VOLATILITY CONNECTEDNESS AND SYSTEMIC RISK IN THE INSURANCE INDUSTRY

by

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Abstract

This thesis studies the systemic importance of the insurance industry in terms of volatility connectedness. We first analyze the volatility connectedness between the banking and insurance industry in the US and then we repeat the same analysis for the insurance companies from 26 countries. In both cases, we obtain both the static and dynamic total connectedness measures. Next, using pairwise directional connectedness measures, we analyze the revealed network structure. First, we display the financial networks, before and after some important systemic events, to understand the relative position of the insurance companies. Second, we use a community detection algorithm based on random walks to see how individual companies creates subgroups within the network. Additionally, we also report results showing how the contribution of the insurance industry to the systemic risk changes over time in the US. In our first result, the analysis of the US banking and insurance industry reveals that the total risk in the US financial system reaches to rather high levels once the insurance companies are included in the analysis. Second, we show that the insurance industry has become more connected globally after the global financial crisis. This is an important result because unlike the banking sector, insurance companies have no bilateral lending practices among each other. In the global insurance industry analysis, we show that the insurance companies are clustered on a geographical basis. In case of the analysis of US banks and insurers, we find that the so-called systemically important financial institutions tend to be clustered on the basis of their size and sector. On the other hand, unlike the large banks and insurers, small-sized banks and insurers tend to fall in the same community.

Keywords: Financial connectedness, risk measurement, systemic risk, systemically important financial institutions, vector autoregression, variance decomposition, nonparametric estimation, lasso, adaptive elastic net, networks, communities

Özet

Bu tez, sigortacılık endüstrisinin sistemik önemini oynaklık bağlanmışlığı kapsamında analiz etmektedir. Bu bağlamda ilk olarak A.B.D. bankacılık ve sigortacılık endüstrilerinin oynaklık bağlanmışlığı incelenmiş olup sonrasında aynı analiz 26 ülkenin sigortacılık endüstrileri için tekrar edilmiştir. Her iki analizde de durağan ve devingen toplam bağlanmışlık ölçütleri elde edilmiştir. Akabinde iki yönlü bağlanmışlık ölçütleri kullanılarak elde edilen ağ yapısı analiz edilmiştir. İlk olarak, sigorta şirketlerinin ağ içerisindeki nispi pozisyonunu anlamak amacıyla bazı sistemik olayların öncesi ve sonrasında finansal ağlar gösterilmiştir. İkinci olarak ise şirketlerin ağ içerisinde alt grupları nasıl oluşturduğunu görmek amacıyla rassal yürüyüş temelli komünite belirleme algoritması kullanılmıştır. İlave olarak, A.B.D.'de sigortacılık endüstrisinin zaman içerisinde sistemik riske ne ölçüde katkıda bulunduğu rapor edilmiştir. A.B.D bankacılık ve sigortacılık endüstrisi üzerine yapılan analiz, sigortacılık endüstrisinin analize dahil edilmesi ile birlikte A.B.D. finansal sistemindeki toplam riskin daha yüksek bir seviyeye ulaştığını ortaya çıkarmıştır. Küresel sigortacılık endüstrisi analizi sonucunda, sigortacılık endüstrisinin son yaşanan finansal krizden sonra daha bağlantılı hale geldiği gösterilmiştir. Bankacılık sektörünün aksine sigorta şirketlerinin karşılıklı borç verme pratiklerinin bulunmaması bu sonucu önemli kılmaktadır. Ayrıca, küresel sigortacılık endüstrisi analizinde sigorta şirketlerinin coğrafi temelde kümelendikleri gösterilmiştir. A.B.D bankacılık ve sigortacılık endüstrisi analizinde ise sistemik öneme sahip finansal kurumların finansal büyüklük ve sektörel benzerlikler temelinde kümelenme eğiliminde olduğu bulunmuştur. Diğer taraftan, büyük banka ve sigorta şirketlerinin aksine küçük ölçekli banka ve sigorta şirketleri aynı komüniteye düşme eğilimindedir.

Anahtar Kelimeler: Finansal bağlanmışlık, risk ölçümü, sistemik risk, sistemik öneme sahip finansal kuruluşlar, vektör otoregresyon, varyans ayrıştırması, esnek ağ, ağlar, komüniteler

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1 Introduction

Financial markets around the world become more and more connected to each other over the last three decades. More integrated financial markets have enhanced the efficiency globally and helped to increase the welfare of the nations. As a result, the integration surely brings many advantages but on the other hand it has a large downside in case of a crisis. In the event of a crisis, financial globalization poses great risks at a global scale and the risks came from it cannot be ignored. Emerging market economies experienced the drawbacks of financial crises in the 90s. Considering the outcomes of the experiences of emerging market economies, recently developed financial markets were exposed to excessive risks. The latest global financial crisis showed that measuring and managing these risks properly is the most important thing to do in this era. Otherwise, poor decision making can lead to disastrous consequences for the global financial system.

The latest financial crisis and the financial events happened afterwards show that systemic risk is more important than ever. Systemic risk concerns all of the financial system which is constituted by connected institutions that have mutual relationships in order to gain benefits. However, the connectedness of firms can lead a quick propagation of financial distresses as well. The financial crisis of 2007-2010, where problems in one sector spread to other sectors and led to system-wide declines, is a recent example.

The crisis started with the problems in the financial sector. At the center of these problems there was the American International Group (AIG). Therefore, suspicions were raised by the authorities whether the insurance sector is a major source of systemic risk. The questions asked about the insurance industry are not unnecessary since insurance companies have started to change their business activities. Insurance companies created new lines of businesses such as insuring financial products and credit default swaps. These new activities make them more vulnerable to financial distresses and also can put them in a position in which they are a possible source of systemic risk.

The contribution of this paper is twofold. Firstly, we contribute to the burgeoning literature on systemic risk measurement in the insurance industry. The majority of papers about the systemic risk in the insurance industry does not make the separation of different type of insurers. We divide the insurers to four different type using the Thomson Reuters Business Classification. We estimate the global insurance industry network by following Demirer et al. (2015). We also use the Diebold-Yilmaz framework to measure the systemic risk in the insurance industry. The Diebold-Yilmaz framework provides easy ways of illustrating the connectedness among countries. Furthermore, we investigate the relationship between banks and insurers in the US. Billio et al. (2012) find that the correlation between the returns of banks and insurers increased over the last decade. As a result, assuming that the insurers' contribution to systemic risk is low may not be right at all. We conduct an analysis to see which type of insurers make more contributions to banks or vice versa. Since we implement a dynamic analysis, we estimate the networks throughout our sample period for everyday. Thus, we have a chance to analyze the relationship between banks and insurers in depth.

Secondly, we link an information theoretic community detection algorithm called Infomap by Rosvall and Bergstrom (2008) with DY connectedness framework. The networks derived from variance decompositions have a very basic intuition that is the contribution of other variables to one variable's variance. By this approach, we get a directed and weighted networks. This is the main reason why we choose Infomap approach beacuse, the method detects communities using the flow of information within the network. The communities in a network are defined in a way that a shock or stress takes more time to leave the community because of the dense structure of the community. Infomap approach provides a way to capture the movements of a random walker to detect the communities in the network since a community shows persistence to a random walker to leave the community. The aim of this analysis is to find out agglomerations of financial stress in terms of volatility shocks. Describing communities both at international level and at institutional level delivers important insight about the systemic risk in the system. First, we want to show who interacts with who more. In networks, nodes tend to interact more with some nodes than other nodes and as a result, create some groupings within the network by means of these interactions. Second, we want to display how a shock is propogated within the network and who are most likely to be affected in case of a distress or a default. The topology of the network when the initial shock hit the network designates the dynamics of the contagion process. Thus, it is crucial to find subset of nodes that are strongly connected to each other. By doing so, we will be able to identify the parts of the network which have the highest probability to be hit by an initial shock to a specific node or subset of nodes. Therefore, community detection in the financial networks might have substantial benefits with regard of measuring systemic risk and preventing contagious defaults.

The findings of our paper make five important contributions. First, we show that the interconnection between the global insurance industry is high and the US is the main source of disturbances in the system. Second, we find that geographical location is important in the insurance industry. Communities are created in terms of geographical closeness, except for the UK. The UK is separated from the rest of the Europe. Asian countries are isolated from the insurance industry, except South Korea. They do not create any significant impact on the system. This fact is also valid for Middle East and African countries. Third, life and health insurers in the US have become more prone to be affected by banks over the last decade in terms of receiving volatility shocks. Property and casualty insurers, multiline insurers and brokers, and reinsurers in the US are more interconnected among them and property and casualty insurers are the main source of systemic risk among the insurers. Fourth, as a result of the modularity analysis for the US, we find that the main actors of the recent financial crisis create an individual group within the network. Large banks tend to be in the same community with large banks. Large insurers also behave like large banks as well. However, small size banks and insurers are in the same group unlike large banks and insurers. In other words, insurers' contribution to systemic risk might seem to be low but there are certainly some insurers that have significant potential to pose systemic risk to the system if we consider the formation of the communities. Lastly, the connectedness index for the US reveals that the accumulated risk in the system rises with the participation of the insurance companies in the crisis periods contrary to the expected role of the insurance industry as a shock absorber.

The remainder of the study is organized as follows. Section two presents the literature on the measurement of the systemic risk and its applications on the insurance industry. Section three describes the dataset we used to conduct our analysis. Section four explains the methodology. Section five presents the results of the Diebold-Yilmaz Connectedness analysis in the US financial system regarding banks and insurers. In section six, we analyze the global insurance industry. The final section concludes the paper.

2 Literature Review

2.1 Systemic Risk Measurement

Systemic risk does not have a common definition that the literature aggrees on. The same is valid for the measurement techniques for the systemic risk. Since there is no consensus on the definition and measurement of the systemic risk, the methods used to assess the systemic risk vary significantly.[1] The probability distribution models are the most direct and acknowledged methods to measure the systemic risk. The method depends on the joint distribution of negative outcomes of a group of important financial institutions. There are two widely accepted examples of this kind of models. First one is CoVaR approach proposed by Adrian and Brunnermeier (2011). Their framework estimates the contribution of a financial institution to the systemic risk by benefiting from Value at Risk (VaR) methodology. They calculate VaR conditional on the financial institution's different states (CoVaR). After that, they define the systemic risk contribution of a financial in-

[1] For a survey see Bisias et al. (2012) and Hansen (2012)

stitution as the difference between CoVaR conditional on the financial institution being in distress and CoVaR conditional on in the middle of the distribution. Second one is systemic expected shortfall (SES) by Acharya et al. (2010). They claim that a financial intitution's performance in distressed times designates an institution's contribution to the systemic risk. They use stress test performance, equity valuation and CDS spreads to calculate the SES which indicates the performance of a financial institution. Following this, they derive marginal expected shortfall (MES) and leverage (LVG) as leading indicators to predict the SES of a financial institution. Apart from these two examples, another important study that focuses on the tail risk is Brownlees and Engle (2015). They argue that a financial institution's contribution to the expected total capital shortfall of the financial system in a future crisis identifies the systemic risk contribution of a financial institution.

Gray and Jobst (2011) use contingent claim analysis to measure systemic risk. They propose a methodology based on the market-implied expected loss. In addition, they say that the contribution of each financial institution is linked with the financial institution's contribution to total contingent liabilities in the case of a systemic event.

Principal component analysis (PCA) is another strand in the systemic risk measurement literature. Although the aim of PCA based studies is different from our goal, we will briefly mention two examples. Firstly, Kritzman and Li (2010) propose a method based on Absorption Ratio (AR) to measure the risk in the system. They calculate AR which is defined as the total variance of a set of asset explained by a smaller set of factors via PCA. According to the results, they describe the financial markets as unified or tightly coupled. They say that a shock to the system propogates very widely and quickly when assets' level of comovement is high which happens in case AR is high. Otherwise, when AR is low, a shock to the system does not cause any serious problems since assets are less connected to each other. Secondly, Billio et al. (2012) use PCA to obtain the connectedness among the monthly returns of hedge funds, banks, brokers and insurance companies. In the sense of capturing the comovement, the rationale of this study is similar to the previous study. They conclude that the systemic risk is high when the first principal component explains a large part of the variance for all institutions in the sample.

2.2 Systemic Risk in the Insurance Industry

In the aftermath of the recent financial crises, alongside with the systemic risk measurement for the banking industry, some authors started to argue that the insurance industry might have become important for the stability of the financial system. In addition, there is a common understanding about which business activities of insurers pose systemic risk. Broadly, they separate the activities into two groups; that is, one is traditional and the other is non-traditional business activities. Most of the studies agree that traditional business activities does not pose systemic risk. On the other hand, non-traditional insurance activities are seen as systemically risky both for the financial system and institutions.[2]

There are some studies that draw attention to industry-specific characteristics of the insurance industry. Harrington (2009) argues that life insurance is potentially more systemically risky than property and casualty (P&C) insurance. The author's conclusion depends on the fact that life insurers have higher leverage than P&C insurers. Additionally, life insurers also have sensitivity to declines in the asset values and potential to face policyholder withdrawals during a financial crisis. Bell and Keller (2009) conclude that non-traditional activities of insurers can pose significant systemic risk, whilst traditional activities do not by analyzing an insurance company's risk factors. The Geneva Association (2010) argues that the long-term liability structures of insurers compared to banks eliminates the possibility of being systemically risky, except for the insurance companies highly engaged in non-traditional insurance activities during the recent financial crisis. Cummins and Weiss (2014) identify primary indicators and contributing factors, such as size of exposure to credit, market and liquidity risk, interconnectedness, and leverage,

[2] For a comprehensive review of the literature on systemic risk in the insurance industry see Eling and Pankoke (2014)

that can be used to measure the financial institutions' degree of systemic risk. They conclude that traditional insurance activities of the US insurers do not pose systemic risk. On the other hand, non-traditional activities such as financial guarantees and derivatives trading have the potential to cause systemic risk. They also claim that both life and P&C insurers may be seriously affected by reinsurance crisis and life insurers can be exposed to intrasector crises. Moreover, they argue that interconnectedness among financial institutions has increased significantly in recent years. Baluch and Parsons (2011) show that non-traditional life insurance activities are more relevant to the system than P&C insurance activities in terms of systemic risk. They also claim that in order to sustain non-traditional life insurance activities which can be seen as bank-like business activities, an insurance company needs to have substantial interconnectedness.

Another strand of the systemic risk in the insurance industry literature focuses on the equity-based systemic risk measures. These measures evaluate the impact of a single financial institution on the system or the effect of the system on an individual financial institution and the system's level of interconnectedness. Acharya et al. (2010) use SES and MES for the US financial industry during the crisis period to estimate spillover effects. They show that insurance companies are the least systemically risky financial institutions in the financial system. Adrian and Brunnermeier (2011) use CoVaR framework to evaluate the systemic relevance of different type of financial institutions. They include banks, investment banks, government sponsored enterprises and insurance companies into their sample. They find no evidence that indicates that insurance companies are less systemically relevant than the other type of financial institutions. In contrast to two previous studies, Billio et al. (2012) perform the linear and non linear Granger causality test on the monthly equity returns of financial institutions. Their sample includes banks, insurers, hedge funds and broker dealers operating in the US. They find that insurance companies were also a source of systemic risk, aside from banks, during the 2008 financial crisis. They also show that all four sectors have become highly interrelated over time. On the other hand, H. Chen et al. (2014) apply the linear and non-linear Granger causality test on the intraday stock prices and daily CDS spreads. They agree with Billio et al. (2012) on the point that states that the linear Granger causality test assigns a comparable systemic importance to insurance companies against banks. However, after correcting for heteroskedasticity, the linear and non-linear Granger causality test do not give the same results. They find that banks show a tendency to pose more systemic risk than insurance companies. In addition, they point out that this tendency lasts longer for banks than insurance companies.

There are other studies that use equity-based systemic risk measures. F. Chen et al. (2013) calculate BANKBETA and MES for a wide range of the US insurers underwriting CDS products. They find that systemic risk levels for financial guarantee insurers are the highest for both measures. Additionally, they show that both measures have higher explanatory powers for the stock market returns of financial guarantee insurers during the financial crisis. They conclude that financial guarantees increase the contribution of an insurer to systemic risk and the vulnerability of an insurer in the financial system. H. Chen et al. (2013) find that life insurers tend to be affected more from economic downturns than non-life insurers. They take MES and SRISK as systemic risk measures and calculate them via a copula approach.

There are some studies that combine equity-based systemic risk measures and industry-specific fundamentals. They try to reveal the link between them in order to discover what drives systemic risk. Weiß and Mühlnickel (2014) calculate CoVaR and MES for a sample of the US insurers during the recent financial crisis in order to obtain the systemic risk contributions. Following this step, their aim is to pick idiosyncratic factors that made systemically important insurers different from other insurers. They find that size, non-policyholder liabilities, and its reliance on investment income are the factors to predict the systemic risk exposure during the recent financial crisis. Bierth et al. (2015) apply a similar analysis in which they also add SRISK with a very large sample including insurers all around the world and over a longer time horizon. They show that the insurance industry's contribution to the systemic risk is small compared to the previous findings for banks. Nevertheless, they argue that the systemic risk contribution of insurers hit the top during the recent financial crisis. Moreover, they find that the insurers' systemic risk exposure is mainly driven by leverage and size. Also, the interconnectedness of large insurers with the insurance industry is an important driver of systemic risk. Finally, Berdin and Sottocornola (2015) use three systemic risk measures (Granger causality tests (Billio et al. (2012)), CoVaR (Adrian and Brunnermeier (2011)), dynamic marginal expected shortfall (DMES) (Brownlees and Engle (2012))) with a sample including banks, insurers and non-financial companies, all listed in Europe. They calculate each institutions systemic relevance according to three measures and rank them by their importance. After that, they investigate how portfolio activities of these institutions affect their systemic relevance. They find that the insurance industry persistently pose systemic risk but not higher than banks, except for some specific periods. They also show that insurers with a relatively higher proportion of life business and non-insurance-related activities in their portfolio display a tendency to create more systemic risk.

There are also some studies that utilize network theory. Dungey et al. (2014) derive a systemic risk index from an undirected, weighted network by using the PageRank algorithm. They designate the links in the network via stock volatilities and the weights by the correlations of volatilities. They use a sample of 500 firms consisting of the banking, insurance and real economy firms. They show that insurance firms demonstrate significant systemic risks for some periods while banking firms are consistently systemically risky.

3 Data

In this study, we focus on the volatility connectedness of financial institutions since volatility reflects the attitude of investors towards the market. In other words, volatility represents the fear of investors as is the case with the VIX often called as "the fear index". We use range-based volatility which is estimated by the intraday stock prices following Diebold and Yilmaz (2016).

We create two different datasets in order to deal with two different analyses. The first dataset is to examine the relationship between the banking sector and the insurance sector in the US and it covers the period from January 2000 to June 2016 with the daily stock market data. The main purpose of this enquiry is to see the development of the relationship during some important events other than only financial events such as 9/11 terrorist attacks. We have 88 financial institutions from the banking and the insurance sector in the US. We also conduct an analysis with 112 financial institutions from the US with the sample period from January 2006 to July 2016. The results from two different analysis do not change significantly within the same period. However, we also present the results of the latter endeavor in the dynamic analysis in order to get a broader coverage of financial institutions.

The second dataset is to investigate the volatility connectedness of insurance industry. The dataset involves intraday stock price data of the interested insurance companies. Data availability issues restrain us to go back to 2000. As a result, our dataset covers the period from January 2006 to July 2016 in order to have good representative sample. We have 98 insurance companies in our sample from 26 countries and from four different type which are identified by Thomson Reuters Business Classification. The chosen period reflects the intention to cover the recent financial crisis and preceding boom in stock markets.

The companies included in both analysis are listed in the appendix.

The disintegration in the insurance sector is based on the Thomson Reuters Business Classification. Here, we briefly describe the four different type of insurers in order to understand what they are stand for. The first type is life and health insurance includes two type of insurance. Life insurance companies offer contracts in return for a premium to pay a sum of money upon the death of the insured person to a predetermined beneficiary. The health insurance companies provide insurance against the risk of incurring medical expenses among individuals. The second type is property and casualty insurance which consists of four type of insurance. Property insurance companies supply protection against risks to property, such as theft and natural disasters. Automobile insurance companies provides insurance for cars, trucks, and other road vehicles. Travel insurance companies offer contracts to cover the losses of the insured person while traveling. Casualty insurance companies are engaged in activities to provide liability insurance, which is a protection against claims from third parties, and ensuring coverage for delinquent acts such as an injury occured in a factory during working hours.

The third type is multiline insurance and brokers. Multiline insurance companies are involved in at least two activities from life and health insurance and property and casualty insurance under the condition that none of them is the dominant business line. Insurance brokers companies act as agents in selling annuities and insurance policies. The fourth type is reinsurance which is also consist of two type of insurance. Life and health reinsurance companies provide reinsurance to life and health insurance companies and property and casualty reinsurance companies supply reinsurance to property and casualty insurance companies.

4 Methodology

There are various approaches in the literature that try to measure systemic risk contribution of insurance industry. Most of them come to a conclusion that indicates that insurance companies contribute to systemic risk less than banks (For a survey see Eling and Pankoke (2014)). Additionally, they claim that insurance companies are less vulnerable to financial distress in the system than banks. However, these studies mostly use low frequency data such as macroeconomic fundamentals, balance sheets etc.. But we know that responses of the financial institutions against to an important news or a distress emerge very rapidly even in minutes. In the light of such information, we take advantage of using high frequency data, i.e. intraday. The reason for choosing high frequency data comes from the view that argues market data reveals most of the information about companies' underlying relationships. In addition to data frequency discussion, most of the studies do not take into account the advantages of the network approach. We acknowledge that we can only approximate the real network structure of the financial system but our aim is to select an approach that discovers the financial connectedness within the system best.

To estimate the financial connectedness among the US banks and insurers and the insurance industry worldwide, we use variance decompositions of a large VAR of the sample to obtain and utilize the Diebold-Yilmaz (DY) connectedness measures proposed and advanced in a series of papers (Diebold and Yilmaz (2009), Diebold and Yilmaz (2012) and Diebold and Yilmaz (2014)).

There are a few advantages of using DY connectedness measures in our analysis. First, they make use of high frequency market data which is very important to capture the market reactions to bad news or a financial distress. Second, the intuition behind DY connectedness measure is very appealing. They show that how much of the future uncertainty of firm i comes from firm j and how much of the future uncertainty is due to the firm i itself. Third, these measures are closely related with the systemic risk measures such as CoVaR (Adrian and Brunnermeier (2011)) and marginal expected shortfall (Acharya et al. (2010)). Fourth, they are able to quickly adapt the changes in data. Arsov et al. (2013) show that DY connectedness measures' predictive power is one of the highest among other existing indicators. Finally, the final product of these connectedness measures can be displayed as a directed and weighted network as they directly correspond to the edge weights in network theory.

We will now briefly describe the Diebold-Yilmaz Connectedness Measures (as in Diebold and Yilmaz (2014)) and the elastic net estimation of the VAR model which we use in order to overcome the large dimensionality issue (as in Demirer et al. (2015)).

4.1 DY Connectedness Measures

In order to estimate the financial connectedness in the insurance industry globally and in the US between banks and insurers, we will use DY connectedness measurement based on the variance decomposition associated with N variable vector autoregression as developed in Diebold and Yilmaz (2009), Diebold and Yilmaz (2012), and Diebold and Yilmaz (2014).

We utilize the Diebold-Yilmaz approach with three lags and use the Generalized Variance Decomposition (GVD) produced by Koop et al. (1996) and Pesaran and Shin (1998) to acquire the connectedness measures from the VAR model. GVD which is an identification technique enables the resulting variance decompositions to be invariant to the ordering of variables in the VAR model. Although it allows for correlated shocks, GVD makes it possible to separate the effects of each shock which is the main objective of the analysis. In the variance decomposition matrix, the row sum of the variables do not add up to unity since the shocks are not orthogonal. Therefore, we divide all entries in the variance decomposition matrix by the corresponding value of the row sum in order to normalize.

4.1.1 DY Connectedness Methodology

We can write a covariance stationary N-variable VAR with lag p as

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t \quad where \quad \varepsilon_t \sim (0, \Sigma) \tag{1}$$

The moving average representation is

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \tag{2}$$

where the NxN, 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 NxN identity matrix and $A_i = 0$ for $i < 0$. We use MA representation of VAR in order to estimate the effects of shocks to variable x_i to the forecast of variable x_j for $i, j = 1, 2, .., N$. The connectedness is defined as fraction of H-step-ahead error variances in forecasting x_i due to shocks x_j for all i, j. Also, a variable's own variance share is defined as the fraction of H-step-ahead error variances in forecasting x_i due to x_i.

Variable j's contribution to variable i's H-step-ahead generalized forecast error variance, $\theta_{ij}^g(H)$, is calculated by the following formula

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \quad H = 1, 2, ... \tag{3}$$

where σ_{jj} is the standard deviation of the error term for the j^{th} equation, Σ is the covariance matrix for the error vector ε and e^i is the selection vector with one as the i^{th} element and zeros otherwise.

After this, we normalize each entry of the decomposition matrix, since the sum of each row is not necessarily equal to one in the variance decomposition matrix. The reason for the normalization is to get the connectedness index from variance decomposition. The procedure is performed by dividing each entry by the corresponding row sum,

$$\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^{N} \theta_{ij}^g(H)} \tag{4}$$

Finally, we are now ready to obtain the four DY connectedness measures by using the normalized entries of the variance decomposition matrix.

The total connectedness, $C(H)$, which can be described as a *system-wide* connectedness measure, is defined as

$$C(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{N} \tag{5}$$

The gross directional connectedness received by variable i from all other variables j, $C_{i \leftarrow \bullet}$ (from connectedness), is defines as

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

The gross directional volatility connectedness transmitted by variables i to all other variables j, $C_{\bullet\leftarrow i}$ (to connectedness), is defined as

$$C_{\bullet\leftarrow i} = \frac{\sum_{\substack{j=1\\j\neq i}}^{N} \tilde{\theta}^{g}_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^{g}_{ji}(H)} \times 100 = \frac{\sum_{\substack{j=1\\j\neq i}}^{N} \tilde{\theta}^{g}_{ji}(H)}{N} \times 100 \tag{7}$$

Finally, the net directional connectedness transmitted from variable i to all other variables $C_i(H)$ (net connectedness), is defined as

$$C_i(H) = C_{\bullet\leftarrow i}(H) - C_{i\leftarrow\bullet}(H) \tag{8}$$

4.2 Volatility

We use intraday prices to estimate the volatility connectedness of the insurance industry globally and between the banks and insurers in the US.

4.2.1 Estimation

In order to estimate volatilities by taking advantage of intraday data, we use realized volatility approach. We take natural logarithms of volatilities which have a right-skewed distribution before performing VAR. We follow the method developed by Garman and Klass (1980) and Alizadeh et al. (2002) which use intraday data to estimate daily realized volatilities. Daily realized volatility is calculated by the following formula

$$\begin{aligned} \tilde{\sigma}^2_{4,it} &= 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) \\ &\quad -2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2, \end{aligned} \tag{9}$$

where H_{it}, L_{it}, O_{it} and C_{it} are the logs of daily high, low, opening and closing prices for a stock i on day t respectively.

4.3 Selecting and Shrinking the Approximating Model

The global financial crisis showed that troubles of one firm can have significant effects over the other members of the financial system and the impairments stemmed from these troubles can be qucikly amplified through the system via affecting other firms. Hence, it becomes crucial to address these direct and indirect links among financial institutions. We can achieve this goal by increasing the number of firms in our analysis. The main intuition behind using large number of firms in our analysis is the search for the origin of the shocks which will be conducive to discover the propogation channels of shocks within the system.

There is one downside of using large number of variables for estimation in a VAR setting. The degrees of freedom will be quickly consumed by the procedure. Thus, to increase the number of observations, we will be in need of a longer estimation period. On the other hand, extending the estimation period hinders the correct estimation of the change in the coefficients over time. To deal with this problem, we use selection and shrinkage methods following Demirer et al. (2015).

The elastic net estimator (Zou and Hastie (1996)) solves

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

Elastic net is an estimator which combines a lasso L_1 penalty and a ridge L_2 penalty. We have two tuning parameters, λ and $\alpha \in [0, 1]$. An important point is that elastic net is lasso when $\alpha = 1$ and ridge when $\alpha = 0$. Unlike lasso, which may move only one of the strongly correlated predictors, elastic net makes sure that the these predictors are in or out of the model together with the aim of improving prediction accuracy relative to lasso.

The adaptive elastic net estimator (Zou and Zhang (2009)) solves

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

where $w_i = 1/\hat{\beta}_i^{\nu}$ with $\hat{\beta}_i$ the OLS estimate (or ridge if regularization is needed). Adaptive elastic net is also a mix of two estimators which are adaptive lasso and elastic net. It blends the good properties of two estimators. It has the oracle property like adaptive lasso and exhibits advanced predictor handling with highly correlated predictors like elastic net.

We will take $\alpha = 0.5$ without cross validation[3] and use 10-fold cross validation to choose λ. We use OLS regression to obtain the weights w_i.

The question whether adaptive elastic net can be used on VAR estimation as it is used on simple linear regressions is answered by Furman (2014). He shows that the adaptive elastic net allows the efficient equation by equation estimation of VAR. Moreover, the impulse responses functions produced are valid and it also leads to accurate forecasts.

4.4 Graphical Display

We will display graphs as large as 112 nodes in the results implying 112^2 edges. We will not present all edges in the network since it would not be very informative. Therefore, we will present 10% of the existing links. We make sure that all graphs have the same percentage of edges visible. Moreover, we calculate all the network statistics using the full network.

We use node size, node color, edge thickness, edge arrow size and edge color to deliver additional information about the graph together with the node location. We use Gephi in order to visualize and analyze network graphs. It is an open-

[3]Cross validating α requires highly time consuming computations, whilst it adds little to teh estimation quality. Moreover, as long as positive coefficients exist for both the ridge and lasso penalties, the estimator works consistently.

source software. We examine directed, weighted, complete networks.

Node Size Indicates Market Capitalization

We use market capitalization of finanncial institutions to determine node sizes. We get the data from Thomson Reuters. According to the market capitalization, a financial institution with higher market capitalization has a bigger node size while a financial institution with lower market capitalization has a smaller node size.

Node Color Indicates Total Directional Connectedness "To Others"

The node color is a sign of total directional connectedness "to others", ranging from 90EE90 (light green), to FFFF00 (yellow), to EEC900 (gold), to FF7F00 (dark orange), to FC4021 (bright red), to EE0000 (red), to 8B0000 (dark red). A less influential financial institution in the sample will be colored close to light green while a highly influential financial institution will be colored closer to dark red. We decide on the cutting points by taking the 30%, 60%, 80%, 90%, and 95% percentiles of the "to" connectedness measures of all the financial institutions throughout the dynamic analysis.

Figure 1: Color Spectrum

Node Location Indicates Strength of Average Pairwise Directional Connectedness

We use the ForceAtlas2 algorithm of Jacomy et al. (2014) in order to determine node location using in Gephi. A steady state is found in the algorithm. In the steady state, repelling and attracting forces exactly balance according to average of the pairwise directional connectedness measures, "to" and "from".

Edge Thickness Indicates Average Pairwise Directional Connectedness

We use the edge color to get a clear visuals. Edge color is lighter for the weakest links and same for all the others.

Edge Arrow Sizes Indicate Pairwise Directional Connectedness "To" and "From"

We use edge arrow sizes to indicate important links in large networks beacuse full set of edge arrow sizes reveals all directional connectedness measures and displaying all of them is unnecessary. Therefore, they are invaluable additions to the examination.

5 Connectedness of the US Banks and Insurers

In this section we present the results of the connectedness analysis we conduct for the US. The US analysis has many advantages in order to see the interactions between different type of financial institutions. Advanced structure of its financial markets and data availability make it very representative regarding connectedness of different type of financial institutions. We present the results of both static and dynamic analysis. After that, we display the results of the network analysis in terms of clustering in a network. Community detection might be very helpful in order to investigate the relations among different type of financial institutions rather than correlations. We take advantage of the community detection algorithm called "Infomap Community Detection" (Rosvall and Bergstrom (2008)). Finally, we try to shed light on insurers' relations to banking sector.

5.1 DY Static Connectedness Analysis

We perform static connectedness analysis using the full sample dataset in order to discover the linkages between the banking sector and the insurance sector in the US. We display the full connectedness table to characterize the links among different type of insurers and banking sector. In the full sample analysis, the main purpose is to see how each type of financial institution receive and transmit volatility shocks. As a result, Table 1 presents the results of full sample analysis for four type of insurers and banking sector with their "to", "from" and "net" connectedness.

Each entry in the table represents the amount of volatility received by the financial institution in the rows from the other financial institutions in the columns. For instance, the entry in the third row and first column gives us the volatility received by multiline insurance and brokers from banking and investment services in consequence of a volatility shock to the banking and investment services industry. Last three rows display summary indicators for each type of insurer. "From" connectedness gives the sum of volatility shocks received from other financial institutions, "to" connectedness sums up the volatility transmitted to other financial institutions and "net" connectedness is the difference between "to" and "from" connectedness of each financial institution.

	Banking & Investment	Life & Health	Multiline Insurance	Property & Casualty	Reinsurance
Banking & Investment (45)	70.54	5.10	5.98	16.78	1.61
Life & Health (5)	49.02	18.34	8.58	21.67	2.38
Multiline Insurance (8)	44.63	6.53	23.02	22.75	3.07
Property & Casualty (27)	43.29	5.75	7.88	40.46	2.62
Reinsurance (3)	40.91	6.02	9.73	24.33	19.02
TO	248.39	41.74	55.18	125.98	28.71
FROM	29.46	81.66	76.98	59.54	80.98
NET	218.93	-39.92	-21.80	66.44	-52.27

Table 1: The connectedness table of the US banking and investment services industry and the insurance industry

Note: Numbers in parentheses shows the number of companies from the industry.

At a first glance, we can easily see that banking and investment services and property and casualty insurance have positive "net" connectedness indicating that they are the main transmitters of volatility shocks over the financial system. The other three are the receivers of volatility shocks in the system. Banking and investment services sector has a dominance over insurers in terms of transmission of volatility shocks. This result is consistent with literature agrees on the fact that banks pose more systemic risk than insurers. In addition, the insurance industry's exposure to banking and investment services industry is not surprising at all with regard to their investment portfolios. At the end of 2015, 8.2% of the life and health insurers' and 16.1% of the property and casualty insurers' total corporate bond holdings was belonged to the banks. Life and health insurers and property and casualty insurers had total corporate bonds worth of $1.7 trillion and $332 billion respectively.

Property and casualty insurance is the only insurer type which transmits volatility shocks over the system. Thus, it might be critical to pay attention to property and casualty insurance. Moreover, we can see the main characteristics of property and casualty insurance and life and health insurance businesses from the connectedness table. Life and health insurance has low own connectedness whereas property and casualty insurance has high own connectedness. The reason might be that life insurers are highly levered and heavily invested in asset-backed securities or mortgage-backed securities making them more prone to outside risk. Cummins and Weiss (2014) show that life insurers more exposed to liquidity and credit risks than property and casualty insurers.

There are more important insights in the connectedness table concerning the financial system. Firstly, banking and investment services has very high own connectedness. This result states that the sector transmits volatility shocks to others but also it is effected mostly by the shocks originated within the sector. Banking and investment services effects life and health insurers most in the sample and it is effected mostly by property and casualty insurers. Secondly, life and health insurance is effected too much from banking and investment services. The reason for that might be the changes in the business lines of life and health insurance, especially life insurance. In terms of shadow banking feature of life insurers, there is a possibility of a run in the system (Foley-Fisher et al. (2015)). This can create a strong relation between these two sectors. Life and health insurance's low "to" connectedness indicates that the sector might not cause serious problems to the system but regulators should be very careful nonetheless. Life and health insurers are also significantly effected from property and casualty insurers.

Thirdly, multiline insurance and brokers resembles to life and health insurers regarding the fact that they operate in multiple business lines. The sector receives volatility shocks mostly from banking and investment services and property and casualty insurance. Fourthly, property and casualty insurance is distinguished from other type of insurers in terms of volatility shock transmission. It has significant impacts on the system if we look at individual "to" connectedness measures. Therefore, property and casualty insurance can pose notable systemic risk that is not negligible. Finally, reinsurance has very low "to" connectedness and low own connectedness measures. This can be attributed to the structure of reinsurance business. There is no feedback mechanism in the insurance system unlike in the banking systems. Reinsurance receives most of volatility shocks from banking and investment services and property and casualty insurance.

5.2 DY Dynamic Connectedness Analysis

By static analysis, we obtained useful insights about industries' relative position in terms of their contribution to volatility shocks and their interactions with each other. However, we aren't able to identify the characteristics of the dynamics of the volatility connectedness through static analysis. Also, we won't be able to fully cover the global financial crisis period if we do not investigate the dynamics of connectedness over the last decade. With this in mind, we take our study forward in order to get hold of the important features of the dynamics of connectedness. Therefore, to achieve this goal, we use rolling estimation window to undertake a dynamic analysis. Rolling window analysis enables us to deeply analyze the position of insurance companies alongside with banks and investment banks. In order to illustrate the total systemic risk the US financial markets, we focus on total connectedness index.

5.2.1 Total Connectedness

In this section, we examine the systemic risk in the US with regard to banks and insurers by analyzing the behavior of the total connectedness index. We use two different samples to demonstrate the results of the dynamic analysis. First, we use the first sample which covers the period between January 2000 and September 2006. After that, we use the second sample which covers the period between September 2006 to July 2016.

The index depicts what percentage of the total volatility shocks in the sample is stemmed from the shocks received from other financial institutions. Total volatility is normalized to 100 by construction. For example, an index value of 90 out of 100 can be construed in a sense that 10 percent of the volatility in the system is coming from own volatility shocks. On the other hand, 90 percent of volatility in the system is explained by shocks originated from other financial institutions. As a result, we can interpret a number from the index as an indicator of risk in the system.

Before the analysis, it seems that most of the reactions of the index comes from the banking related issues. However, one interesting result by a general evaluation of the index is that the accumulated risk in the system rises with the participation of the insurance companies in the crisis periods contrary to the expected role of the insurance industry as a shock absorber. The main reason might be that the insurance industry heavily invested in the debt instruments and structured financial products before the financial crisis. The insurance industry did not suffer from the economic downturns unlike other sectors but the deterioration of investment performance led insurers to failure as in the case with AIG. Moreover, the bankruptcy of AIG would have caused a much more severe crisis than the one caused by the failure of Lehman Brothers. AIG was the main actor in the unregulated credit default swap market and most of the financial institutions alongside of Lehman Brothers relied on AIG to insure their mortgage backed securities. McDonald and Paulson (2015) emphasize that if several of AIG's insurance subsidiaries did not receive injections from the AIG rescue, they could have been collapsed. The panic and repercussions would have been much worse for the financial markets worldwide in case of a collapse. Therefore, it may be wrong to say that the insurance industry acts as a cushion in times of crisis.

We plot total volatility connectedness over 150-day rolling-sample windows. On a brief look, we can see three distinct periods in Figures 1 and 2. The first one covers the period between August 2000 and September 2007. In this period, index goes up and down within 60-80 range. There is a one large fall and a consecutive jump in mid-2002. The second period comprise of the times of multiple crisis. The 2008-2010 financial crisis and the European Sovereign Crisis caused several spikes over the period. The second period started in October 2007 and ended in September 2012. The index hovered in the 80-95 range within this period. The third one covers the period between October 2012 and July 2016. In this period, the index gradually increases from 75% up to 92% with fluctuations.

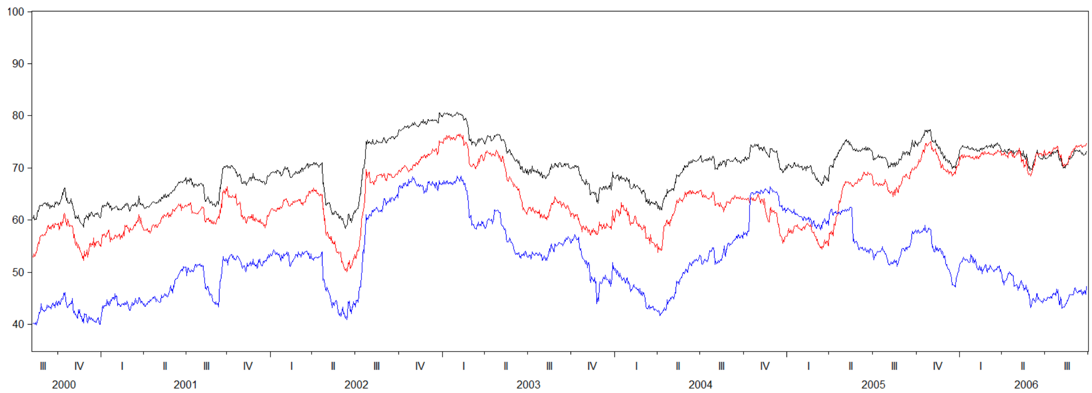

Figure 2: Total volatility connectedness index for the first sample

Note: Black line represents the total volatility connectedness index for all companies in the sample. Red line represents the total volatility connectedness index of only banks and blue line is for only insurers.

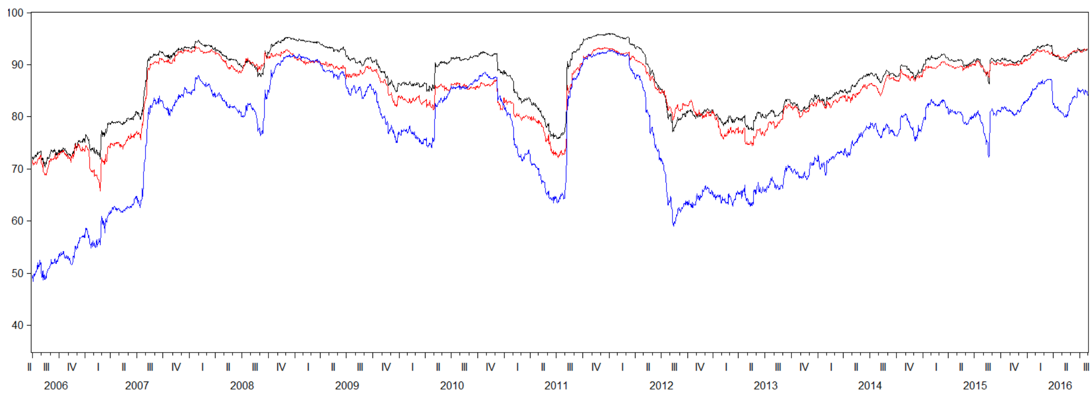

Figure 3: Total volatility connectedness index for the second sample

Note: Black line represents the total volatility connectedness index for all companies in the sample. Red line represents the total volatility connectedness index of only banks and blue line is for only insurers.

In the first period, there were couple of important events happened. The dot-com bubble started to burst in March 2000. Total volatility connectedness of financial stocks were severely affected by the bursting of the bubble. Total connectedness index increased by 6% after the bursting of the dot-com bubble. Starting from this point, total connectedness index began to rise until the terrorist attacks of 9/11. The attacks caused markets to be closed for a week. However, in the following week, the total connectedness index jumped almost 10%. Insurance was one of the industries substantially affected by 9/11 attacks. It was the largest property and casualty claim in the history due to the loss of property and life. It led to great uncertainty over the insurance industry since it was hard to determine the total impact on the industry. This condition of the insurance industry affected the other financial stocks as well.

Starting from the late 2001, there were two corporate scandals exercised influence over the US financial markets. The Enron scandal of late 2001 did not have a significant impact on financial stocks but, on the other hand, the MCI WorldCom scandal undermined the US financial markets in June 2002. MCI WorldCom, the second-largest long distance phone company in the US, declared bankruptcy. Unfortunately, all major US banks provided credits to MCI WorldCom and when the bankruptcy occured, they were all hit hard and sustained great losses as this was not the case in the Enron scandal. Also, the insurance industry was affected severely from the scandal since the US insurers held $7.3 billion in WorldCom investments at the end of 2001, by S&P estimates. At that time, the total connectedness index experienced a sudden increase by almost 20% points following the scandal.

After that, the index slowly decreased until the Fed announcement in June 2004. In June-July 2004, the Fed declared that the low interest rate policy was ended in consideration of the burst of the dot-com bubble. After more than four years, the Fed started to raise the interest rates. In response to that news, the connectedness index jumped 10% points. On 14 October, 2004, New York Attorney General Eliot Spitzer declared a probe against a number of the country's largest insurance brokers due to violating fraud and competition laws. The companies involved included AIG, Hartford Financial, Chubb Group and Marsh & McLennan. As a result, we can see a jump of 8% in the index for insurers and 3% jump in the total volatility connectedness index for all companies.

At the beginning of 2005, two large car makers GM and Ford experienced financial troubles which threatened their ability to pay their debts. In May 2005, S&P downgraded the car makers GM and Ford from investment grade into junk status resulting in a crisis in the credit market with a record level CDS spreads. The index increased almost 10% points during this period. However, the insurance companies were forced to sell GM and Ford bonds to raise their liquidity in order to meet the regulatory restrictions as a result of the distress started in the March 2005 in GM and Ford. This behavior of the insurance companies enabled them to protect themselves against an inevitable downgrade in the GM and Ford bonds. After the downgrade on May 5, 2005, the connectedness index for the insurers started to decrease regarding the already decreased exposure to GM and Ford. In the following months, there was another spike after the Hurricane Katrina which was the costliest natural disaster in the US history.

The second period corresponds to the two crises. In the first part of this period, the initial signs of the subprime mortgage crisis were manifest itself at the end of February 2007 with the effect of Chinese stock market crash at that time. In the following months, the two hedge funds of the Bear Sterns which were heavily invested in mortgage backed securities declared bankruptcy and afterwards, the hedge funds of BNP Paribas which were specialized in mortgage market collapsed in the August 2007. The total volatility connectedness index started to increase from 77% in June to 92% in August and reached the highest point in the history until that time. In the fall of 2007, investments in the derivatives market, especially mortgage backed securities, in the US led to major losses for all major US banks. The subsequent interventions of EU central banks and the Fed to reduce the tension in the markets which was a result of the accumulated losses of major EU and US banks was followed by a gradual increase in the volatility connectedness index. Despite all efforts, these precautions were not be able to stop the rot in the US financial markets. In March 2008, Bear Stearns collapsed as a result of its great exposure to the mortgage backed securities that were central to the sub-prime mortgage crisis. The Federal Reserve Bank of New York tried to avert the sudden collapse of the company by providing a loan but Bear Stearns was beyond saving. Consequently, the company was sold to JP Morgan Chase for a price far below its pre-crisis value. After this operation, the volatility connectedness index decreased by 8% points and made the lowest point of all crisis period by 86% at early September 2008.

After a short relatively tranquil period, the largest bankruptcy in the history of the US took place. Lehman Brothers filed for Chapter 11 bankruptcy protection on September 15, 2008. The failure of Lehman Brothers was accompanied by further troubles in the US financial markets. It seemed that AIG insured Lehman Brothers' debt by selling billions of dollars worth of Credit Default Swaps. On top of these, Fannie Mae and Freddie Mac were taken over by the US government and Bank of America Merrill Lynch acquired Merrill Lynch. The connectedness index jumped by 6% points on September 16, one day after the bankruptcy of Lehman Brothers and came up to 92% points at the end of September. From this point on, the index rose gradually to reach one of the two highest points of all time at the end of 2008.

In the second part of the period, the index started to decline with the optimistic atmosphere around the world. Most of the policy makers and financial market participants thought that the bad times are over as a result of the thriving financial conditions. The decline continued until the end of 2009. However, the mood of optimism did not last long due to the outbreak of another crisis in the sovereign debt market because of some European countries. In the last days of 2009, the Greek sovereign debt crisis led to little hike in the connectedness index. After this point, it remained steady around 83% for the first four months of 2010 resulting from worries about the Eurozone. The spike in the connectedness index on the first days of May 2010 was caused by the flash crash in the US stock markets on May 6,

2010. The gradual increase of the index was a response to the European Council meeting which made apparent the inability of the EU to offer a countermeasure. The connectedness index increased slowly until the end of 2010, before dropping down to 72% all time low for the two crisis periods by mid-2011.

In the second half of the 2011, the concerns about Italy and Spain regarding the problems in their banking sector and sovereign debt stirred the financial markets again. The main reason is that compared to the other European countries that had problems before, Italy and Spain are two EU members with much larger economies. In addition to all these developments, S&P downgraded the US bond from AAA to AA+ on August 5, 2011. As the problems with the European banks persisted and the US bond was downgraded, the connectedness index jumped 14% point in the first week of August. Following these events, the cycle in the index began with under these conditions came to an end in the middle of the third quarter of 2012 by the announcements of the president of the European Central Bank Mario Draghi.

In the third period, the total volatility connectedness index displayed a different behavior compared to two other periods. The index had some ups and downs but in general it piled up after every rise. The index started to increase slowly until the end of October 2012. Hurricane Sandy interrupted this rising since stock markets were closed for two days and opened in October 31, 2012. The political debates about the US fiscal policy which was called "fiscal-cliff" disturbed the financial markets until the end of 2012. In May 2013, the index jumped 4% points due to the announcements of the Fed about the QE policies. In late 2012 and 2013 some of the major banks of Europe and the US were forced to pay fines amounting billions of dollars in connection with the Libor scandal. The connectedness index maintained its general increase during these periods. There was a jump by 3% in October 2014 as a result of the flash crash in the US bond market.

The largest spike since 2012 was in August 2015 related to the losses in the Chinese stock market. From June 12 to August 24, the Shanghai Composite Index lost 38%

of its value. The so-called fear gauge, the VIX, rose to its highest level since 2009 on August 24. As a result, the connectedness index increased by 5% in five days and reached 90% on August 26, 2015. The effects of economic dowturn in China and the oil price fall which led to downgrades in energy bonds caused a gradual increase in the index until the end of March 2016. At the end of March 2016, MetLife, the largest US insurer by assets, won the case against the US regulators that declared the company as a systemically important financial institution (SIFI). MetLife filed a claim against the regulators since they asserted that becoming a SIFI will lead them to tougher regulations and higher capital requirements. The ruling made an example for other insurers declared as SIFIs. As a response to this verdict which was seemed to be in favor of the insurance industry, the index started decline and it decreased by 3% point until the mid-May 2016. The index for insurers fell by 7% points during the same period. In June, the UK voted the so-called "Brexit". The result was announced on the morning of 24 June and 52% voted in favour of leaving the European Union. This major decision had severe effects on the US banks and insurers since markets were concerned about the spillover effects of Brexit on the US economy. Additionally, almost the half of the US insurance industry's total exposure to the EU corporate bonds was in the UK with a worth of $21.5 billion by the end of 2015. In the US, Morgan Stanley, Citigroup, Bank of America, JPMorgan Chase, and Goldman Sachs dropped about 9%, 8%, 7%, 5%, and 6% respectively. On top of the banks, MetLife, Prudential Financial, and AIG were down about 7%, 7%, and 5% respectively. The total connectedness index rose up to 93% points by a 2% increase and the index for insurers increased by 6% points.

At the beginning of the sample on August 9, 2000, the index was 60% and as of the end of the sample, on July 29, 2016, the connectedness index is 93%. Despite the ending of the two major crisis, the risk in the financial markets never returned to the levels of pre-crisis periods. On top of that, the financial markets in the US gradually accumulated risk which is a very alarming situation regarding the past events.

5.3 Insurance Industry's Contribution to Systemic Risk

In this section, we take advantage of the structure of the total connectedness index and calculate the two industries' share in the index in order to investigate the insurance industry's contribution to systemic risk. We use the same samples in the dynamic analysis part. Figure 7 is the result of the first sample which covers the period between January 2000 and September 2006 and Figure 8 is the outcome of the second sample which covers the period between September 2006 to July 2016. We mark the important days on the figures to clearly see how the insurance industry's contribution to systemic risk changes. Since the insurance companies do not have a market among themselves like banks, an important way to examine the insurance companies' contribution to systemic risk is to look at their bond market activities. As it turns out that their contribution to systemic risk might be related with the bond market events.

After the recent financial crisis, there has been a growing interest on the insurance industry's contribution to the systemic risk. In particular, rescue of AIG showed that there is a potential for a large insurance firm to be a systemically important financial institution and cause serious problems to the financial system. Given the role of the insurance industry in the US debt markets, the industry's interactions in the bond market is an important aspect to assess the industry's potential contribution to systemic risk. For example, the insurance industry held 10% of total debt securities at the end of 2015 in the US.[4] Moreover, in the corporate bond market, the insurance industry is a key actor in the US. They possessed 24% of total corporate bond market assets at the end of 2015.[5] Therefore, the insurance industry has the potential to spread systemic risk through the bond market, especially from their corporate bond market activities. They have the power to disrupt the bond market by dramatically changing their bond market activity in case of a bad scenario. Brunnermeier and Pedersen (2009) showed that problems in a specific market can trigger extensive complications over all asset markets. Hence,

[4]Flow of Funds data from the Federal Reserve Board.

[5]See footnote 4.

the impairments caused by the insurance industry in the bond market can lead to system-wide deteriorations.

Interactions in the bond market can also have a destabilizing effect when a liquidity crisis is in presence. Rosen and Paulson (2016) find that the US life insurers purchasing behavior changes with the liquidty of bonds. Life insurers purchase bonds when the bonds are less liquid than average. As a result, they claim that life insurers abosorb liquidity risk. However, they find no evidence of this behavior during the recent financial crisis. Thus, we should be careful to say that insurers act as a cushion during crises.

Figure 4: Shares of industries in the total volatility connectedness index for the US banks and insurers (1)

Note: Black line represents the share of banking and investment services industry and red line represents the share of insurance industry. Three vertical blue lines indicate the important days:

1: MCI WorldCom bankruptcy (July 21, 2002),

2: Lawsuits against the country's largest insurance brokers (October 13, 2004),

3: S&P downgraded GM and Ford bonds to junk level (May 5, 2005)

In the first sample analysis which can be seen in Figure 4, we detect three substantial alterations in the industry's contribution to systemic risk. From the beginning of the sample period to the early third quarter of 2002, the banking and investment services industry had the upper hand against the insurance industry. The banking and investment services and insurance industries' shares were approximately 60% and 40% respectively. From the beginning of 2002, the shares started to close up. On July 21, 2002, when MCI WorldCom declared bankruptcy, the shares of the banking and investment services and the insurance industries were 52% and 48% respectively. The main reason of the increase in the share of the insurance industry is due to their investment portfolios. They held $7.3 billion in WorldCom investments at the end of 2001, by S&P estimates. Also, all major US banks faced serious losses since they provided credits to MCI WorldCom. The problems of banks also affected the insurance industry, because they had large corporate bond holdings in their investment portfolios.

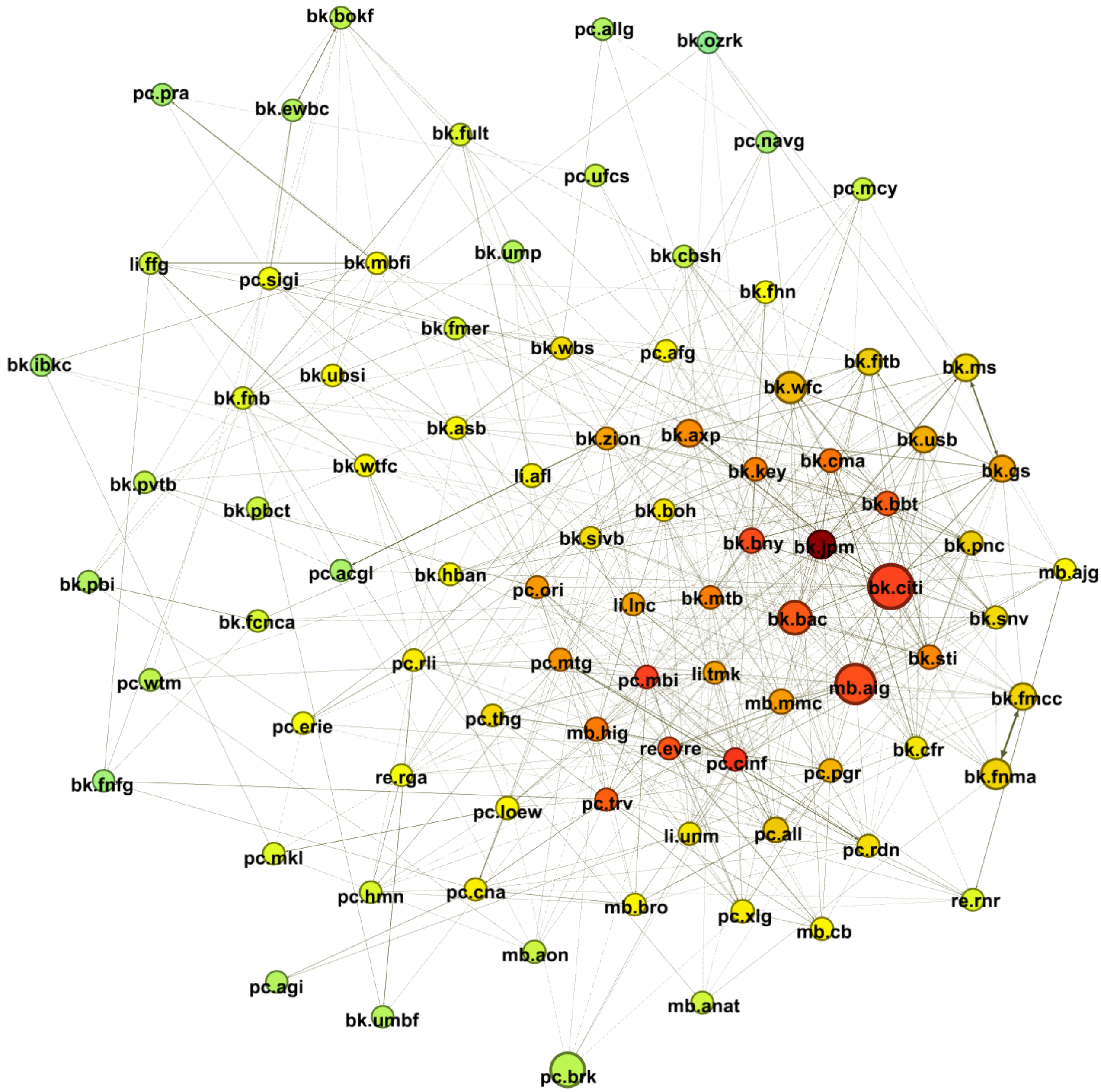

Figure 5: Network before the MCI WorldCom bankruptcy on July 19, 2002 (The total connectedness index was 69.7%)

In Figure 5 and 6, we can see the networks before and after the MCI WordlCom collapse. Before the banktruptcy, banks are the main volatility shock transmitters

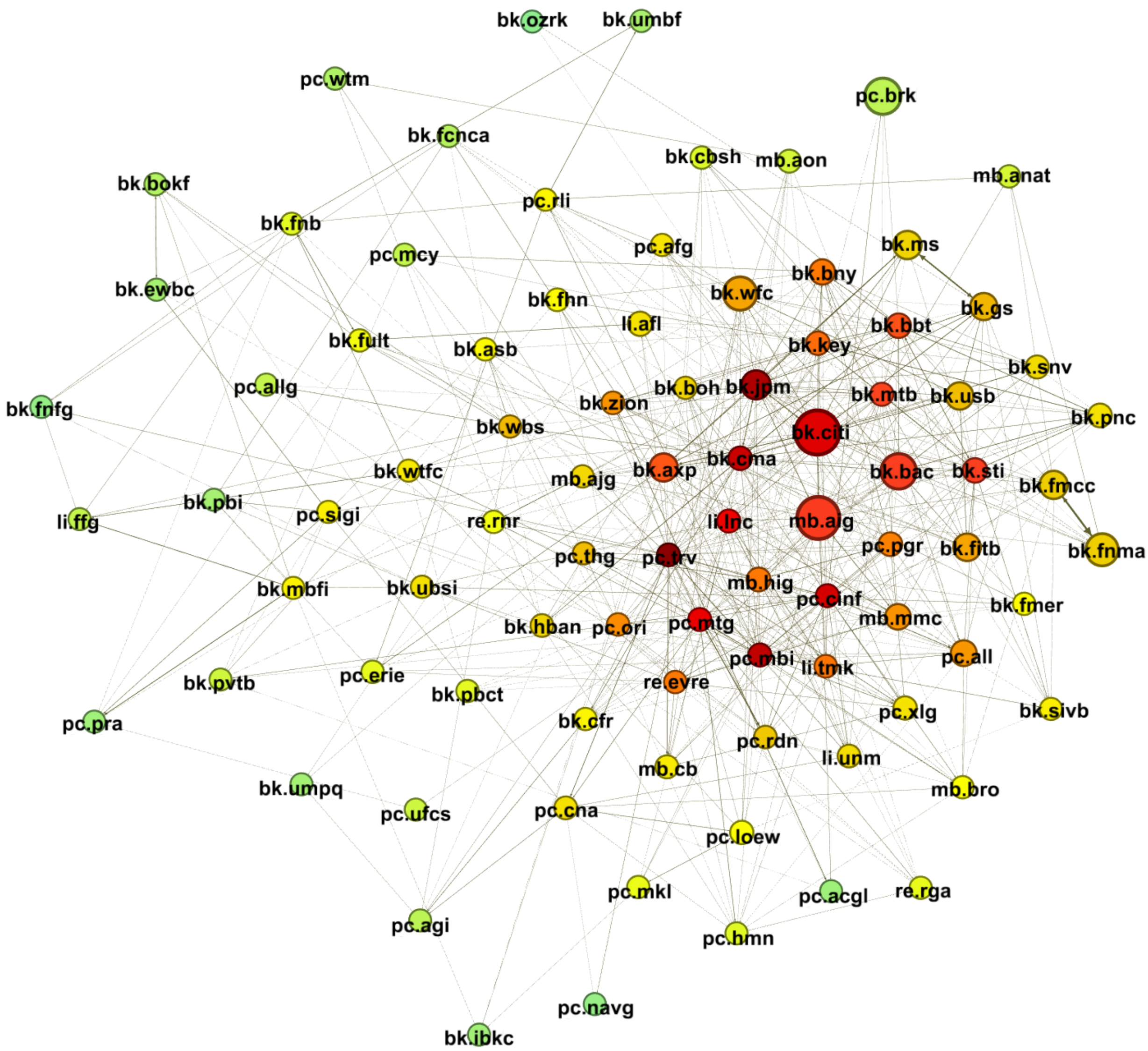

Figure 6: Network after the MCI WorldCom bankruptcy on July 24, 2002 (The total connectedness index was 75.1%)

in the system. However, after the collapse, the insurance companies started to transmit and generate risk to the system due to their MCI WorldCom investments.

After the effects of MCI WorldCom collapse were obliterated, the gap between the shares of the banking and investment services industry and the insurance industry started to widen. Until October 2004, the banking and investment services industry had the large portion in the systemic risk. On October 14, 2004, a probe was declared against several insurance brokers due to violating fraud and competition laws. The insurers stock prices plunged and this led to an increase in the sytemic risk contribution of insurers.

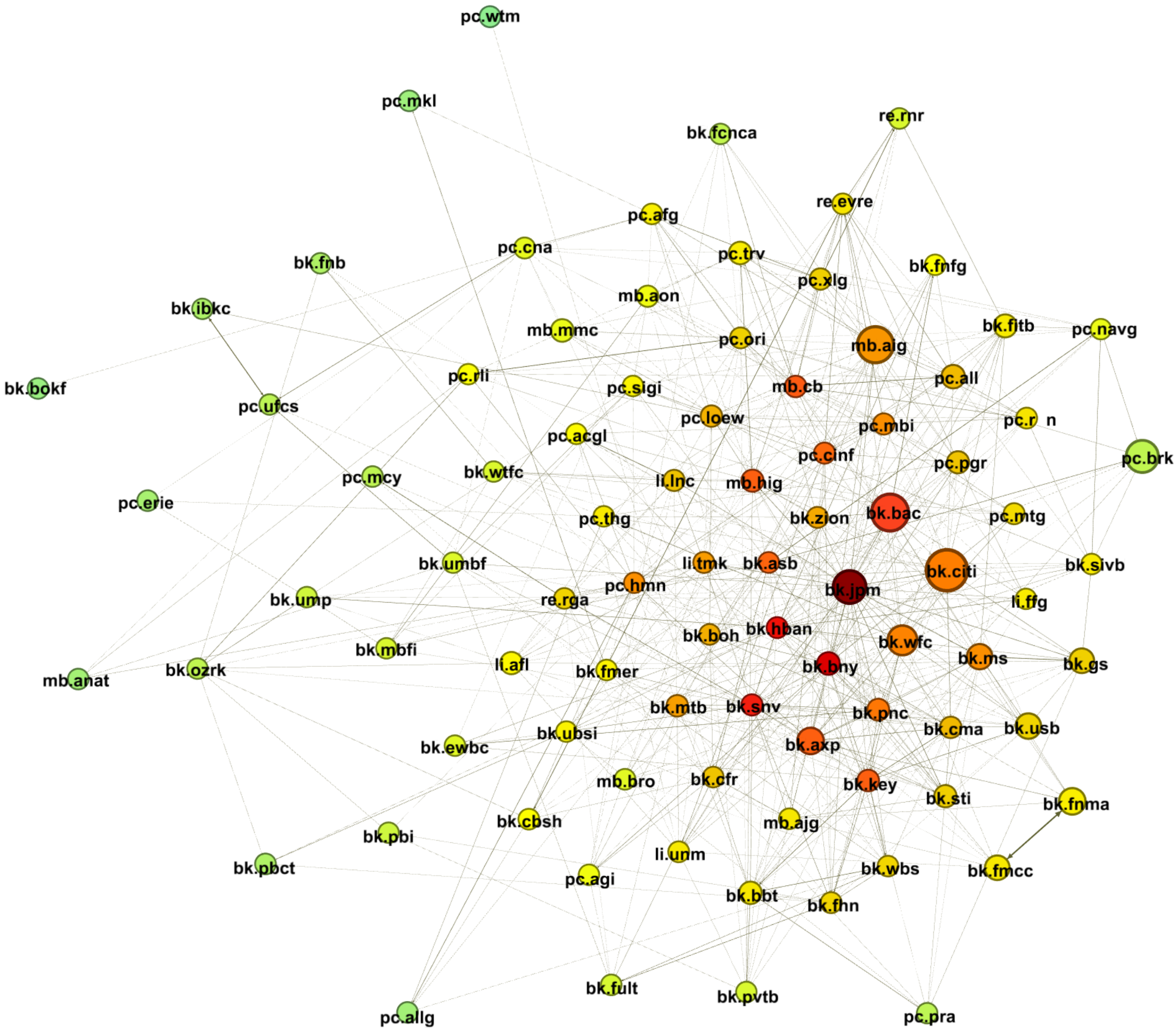

Figure 7: Network on the day before the lawsuits on October 13, 2004 (The total connectedness index was 71.8%)

In Figure 7 and 8, we display the financial networks before and after the lawsuit agianst the insurers. Insurance companies were not systemically important as much as banks in the system before the criminal probe. Nevertheless, the day after the declaration of an investigation, the insurance companies involved became important regarding their effect in terms of volatility shocks in the financial system.

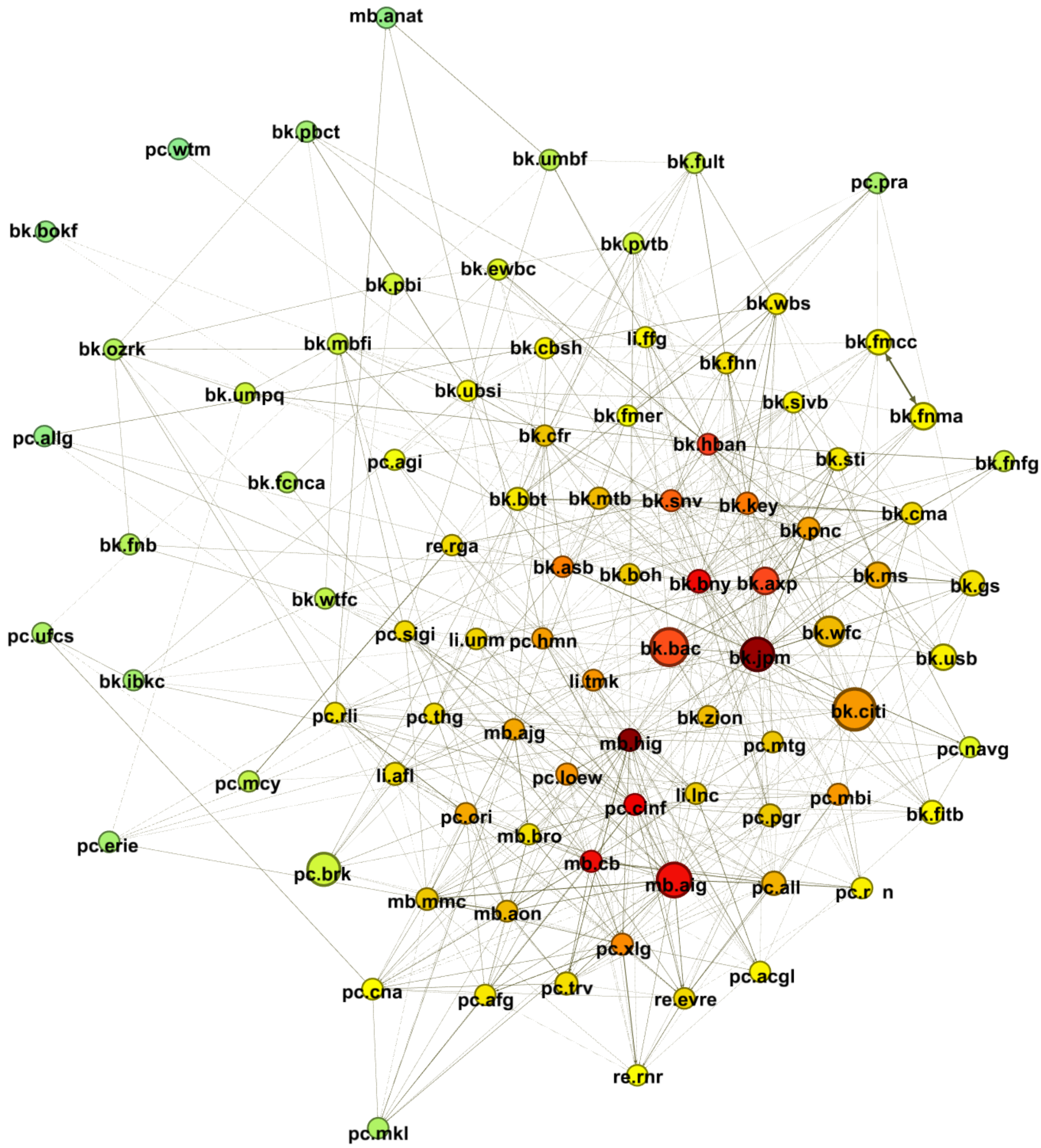

Figure 8: Network on the day after the lawsuits on October 15, 2004 (The total connectedness index was 73.4%)

In the period between the lawsuits and GM and Ford bond downgrades, the share of the insurance industry rose above the banking and investment services industry for a time. The distress caused by the probe and the credit-quality deterioration of GM and Ford led to an increase in the insurance industry's contribution to systemic risk. However, after S&P downgraded GM and Ford bonds to junk status on May 5, 2005, the spread between the shares of the banking and investment services industry and the insurance industry started to expand rapidly. The reason for that might be the insurance industry's investment behavior before the downgrade. When it became clear that the downgrade is imminent, insurance companies that owned GM and Ford bonds had to liquidate them in order to meet the regulatory obligations (Acharya et al. (2015)). Their GM and Ford bond holdings declined rapidly from the first quarter to third quarter of 2005.

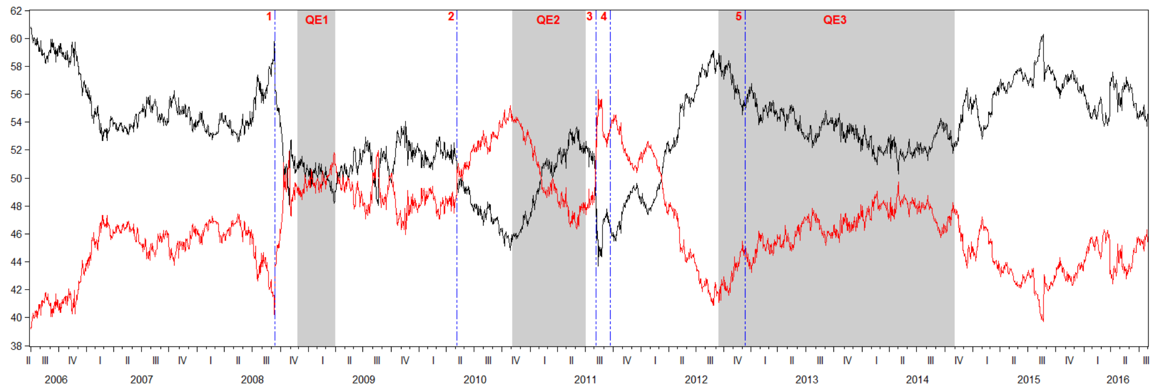

Figure 9: Shares of industries in the total volatility connectedness index for the US banks and insurers (2)

Note: Black line represents the share of banking and investment services industry and red line represents the share of insurance industry. Shaded areas displays the three round of quantitative easing policies of the Fed. Five vertical blue lines indicate the important days:

1: Lehman Brothers' collapse (September 15, 2008),

2: Stock market flash crash (May 6, 2010),

3: S&P downgraded US government bond to AA+ from AAA (August 5, 2011),

4: The Fed announced "Operation Twist"(September 21, 2011),

5: "Operation Twist" was completed (December 12, 2012)

Figure 9 demonstrates the evolution of shares for the second sample. The initial signs of the subprime mortgage crisis emerged in February 2007. During the build-up period of the global financial crisis, the insurance industry's share in the systemic risk increased from 40% up to 48%. In the following months, the shares of the banking and investment services industry and the insurance industry kept an average of 54-46%. After the collapse of Bear Stearns in March 2008, the insurance sector's share started to decline until the bankruptcy of Lehman Brothers, the largest bankruptcy in the history of the US. took place. We mark the day of the collapse, September 15, 2008. Starting with the Lehman's failure, the insurance industry's contribution to the systemic risk rose very qucikly. The share of the insurance companies in the index increased by 10% and ranged between 50-52%

for a period. In Figure 10 and 11, we can see the financial networks before and after the failure of Lehman Brothers. Before the collapse, banks were the main contributors to the systemic risk. However, after a one month period, insurers took the role of the banks and generated more risk to the financial system.

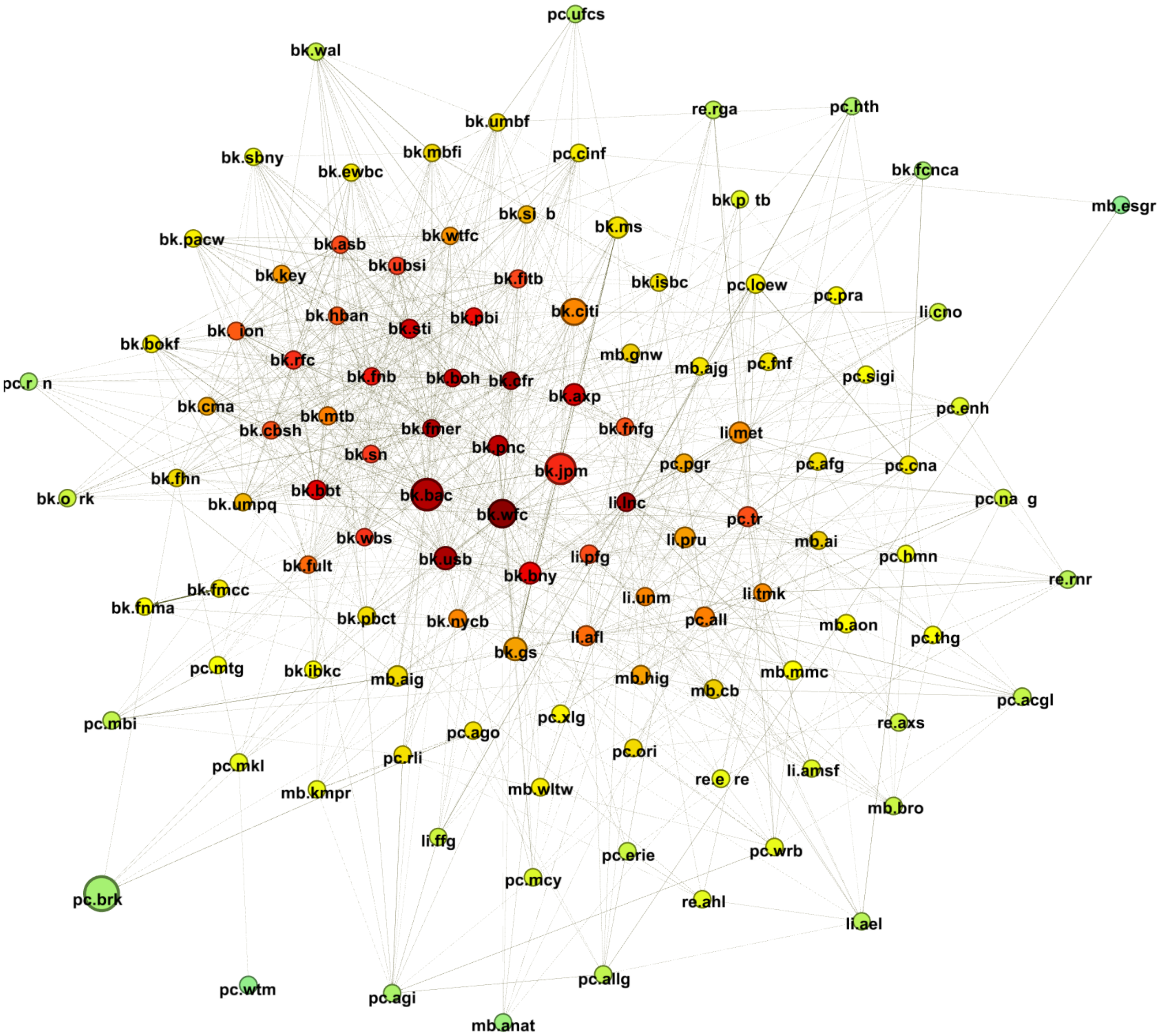

Figure 10: Network before the collapse of Lehman Brothers on September 12, 2008 (The total connectedness index was 89.8%)

In November 25, 2008, the Fed announced its first quantitative easing (QE) policy. The Fed will buy \$100 Billion GSE direct obligations, \$500 billion in MBS. During the QE1, the contribution of the insurance industry to the systemic risk gradually increased and passed the banking and investment services industry's contribution in March. On March 18, 2009, the Fed expanded the MBS program to \$1.25 trillion and announced to buy up to \$300 billion worth of longer-term Treasury

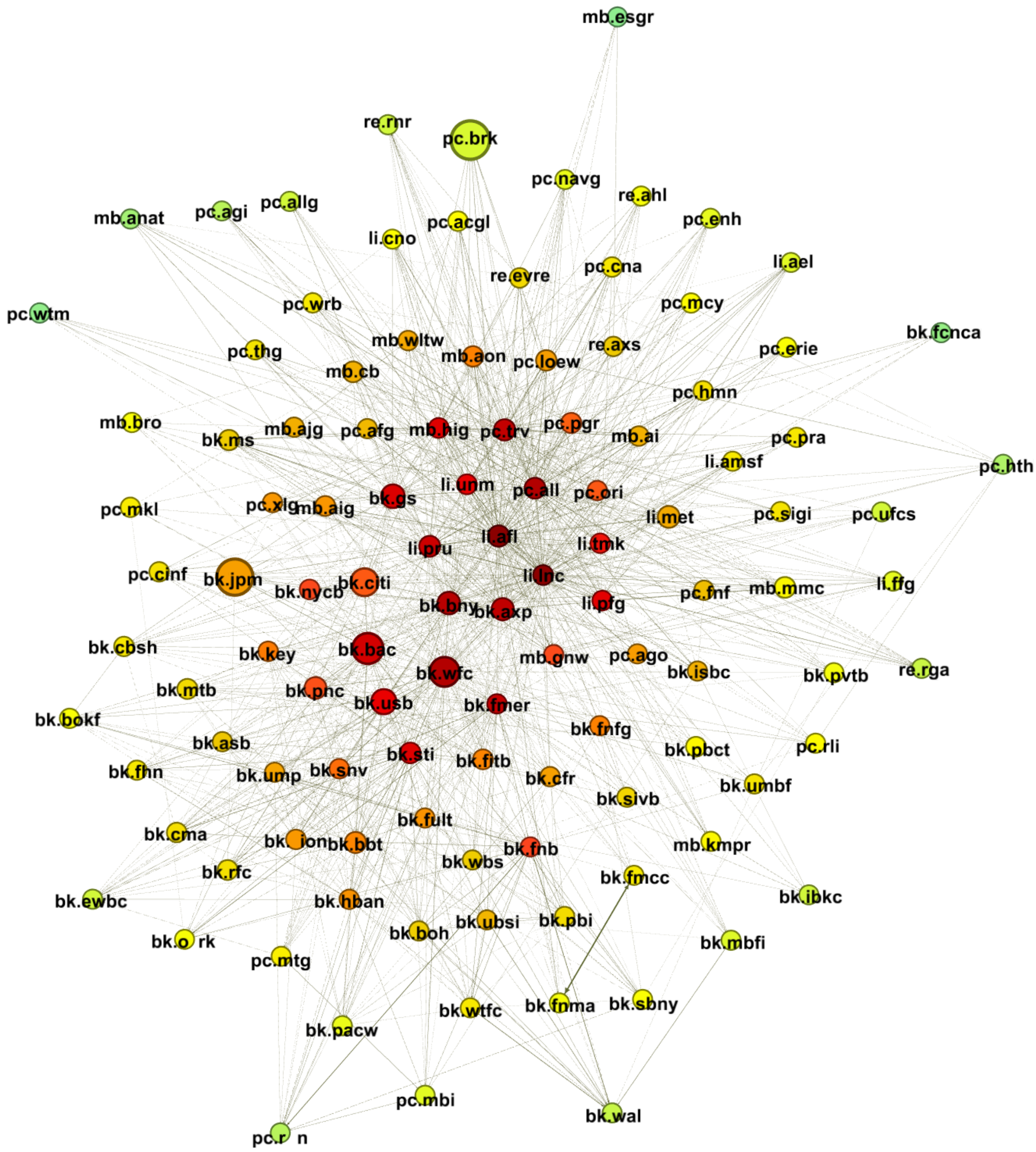

Figure 11: Network after the collapse of Lehman Brothers on October 10, 2008
(The total connectedness index was 93.8%)

securities. The first QE ended at the end of the first quarter of 2009. Until the end of QE1, the share of the insurance sector increased and when the QE1 was finished, it started to decrease slowly. The fluctuations between the shares of two industries continued for a period. The rise in the share of the insurance sector in the systemic risk after the Lehman's collapse can also be attributed to troubles stemmed from AIG and the rescue of AIG by the Fed.

On May 6, 2010, a flash crash which was a trillion-dollar stock market crash occured in the US stock markets. Stock indexes, such as the S&P 500, Dow Jones Industrial Average and Nasdaq Composite, collapsed and recovered large part of the losss within minutes. The Dow Jones Industrial Average plunged 998.5 points (about 9%) in minutes. After this incident, the share of the insurance industry started to increase above the banking and investment services industry. The incremental move lasted until the starting of the second QE by the Fed. At that time, the insurance industry' contribution to the systemic risk was 55%. On November 3, 2010, the Fed declared the second QE worth of $600 billion. From the starting of the QE2, the contribution of the insurance sector to the systemic risk declined to 47% when the Fed announced that the QE2 purchases were completed at the end of second quarter of 2011.

Not long after, in August 5, 2011, S&P downgraded the US bonds to AA+ from AAA. In couple of days, the systemic risk contribution of the insurers spiked to 56%. By the end of 2011, life insurers and property and casualty insurers held 3% and 7% of their total assets in treasury securities, respectively.[6] The effect of the downgrade was severe on insurance companies since the US government bonds is the benchmark to price fixed-income assets. In Figure 12 and 13, we can see the financial networks before and after the US government bond downgrade by S&P. Prior to the downgrade, total risk in the system and the number of financial institutions that posed systemic risk were both low. On the other hand, after the downgrade, insurance companies, in particular life insurance companies, started to transmit volatility shocks to the financial system more than banks.

Afterwards, the insurance industry's share in the systemic risk started to decline again. On September 21, 2011, the Fed announced "Operation Twist". The aim of this operation was to sell treasury securities with remaining maturities of 3 years or less and to purchase treasury securities with remaining maturities of 6 years to 30 years. The operation was intended to worth $400 billion and to be ended by the end of June 2012 but on June 20, 2012, the Fed extended the duration of the

[6] Flow of Funds data from the Federal Reserve Board.

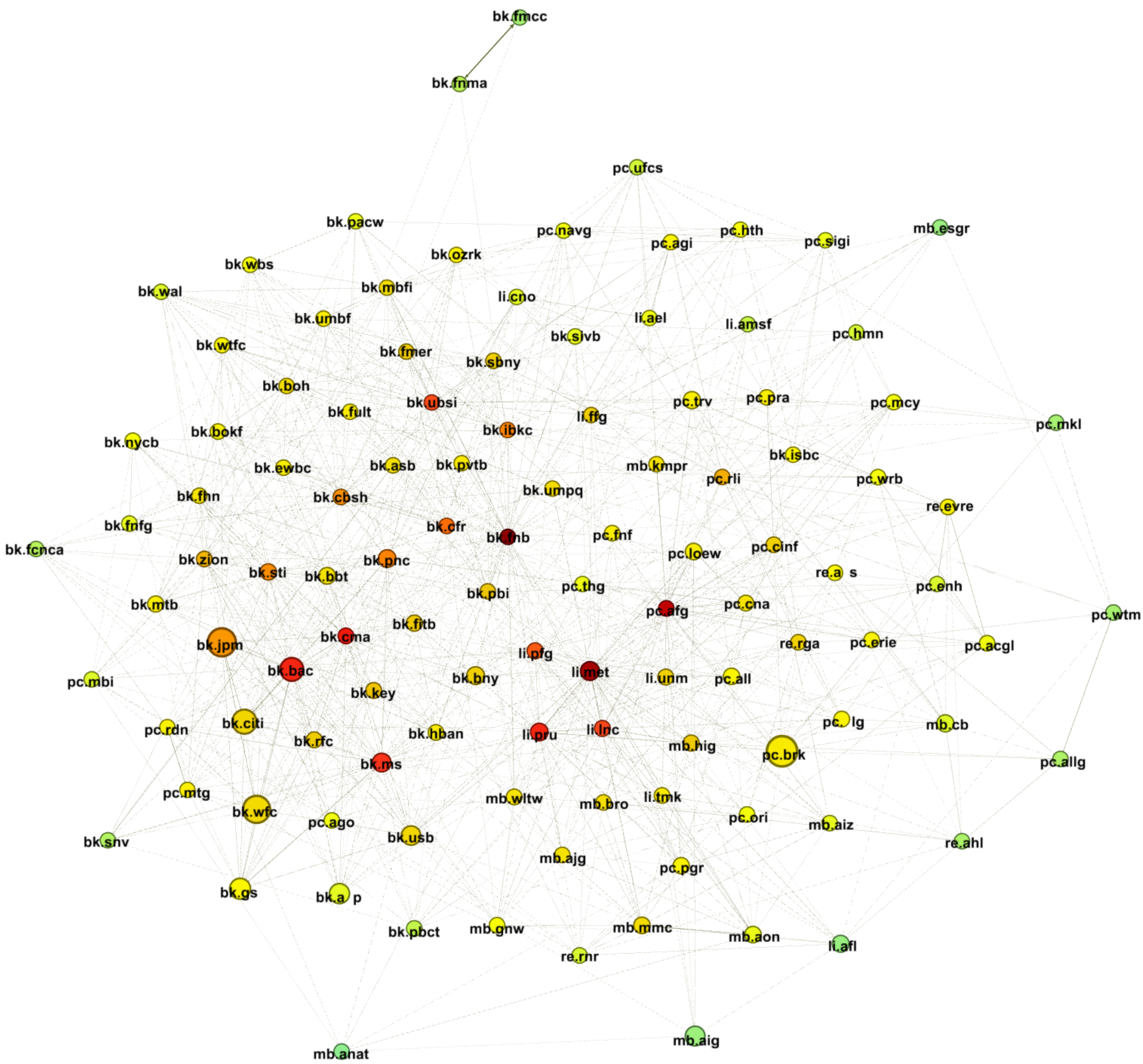

Figure 12: Network before the US government bond downgrade on August 3, 2011 (The total connectedness index was 78.2%)

operation. On September 13, 2012, the Fed released a statement about the QE3 worth of $40 Billion per month. Soon after, at the end of 2012, on December 12, 2012, the Fed announced that they expanded the QE3 to $85 Billion per month and finished the "Operation Twist". During "Operation Twist", the contribution of the insurance industry to the systemic risk fell to pre-crisis levels and declined to 41% when the QE3 was announced. In the second quarter of 2013, the Fed Chairman Ben Bernanke's comments on the QE policies led to so-called "Taper

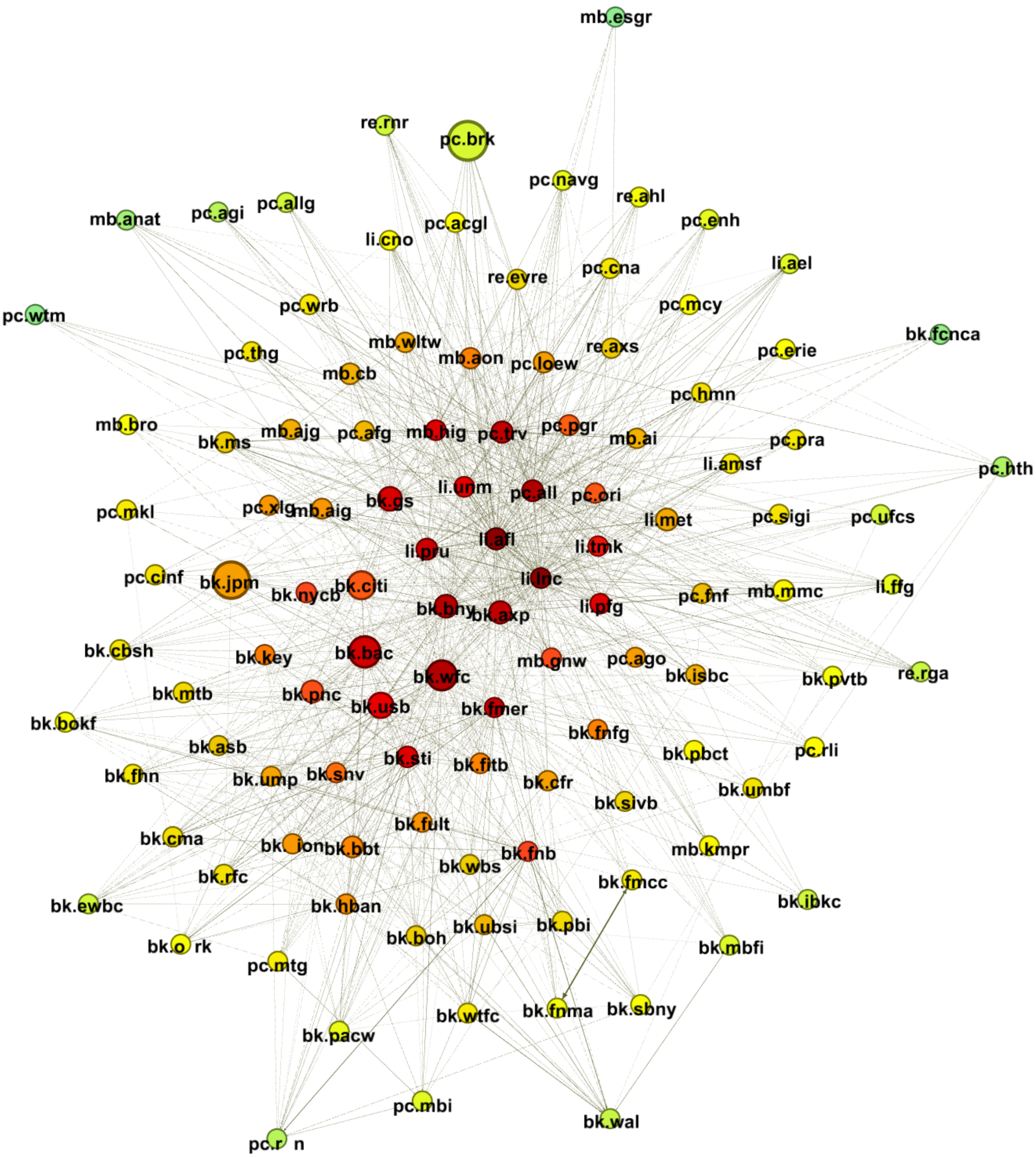

Figure 13: Network after the US government bond downgrade on August 12, 2011 (The total connectedness index was 89.6%)

Tantrum". On December 18, 2013, the Fed started to taper QE3 to $10 billion per month at each meeting of 2014. The Fed ended its monthly asset purchases program (QE3) at the end of October 2014. During QE3, the share of the insurance industry in the total connectedness index gradually rose from 41% to 48% when QE3 was finished.

In conclusion, it seems that the insurance industry's contribution to the systemic risk is related to the developments in the bond markets closely. Therefore, it might be of interest for regulators to investigate the relationship between the insurers and the bond market related incidents in order to assess the systemic risk contribution of the insurance sector.

5.4 Communities in the US Financial Network

In this section, we utilize community detection of network literature to provide a deeper analysis of the financial networks. Mainstream measures to detect the systemically important financial institutions (SIFIs) are local approaches rather than overall views of the financial networks. They are not able to identify the possible communities in the network where a disturbance to a subgroup or the joint default of a subgroup can put much more pressure on the financial system. Finding communities in a network provides valuable information about the dissemination of the shocks. We can see when shocks that hit the financial system spread quickly systemwide and when they are likely to have local effects. Hence, we should evaluate the financial system as a whole not just one by one. Otherwise, we can miss the possible consequences of a systemic event.

We take advantage of the Diebold-Yilmaz framework and estimate daily networks over time on a rolling-window basis to start the community detection. However, the communities does not make sense if the structure of the network is very dense as this is the case with the networks derived from variance decompositions. We need to create a sparse graph in order to ensure the existence of well-defined communities (Fortunato (2010)). For this purpose, we select the top 25% and top 10% of the weighted links for every node in the network to keep the most important information about the linkages between the financial institutions. After that, we use the community detection algorithm called Infomap to detect communities in the networks over our sample period. The Infomap method is widely held as the most reliable method for community detection in directed and weighted networks (Fortunato (2010)). Fortunately, Diebold and Yilmaz (2014) showed that the connectedness measures are closely related to aspects of network connectedness. We can easily say that variance decompositions are basically directed and weighted networks. The Infomap method is based on random walks and the intuition is that a random walker will be trapped in a community if she meets one, because of the dense structure of the community. Thus, the random walk concept can be seen as an information flow process in the networks. This aspect of the community detection can be conducive to see the consequences of a possible systemic event. Also, it might be of interest for regulators to design more effective regulatory frameworks.

We use R to display the communities in the financial networks. Node size represents the market capitalization of companies. We select intervals in order to determine the node sizes. Thus, some of the nodes will have the same size implying that they are in the same interval for theie market capitalization. The node colors are assigned automatically by R. Every color indicates a community. If two nodes have the same color, this means that they are the member of the same community.

In the US analysis, we detect three communities in the full sample network when we select the top 25% of the weighted links. On a cursory look, we can say that large banks tend to be in the same community (blue) with large banks. Same situation is valid for the insurance sector as well. Large insurers create a community (red) among themselves. The surprising result is that some small banks and insurers are gathered in the same community (green) unlike relatively large banks and insurers. In the large bank community, there are three property and casualty insurers. Radian Group Inc, MGIC Investment Corp and MBIA Inc provide financial guarantee insurance and mortgage insurance through its subsidiaries and this might be the reason why they are in the large bank community. Also, Fannie Mae and Freddie Mac are in the same community with large banks.

We perform another analysis by selecting the top 10% of the weighted links. Now, we get a more fancy picture of the financial system in the US. Banking sector is

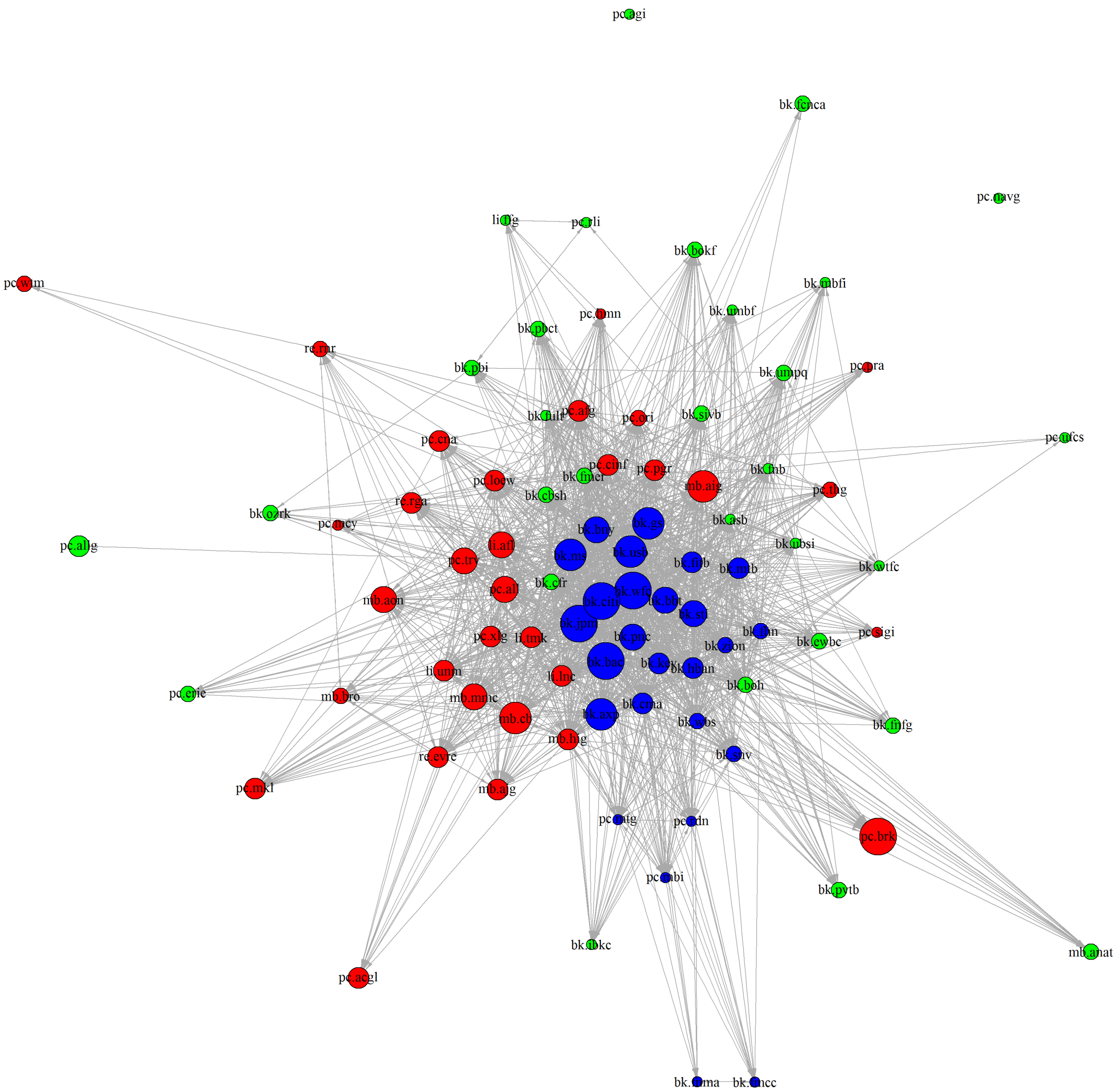

Figure 14: Communities in the network when top 25% of the existing edges for every node selected

divided into three communities. The first community (blue) has nine members and all of these members are among the largest banks of the financial system. The second community (green) is constituted by medium-sized banks. The small-sized banks form the third community (yellow) within the banking sector. Ten small-sized insurers create a community (light blue) but they all are scattered at the periphery. Medium-sized and large insurers are in the same community (red). Finally, the most notable community consists of the main actors of the subprime mortgage crisis. AIG, Fannie Mae, Freddie Mac, two mortgage insurers, namely, Radian Group and MGIC, and one financial product insurer, MBIA, are clustered together (purple). These observations indicate that the community analysis is proved to be very useful. We can easily pin down the possible directions or outcomes of a volatility shock by looking at the modules in a network.

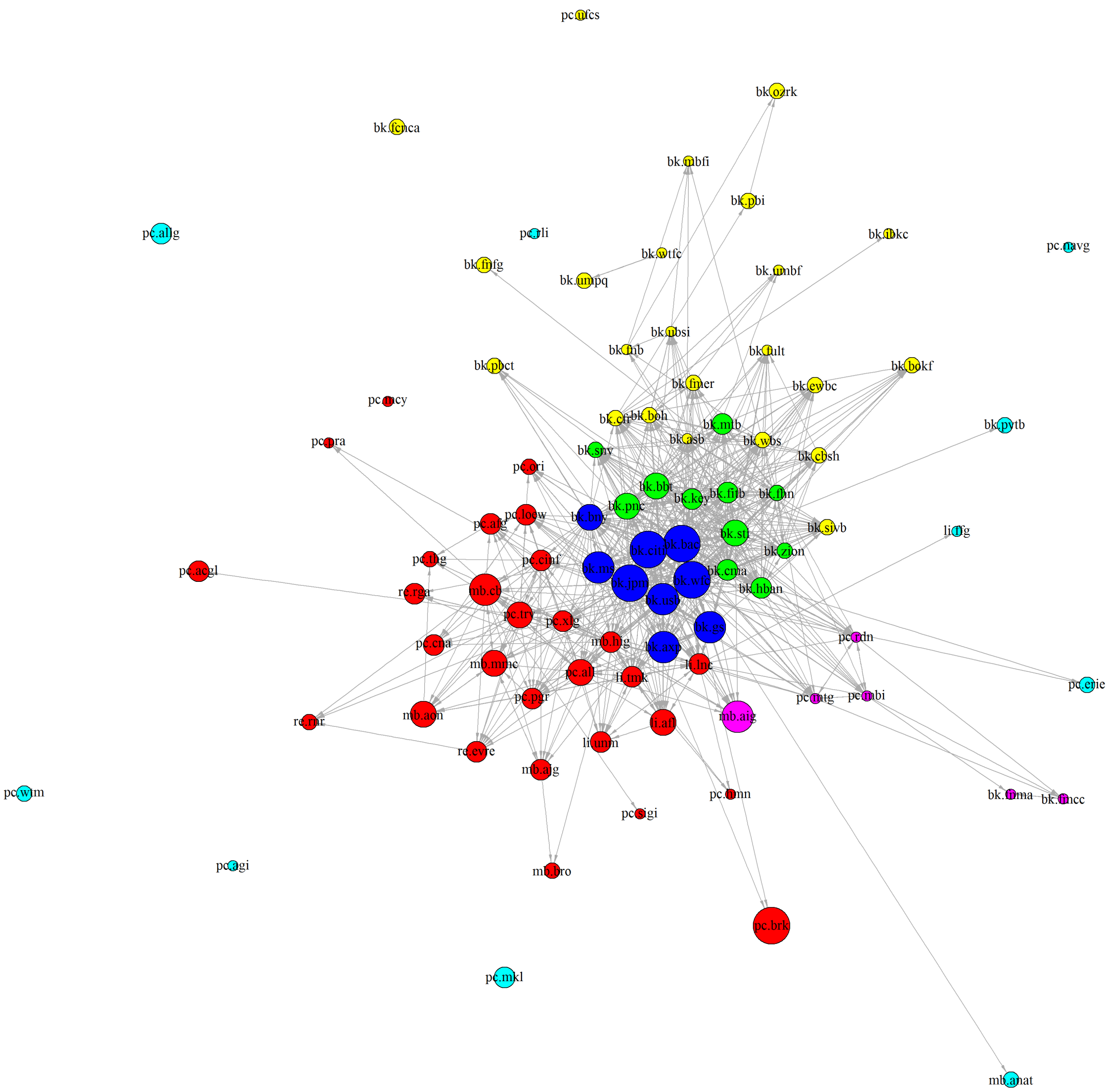

Figure 15: Communities in the network when top 10% of the existing edges for every node selected

Undoubtedly, the modular structure of a network changes over time. Therefore, we perform community analysis over time and report the number of communities throughout our sample period in order to provide a way to understand how the modular structure was affected during the crisis periods. The analysis with top 25% of the weighted links demonstrates the change in modularity as a response to crisis periods more clear. However, when we select the top 10% of the weighted links, we are able to see the impacts of every financial turmoil period on the modularity. For example, before the collapse of Lehman Brothers, modularity of the top 25% network pointed out for just one community which was the network itself. On the other hand, the top 10% network gives more detailed results. We can see the effects of 9/11 terrorist attacks, WorldCom scandal, problems in credit markets caused by the two major car makers, the run-up period of the financial crisis, and even the tranquil periods on the modular structure of the network.

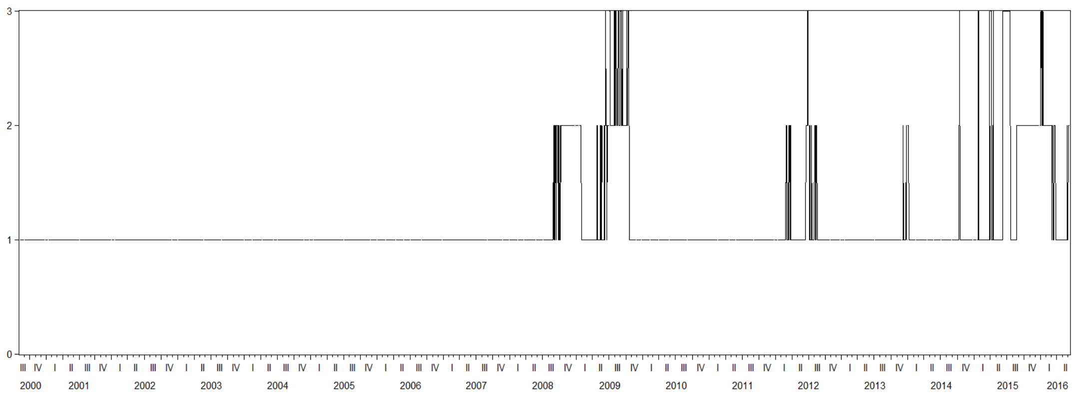

Figure 16: Number of communities in the network when top 25% of the existing edges for every node selected

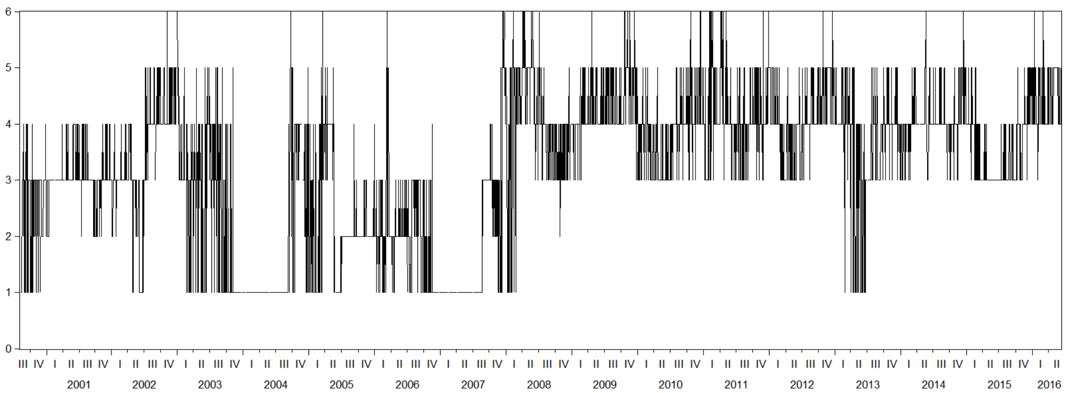

Figure 17: Number of communities in the network when top 10% of the existing edges for every node selected

Following these observations, we can say that the community analysis could be a conducive tool in order to discover the effects of crisis periods and much more importantly it might provide warning mechanisms since it shows likely outcomes of a financial distress in the system.

6 Connectedness of the Insurance Industry

In this section we present the results of the DY connectedness analysis. The main goal of this section is to see how countries and different type of insurance companies interact to each other in terms of volatility transmission. After that, we display the result of total volatility index and directional volatilities for countries and different type of insurers in order to pin down the dynamic feature of volatility connectedness. Lastly, we interpret the results in consideration of financial events happened in the corresponding time period.

6.1 DY Static Analysis

We perform static analysis of connectedness using the full sample dataset with the aim of revealing the linkages among different type of insurers and among countries. Firstly, we start by characterizing the links between different type of insurers. In the full sample analysis, the attention is on the volatility spillovers across four type of insurers in order to identify how each type of insurers receive and transmit volatility shocks. As a result, Table 2 presents the results of full sample analysis for four type of insurers. In Table, we report the connectedness table of insurers with their "to", "from" and "net" connectedness.

Secondly, we turn our attention to the country level volatility spillovers. We interpret full sample connectedness table for 26 countries to describe how a volatility shock to a country affects other countries in our sample. Consequently, Table 4 and 5 display the connectedness table of 26 countries together with their "to", "from" and "net" connectedness measures. We interpret full sample connectedness table of countries and try to unveil regional links.

6.1.1 Comparison of different type of insurers

Reinsurance companies have lower "to" connectedness and higher "from" connectedness compared to other type of insurers. Multiline insurers and brokers have the lowest "net" connectedness in absolute value. Moreover, Property and casualty insurers and life and health insurers have positive "net" connectedness measures. These observations indicate important facts about different type of insurers. Firstly, negative "net" connectedness of multiline insurance and brokers and reinsurance companies implies that these two type of insurers receive more volatility shocks from the system than they give to the system. However, low "net" connectedness of multiline insurers and brokers in absolute value can be attributed to their business line characteristics since they operate on every type of insurance category. This claim can be supported by their relatively low own connectedness meaning that they are more integrated to the system and they are active players in the system regarding their high "from" and "to" connectedness. They give the others nearly as much as they receive from others which also applies to property and casualty insurers. On the other hand, life and health insurers and reinsurance companies have large gaps between their "to" and "from" connectedness measures.

	Life & Health	Multiline Insurance	Property & Casualty	Reinsurance
Life & Health (35)	60.51	17.08	15.74	6.67
Multiline Insurance (22)	29.17	44.63	17.82	8.39
Property & Casualty (32)	22.43	15.54	55.00	7.04
Reinsurance (9)	27.15	20.49	20.83	31.52
TO	78.75	53.11	54.40	22.09
FROM	39.49	55.37	45.00	68.48
NET	39.26	-2.27	9.39	-46.39

Table 2: The connectedness table for four type of insurers

Note: Numbers in parentheses shows the number of companies from the insurance type.

Secondly, life and health insurers' positive "net" connectedness shows that they are the net transmitter of volatility shocks. In addition, life and health insurers have very high own connectedness which can be explained by their position in the insurance industry. Life and health insurers are in control of 85 percent of the financial assets held by insurance companies.[7] They are among the largest institutional investors within the financial system regarding the fact that insurance

[7] Global Financial Stability Report, IMF, pg:88, April 2016.

companies are keeping approximately 12 percent of global financial assets. Furthermore, low interest rates are a significant risk factor for the life insurance sector since life insurance companies have longer investment horizons than other type of insurers. In terms of business characteristics, non-life insurers can change conditions in the contract more easily which enables them to be more flexible against the risks stemmed from the economic conditions. In the sense of traditional life insurance business characteristics, long-term liabilities are met by assets with akin terms. Thus, high returns on these assets are what sustains profitability. Keeping that in mind, when interest rates started to fall and capital requirements started to rise life insurers began to experience problems in order to match the liabilities. Thus, economic growth and changes in the regulatory framework that affected the insurance industry emerged a need for liquidity for life insurers. In response to these changes, life insurers headed for non-traditional activities including issuance of funding agreement backed securities and transfer of risk arising out of insurance liabilities to off-balance sheet captive reinsurers. Consequently, life insurers become more prone to runs because of their non-traditional insurance avitivities (Foley-Fisher et al. (2015)). One can claim that life insurers function as shadow banks in the financial system and high own connectedness can be attributed to these features of life insurance business.

Thirdly, given their low profile in the system, reinsurance companies' own connectedness is relatively low. Reinsurance is a business model that bears the risk primary insurers do not want to retain. In a word, reinsurers act as an insurer for other type of insurers just like the primary insurers' function for individuals or firms.[8] Therefore, low own connectedness is expected considering the business model of reinsurers since reinsurers mainly make contracts with primary insurers. Moreover, in insurance system, interconnectedness is disparately different as in the banking system. There is an insurance contract establishes the relationship and payments depend on the emergence of an insured event. On the contrary with the banking system, one side of the contract can't demand a payment at will

[8] IAIS, 2012. Reinsurance and Financial Stability.

or can't borrow overnight to met its liabilities like in the interbank market. As a result, there is no event that could potentially trigger a run. The hierarchical structure of the reinsurance market doesn't allow for any feedback mechanism in the system (Kanno (2016)). Reinsurance companies' low "to" connectedness and high "from" connectedness can support this argument. Almost 70 percent of the volatility shocks comes from other type of insurers for reinsurers.

Lastly, property and casualty insurers have positive "net" connectedness that is to say that they transmit volatility shocks over the system more than they receive from the system. The property and casualty insurers main function is to share the potential risks of unexpected losses associated with damage or destruction to property. Property and casualty insurance companies offer contracts to individuals or firms with periodic payments, known as premiums. These preimum prices are determined regarding the interest rates as in the life and health insurers. Low interest rates impair the profitability of companies but short-term structure of property and casualty insurance contracts provides them an opportunity to tolerate low interest rates by giving them a chance to react quickly and appropriately. This structure of property and casualty insurance industry can be the possible reason of more integration to the system than life and health insurers.

6.1.2 Country level analysis

Regional table represents the connectedness among different parts of the world. We treat USA as a region, because it is very large in terms of financial system. Table 3 shows that global linkages among the insurance industry is actually weak. Every region has very high own connectedness suggesting that geographical location matters in the insurance industry. USA and Europe have positive "net" connectedness meaning that they are the main volatility shock tranmitters around the world. Another interesting fact is that all regions receive most of their shocks from USA confirming the dominance of USA over the global insurance industry. It can be also attributed to highly developed structure of the financial markets of

USA.

	Asia & Pacific	Europe	S.America & Canada	USA	M.East & Africa
Asia & Pacific (18)	67.32	10.56	2.24	19.30	0.58
Europe (34)	1.75	66.50	3.69	27.69	0.38
S.America & Canada (9)	2.20	14.43	61.43	21.10	0.84
USA (32)	1.89	14.88	4.59	78.38	0.25
M.East & Africa (5)	2.18	5.36	1.88	6.35	84.23
TO	8.02	45.24	12.41	74.43	2.05
FROM	32.68	33.50	38.57	21.62	15.77
NET	-24.66	11.73	-26.16	52.80	-13.72

Table 3: The connectedness table of regions

Note: Numbers in parentheses shows the number of companies from the region.

To give more meaning to connectedness table analysis, we want to highlight a few characteristics of insurance industry in different regions. In the Continental Europe, the insurance industry's investments are conservative regarding their assets in equities. As a result, they are more resilient to stock market plunges in times of financial crises. Hartley et al. (2016) showed the difference between the US and the UK life insurers sensitivity to interest rate risk. They argue that the difference is caused by the life insurers' product structures. In the US, life insurers sell annuities and other savings products with minimum rate guarantees. On the other hand, in the UK, life insurers sell saving elements with a return that is a function of the return of investment earnings of insurers. In addition, Germany's life insurers products are more similar to the US life insurers. In Asia, Japan is seen as the most influential insurance market and catastrophe exposure is among the main concerns of the insurers.

Asian countries have very low "to" connectedness measures compared to their "from" connectedness, except for South Korea. Their "net" connectedness measures are negative meaning that they are receivers of volatility shocks. This highlights the fact that their insurance system volatility is influenced primarily by the global powers. However, when we examine "to" and "from" connectedness measures separately, we can easily identify that the reason is not high "from" connectedness but very low "to" connectedness. In addition, when we closely look at the links between Asian countries and the rest of the world, we see that Asian countries receives shocks mostly from USA. UK, Switzerland, France and Germany also have noteworthy effects on Asian countries' insurance system volatility. This means that Asian countries' connections to the global financial system, on top of their unobtrusive profile in terms of financial institutions, are not so strong considering their ability to affect other countries when they are hit by a volatility shock. This point indicates that the volatility contribution of Asian countries' insurance systems to the global financial system is substantially less than what they give.

South Korea has the highest "to" connectedness and distinctly separated from other Asian countries in that sense. The reason for that might be the fact that South Korean insurers generally owned by globally recognized corporations such as Samsung and Hyundai. Another interesting fact is the position of Japan in the global insurance system in the sense of volatility spillovers. One may simply anticipate that the position of Japan should be better than other Asian countries taking into account its developed economy and its financial markets closely watched by investors around world. However, Japan has struggled with deflation and poor growth performance over the last two decades. Consequently, this struggle held Japan back and led Japan to diverge from the world economy both before and during the crisis. "Net" connectedness of Japan is the second highest in terms of absolute value among the Asian countries implying that Japan has no significant impact on either the global system or other Asian countries.

India and Malaysia have almost zero "to" connectedness measures and low "from" connectedness measures. We can ascribe this outcome to their economies' isolated characteristic. Also, in Malaysia the financial system is particularly different from the rest of the world. This might be another reason for Malaysia to be separated from the world. These facts can be highlighted with their very large own connectedness numbers 71.6% and 84.5%, respectively.

The European insurance systems behave very differently than Asian insurance systems. Almost all of the European countries included in our sample have low own connectedness measures ranging from 13.4% to 50.5%. This observation reflects the high integration level of European insurance systems. When we look at the European insurers' "to" and "net" connectedness, we can separate European countries into two subgroups. These two groups are like the two sides of the same coin regarding their part in transmission of volatility shocks originated in Europe. The first group is the receivers of the European insurance system. Austria, Belgium, Denmark, Finland, Netherlands, Norway and Spain constitutes the first group in terms of their low "to" and "net" connectedness. Italy also has a negative "net" connectedness but it is low in absolute value and its "to" connectedness is high indicating that Italy has a strong effect on volatility shock transmission in Europe. Additionally, countries in the first group are relatively small economies in Europe with the exception of Spain whereas Italy is one of the largest economies among European economies. Therefore, we count Italy in the second group. Positive "net" connectedness and very high "to" connectedness measures are characteristics of countries in the second group. France, Germany, Italy, Switzerland and UK are the members of volatility shock transmitters within Europe. UK, Switzerland and Germany's "to" connectedness measures are the highest of the second group with 107.8%, 108.2%. and 89.7% respectively. These values and the fact that they are the main driving forces of the volatility shock transmission are a consequence of their economies' size. Actually, all members of the second group are among the largest economies in Europe.

The "net" connectedness of countries in both groups underlines the point that there is a distinction between two groups. The strong players of the European insurance system are widely apart from the others. However, there is an interesting outcome of the full sample analysis showing the obscure role of Italy and Spain. They are among the biggest economies of Europe. Nevertheless, they have negative "net" connectedness unlike other large European economies. The primary cause of this situation can be the sovereign debt crisis. Italy and Spain were among the problematic European countries at that time and they are still not able to fully recover from the detrimental effects of the crisis. Furthermore, UK has the highest numbers in both "to" and "net" volatility connectedness. These numbers puts UK in the second place in our sample after USA in terms of a source of global volatility shocks. By taking into account London's historical role in the development of the global financial markets, it is reasonable to think that a volatility shock to UK insurers spreads to the other insurers. Hence, 48.4% "net" connectedness of UK confirms the significance of London as a pivotal financial center around the globe.

We include two countries from South America and two countries from North America when we cross the Atlantic. Brazil and Colombia's negative "net" connectedness and very low "to" connectedness reflect their inability to contribute to volatility of other countries' insurance systems. There is a slightly different story lies behind the "from" connectedness measures. Colombia has low "from" connectedness and high own connectedness. As a result, we can say that its insurance system is mainly driven by its own dynamics. On the other side, Brazil has high "from" connectedness than Colombia. Brazil receives volatility shocks from Europe as much as USA. As an emerging market, Brazil's position in the insurance system is more integrated than Colombia. When we go up to the north, Canada and USA are the countries in our sample. Canada's "to" and "from" connectedness is lower than the largest economies of Europe but quite higher than that of Asian countries. This observation highlights the fact that Canadian insurers are more closely connected with the global financial system. They are the biggest source of volatility shocks for USA. On the other side, USA is the core country in our sample from the point of the volatility shock transmission. On top of the fact that USA is the largest economy of the world, USA is the most important driving force of the global insurance markets in terms of transmission of volatility shocks. With a "to" connectedness of 549.6% and a "net" connectedness of 528%, USA has the strongest influence over the global insurance markets.

Finally, we include three countries from Middle East and Africa. Qatar and Saudi Arabia are very isolated from the global financial system as Malaysia. The reason for that may be the entirely different structure of their financial markets. Their own connectedness are very high with 92.1% and 90% respectively. On the other hand, South Africa has negative "net" connectedness with low "to" connectedness. This observation points out that South African insurers' contribution to the volatility of global insurance system is less than what they receive from the global system. This result may be a consequence of the isolated characteristic of the South African economy.

	Australia	Austria	Belgium	Brazil	Canada	Colombia	Denmark	Finland	France	Germany	Hong Kong	India	Italy
Australia (4)	48.25	0.42	0.72	0.13	3.42	0.04	0.22	0.68	1.95	2.40	0.55	0.17	1.17
Austria (2)	0.36	50.48	1.04	0.60	2.70	0.23	0.26	0.56	2.59	3.43	0.17	0.08	3.09
Belgium (1)	0.37	0.77	15.21	0.17	3.50	0.10	0.26	1.30	6.12	6.65	0.15	0.06	4.46
Brazil (1)	0.52	0.84	0.67	59.48	2.37	0.08	0.39	0.61	1.91	2.48	0.54	0.13	2.98
Canada (7)	0.54	0.42	0.65	0.11	41.20	0.07	0.17	0.62	1.85	2.27	0.19	0.05	1.24
Colombia (1)	0.13	0.59	0.23	0.02	1.14	79.82	0.57	0.16	1.49	1.06	0.16	0.00	0.40
Denmark (1)	0.44	0.52	1.06	0.21	2.50	0.52	39.38	1.57	4.51	5.20	0.15	0.09	2.56
Finland (1)	0.53	0.59	2.02	0.15	3.58	0.06	0.51	18.76	6.00	7.14	0.22	0.09	3.74
France (4)	0.33	0.67	2.04	0.15	3.20	0.14	0.48	1.59	29.43	7.22	0.17	0.03	4.72
Germany (4)	0.48	0.72	1.72	0.14	3.08	0.10	0.40	1.34	5.50	37.55	0.25	0.05	3.75
Hong Kong (2)	0.97	0.32	0.43	0.32	1.86	0.05	0.13	0.40	1.54	1.64	63.23	0.23	0.46
India (1)	0.46	0.43	0.41	0.16	1.74	0.05	0.16	0.39	0.98	1.33	0.67	71.58	0.55
Italy (3)	0.22	1.17	1.99	0.28	2.59	0.03	0.36	1.47	6.87	7.68	0.06	0.03	36.94
Japan (2)	0.78	0.28	0.34	0.17	2.35	0.09	0.14	0.60	1.56	1.81	0.23	0.05	0.94
Malaysia (1)	0.26	0.44	0.01	0.02	0.42	0.17	0.13	0.14	0.40	0.24	0.43	0.03	0.90
Netherlands (1)	0.43	1.19	2.75	0.40	4.82	0.08	0.40	1.69	7.44	8.16	0.13	0.04	5.64
Norway (1)	0.52	1.22	1.53	0.33	4.21	0.14	0.52	1.63	5.09	5.96	0.21	0.03	3.81
Qatar (1)	0.04	0.12	0.02	0.01	0.56	0.46	0.00	0.01	0.15	0.17	0.04	0.12	0.87
S.Africa (3)	1.11	0.60	0.29	0.82	1.96	0.16	0.36	0.36	1.37	1.46	0.27	0.11	0.91
S.Arabia (1)	0.05	0.21	0.00	0.27	1.29	0.11	0.05	0.01	0.19	0.48	0.15	0.20	0.47
S.Korea (5)	0.32	0.24	0.40	0.05	1.86	0.38	0.22	0.38	1.21	1.34	0.47	0.08	0.36
Spain (2)	0.26	0.87	2.01	0.18	2.79	0.03	0.31	1.43	5.66	5.37	0.08	0.02	5.97
Switzerland (5)	0.33	0.81	1.79	0.13	3.82	0.14	0.54	1.64	5.76	7.31	0.17	0.06	3.78
Taiwan (3)	0.64	0.24	0.45	0.16	2.18	0.08	0.20	0.60	1.54	1.94	0.82	0.09	0.65
UK (9)	0.57	0.71	1.31	0.20	2.87	0.14	0.43	1.21	4.20	4.69	0.28	0.13	2.32
USA (32)	0.39	0.31	0.80	0.10	4.44	0.06	0.14	0.61	1.90	2.26	0.17	0.04	1.13
TO	11.05	14.68	24.69	5.29	65.26	3.51	7.36	20.98	77.79	89.70	6.74	2.01	56.88
FROM	51.75	49.52	84.79	40.52	58.80	20.18	60.62	81.24	70.57	62.45	36.77	28.42	63.06
NET	-40.70	-34.84	-60.10	-35.23	6.46	-16.67	-53.25	-60.25	7.21	27.25	-30.03	-26.41	-6.17

Table 4: The country connectedness table (1)

Note: Numbers in parentheses shows the number of companies from the country.

	Japan	Malaysia	Netherlands	Norway	Qatar	S.Africa	S.Arabia	S.Korea	Spain	Switzerland	Taiwan	UK	USA
Australia (4)	0.46	0.03	0.74	0.39	0.002	0.63	0.01	0.59	0.65	2.94	0.36	3.77	29.31
Austria (2)	0.13	0.05	1.29	0.79	0.05	0.33	0.02	0.57	1.18	3.97	0.17	4.29	21.57
Belgium (1)	0.05	0.002	2.96	0.80	0.03	0.10	0.002	0.46	1.89	7.36	0.48	7.24	39.52
Brazil (1)	0.33	0.02	1.20	0.62	0.04	1.06	0.25	0.25	0.66	2.82	0.31	3.24	16.20
Canada (7)	0.19	0.02	0.86	0.48	0.05	0.46	0.05	0.76	0.63	2.88	0.35	2.90	40.99
Colombia (1)	0.15	0.04	0.41	0.60	0.36	0.14	0.13	1.71	0.11	1.75	0.17	2.54	6.10
Denmark (1)	0.17	0.06	1.48	0.81	0.002	0.72	0.03	1.11	1.18	7.42	0.42	6.78	21.12
Finland (1)	0.22	0.03	2.25	1.23	0.06	0.32	0.002	0.84	1.93	8.89	0.58	8.16	32.11
France (4)	0.16	0.02	2.63	0.99	0.01	0.29	0.02	0.59	1.95	8.29	0.32	7.51	27.06
Germany (4)	0.20	0.03	2.21	0.80	0.01	0.33	0.06	0.60	1.36	7.76	0.28	6.76	24.52
Hong Kong (2)	0.26	0.04	0.49	0.32	0.02	0.64	0.14	1.78	0.27	1.89	1.83	3.11	17.63
India (1)	0.14	0.02	0.38	0.17	0.11	0.45	0.04	0.77	0.24	1.89	0.23	3.02	13.64
Italy (3)	0.13	0.02	2.86	0.94	0.05	0.26	0.01	0.14	2.96	7.84	0.07	5.90	19.13
Japan (2)	58.78	0.05	0.54	0.53	0.06	0.51	0.01	1.03	0.48	1.86	0.74	3.00	23.08
Malaysia (1)	0.05	84.46	0.02	0.04	0.20	0.33	0.03	0.78	0.06	0.32	0.45	0.81	8.84
Netherlands (1)	0.12	0.004	13.36	1.33	0.0006	0.32	0.02	0.31	1.91	10.14	0.24	7.66	31.43
Norway (1)	0.25	0.004	2.59	23.09	0.09	0.22	0.01	1.03	1.98	7.30	0.51	6.33	31.40
Qatar (1)	0.24	0.21	0.02	0.01	92.10	0.22	1.05	0.57	0.31	0.18	0.13	0.24	2.16
S.Africa (3)	0.27	0.08	0.57	0.22	0.04	68.80	0.04	0.59	0.40	1.78	0.53	3.21	13.67
S.Arabia (1)	0.03	0.03	0.10	0.01	0.28	0.11	90.04	1.54	0.34	0.13	0.26	0.48	3.20
S.Korea (5)	0.28	0.08	0.35	0.36	0.03	0.22	0.11	62.89	0.38	1.71	1.21	1.83	23.25
Spain (2)	0.06	0.01	2.04	0.97	0.05	0.23	0.04	0.24	32.98	7.98	0.29	5.80	24.32
Switzerland (5)	0.09	0.01	2.51	0.92	0.01	0.30	0.02	0.61	1.89	29.25	0.37	7.15	30.58
Taiwan (3)	0.37	0.11	0.53	0.47	0.02	0.40	0.07	2.46	0.44	2.47	60.71	3.01	19.33
UK (9)	0.18	0.04	1.44	0.63	0.03	0.48	0.02	0.71	1.20	5.72	0.41	40.62	29.46
USA (32)	0.11	0.03	0.78	0.38	0.01	0.22	0.02	0.85	0.63	2.90	0.29	3.05	78.38
TO	4.66	1.02	31.23	14.79	1.61	9.30	2.20	20.89	25.00	108.19	10.98	107.79	549.63
FROM	41.22	15.54	86.64	76.91	7.90	31.20	9.96	37.11	67.02	70.75	39.29	59.38	21.62
NET	-36.56	-14.52	-55.41	-62.12	-6.29	-21.89	-7.76	-16.22	-42.02	37.44	-28.30	48.40	528.01

Table 5: The country connectedness table (2)

Note: Numbers in parentheses shows the number of companies from the country.

6.2 DY Dynamic Analysis

We repeat the dynamic analysis for our sample which contains the insurance companies all around the world.

6.2.1 Total Connectedness

In this section, we investigate the systemic risk in the insurance industry by interpreting the behavior of the total connectedness index. The index remarks the connectedness of the international insurance systems. Figure 18 demonstrates the evolution of index from 2006 to 2016 alongside of the connectedness index from the US analysis. Since we explain the movements of the index in the US analysis and the variations in the index for the insurance industry mostly coincides with the index from the US analysis, we will not examine the connectedness index in detail again. We will mostly draw attention to the insurance related issues.

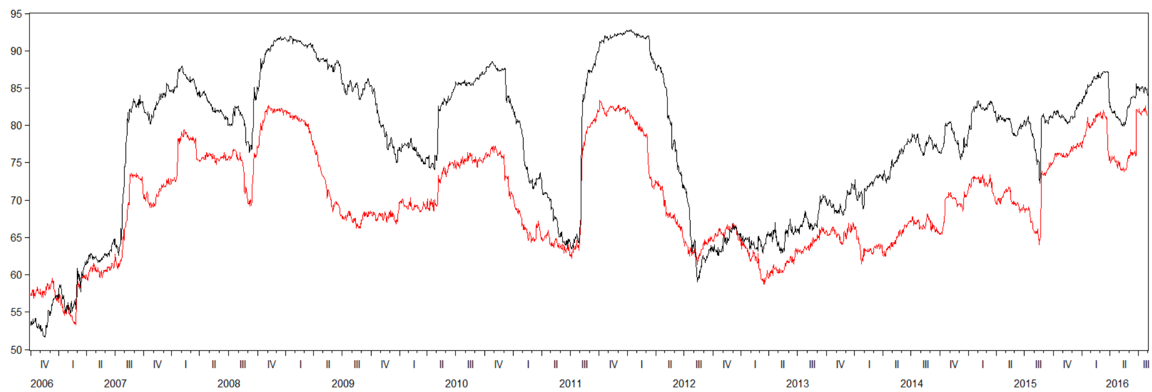

Figure 18: Total volatility connectedness index for the US and global insurance industry

Note: Black line represents the total connectedness index for only the US insurers from the previous analysis. Red line represents the connectedness index for insurance companies around the world.

The similar behavior of the two indices can be interpreted in a way that the US insurers drives the systemic risk in the insurance industry. In Figure 19, we can see how the contribution of the US to the total connectedness index changes over the sample period. This also is a result from the static anaylsis where we reported the connectedness table of countries. On a brief look, we can easily say that the general

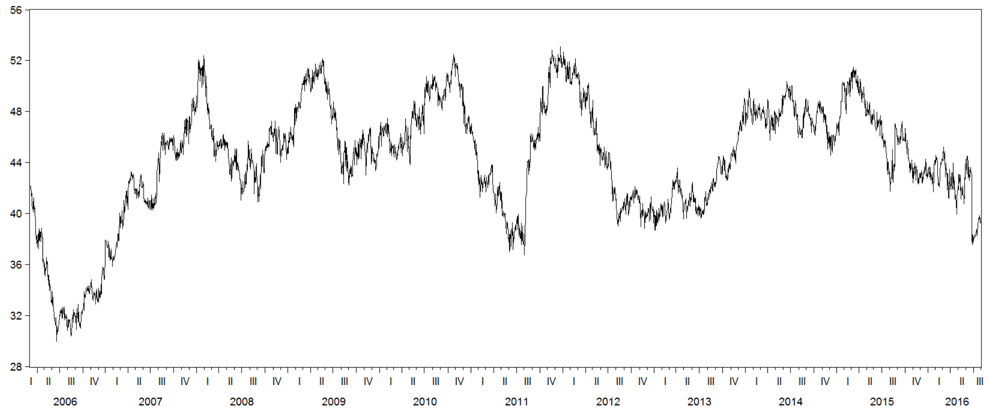

Figure 19: The share of the US in the total volatility connectedness index for the global insurance industry

level in the index is lower than the index from the US analysis. However, we should keep in mind that the connectedness index for the global insurance industry is a result of an international level examination. Thus, lower connectedness levels are expected.

During the recent financial crisis, the total connectedness index of global insurance industry demonstrated a similar behavior with the US insurance industry index. However, there were couple important incidents that affected the connectedness index in the insurance inddustry around the world. On November 19, 2007, Swiss Re reported a loss due to its activities in the credit underwriting business worth of CHF 1.2 billion. The index started to increase before this incident from 69% to 72% points. In the beginning of 2008, Bank of America took over Countrywide Financial which financed 20% of all mortgages in the US in 2006 for $4.1 billion. At that time, the index jumped 7% points. In March, the Fed and JPMorgan agreed to provide secured funding to Bear Stearns. The index declined 3% points after the agreement. After the Lehman Brothers collapse, the index jumped 13% points. On October 10, 2008, Yamato Life Insurance filed for bankruptcy after the financial crisis significantly devalued its assets with Y269.5bn ($2.7bn) in liabilities. It was the first collapse in Japan related to the US subprime mortgage crisis. In late 2008, during the height of the financial crisis, Aegon Group used the Dutch government aid to financial institutions that faced difficulties and took EUR 3 billion government capital injection.[9]

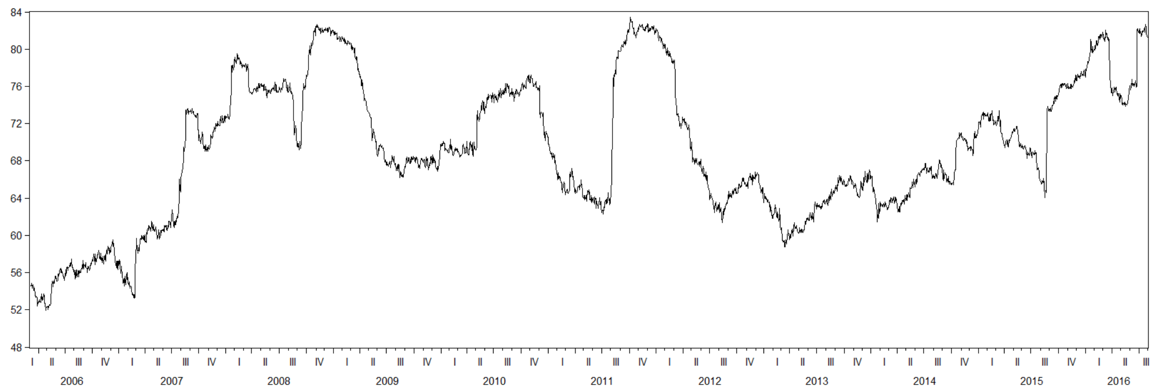

Figure 20: The total volatility connectedness index for the global insurance industry

In March 11, 2011, Japan was hit very hard by an earthquake and tsunami. Following these natural disasters, a nuclear crisis and shortage of electricity were happened. Japan's government estimated the economic losses from the earthquake and tsunami at as much as $309 billion that was almost four times as much as the damage done by Hurricane Katrina ($81 billion). Insured losses were expected to exceed $30 billion. The disasters had a serious effects on the economy and financial markets. The Bank of Japan had to offer $183 billion to the banking system in order to soothe the financial markets conditions. The total connectedness index increased by 3% points in response to these incidents. In May 2013, floods hit some central European countries. Germany, Austria and the Czech Republic were the most effected ones. The total combined economic losses caused by these floods were about EUR 16 billion ($22 billion). Insured losses were calculated at between EUR 2.4 billion ($3.3 billion) and EUR 3.8 billion ($5.3 billion). In particular, Germany accounted for most of these losses. Economic losses in Germany were reported to be EUR 10 billion and insured losses EUR 2.4 billion. At this period the total connectedness index started to increase gradually.

On June 24, 2016, the UK voted the Brexit and decided to leave the EU. The insurance industry's shares were hit hard in the UK. In particular, life insurers

[9]IAIS, 2012. Insurance and Financial Stability.

shares were fell heavily. Aviva, Legal & General and Standard Life all fell by more than 15%. Also, Axa in France and Generali in Italy were also sharply down. The connectedness index jumped by 6% point after the Brexit vote.

On overall, the risk in the insurance inustry globally increased with respect to the beginning of the sample period. Even though two major crisis ended, their effects on the financial markets still is effective. The risk levels did not return to the levels before the global financial crisis.

6.3 Communities in the Global Insurance Industry

In this section, we conduct the community detection analysis. We follow the same procedure as in the US analysis. We again select the top 25% and top 10% of the weighted links for every node in the network for the dynamic analysis. Again, we use R to display the communities in the networks. We apply the same procedure as in the US analysis.

We find three communities in the full sample network if the top 25% of the weighted links are selected. The first community is created by the US and Canadian insurers. The second community is formed by the European insurers. Finally, the third community includes all companies from the rest of the sample. In the third community, there are some exceptions regarding the inclusion of a few European and one Canadian insurers in the community. This is an expected result as the regional connectedness table shows that own connectedness is high for every region.

The results are surprising when we select the top 10% of the weighted links in the full sample network. We spot six communities in the network. This time, the US insurers are separated into two communities. All the US life and health insurers are in the same community alongside of three multiline insurers and brokers including AIG and one reinsurance company. The second community in the US is constituted by all of the property and casualty insurers and the rest of the multiline insurers and brokers and reinsurers. The disintegration of the US insur-

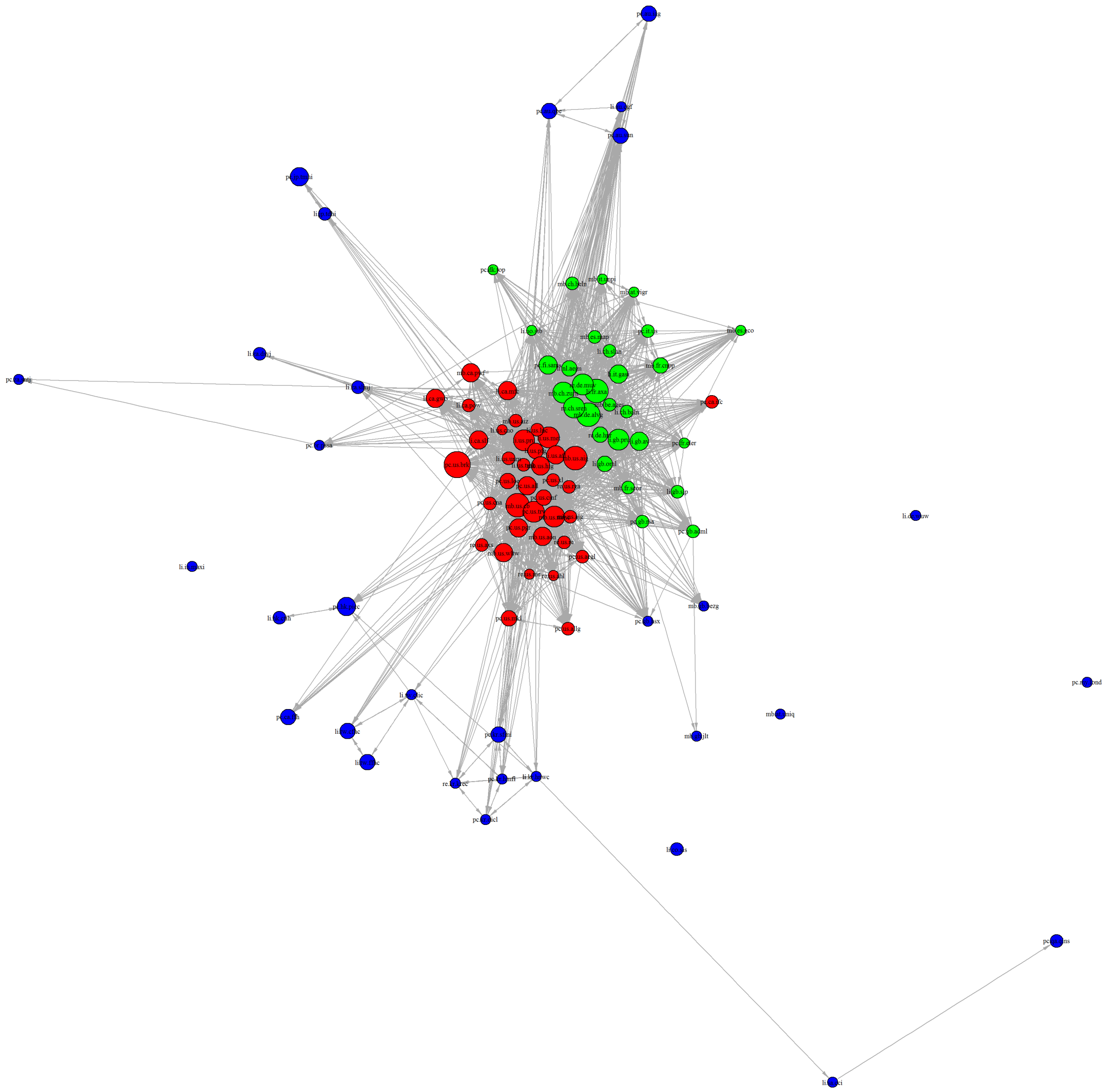

Figure 21: Communities in the network when top 25% of the existing edges for every node selected

ers proves that regulations for the insurance industry should be well reasoned. In other words, uniform policies towards the insurance industry might led to unprecedented outcomes as we show that to whom the volatility shocks are transmitted at first place. Another interesting result is the separation of Europe. There are two communities formed within Europe. The UK is split up from the rest of Europe and establishes a community by itself. This result can be attributed to the fact that the UK is an EU member but it has not replaced its currency with Euro. In consequence, this result raises a future research question. Does the currency affect the transmission of volatility shocks across individual stocks?

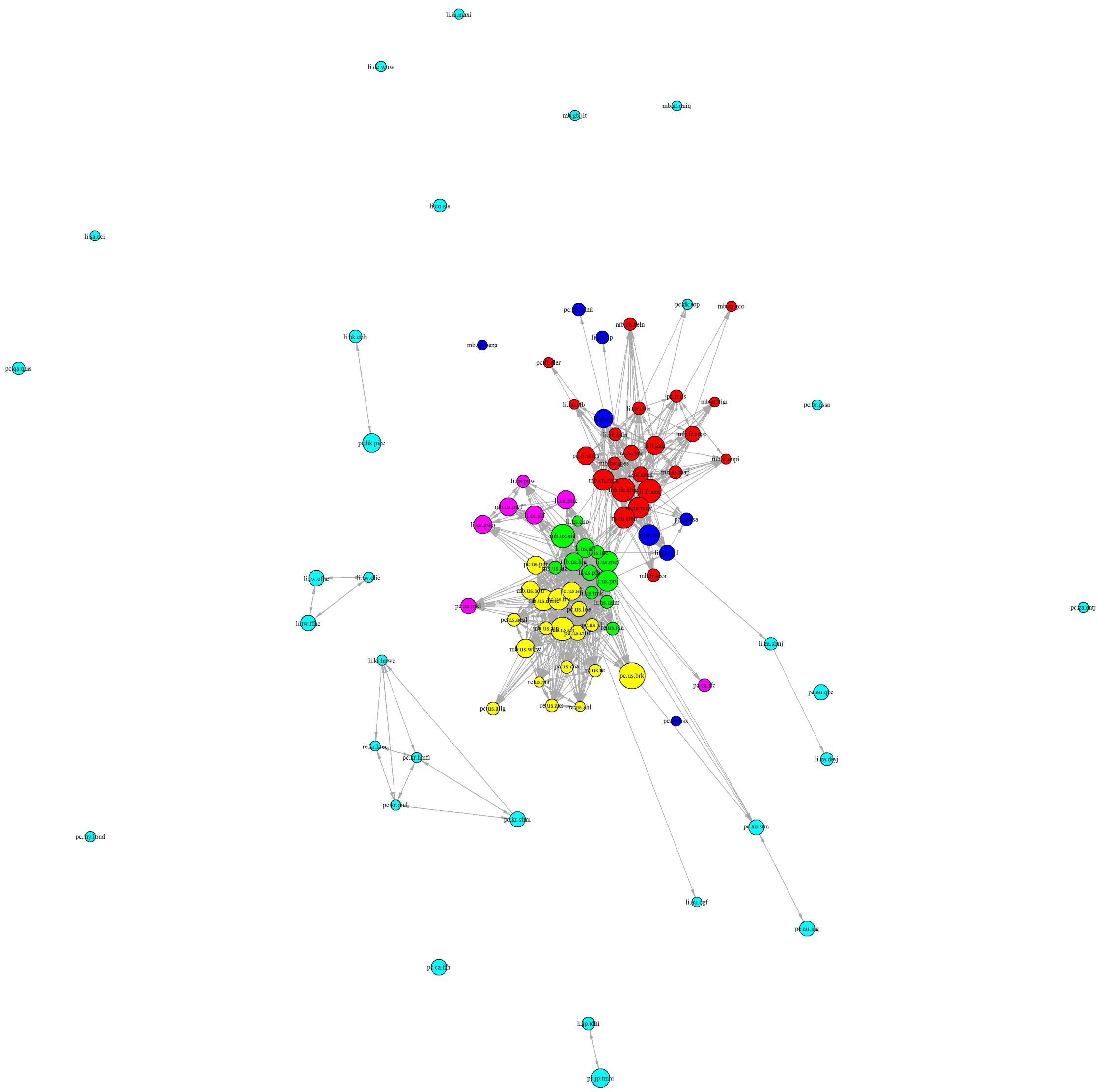

Figure 22: Communities in the network when top 10% of the existing edges for every node selected

Canada is the one of the few countries create a community by itself. The close economic relations with the US is not apparent in the insurance industry. One US insurer Markel Corporation is in the Canadian community. This is a reflection of the company's close relations with the Canadian insurer Fairfax Financial Holdings Limited which was the former Canadian branch of Markel Corporation but surprisingly Fairfax Financial is not in the same community. It is separated and find itself a place in the last community where the rest of the companies are. The last community has a very sparse structure. All the members are scattered except Australian insurers. They are in the last community but they have ties with the US insurance market. All of the Asian countries exhibits the same behavior. They are disintegrated but they have strong links among them. Some of the small European insurers are in the last community. This result can be interpreted as in a way that the size matters in the European insurance industry. In addition, insurers from Malaysia, Qatar and Saudi Arabia are placed far away from the center of the network as their own connectedness is very high.

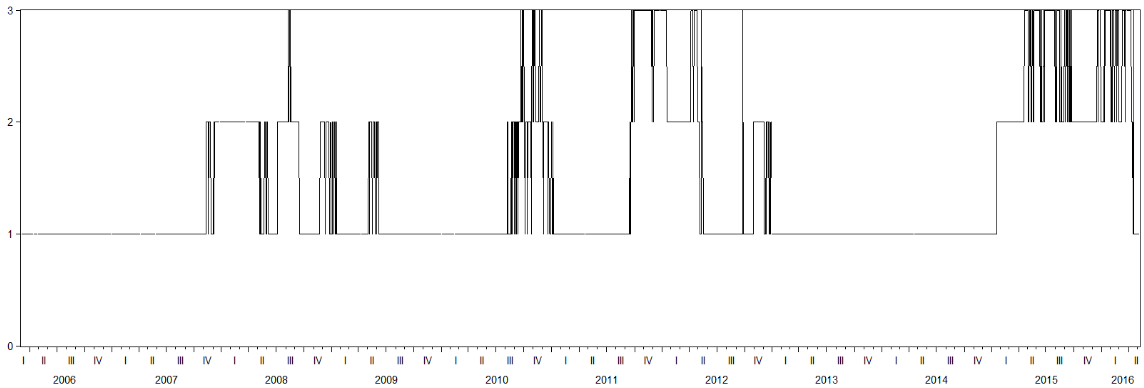

Figure 23: Number of communities in the global network when top 25% of the existing edges for every node selected

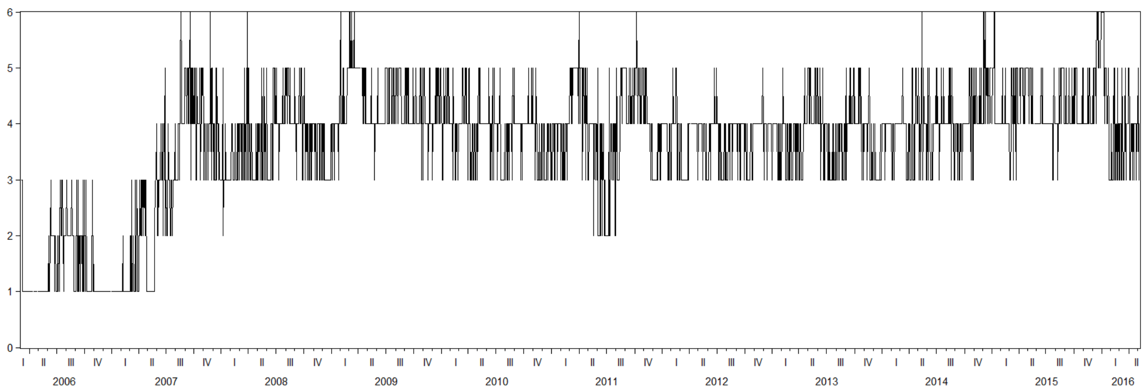

Figure 24: Number of communities in the global network when top 10% of the existing edges for every node selected

The dynamic modularity analysis gives similar results to the US analysis. However, being an international network is seemed to affect the modularity structure, particularly for the top 10% networks.

7 Conclusion

In this paper, we seek to contribute to measurement of systemic risk in the insurance industry literature by using the Diebold-Yilmaz connectedness framework and a community detection method. The goal of the paper is threefold. Firstly, we want to investigate the relationship between banks and insurers using a sample from the US. We conduct the connectedness analysis with two different samples. In the first sample, the period starts from August 2000 and ends in August 2006. The second sample starts from August 2006 and ends in July 2016. The reason for using two samples is that we want to use a broader coverage of banks and insurers to investigate the financial crisis periods. We perform both static and dynamic analysis to present the spillover effects between banks and insurers.

Secondly, we want to estimate the global network of the insurance industry with full sample data in order to see how volatility shocks are transmitted across countries in the insurance industry. A correct estimation would benefit both the regulators and the investors. As a result, we are able to show the each country's contribution to the connectedness over the last decade. In addition, we are able to display the spillovers from different type of insurers since we partition insurers into four group by using Thomson Reuters Business Classification. We measure the systemic risk at both the country level and the institutional level. In the dynamic analysis, we examine the total connectedness index claimed by Diebold and Yilmaz (2014) as a measurement method to assess systemic risk.

Finally, with the purpose of introducing information theoretic community detection algorithm to the Diebold-Yilmaz framework, we implement both static and dynamic community detection analysis as we do in connectedness analysis. We need to make our networks sparse in order to get sound community structures. Therefore, we select both top 25% and top 10% of the weighted links for every node. We report both the results of the static analysis with full sample data and the results of the dynamic analysis with rolling-window estimations. With the perspective provided by the dynamic analysis, we try to link the changing modular structure of networks over time with the systemic risk in the system.

Our analysis focused on the US provides some important insights regarding the role of the insurance industry. Firstly, life and health insurers are more open to shocks from banks than other type of insurers. This result can be attributed to the banking-like activities of life and health insurers, especially life insurers. Another reason might be the contract durations of life and health insurers. Long term contracts put them in a more prone position where low interest rate risk is very significant. Secondly, contrary to the general opinion, the insurance industry did not act as a shock absorber in the financial system in times of crisis as our total connectedness index showed. The total connectedness indicating the systemic risk in the financial markets is higher than the total connectedness of just banks. Lastly, network analysis by communities reveals that size matters for communities on top 25% networks. Large banks are tend to be in the same community as large insurers. However, small-sized banks and insurers create a separate community regardless of their type. On the other hand, the size is also a valid condition for communities on top 10% networks but this time communities are revealed in a way that pinpoints the so-called SIFIs. This result shows that measuring systemic risk of a financial institution individually or by type can give misleading directions to regulators. A network approach can be a more appropriate approach when thinking of systemic risk of an individual financial institution.

Our results provide important insights on how insurance systems are connected to each other before, during and after the financial crisis. First, thanks to the total connectedness index, we are able to track the behavior of systemic risk on a daily basis. We find that the US is the dominant source of volatility shocks over the entire sample. We also find that regional ties have a significant effect on community structure, except for the UK. All the Asian countries but South Korea, net receivers of volatility shocks over the entire sample period. More isolated economies such as Malaysia, Qatar and Saudi Arabia have very high own connectedness. Moreover, community analysis also supports these results. The modular structure of the international insurance network substantially changed over time with both top 25% networks and top 10% networks and reacted to the downturns in the financial markets by increasing the number of communities.

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A Company List

Industry	RIC	Company Name	Identifier	Total Assets		
				06/30/2016	06/30/2006	09/30/2000
Banking & Investment Services	FNMA.PK	Federal National Mortgage Association	bk.fnma	3,234.89	865.14	638.15
	JPM.N	JPMorgan Chase & Co	bk.jpm	2,466.10	1,328.00	707.50
	BAC.N	Bank of America Corp	bk.bac	2,186.61	1,445.19	671.73
	FMCC.PK	Federal Home Loan Mortgage Corp	bk.fmcc	1,986.44	804.91	433.35
	WFC.N	Wells Fargo & Co	bk.wfc	1,889.24	499.52	261.32
	C.N	Citigroup Inc	bk.citi	1,818.77	1,626.55	804.29
	GS.N	Goldman Sachs Group Inc	bk.gs	896.84	798.31	284.41
	MS.N	Morgan Stanley	bk.ms	828.87	1,028.87	421.28
	USB.N	U.S. Bancorp	bk.usb	438.46	213.41	157.25
	BK.N	Bank of New York Mellon Corp	bk.bny	372.35	108.88	75.41
	PNC.N	PNC Financial Services Group Inc	bk.pnc	361.34	94.91	69.88
	BBT.N	BB&T Corp	bk.bbt	221.86	116.28	63.42
	STI.N	SunTrust Banks Inc	bk.sti	198.89	181.14	100.71
	AXP.N	American Express Co	bk.axp	159.64	117.28	153.63
	FITB.OQ	Fifth Third Bancorp	bk.fitb	143.63	106.11	66.88
	RF.N	Regions Financial Corp*	bk.rfc	126.21	86.06	-
	MTB.N	M&T Bank Corp	bk.mtb	123.82	56.51	22.01
	KEY.N	KeyCorp	bk.key	101.15	94.79	85.50
	HBAN.OQ	Huntington Bancshares Inc	bk.hban	73.95	36.27	28.58
	CMA.N	Comerica Inc	bk.cma	71.28	57.08	48.33
	ZION.OQ	Zions Bancorp	bk.zion	59.64	45.14	21.92
	NYCB.N	New York Community Bancorp Inc*	bk.nycb	49.04	28.73	-
	SIVB.OQ	SVB Financial Group	bk.sivb	43.13	5.47	5.50
	PBCT.OQ	People's United Financial Inc	bk.pbct	40.15	11.00	11.00
	FNFG.OQ	First Niagara Financial Group Inc	bk.fnfg	39.99	8.11	2.04
	SBNY.OQ	Signature Bank*	bk.sbny	34.90	4.70	-
	EWBC.OQ	East West Bancorp Inc	bk.ewbc	32.95	10.02	2.39
	FCNCA.OQ	First Citizens BancShares Inc	bk.fcnca	32.23	15.53	10.36
	BOKF.OQ	BOK Financial Corp	bk.bokf	31.97	16.92	9.02
	SNV.N	Synovus Financial Corp	bk.snv	29.46	30.53	14.11
	ASB.N	Associated Banc-Corp	bk.asb	29.04	21.13	13.12
	CFR.N	Cullen/Frost Bankers Inc	bk.cfr	28.98	11.40	7.35
	FHN.N	First Horizon National Corp	bk.fhn	27.54	37.47	19.22
	FMER.OQ	FirstMerit Corp	bk.fmer	26.15	10.25	10.37
	WBS.N	Webster Financial Corp	bk.wbs	25.12	18.02	11.26
	CBSH.OQ	Commerce Bancshares Inc	bk.cbsh	24.71	14.27	10.96
	WTFC.OQ	Wintrust Financial Corp	bk.wtfc	24.42	9.17	2.00
	UMPQ.OQ	Umpqua Holdings Corp	bk.umpq	24.13	7.18	0.42
	PB.N	Prosperity Bancshares Inc	bk.pbi	21.80	4.53	0.69
	ISBC.OQ	Investors Bancorp Inc*	bk.isbc	21.72	5.50	-
	FNB.N	F.N.B. Corp	bk.fnb	21.21	6.07	4.02
	PACW.OQ	PacWest Bancorp*	bk.pacw	21.15	4.56	-
	IBKC.OQ	IBERIABANK Corp	bk.ibkc	20.16	2.98	1.40
	UMBF.OQ	UMB Financial Corp	bk.umbf	19.73	7.63	7.25
	FULT.OQ	Fulton Financial Corp	bk.fult	18.48	14.56	7.23
	PVTB.OQ	PrivateBancorp Inc	bk.pvtb	18.17	3.65	0.76
	WAL.N	Western Alliance Bancorp*	bk.wal	16.73	3.89	-
	MBFI.OQ	MB Financial Inc	bk.mbfi	16.00	5.91	1.46
	BOH.N	Bank of Hawaii Corp	bk.boh	15.86	10.33	13.94
	UBSI.OQ	United Bankshares Inc	bk.ubsi	14.34	6.72	4.95
	OZRK.OQ	Bank of The Ozarks Inc	bk.ozrk	12.28	2.42	0.83

Table 6: List of companies in the US analysis (1)

Note: All the values are in billions of dollars.
* These companies are added for the second sample.

Industry	RIC	Company Name	Identifier	Total Assets		
				06/30/2016	06/30/2006	09/30/2000
Life & Health Insurance	MET.N	Metlife Inc*	li.met	942.57	500.31	-
	PRU.N	Prudential Financial Inc*	li.pru	796.49	440.68	-
	LNC.N	Lincoln National Corp	li.lnc	263.03	167.38	103.24
	PFG.N	Principal Financial Group Inc*	li.pfg	223.07	131.43	-
	AFL.N	Aflac Inc	li.afl	141.29	57.43	37.90
	UNM.N	Unum Group	li.unm	63.85	50.40	40.20
	AEL.N	American Equity Investment Life Holding*	li.ael	53.72	14.78	-
	CNO.N	CNO Financial Group Inc*	li.cno	32.02	31.55	-
	TMK.N	Torchmark Corp	li.tmk	21.57	14.78	12.86
	FFG.N	FBL Financial Group Inc	li.ffg	9.56	10.65	3.75
	AMSF.OQ	Amerisafe Inc*	li.amsf	1.59	0.96	-
Multiline Insurance & Brokers	AIG.N	American International Group Inc	mb.aig	510.35	900.67	295.41
	HIG.N	Hartford Financial Services Group Inc	mb.hig	227.62	294.94	177.25
	CB.N	Chubb Ltd	mb.cb	160.20	65.39	31.53
	GNW.N	Genworth Financial Inc*	mb.gnw	108.21	103.65	-
	WLTW.OQ	Willis Towers Watson PLC*	mb.wltw	32.41	15.27	-
	AIZ.N	Assurant Inc*	mb.aiz	29.80	24.53	-
	AON.N	Aon PLC	mb.aon	26.69	30.10	21.83
	ANAT.OQ	American National Insurance Co	mb.anat	24.29	17.49	9.20
	MMC.N	Marsh & McLennan Companies Inc	mb.mmc	18.08	17.44	13.62
	ESGR.OQ	Enstar Group Ltd*	mb.esgr	12.66	0.20	-
	AJG.N	Arthur J Gallagher & Co	mb.ajg	11.38	3.64	0.94
	KMPR.N	Kemper Corp*	mb.kmpr	8.31	9.16	-
	BRO.N	Brown & Brown Inc	mb.bro	5.21	1.72	0.26
Property & Casualty Insurance	BRKb.N	Berkshire Hathaway Inc	pc.brk	592.82	232.33	130.48
	ALL.N	Allstate Corp	pc.all	107.28	157.09	105.70
	TRV.N	Travelers Companies Inc	pc.trv	102.45	113.89	41.66
	L.N	Loews Corp	pc.loew	79.18	71.71	73.45
	XL.N	XL Group PLC	pc.xlg	60.65	58.53	16.37
	CNA.N	CNA Financial Corp	pc.cna	56.91	58.91	63.52
	AFG.N	American Financial Group Inc	pc.afg	52.73	23.10	16.23
	PGR.N	Progressive Corp	pc.pgr	31.96	19.60	10.49
	MKL.N	Markel Corp	pc.mkl	26.34	9.69	5.28
	ACGL.OQ	Arch Capital Group Ltd	pc.acgl	24.41	13.09	0.28
	Y.N	Alleghany Corp	pc.allg	23.81	6.19	2.71
	WRB.N	W. R. Berkley Corp*	pc.wrb	23.03	14.69	-
	CINF.OQ	Cincinnati Financial Corp	pc.cinf	20.15	16.94	11.79
	ORI.N	Old Republic International Corp	pc.ori	17.99	11.65	7.09
	ENH.N	Endurance Specialty Holdings Ltd*	pc.enh	14.83	6.87	-
	FNF.N	Fidelity National Financial Inc*	pc.fnf	14.44	6.20	-
	THG.N	Hanover Insurance Group Inc	pc.thg	14.16	9.69	32.63
	AGO.N	Assured Guaranty Ltd*	pc.ago	14.09	2.74	-
	HTH.N	Hilltop Holdings Inc*	pc.hth	13.08	1.60	-
	MBI.N	MBIA Inc	pc.mbi	12.06	35.63	13.22
	HMN.N	Horace Mann Educators Corp	pc.hmn	10.47	6.00	4.35
	SIGI.OQ	Selective Insurance Group Inc	pc.sigi	7.19	4.49	2.60
	WTM.N	White Mountains Insurance Group Ltd	pc.wtm	7.07	18.73	3.25
	AGII.OQ	Argo Group International Holdings Ltd	pc.agi	6.96	1.63	0.80
	RDN.N	Radian Group Inc	pc.rdn	6.07	7.51	2.12
	MTG.N	MGIC Investment Corp	pc.mtg	5.74	6.30	3.58
	PRA.N	ProAssurance Corp	pc.pra	4.98	3.80	1.15
	NAVG.OQ	Navigators Group Inc	pc.navg	4.90	2.92	0.62
	MCY.N	Mercury General Corp	pc.mcy	4.72	4.18	2.11
	UFCS.OQ	United Fire Group Inc	pc.ufcs	4.11	2.76	1.61
	RLI.N	RLI Corp	pc.rli	2.89	2.68	1.27
	ERIE.OQ	Erie Indemnity Co	pc.erie	1.41	2.91	1.68
Reinsurance	RGA.N	Reinsurance Group of America Inc	re.rga	53.88	17.82	5.92
	RE.N	Everest Re Group Ltd	re.evre	21.28	16.54	6.51
	AXS.N	AXIS Capital Holdings Ltd*	re.axs	21.25	12.80	-
	RNR.N	Renaissancere Holdings Ltd	re.rnr	12.54	7.74	1.72
	AHL.N	Aspen Insurance Holdings Ltd*	re.ahl	11.79	6.79	-

Table 7: List of companies in the US analysis (2)

Note: All the values are in billions of dollars.
* These companies are added for the second sample.

Industry	RIC	Company Name	Country	Identifier	Total Assets	
					12/31/2015	12/31/2005
Life & Health Insurance	AXAF.PA	AXA SA	France	li.fr.axa	963.36	681.96
	MET.N	Metlife Inc	USA	li.us.met	877.93	481.65
	PRU.N	Prudential Financial Inc	USA	li.us.pru	757.26	413.37
	AV.L	Aviva PLC	UK	li.gb.av	571.58	453.42
	PRU.L	Prudential PLC	UK	li.gb.pru	570.34	357.02
	GASI.MI	Assicurazioni Generali SpA	Italy	li.it.gasi	543.60	409.14
	MFC.TO	Manulife Financial Corp	Canada	li.ca.mfc	509.17	157.15
	AEGN.AS	Aegon NV	Netherlands	li.nl.aegn	451.48	368.48
	POW.TO	Power Corporation of Canada	Canada	li.ca.pow	305.56	97.22
	GWO.TO	Great-West Lifeco Inc	Canada	li.ca.gwo	288.99	87.90
	LNC.N	Lincoln National Corp	USA	li.us.lnc	251.91	124.86
	2882.TW	Cathay Financial Holding Co Ltd	Taiwan	li.tw.cfhc	230.66	93.56
	PFG.N	Principal Financial Group Inc	USA	li.us.pfg	218.66	127.04
	OML.L	Old Mutual PLC	UK	li.gb.oml	196.82	138.68
	SLHN.S	Swiss Life Holding AG	Switzerland	li.ch.slhn	188.91	135.21
	2881.TW	Fubon Financial Holding Co Ltd	Taiwan	li.tw.ffhc	182.46	50.48
	SLF.TO	Sun Life Financial Inc	Canada	li.ca.slf	178.37	147.85
	000880.KS	Hanwha Corp	South Korea	li.kr.hnwc	123.94	46.07
	8795.T	T&D Holdings Inc	Japan	li.jp.tdhi	122.08	121.80
	AFL.N	Aflac Inc	USA	li.us.afl	118.26	56.36
	SJP.L	St. James's Place PLC	UK	li.gb.sjp	87.36	18.61
	WUWGn.DE	Wuestenrot & Wuerttembergische AG	Germany	li.de.wuw	80.46	84.24
	BALN.S	Baloise Holding AG	Switzerland	li.ch.baln	78.64	46.68
	0966.HK	China Taiping Insurance Holdings Co Ltd	Hong Kong	li.hk.ctih	62.97	3.53
	UNM.N	Unum Group	USA	li.us.unm	60.56	51.87
	STB.OL	Storebrand ASA	Norway	li.no.stb	58.98	29.94
	SLMJ.J	Sanlam Ltd	South Africa	li.za.slmj	43.63	43.88
	2823.TW	China Life Insurance Co Ltd	Taiwan	li.tw.clic	36.65	6.28
	CNO.N	CNO Financial Group Inc	USA	li.us.cno	31.13	31.53
	TMK.N	Torchmark Corp	USA	li.us.tmk	19.85	14.77
	SIS.CN	Grupo de Inversiones Suramericana SA	Colombia	li.co.sis	17.52	4.91
	CGF.AX	Challenger Ltd	Australia	li.au.cgf	14.28	16.31
	DSYJ.J	Discovery Ltd	South Africa	li.za.dsyj	7.88	0.79
	MAXI.NS	Max Financial Services Ltd	India	li.in.maxi	5.70	0.32
	8010.SE	Company for Cooperative Insurance SJSC	Saudi Arabia	li.sa.cci	3.08	1.11
Multiline Insurance & Brokers	ALVG.DE	Allianz SE	Germany	mb.de.alvg	921.95	1,248.72
	AIG.N	American International Group Inc	USA	mb.us.aig	496.84	853.05
	CNPP.PA	CNP Assurances SA	France	mb.fr.cnpp	427.59	286.06
	ZURN.S	Zurich Insurance Group AG	Switzerland	mb.ch.zurn	381.97	339.61
	PWF.TO	Power Financial Corp	Canada	mb.ca.pwf	301.78	95.41
	HIG.N	Hartford Financial Services Group Inc	USA	mb.us.hig	228.35	285.56
	AGES.BR	Ageas SA NV	Belgium	mb.be.ages	113.47	863.13
	CB.N	Chubb Ltd	USA	mb.us.cb	102.31	62.44
	UNPI.MI	Unipol Gruppo Finanziario SpA	Italy	mb.it.unpi	97.49	47.47
	MAP.MC	Mapfre SA	Spain	mb.es.map	68.95	32.47
	HELN.S	Helvetia Holding AG	Switzerland	mb.ch.heln	54.05	23.33
	VIGR.VI	Vienna Insurance Group AG	Austria	mb.at.vigr	48.41	23.02
	SCOR.PA	Scor SE	France	mb.fr.scor	45.18	16.08
	UNIQ.VI	UNIQA Insurance Group AG	Austria	mb.at.uniq	35.92	26.72
	AIZ.N	Assurant Inc	USA	mb.us.aiz	30.04	25.37
	AON.N	Aon PLC	USA	mb.us.aon	26.99	27.83
	WLTW.OQ	Willis Towers Watson PLC	USA	mb.us.wltw	18.84	12.19
	MMC.N	Marsh & McLennan Companies Inc	USA	mb.us.mmc	18.22	17.89
	GCO.MC	Grupo Catalana Occidente SA	Spain	mb.es.gco	14.44	7.29
	AJG.N	Arthur J Gallagher & Co	USA	mb.us.ajg	10.91	3.39
	BEZG.L	Beazley PLC	UK	mb.gb.bezg	6.75	2.66
	JLT.L	Jardine Lloyd Thompson Group PLC	UK	mb.gb.jlt	3.30	1.48

Table 8: List of companies in the global insurance industry analysis (1)

Note: All the values are in billions of dollars.

Industry	RIC	Company Name	Country	Identifier	Total Assets	
					12/31/2015	12/31/2005
Property & Casualty Insurance	BRKb.N	Berkshire Hathaway Inc	USA	pc.us.brk	552.26	198.33
	8766.T	Tokio Marine Holdings Inc	Japan	pc.jp.tmhi	173.91	108.55
	ALL.N	Allstate Corp	USA	pc.us.all	104.66	156.07
	TRV.N	Travelers Companies Inc	USA	pc.us.trv	100.18	113.19
	L.N	Loews Corp	USA	pc.us.loe	76.01	70.91
	US.MI	UnipolSai Assicurazioni SpA	Italy	pc.it.us	74.63	44.97
	SUN.AX	Suncorp Group Ltd	Australia	pc.au.sun	73.69	40.02
	2328.HK	PICC Property and Casualty Co Ltd	Hong Kong	pc.hk.picc	64.76	11.79
	XL.N	XL Group PLC	USA	pc.us.xl	58.68	58.45
	CNA.N	CNA Financial Corp	USA	pc.us.cna	55.05	59.02
	000810.KS	Samsung Fire & Marine Insurance Co Ltd	South Korea	pc.kr.sfmi	53.82	14.24
	QBE.AX	QBE Insurance Group Ltd	Australia	pc.au.qbe	42.18	21.75
	FFH.TO	Fairfax Financial Holdings Ltd	Canada	pc.ca.ffh	41.53	27.54
	SAMAS.HE	Sampo Oyj	Finland	pc.fi.sams	38.70	50.89
	005830.KS	Dongbu Insurance Co Ltd	South Korea	pc.kr.dicl	34.06	6.01
	RSA.L	RSA Insurance Group PLC	UK	pc.gb.rsa	30.38	42.38
	PGR.N	Progressive Corp	USA	pc.us.pgr	29.82	18.90
	001450.KS	Hyundai Marine & Fire Insurance Co Ltd	South Korea	pc.kr.hmfi	27.90	5.50
	MKL.N	Markel Corp	USA	pc.us.mkl	24.94	9.81
	IAG.AX	Insurance Australia Group Ltd	Australia	pc.au.iag	24.19	13.04
	ACGL.OQ	Arch Capital Group Ltd	USA	pc.us.acgl	23.18	11.49
	Y.N	Alleghany Corp	USA	pc.us.allg	22.84	5.80
	CINF.OQ	Cincinnati Financial Corp	USA	pc.us.cinf	18.89	16.00
	IFC.TO	Intact Financial Corp	Canada	pc.ca.ifc	15.35	8.54
	TOP.CO	Topdanmark A/S	Denmark	pc.dk.top	9.85	6.53
	HSX.L	Hiscox Ltd	UK	pc.gb.hsx	7.82	4.73
	ELER.PA	Euler Hermes Group SA	France	pc.fr.eler	7.16	5.56
	QINS.QA	Qatar Insurance Co SAQ	Qatar	pc.qa.qins	6.62	1.09
	ADML.L	Admiral Group PLC	UK	pc.gb.adml	6.19	1.14
	PSSA3.SA	Porto Seguro SA	Brazil	pc.br.pssa	5.86	1.91
	SNTJ.J	Santam Ltd	South Africa	pc.za.sntj	1.80	2.36
	LOND.KL	LPI Capital Bhd	Malaysia	pc.my.lond	0.85	0.19
Reinsurance	MUVGn.DE	Munich Re AG	Germany	re.de.muv	291.99	258.99
	SRENH.S	Swiss Re AG	Switzerland	re.ch.sren	196.14	168.48
	HNRGn.DE	Hannover Rueck SE	Germany	re.de.hnr	68.65	47.11
	RGA.N	Reinsurance Group of America Inc	USA	re.us.rga	50.38	16.19
	RE.N	Everest Re Group Ltd	USA	re.us.re	20.55	16.47
	AXS.N	AXIS Capital Holdings Ltd	USA	re.us.axs	19.98	11.93
	RNR.N	Renaissancere Holdings Ltd	USA	re.us.rnr	11.56	6.87
	AHL.N	Aspen Insurance Holdings Ltd	USA	re.us.ahl	11.05	6.54
	003690.KS	Korean Reinsurance Co	South Korea	re.kr.krec	7.64	2.42

Table 9: List of companies in the global insurance industry analysis (2)

Note: All the values are in billions of dollars.