij}(H)}{N} \tag{4}$$

$$C_{i\leftarrow\bullet} = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}^g_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ij}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}^g_{ij}(H)}{N} \times 100 \tag{5}$$

$$C_{\bullet\leftarrow i} = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}^g_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^g_{ji}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}^g_{ji}(H)}{N} \times 100 \tag{6}$$

$$C_i(H) = C_{\bullet\leftarrow i}(H) - C_{i\leftarrow\bullet}(H) \tag{7}$$

To estimate high dimensions with Diebold and Yilmaz methodology, regression shrinkage is a good way to start. Demirer, Diebold and Yilmaz (2014) use “Lasso” method to minimizes the residual sum of squares. In my thesis, I also apply Lasso to analyse connectedness of Europe banks. Detailed explanation and methodology of Lasso is given in the following section.

## 3.2 "Lassoed" VAR's for Connectedness in Sample

### 3.2.1 Methodology

For compelling applications, it's crucial that the approximating model be estimable in very high dimensions, somehow recovering degrees of freedom.[1] One can do so by pure shrinkage (as with traditional informative-prior Bayesian analyses, or ridge regression) or pure selection (as with traditional criteria like AIC and SIC), but *blending* shrinkage and selection, using variants of the lasso, proves particularly appealing.

### 3.2.2 Penalized Estimation

Consider the least-squares estimator,

$$\hat{\beta} = \arg\min_{\beta} \sum_{t=1}^{T} \left( y_t - \sum_i \beta_i x_{it} \right)^2,$$

subject to the constraint:

$$\sum_{i=1}^{K} (|\beta_i|^q \leq c.$$

Equivalently, consider the penalized estimation problem:

$$\hat{\beta} = \arg\min_{\beta} \left( \sum_{t=1}^{T} \left( y_t - \sum_i \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} |\beta_i|^q \right).$$

Concave penalty functions non-differentiable at the origin produce subset selection (e.g., $q \to 0$) , whereas smooth convex penalties produce shrinkage (e.g., $q = 2$). Hence penalized estimation nests and can blend selection and shrinkage. The case of $q = 1$, to which we now turn, is of special interest.

### 3.2.3 Lasso (Tibshirani (1996))

The lasso (short for "least absolute shrinkage and selection operator") solves the $L_1$-penalized regression problem:

[1] In what follows we refer to estimators that achieve this as "regularized," and associated environments as involving "regularization."

$$\hat{\beta}_{Lasso} = \arg\min_{\beta} \left( \sum_{t=1}^{T} \left( y_t - \sum_{i} \beta_i x_{it} \right)^2 + \lambda \sum_{i=1}^{K} |\beta_i| \right).$$

Lasso shrinks *and* selects. It uses the smallest $q$ for which the minimization problem is convex, which is valuable computationally. Lasso has some undesirable properties, however. First, the oracle property does not obtain. Second, when explanatory variables are highly correlated, lasso tends to pick only one of them and shrinks others to zero. To overcome these limitations, different variants of lasso have been proposed.

## 3.3 Connectedness Measurement Plots and Architecture

After introducing the methodology of my thesis, giving brief information about visual architecture and connectedness properties is a vital course. Graph is a combination of points and links. In my approach, my analysis focused on weighted directed graphs and most of the time we are not so much familiar with these concepts. Therefore, I illustrate definitions and elements of graphs.

In my thesis, I use Diebold and Yilmaz volatility connectedness measurement in architecture where points are banks and links are their corresponding connectedness values. Connectedness graph topology is fully-connected mesh graph because connectedness value cannot be zero empirically. I used daily market capitalization values as a point attribution. Instead of using simple Gaussian methods, which can be used to define undirected graphs, it is more reasonable to use a concrete approach which directly presents pairwise link values in a graph. Diebold and Yilmaz framework creates an excellent ground to work on empirical financial mesh graphs. Technical details about the visualization of pairwise volatility connectedness can be found in Appendix.

# 4 Empirical Data

At the beginning of my study, my dataset consists of 97 banks from 28 European countries and their stock market prices from 1995 to 2014. However, it is not possible to obtain stock market values of all equities and only 32 of equities have been traded during this period. To get a better picture and make a clear analysis, my main aim was to study on maximum number of banks for largest time period. At the same time, removal of outlier banks are required to develop a coherent economic evaluation. Outlier banks are removed from my analysis which prevents system from having a dense visualization.

After final adjustments, I have decided to use 45 banks from 17 European countries[2], which consists of both EU and non-EU countries. Data series are primarily drawn from Bloomberg database. The database includes four daily indicators of each stock, which are opening price, closing price, highest price and lowest price for a given day, during the span of 1998 to 2014. Daily return volatilities of each stock are calculated by using these daily return values. If the number of traded stocks is less than half of total stock prices in given days, these particular dates are removed from my analysis not only for sake of calculation but also for the sake of robustness. If a stock is not traded in a specific day, volatility index of previous day is copied for that day. In addition to stock market prices, daily market capitalization (mcap) values of each bank are also drawn from Bloomberg database. The list of banks with their market capitalizations, country names and ticker representation can be found in appendix.

[2]Austria, Belgium, Denmark, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Spain, Sweden, Switzerland, Turkey, UK

## 5 Static Analysis

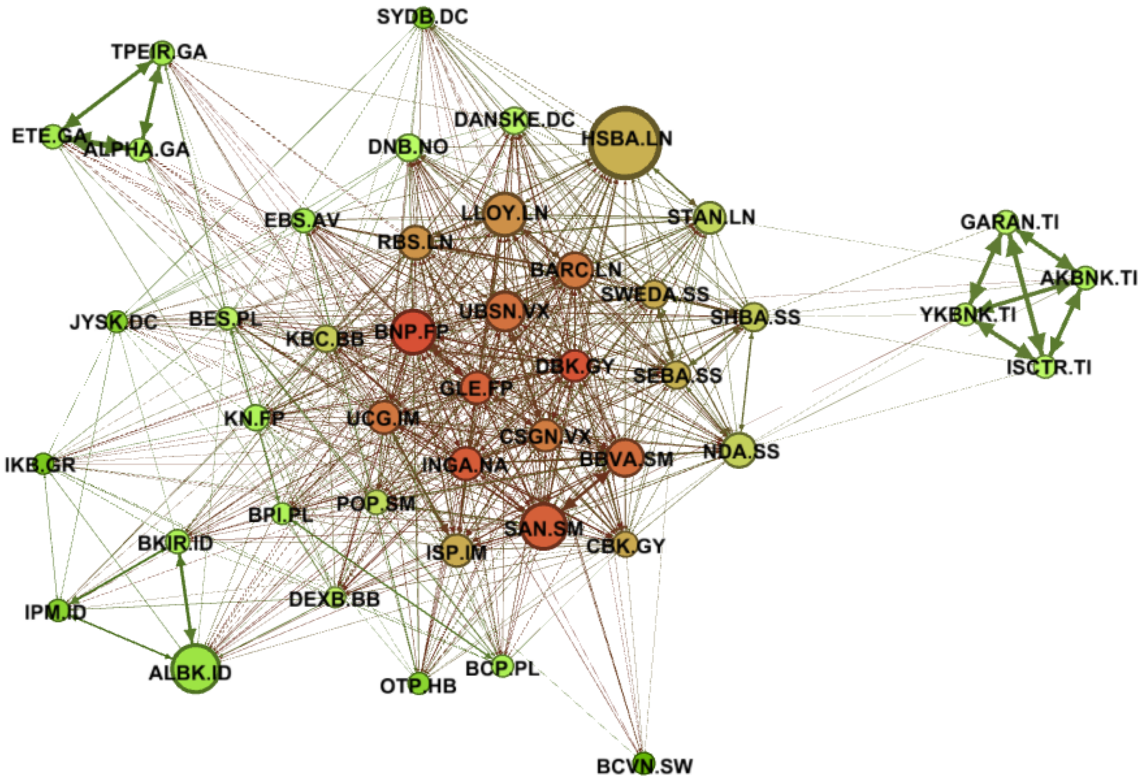


Figure 1: Pairwise Volatility Connectedness Graph of European Banks (index=67.4) 1998-2014

In full sample analysis, my dataset includes stock return volatilities of 45 European banks, whose data spans from January 1998 to March 2014. I employed Diebold-Yilmaz framework with Lasso shrinkage method and double cross-validation. To illustrate the result concretely, my successive approach is to use mesh graph topology to represent connectedness index. The resulted graph architecture appears as graph above. Each bank represented with their Bloomberg tickers and self-loops are filtered out for the sake of simplicity. Point size is proportional to market capitalization as of March 2014.

With a value of 67.4% the measure of total connectedness among stocks of 45 banks is a reasonable value by comparing with other empirical analysis made by Diebold & Yilmaz. Specifically, Diebold & Yilmaz reports that they obtained the value of 78.3% as the measure of total connectedness after analyzing 13 financial stocks from US. They argue that the underlying reason of such a high level of connectedness is that these stocks show similar reactions to both industrial shocks and financial shocks. However, the same situation does not hold for my analysis because of two main reasons. First, the banks used in my analysis are chosen from 17 European countries, and even some of them are not from European Union or European Monetary Union. Therefore, their reactions to external and internal shocks ultimately follow different paths. Second, US stocks are affected by the same government initiative; however, there are strict regulations on stock markets. Lack of government initiative precludes effective similarities between stock markets.

After delving deeper into the connectedness between banks, a high value of own connectedness can be observed in BCVN with 66%, which location also signals to this result. As expected from graph visualization, DBK and GLE have the lowest own connectedness with 16% and their weighted-out degrees are near to 120, which corresponds to 120% in directional connectedness from these banks to whole system. Total directional connectedness index ranges from 43% to 209%. The values of "to" connectedness index vary from 9% to 126%; whereas, "from" connectedness vary from 33% to 82%. It is hard to add connectedness matrix to my thesis because of its 45x45 size, which representation is not suitable in word format. My motivation becomes presenting largest directional connectedness to enrich our perspective on my analysis. Largest values are mostly connecting banks from the same countries. To ensure a better alignment, presenting largest connectedness values between two banks from different countries seems more rational(table 1).

As we have seen in table, there are three clear tandems which actually provide us crucial insights into form of Europe. The highest values of pairwise connectedness take places between BNP Paribas and Deutsche Bank with approximately 5.1%. The effectiveness of both banks can be seen in the whole table and also in the graph architecture, where locate in the center of graph. The domination of French and German banks continues throughout the table and more sophisticatedly, notably in tranquil times, this Franco-German tandem plays a crucial role in my dynamic analysis as well. To have a better understanding, we should elaborately examine the economic relationships of these two countries. In 90s, France and Germany had stronger economic position in Europe, which are also the founders of European Monetary Union. Especially after the use of Euro as currency, the currency of German side, D-Mark, overvalued. In addition, Germany becomes more reliable because there were not any worries about the current account deficit. France and Germany are also pivotal countries, which pledge their support for efforts to stabilize European Union. For that reason, Franco-German tandem serve as main economic artery for Europe; and, their high values in pairwise connectedness analysis attest to their roles.

| source | target | Csource[3] | Ctarget[4] | "to"[5] |
|---|---|---|---|---|
| BNP Paribas | Deutsche Bank | France | Germany | 5.173 |
| Deutsche Bank | BNP Paribas | Germany | France | 5.133 |
| ING Bank | Credit Suisse Group | Netherlands | Switzerland | 5.060 |
| Deutsche Bank | Credit Suisse Group | Germany | Switzerland | 4.919 |
| ING Bank | Commerzbank | Netherlands | Germany | 4.902 |
| Credit Suisse Group | ING Bank | Switzerland | Netherlands | 4.798 |
| ING Bank | Deutsche Bank | Netherlands | Germany | 4.758 |
| BNP Paribas | ING Bank | France | Netherlands | 4.713 |
| Deutsche Bank | ING Bank | Germany | Netherlands | 4.661 |
| Societe Generale | Deutsche Bank | France | Germany | 4.634 |
| Deutsche Bank | Societe Generale | Germany | France | 4.620 |
| ING Bank | BBVA | Netherlands | Spain | 4.576 |
| BNP Paribas | Intesa Sanpaolo | France | Italy | 4.553 |
| ING Bank | BNP Paribas | Netherlands | France | 4.537 |
| BBVA | Intesa Sanpaolo | Spain | Italy | 4.535 |
| BBVA | ING Bank | Spain | Netherlands | 4.518 |
| BNP Paribas | BBVA | France | Spain | 4.503 |
| Banco Santander | Intesa Sanpaolo | Spain | Italy | 4.454 |
| BNP Paribas | Banco Santander | France | Spain | 4.429 |

Table 1: Major Directional Pairwise Connectedness

Second, the location of ING Bank and Credit Suisse in my static connectedness analysis is a result of a strong banking tandem in Europe. The driving force of this tandem does not emerge from political and economic background of countries. Financial flows are fuelled by banking sector in this specific tandem because these banks are responsible for high money flows in Europe. They cannot be considered as main artery for European body, such as Germany and France, but their role is much more similar to ventricles of heart. Their values of pairwise connectedness to each other are both approximately 5%

[3] Country of Source
[4] Country of Target
[5] "to" connectedness

and 4.8%. Finally, high pairwise connectedness share of Spanish-Italian banks encourages me to think about their importance for Europe. These two Mediterranean countries deal with political issues during the last decades by comparing with other countries. Therefore, their economic conditions never give them a chance to take lead in Europe. This factor eventually makes these countries to squeeze between core countries and periphery countries. In tranquil times, Banco Santander, BBVA, UniCredit and Intesa Sanpaolo, which are the main banks of Italy and Spain, move to the outside of core; whereas, they just move forward to core during crisis periods.

Apart from these tandems, graph and pairwise connectedness table together clarify the positions of other banks during these periods. The banks of periphery countries, Turkey and Greece, located in the outside of core. Hence, they behave like islands in static analysis; which also holds for Irish banks even they are not considered as periphery countries. Greek banks sometimes show similar behaviors with other European banks; however, Turkish banks put their islands away from core mesh graph. The absence of economic integration between EU and Turkey may be the main basis for this argument. Furthermore, English, Portuguese and Swedish banks behave like vicious circles that cover core countries in graph. Specifically in crisis times, these banks located as if they draw the border of core.

# 6 Dynamic Analysis

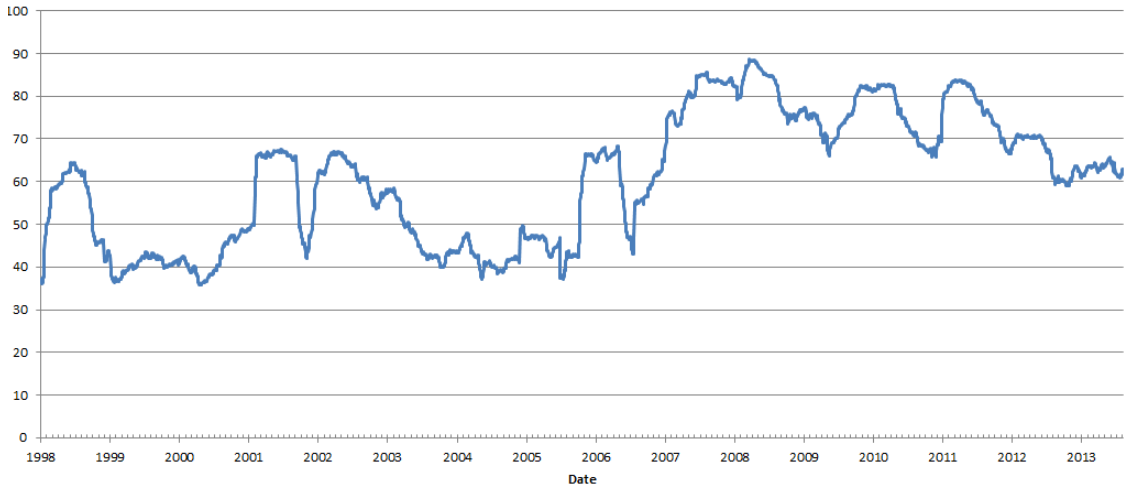


Figure 2: Connectedness Index of European Banks

I calculated total connectedness index over 150-day rolling-sample windows. In static analysis, total volatility index is equal to 67.4%. This index value actually gives an idea on dividing timeline into the two parts as before 2007 financial crisis and after. The first period can be considered as low-connectedness area because even the largest index value cannot reach the static level from 1998 to 2007. The second period starts with last financial crisis and after mid-2007 total volatility connectedness index varies between 65-88 %.Now we can go further and analyse dynamic trends.

At the first glance, we can observe a rising trend which starts in early months of 2007 and kept connectedness index in higher levels until mid-2009. Our connectedness index is around 43% levels for February 2007 and reaches up to global peak value in October 2008 with 88%. In addition to this uprising trend, there are other jumps includes Russian Financial Crisis, 9/11 Terrorist Attacks, WorldCom Scandal, Eurozone Crisis. After these shocks, our dynamic graph is not completely smooth and there are still rocky moments. Instead of analysing these cycles in here, I focus on each shock separately throughout this section, where related graph architectures presented in the appendix.

## 6.1 Russian Financial Crisis

This crisis is also known as Ruble crisis which caused the devaluation of Ruble. Both chronic budget deficit and high fixed exchange rate are the main underlying reasons of crisis. My analysis, unfortunately, does not include any Russian banks; hence, the full evaluation of crisis cannot be possible with these variables. We are still nevertheless sure that this crisis has a direct impact on other major Europe banks. Total volatility connectedness index jumps from 40% to 62% in just two months. This short period seems enough on the transmission of shock to the wall of Europe.

This crisis; however, do not have crucial impacts on graph configuration. All major countries are affected similarly. Total volatility connectedness graph shows similar behaviours before and after crisis. Pairwise directional connectedness of each bank is increasing relatively. As a final note, Deutsche Bank come to the center of graph, which is the main transmitter bank of Europe for this specific shock.

## 6.2 9/11 Terrorist Attack

9/11 terrorist attacks have a profoundly negative impact on world economies; eventually this wave hits the walls of Europe. In my connectedness analysis, increase in the density of structure provides us an empirical support. Before this attack, sparse graph architecture can be observable and many points have lower weighted-out degree, where green color represents lower out-degree as also stated in the visualization of connectedness under appendix. On the other hand, this shock causes profound changes in placement of banks, notably in core countries. The banks of peripheral countries, such as Turkey, Denmark, Greece, are still in out of core. There may be two main underlying reasons behind this behaviour of countries. First, peripheral countries have weak ties with US and their trade relationship is mainly driven by other European countries. However, this case does not hold for UK, Switzerland and Germany, which have strong financial link between US. The centrality and strength of banks of these three core countries show a rising trend.

Second, the insurance firms with largest loss are Lloyd's, Swiss Re, and Munich Re, which are companies of UK, Switzerland and Germany respectively (Hubbard et al., 2005).

Moreover, Swiss Re has tenacious financial link between Credit Suisse, which located in the center of graph. The same insurance company effect can be seen in Lehman Bankruptcy where the strength of AIG became extremely large only the day after the declaration of bankruptcy.

## 6.3 WorldCom Scandal

WorldCom Inc. filed for Chapter 11 bankruptcy protection in July 2002, which had been the largest bankruptcy until that time and it is the third largest bankruptcy in US history after Lehman Brothers Holdings Inc. and Washington Mutual. The main reason of this default was the fraud scandal which was revealed one month before the declaration of bankruptcy. WorldCom has strong financial ties between Citigroup and JPMorgan Chase which are two of the largest banks in the US. Though this financial shock emerged in US, Europe banks also suffered. There are two major differences between June and August 2002 in my connectedness analysis. Firstly, all banks are coming closer to center with the exception of banks of Greece and Turkey. Before this external shock, links sparsely scatter through all graph structure whereas UK banks and the banks of core countries near to center the same as full sample analysis. However, just after this scandal, we can see German-Franco-Dutch tandem in the center where other banks viciously circulate core. In addition to that, UK banks aggressively stay in core, notably Royal Bank of Scotland. Not surprisingly, Prudential Financial insured WorldCom and Royal Bank of Scotland at the same time, and Prudential have 150 million dollar exposure to WorldCom's debt.

My second evaluation on this graph is about the strength and location of Sweden banks. Even though average weighted-out degrees increase for almost all banks, Sweden banks show a strong resilience and their weighted-out degrees are decreasing with this scandal. However, their location comes closer to the core surprisingly at the first glance but just looking back to early 2000s provide us a chance for clear judgement. Ericsson, which is a Swedish provider of graph and communication services, makes strength its position in this market and gets top place. This information is consistent with my analysis and we can conclude that this man-made negative shock in the world markets flows to

Europe but the channels of Sweden was protected by Ericsson for any dangerous contagion.

## 6.4 2007 Financial Crisis

HSBC announced that their loss linked to US subprime mortgage market in February 2007. Their bad debts were approximately 20 percent above average forecasts. That day HSBC also stated that its chief executive involved in managing this mortgage problem. Unfortunately, their chief executive failed to prevent the worst global financial crisis since the Great Depression. After the announcement of HSBC, the number of mortgage defaults started to rising. The authorities were arguably optimistic and they tried to persuade that these defaults would not be resulted with a financial crisis. However, the duration of the slump was long and instead of following a steep falling, its severity has been deepening day by day: downturns in stock markets, long-lasting depression, and liquidity crisis. This crisis was not archetype of the other financial crisis. In this crisis, domino effect of defaults and risk of contagion were higher. I report changes in the graph architecture of European banks and connectedness index from the beginning of 2007 to the end of 2008.

As a preliminary step, it is an effective course to look whole system and connectedness index, where graphics can be found in appendix. From late February to early March, only in 10 days, total volatility connectedness index climbed from 43% to 55%. This increase was not only a result of the default of New Century Financial Corporation in US, but also banking stocks encountered with a shock in MBS market. The dominant transmitter of shock is Deutsche Bank and most banks tend to locate near the core, especially UK banks. In this ten days period, notable decreasing point sizes, lowering in market capitalization values, is an early signal for upcoming storm in market. Total connectedness index increased gradually and hits 62% level in early July. During this span of time, graph became denser and the color of points began to turn red and orange. After examining system more carefully, it is observable that main transmitter of shock became BNP Paribas and interestingly it also come to center of graph. Not surprisingly, BNP Paribas revealed that they suffered from complete evaporation of liquidity in August 2007. The ECB pumps approximately 200bn Euro to the banking market to solve illiquidity problem. Total volatility connectedness index rose to 75% level which is the highest value of total connectedness index of European bank until that time. As expected, German banks came closer to BNP Paribas and they also announced their losses at the end of August officially. At the end of 2007, total volatility index hit 80% level.

Though there were still optimistic economists, big falls in global markets seemed to belie all of them in the late January of 2008. After decrease in global stock markets, FED immediately cut rates to recover markets but at the end January total volatility connectedness index reached to 85%. In addition to rise in index, UK banks get closer to core with periphery country banks. The possibility of global recession had a direct impact in both core and periphery countries. BBVA, UniCredit, BNP Paribas, ING Bank and Standard Chartered behave like a transmitter circle with their higher weighted-out degree distribution.


Figure 3: Total market capitalization of 45 European Banks

The final but most effective shock came in 15 September 2008 when Lehman Brothers filed for Chapter 11 bankruptcy protection, which is the largest bankruptcy in the history with $639 billion. Total connectedness index jumped from 79% to 85% in just three days; total weighted-out degree of core country banks exceeded 120%. In following days, it was announced that Ireland had become first country suffer from recession in Europe. Fortis was nationalized. British, German, Sweden and Netherlands governments set out rescue plans. Total connectedness index hit its highest value in my analysis with 89% and graph architecture was at its denser form in 27 October 2008. Market capitalizations of all European banks fell in dramatic rates. The graph shows the change of total market capitalizations from the beginning of 2007 to the end of 2008. After this global crisis episode, total volatility connectedness index began to decrease to until the end of 2009, where another episode was about to start: Eurozone Crisis.

## 6.5 Eurozone Crisis

Slowing trajectory of growth, asset market collapses, current account deficits, liquidity crises and biggest historical recessions were not only the problem of Europe but all continents in the aftermath of 2007 financial crisis. Hence, it is hard to draw a certain line between global financial crisis and Eurozone crisis timeline. The onset of Eurozone crisis can be considered as the sovereign debt crisis that occurred in Greece at the end of 2009; however, the underlying reason was that core country banks continued to lend to periphery countries. These banks considered periphery countries as a safe haven but these havens became headache of Europe. In such circumstances, I decide to follow my dynamic analysis graphs, where there are two rises during Eurozone crisis. The first one starts at the end of 2009 and last until July 2010. Total volatility connectedness index climbs from 66% to 82% in six months period. Throughout this span of time, the first effects of bubbles in the periphery can be seen because of stagnation in Franco-German tandem. Both Sarkozy and Merkel approved stimulus packages to save their banks that suffer from worst losses in their histories since WWII. As a result of this, BNP Paribas, Societe Generale and Deutsche Bank locate at the center of the graph visualization European bank at the end of June. Apart from Barclays, total weighted out degree of UK banks are lower than other core banks. Barclays is getting closer to core after its shares fallen 13.5% at the beginning of June 2009. The position of IKB in graph architecture may lead us to think about the reason of his outlier behavior. IKB generated only 4% volatility connectedness to others. Its outlier position was inevitable consequence of their earlier collapse in the mid-2007. Greek banks and Irish banks produce less than 20% volatility connectedness to other country banks. The fiscal crisis in Greece and Ireland results with a financial (banking) crisis, which impair their effectiveness in the graph topology.

According to my connectedness analysis, second wave of Eurozone crisis hits graph architecture in mid-2011. From mid-2010 to mid-2011 total volatility connectedness index fell from 82% to 65%. Points scatter and there is no certain core formation in mid-2011, like calm before the second storm. After months of procrastination, in the summer of 2011, ECB, Germany and France governments agreed to make a rescue plan to solve Greek debt crisis. Total volatility connectedness index reached 65% which is the lowest value during Eurozone crisis period. However, European stock markets suffered heavy falls in August and international alarm over Eurozone crisis grows according to Reuters in mid-September. Credit ratings of Italy and Spain are cut after Greece and Ireland. Greece and Ireland banks produced less than 7% volatility connectedness to others, which is the lowest degree in dynamic analysis. Total volatility connectedness index climbed to 84% in October 2011. French, German and Swiss banks were in the first layer of vicious circle; Spanish, English and Italian banks were in the second layer of vicious circle; Irish, Greek and Turkish banks located in the out of circle. After large banking losses and sovereignty debt stress, Euro Summit Statement declared to implement country specific recommendation in 26 October 2011. After that day, total volatility connectedness index of European banks started to fall 60% levels, where it is in these levels currently.

# 7 Conclusion

In my thesis, I have studied volatility connectedness of major European banks from 17 European countries. Demirer, Diebold and Yilmaz have studied on volatility connectedness across major global banks. I have analysed the effects of global and local shocks to the connectedness. It is notable that total volatility connectedness index increases in crisis periods and core countries play major role in the transmission of shocks. In particular, Franco-German axis behave like main transmitter of shocks, whereas, Switzerland and UK behave like swing countries located in second layer of core. Periphery countries of my analysis, Turkey and Greece, are mostly marginalized and founded themselves in a subordinate role. When we focus on dynamic analysis, it is possible to classify pre-financial crisis period as low-volatility and post-financial crisis period as high volatility period.

In empirical analysis, I prefer to use "to" connectedness for the sake of convenience because of high volatile distribution of "to" connectedness by comparing with "from" connectedness. If a bank has high value of "to" connectedness, this bank can be considered as the transmitter of shock. This idea helps to evaluate each banks during tranquil and crisis periods.

In addition to studying on Europe banks, there are a number of interesting empirical studies to be explored in the future. It would be very useful to study on the connectedness of major European firms or make a sector specific analysis. By the help of these analysis, it is possible to see which sectors play transmission role or getting closer to core. It is also a good way to analyse graph and decide whether each sector creates its own group or country factor has a domination.

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# A Visualization of Connectedness Plots

The software program that I use to visualize and analyze the connectedness of European banks is Gephi, which is an open-source software developed by Bastian et al. (2009). Gephi includes many features for both visualization and analysis which consists of filtering, ranking, importing and other built-in functions. In my analysis, data plot has 45 points and 1980 directional weighted links, which makes Gephi ideal software due to its compatibility with large graphs. Throughout this section, I explain how each graph presented in next section should be interpreted.

*Filtering*: By the help of this feature we can remove links or points according to some of their properties. In my analysis, I used self-loop filter to remove self-links and use link-weight filter to remove lowest links to provide a better visualization. In the context section of program, we can see how many points are filtered-out.

*Layout*: I prefer to use ForceAtlas2, which is the latest force-directed graph layout of Gephi, in my analysis. This method is developed by Jacomy et al. (2011). This layout uses energy-model; points repulse each other whereas links try to keep these points together. After iterations, the balance between points and links finalize visualization. If a point has higher weighted degrees, its relative centrality will be higher; hence, more central points tend to locate in core zone. As a vital comment, the locations of points are relative to each other such that the same graphical properties can be represented in two different graphs; however, their relative positions stay same.

*Point Color*: The intensity of point color, from light green to dark red, is proportional to the "to connectedness". Lowest degree is represented with light green and highest degree with dark red correspondingly. The main analogy of this editor is to color points according to their distribution on whole graph instead of linear function of ranking.

*Point Size*: Size of point is proportional to market capitalization values of banks for given day.

*Link Thickness*: In my connectedness graph, two points are connected with two links; where direction of each link can be understood by its arrow direction. It is my preference to choose straight links instead of curved links for the sake of visualization. Two links between two points overlaps; where thickness of highest weighted link dominates other. Hence, in the visualization, we can observe only the thicker link. On the other hand, the arrow size is proportional to corresponding link weight.

# B List of Banks

| Name | Ticker | Country | MCap[6] |
|---|---|---|---|
| BNP Paribas SA | BNP.FP | France | 98161.34 |
| Deutsche Bank AG | DBK.GY | Germany | 46037.97 |
| ING Groep NV | INGA.NA | Netherlands | 54091.27 |
| Banco Santander SA | SAN.SM | Spain | 104510.12 |
| Societe Generale SA | GLE.FP | France | 49894.94 |
| Banco Bilbao Vizcaya Argentaria SA | BBVA.SM | Spain | 71418.88 |
| UBS AG | UBSN.VX | Switzerland | 79224.21 |
| UniCredit SpA | UCG.IM | Italy | 52234.35 |
| Barclays PLC | BARC.LN | UK | 65726.99 |
| Credit Suisse Group AG | CSGN.VX | Switzerland | 49907.24 |
| Lloyds Banking Group PLC | LLOY.LN | UK | 94185.77 |
| Royal Bank of Scotland Group PLC | RBS.LN | UK | 56731.92 |
| Commerzbank AG | CBK.GY | Germany | 20493.52 |
| Intesa Sanpaolo SpA | ISP.IM | Italy | 51327.01 |
| Swedbank AB | SWEDA.SS | Sweden | 32740.51 |
| HSBC Holdings PLC | HSBA.LN | UK | 185665.03 |
| Skandinaviska Enskilda Banken AB | SEBA.SS | Sweden | 30992.19 |
| KBC Groep NV | KBC.BB | Belgium | 26420.79 |
| Svenska Handelsbanken AB | SHBA.SS | Sweden | 33760.54 |
| Nordea Bank AB | NDA.SS | Sweden | 59077.33 |
| Standard Chartered PLC | STAN.LN | UK | 47907.21 |
| Banco Popular Espanol SA | POP.SM | Spain | 15814.9 |
| Dexia SA | DEXB.BB | Belgium | 135.61 |
| Banco Espirito Santo, S.A. | BES.PL | Portugal | 7704.88 |
| Yapi ve Kredi Bankasi AS | YKBNK.TI | Turkey | 7234.98 |
| Turkiye Garanti Bankasi A.S. | GARAN.TI | Turkey | 12809.14 |
| Danske Bank A/S | DANSKE.DC | Denmark | 27359.61 |
| Turkiye Is Bankasi | ISCTR.TI | Turkey | 8787.16 |
| DNB ASA | DNB.NO | Norway | 28695.19 |
| Alpha Bank AE | ALPHA.GA | Greece | 11233.03 |
| Akbank TAS | AKBNK.TI | Turkey | 11281.54 |
| Bpi Portugal | BPI.PL | Portugal | 3545.62 |
| Natixis | KN.FP | France | 22499.44 |
| Bank of Ireland | BKIR.ID | Ireland | 13826.28 |
| Banco Comercial Portugues SA | BCP.PL | Portugal | 6115.66 |

[6]Market Capitalization in million USD. It is drawn from Bloomberg database as of 19 March 2014

| | | | |
|---|---|---|---|
| Erste Group Bank AG | EBS.AV | Austria | 14560.98 |
| National Bank of Greece SA | ETE.GA | Greece | 13675.01 |
| Piraeus Bank SA | TPEIR.GA | Greece | 14188.56 |
| Allied Irish Banks PLC | ALBK.ID | Ireland | 113160.38 |
| OTP Bank Nyrt | OTP.HB | Hungary | 5014.23 |
| Permanent TSB Group Holdings PLC | IPM.ID | Ireland | 6353.66 |
| Jyske Bank A/S | JYSK.DC | Denmark | 4094.29 |
| Sydbank A/S | SYDB.DC | Denmark | 1924.11 |
| IKB Deutsche Industriebank AG | IKB.GR | Germany | 1182.86 |
| Banque Cantonale Vaudoise | BCVN.SW | Switzerland | 5008.06 |

Table 2: List of Banks

# C Pairwise Volatility Connectedness Plots

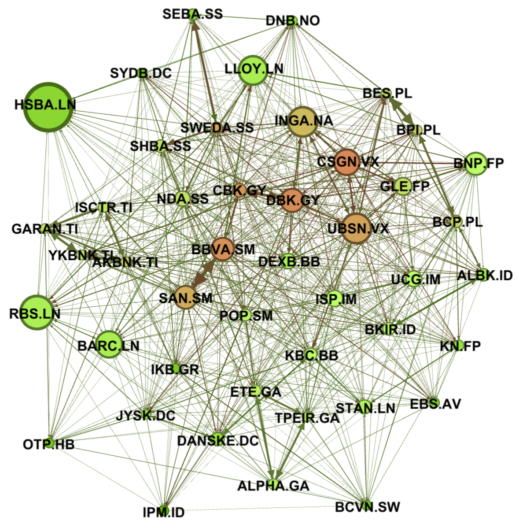


Figure 4: Russian crisis (index=36.3)
08/11/1998

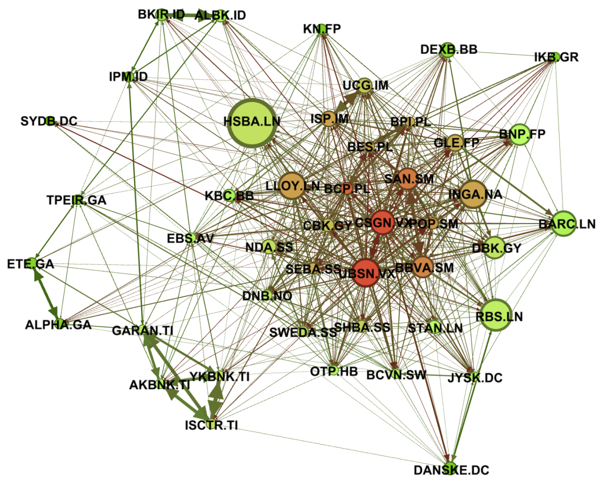


Figure 5: Russian Crisis (index=61.7)
03/25/1999

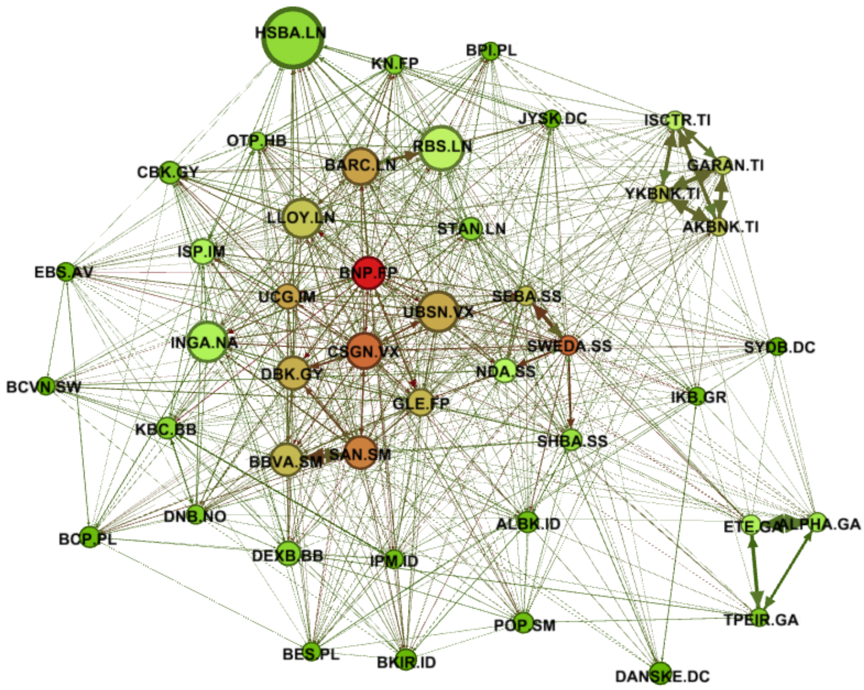


Figure 6: 9/11 Terrorist Attack (index=49.8)
09/04/2001

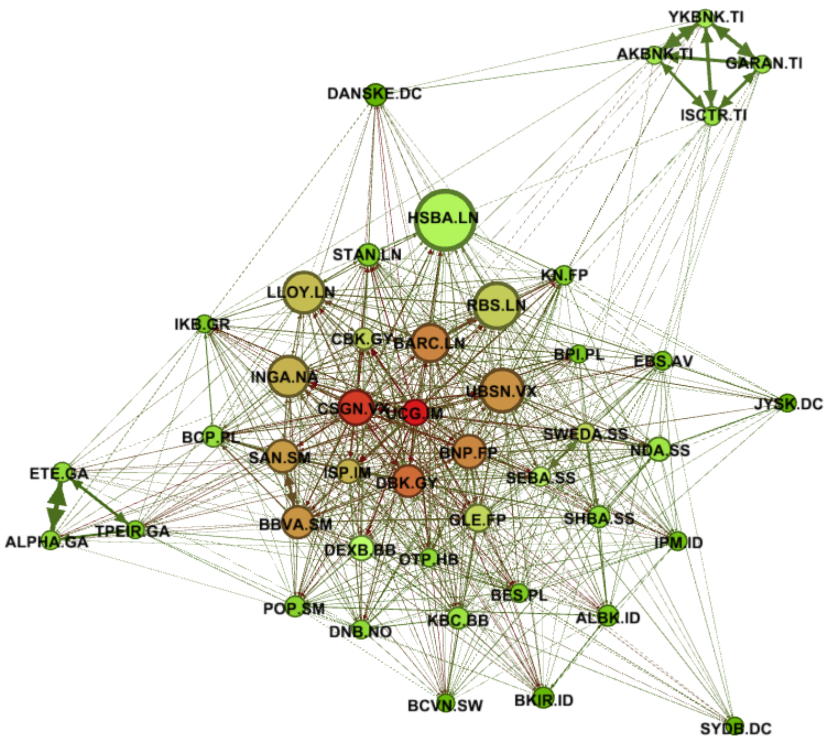


Figure 7: 9/11 Terrorist Attack (index=66.3)
09/26/2001

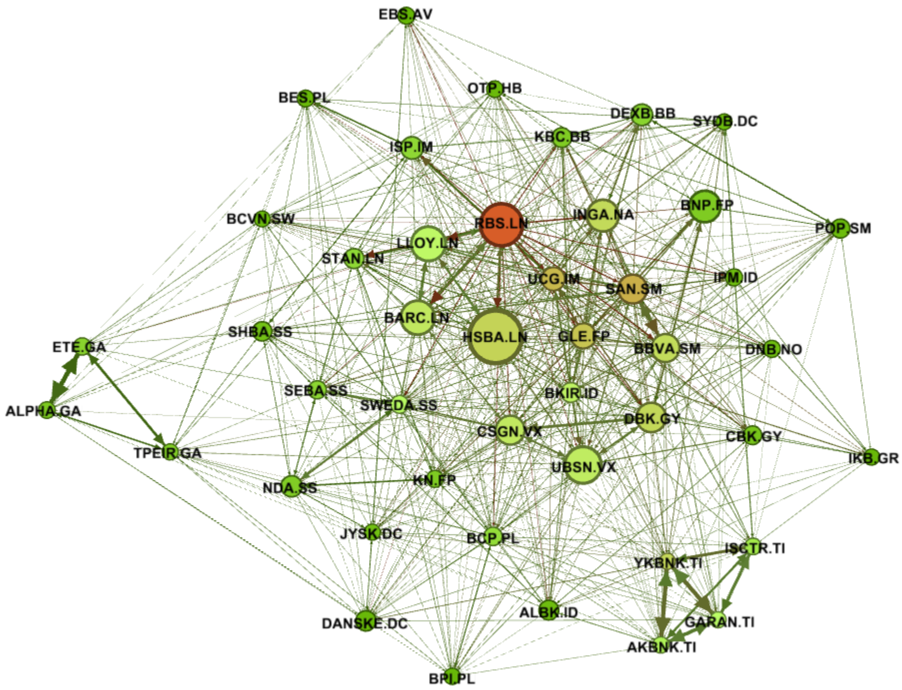


Figure 8: WorldCom Scandal (index=43.4)
06/17/2002

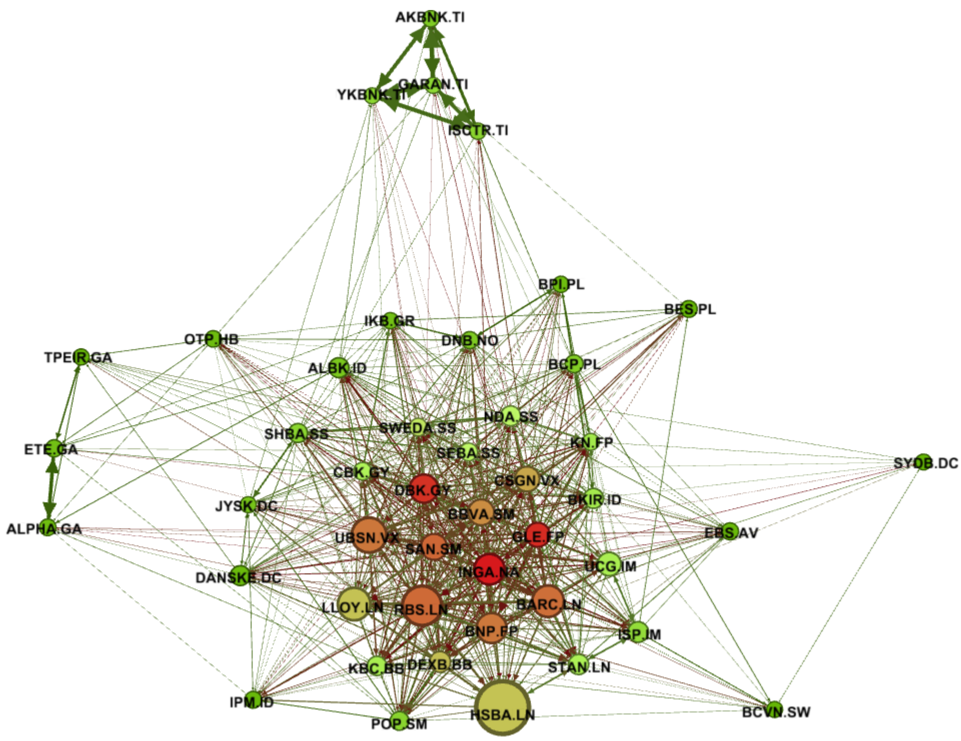


Figure 9: WorldCom Scandal (index=62.4)
08/16/2002

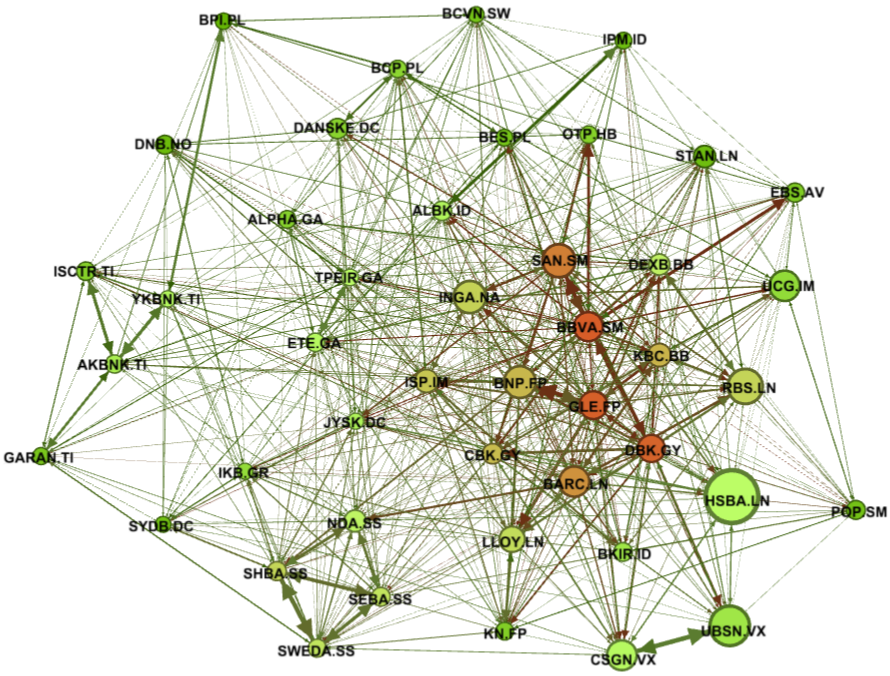


Figure 10: Fed's Rate Hikes (index=42.3)
05/08/2006

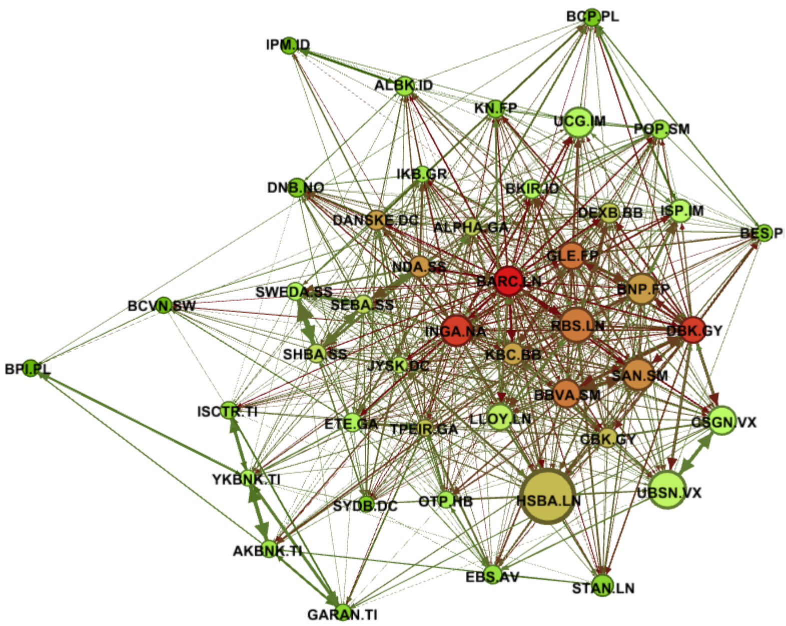


Figure 11: Fed's Rate Hikes (index=66.2)
06/15/2006

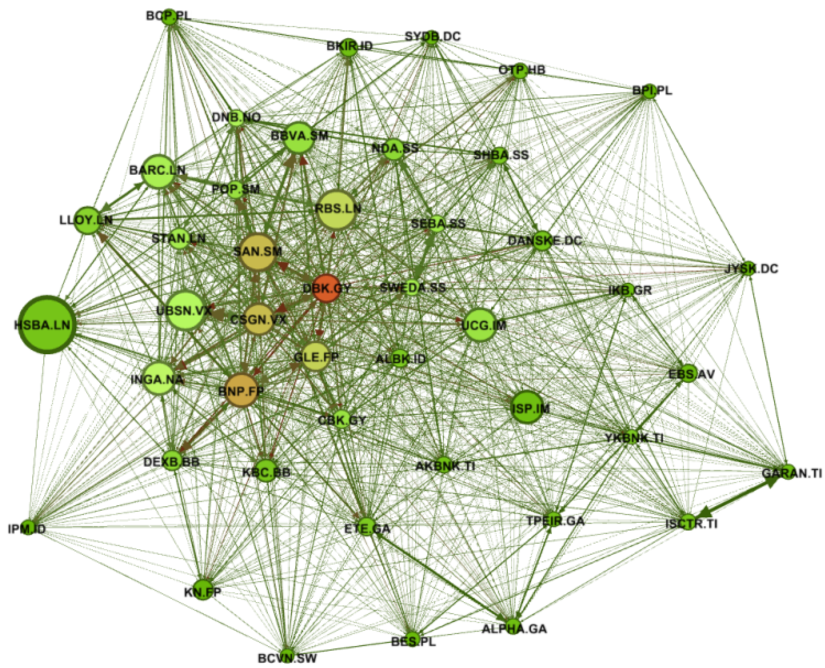


Figure 12: 2007 financial crisis (index=42.9)
02/22/2007

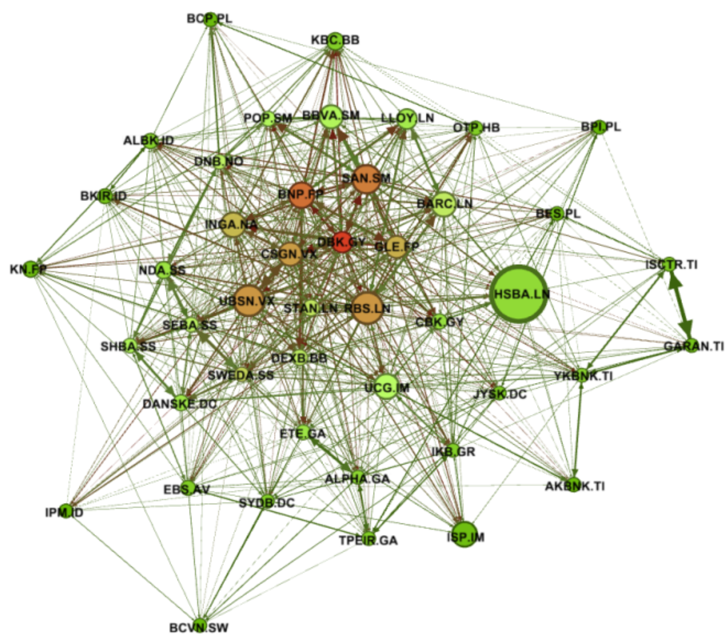


Figure 13: 2007 financial crisis (index=54.8)
03/05/2007

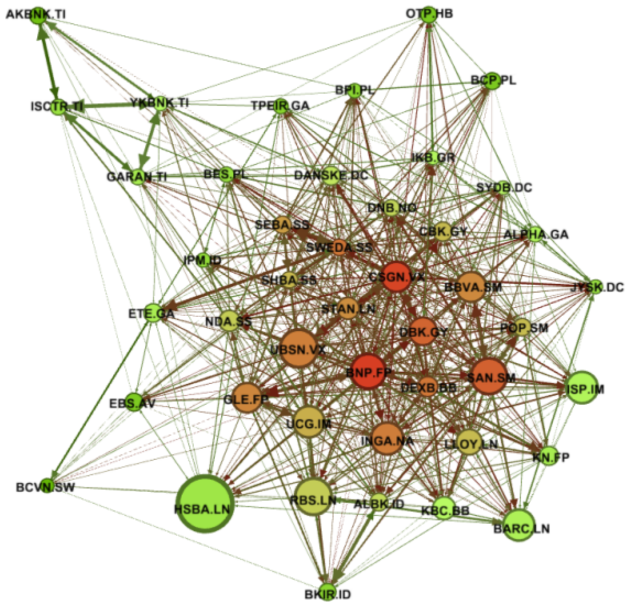


Figure 14: 2007 financial crisis (index=61.9)
07/05/2007

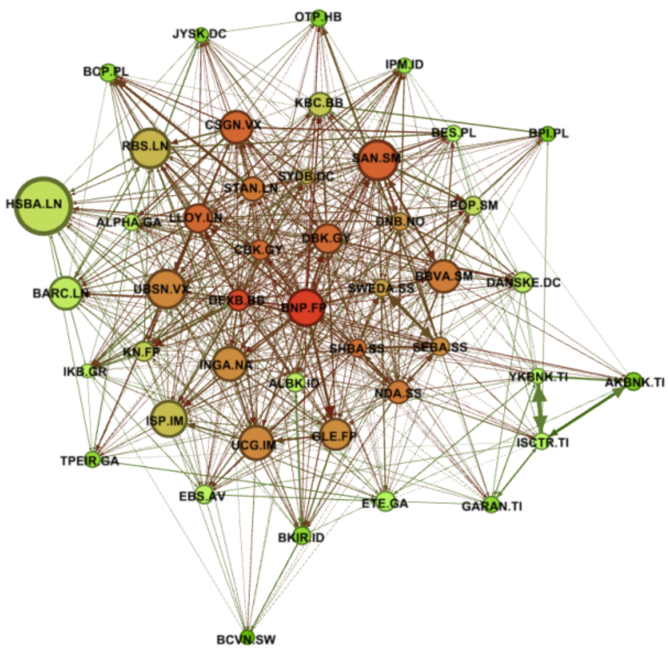


Figure 15: 2007 financial crisis (index=75)
08/22/2007

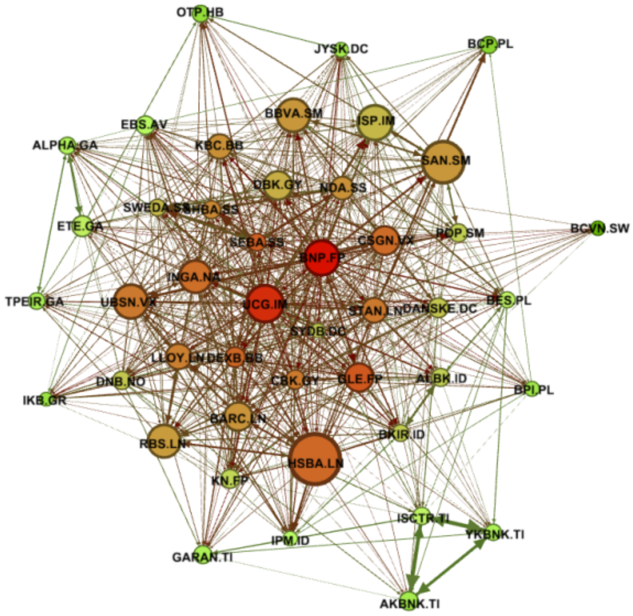


Figure 16: 2007 financial crisis (index=79.6)
12/27/2007

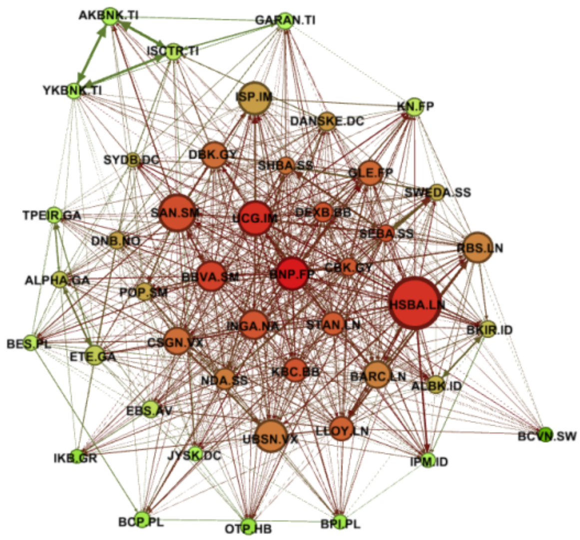


Figure 17: 2007 financial crisis (index=84.3)
01/29/2008

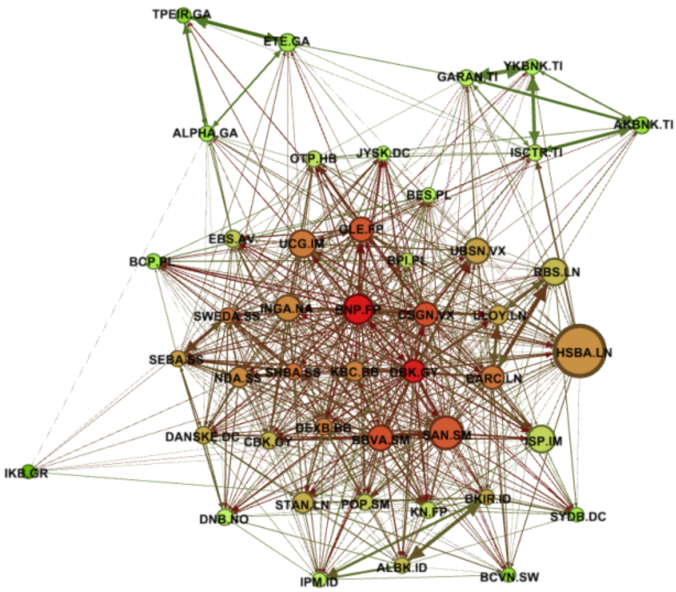


Figure 18: 2007 financial crisis (index=79.5)
09/11/2008

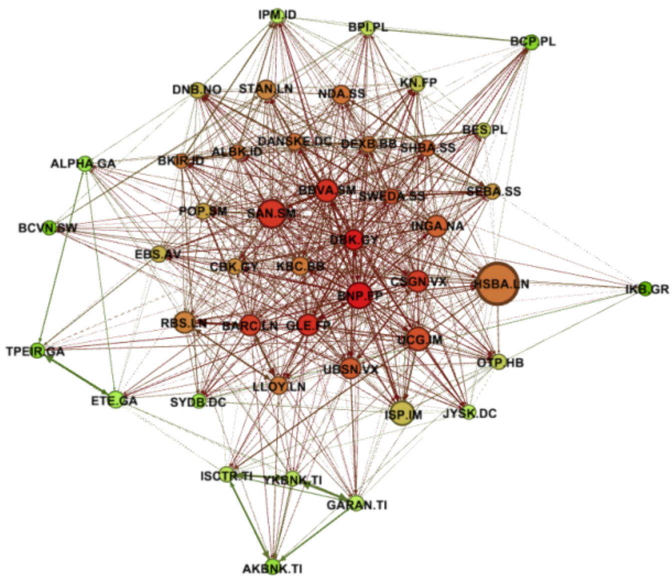


Figure 19: 2007 financial crisis (index=83.7)
09/18/2008

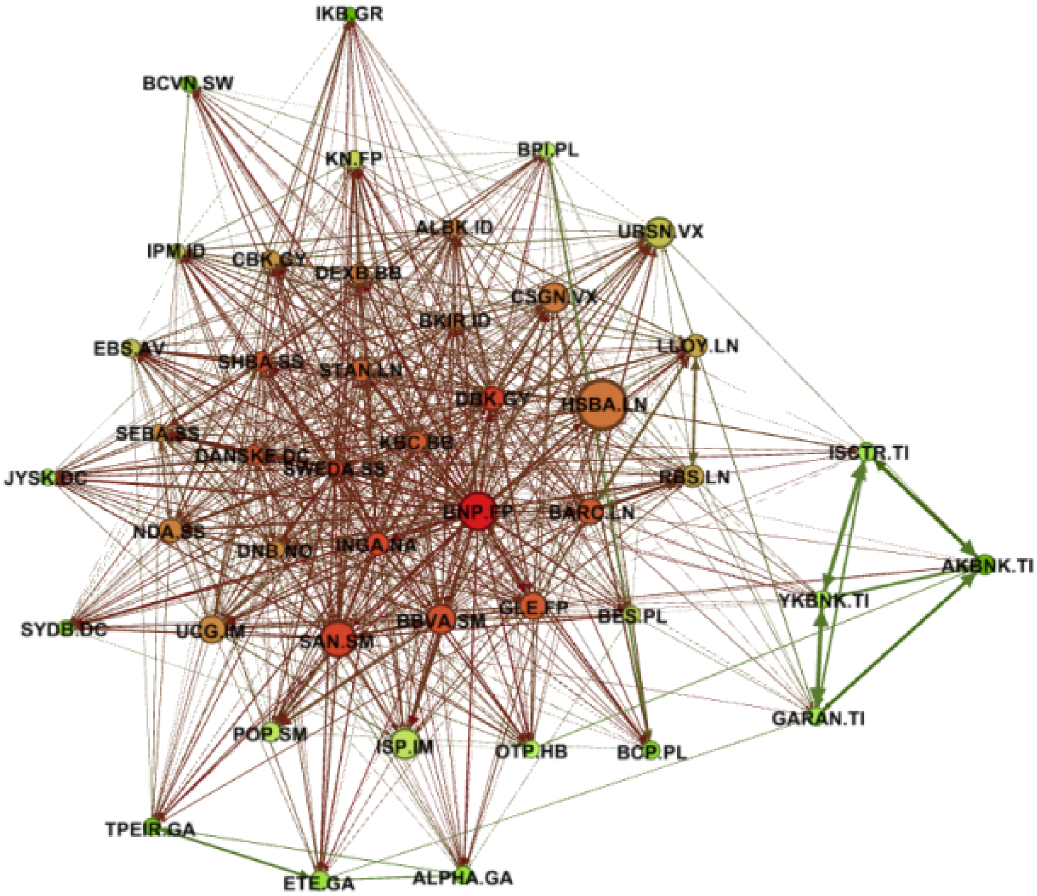


Figure 20: 2007 financial crisis (index=88.5)
10/27/2008

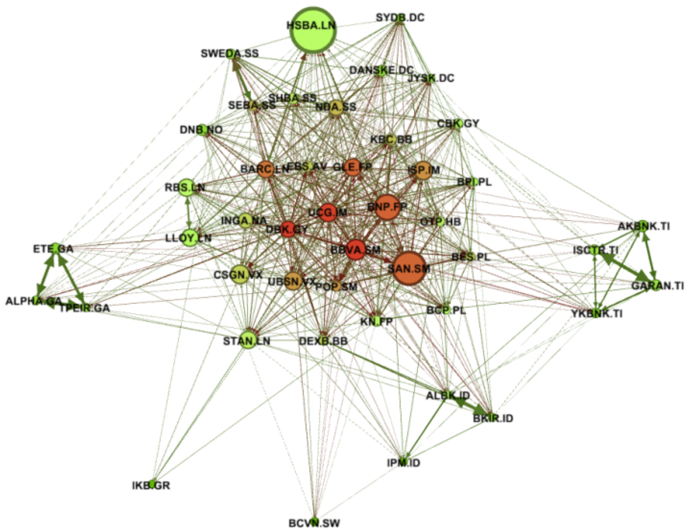


Figure 21: Eurozone crisis (index=66)
12/21/2009

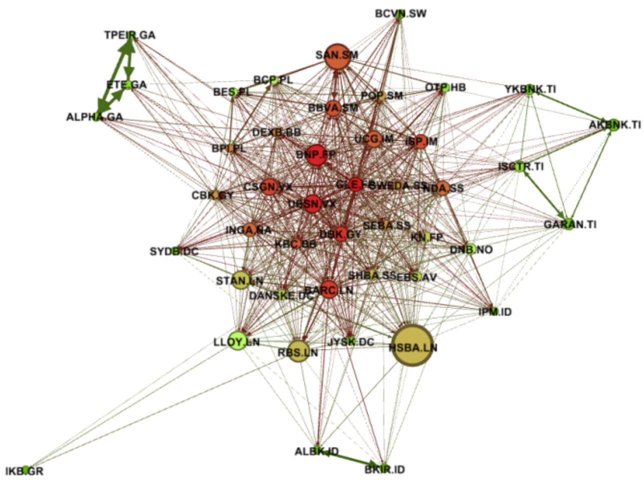


Figure 22: Eurozone crisis (index=82.2)
06/22/2010

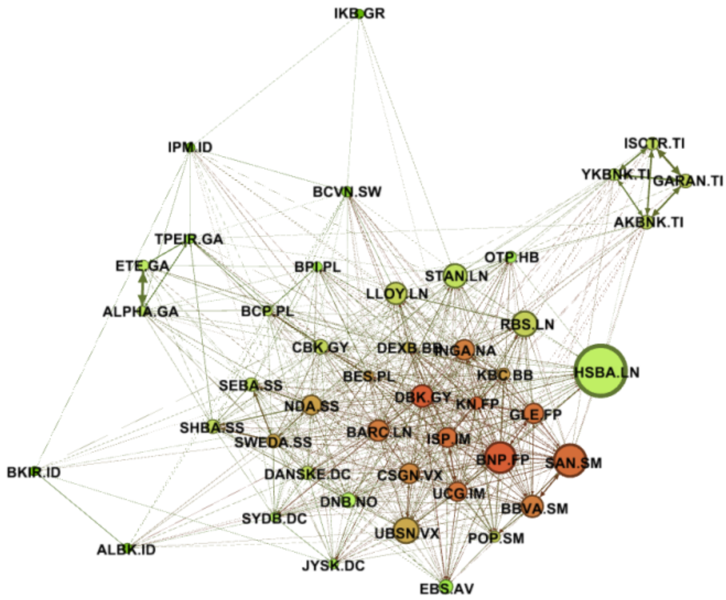


Figure 23: Eurozone crisis (index=65.6)
07/04/2011

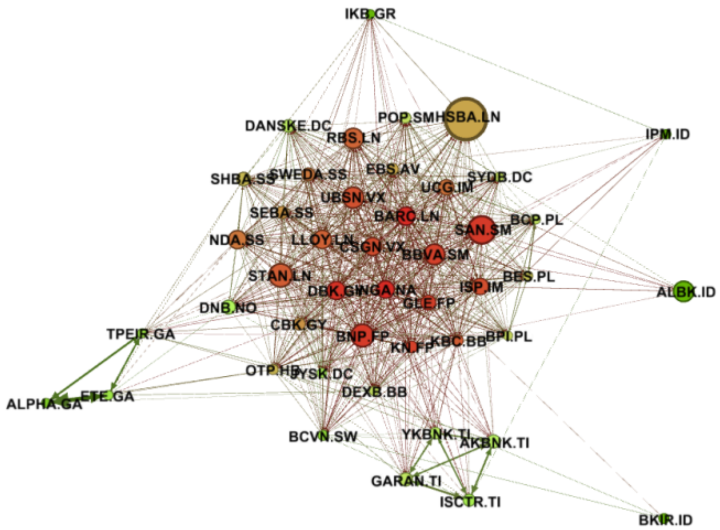


Figure 24: Eurozone crisis (index=83.8)
10/17/2011