ESSAYS ON THE APPLICATIONS OF NETWORK ANALYSIS TO THE REINSURANCE MARKET

A Dissertation
Submitted to
the Temple University Graduate Board

In Partial Fulfillment
of the Requirements for the Degree of
DOCTOR OF PHILOSOPHY

---

by
Tao Sun
May, 2015

Examining Committee Members:

David J. Cummins, Advisory Chair, Risk, Insurance and Healthcare Management
Hua Chen,Co-chair, Risk, Insurance and Healthcare Management
Mary A. Weiss, Risk, Insurance and Healthcare Management
Elyas Elyasiani, Finance
Yan Li, External Member, Finance

ABSTRACT

This dissertation consists of two topics. Chapter 1 The Microstructure of the Reinsurance Network among US Property-Casualty Insurers and Its Effect on Insurers' Performance models the connectivity within the US property-casualty (P/C) reinsurance market as a network. It provides the first detailed empirical analysis of the microstructure of the reinsurance network including both affiliated and unaffiliated insurers. I find that reinsurance networks are highly sparse and yet largely connected, and exhibit hierarchical core-periphery structure. Moreover, an insurer's network position, measured by its network centrality, has economically significant implications for its loss experience and performance. Particularly, I find that there is an inverse U-shaped relationship between an insurer's network position and its combined ratio, and a U-shaped relationship between an insurer's network position and its performance measured by risk adjusted return on assets and risk adjusted return on equity. I also analyze the resilience of the reinsurance network against possible contagion risk by simulating economic impacts resulting from failures of one or more strategically networked reinsurers. The simulation results suggest that US Property-Casualty insurance industry is resilient to the failure of one or more top reinsurers.

Chapter 2 Tail Risk Spillover and Its Contribution to Systemic Risk: A Network Analysis for Global Reinsurers analyzes the dynamic short-run tail risk dependence among global reinsurers and studies its contributions to global reinsurers' systemic risk, where a reinsurer's tail risk is measured by the Value-at-Risk. The tail risk dependence or tail risk spillover among global reinsurers is modeled as networks based on Granger

Causality test. The results show that the tail risk interconnectedness among global reinsurers is subject to the impacts of both the insurance industry-wide shock and economy-wide shocks, where the former seems to have a larger effect than the latter. Moreover, I find that a reinsurer's role in the tail risk network as measured by degree/eigenvector centrality contributes significantly to its systemic risk, i.e., a more central tail risk network position will cause a higher level of systemic risk. I also find that there is a threshold effect of tail risk connectedness to systemic risk. That is, when the tail risk connectedness, as measured by daily network density, is below its median state, an increase in a reinsurer's tail risk network centrality will result in a decrease in its systemic risk possibly through risk diversification. In contrast, when the tail risk connectedness is above such threshold, an increase in the reinsurer's tail risk network centrality will lead to an increase in its systemic risk.

THIS DISSERTATION IS DEDICATED TO MY WIFE, XUEJUAN ZHANG, AND MY DAUGHTERS, MEIXI (MICHELLE) SUN AND JINGXI (JESSICA) SUN.

ACKNOWLEDGMENTS

I would like to express my deepest gratitude to my research advisor, Dr. David J. Cummins, for the encouragement, guidance and support throughout my research. Without his direction, I would not have accomplished this work. I sincerely appreciate his professional and financial support during my years at Temple.

I am earnestly grateful to my co-advisor, Dr. Hua Chen, who has always been there to listen and give advice. I am deeply indebted to him for his guidance, professional and personal support for my research and academic career. I am also grateful to Dr. Mary A. Weiss, for being my committee member, providing me insightful comments, and carefully reading and revising on numerous revisions of this dissertation.

I sincerely thank Dr. Elyas Elyasiani and Dr. Yan Li, for being on my advisory committee and providing instructions for my research.

I thank Dr. R.B. Drennan, the department chair, Dr. Barbara Manaka, my teaching mentor, and my colleagues at the Department of Risk, Insurance and Healthcare Management at Temple University. They have created a wonderful and enjoyable environment during my work in the Ph.D. program.

I would like to express my gratitude to all faculties and staff at Fox School of Business, Temple University for helpful nature and inspiring me to grow as a researcher.

Most importantly, I thank my wife, Xuejuan Zhang, for encouraging me in all of my pursuits, and standing by me through good times and bad. To my daughters, Meixi Sun and Jingxi Sun, I thank you for all the joy that you brought to me, and for all the new things that I learned from you. To my family, I thank you for your love, encouragement and support throughout this work.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

THE MICROSTRUCTURE OF THE REINSURANCE NETWORK AMONG US PROPERTY-CASUALTY INSURERS AND ITS EFFECT ON INSURERS' PERFORMANCE

1.1. Introduction

Economic agents do not exist in isolation, but rather are connected by various economic relationships. One common driver of interconnectedness is financial transactions among financial institutions (for instance, borrowing and lending among banks) which comprise the so-called "financial network" (Upper, 2011). A growing body of evidence has shown that characteristics of the financial network have important economic implications for contagion risk and the stability of a particular financial market (Haldane, 2009; Billio et al., 2011; Kaushik and Battiston, 2012; Markose, Giansate and Shaghaghi, 2012; Hasman, 2013; Acemoglu, Ozdaglar and Tahbaz-Salehi,2013). The most recent financial crisis of 2007-2008 is a good example. Literature also indicates that financial network characteristics can affect an individual economic agent's decisions and performance (Ahern and Harford, 2014; Li and Schurhoff, 2012; Cohen-Cole, Kirilenko and Patacchini, 2014; Lin, Yu and Peterson, 2014).

As the insurance of insurers, reinsurance plays a fundamental role in the insurance industry, allowing insurers to transfer risk among each other, thereby enhancing risk sharing and risk diversification. At the same time, reinsurance transactions connect insurers in a complex network where insurers hold bilateral exposures to each other, leading to potential contagion risk. Therefore, reinsurance has been recognized as the primary source of interconnectedness in the US property-casualty (P/C) insurance industry (Cummins and Weiss, 2014). As such, reinsurance interconnectedness can serve as a transmission mechanism for financial shocks and may exacerbate insurers' exposure to contagion and/or systemic risk.

Prior studies, however, have concluded that that the reinsurance industry is not subject to systemic risk (e.g., Swiss Re, 2003; Geneva Association, 2010; International Association of Insurance Supervisors (IAIS) 2011, 2012, 2013; Park and Xie, 2014; Cummins and Weiss, 2014). Caution is necessary when interpreting this conclusion because of the existence of some limitations in these studies. First of all, most of the prior studies focus on the conventional "primary insurer - professional reinsurer" relationship, where "professional reinsurers" are identified as the key players in the reinsurance market. This identification could be arbitrary because there is no clear definition of "professional reinsurers" in the insurance literature (Cole and McCullough, 2008). Second, reinsurance transactions can occur not only between primary insurers and professional reinsurers, but also among primary insurers themselves. Without taking into account all types of reinsurance transactions, we might underestimate the complexity and interconnectedness of the reinsurance market. Third, previous studies rest on a simplified reinsurance market structure: the dominant connections are between primary insurers and reinsurers; connections among reinsurers (i.e. retrocession) are usually ignored; and in general connections among primary insurers are not assumed to be important (IAIS, 2012). Little empirical evidence has been provided to support these assumptions. Lastly, although the effects of reinsurance decisions on insurer's performance have been extensively studied in the insurance literature, prior research mainly focuses on analyzing the impact of some firm characteristics such as capital, risk, and insurers' group affiliation on reinsurance usage and performance. Another important dimension, i.e., reinsurers' roles in the reinsurance market, has not been fully explored. Little is known about whether (and how) an (re)insurer's reinsurance market position affects its performance.

The purpose of this study is threefold. First, I aim to broaden the work of previous studies by treating the reinsurance market of the US P/C insurance industry as a whole, i.e., considering both affiliated and nonaffiliated reinsurance transactions at the individual firm level. Particularly, I examine the microstructure of insurer-reinsurer relationships and their main characteristics by adopting a network analysis framework. Second, I investigate the stability of the US P/C insurance industry under our reinsurance network. I determine whether a default cascade can be triggered by reinsurer insolvencies. Third, I empirically analyze the impact of an (re)insurer's network position on its performance.

This research is most closely related to Park and Xie (2014) and Lin, Yu and Peterson (2014). Park and Xie (2014) study reinsurance counterparty risk in the US P/C insurance industry between 2003 and 2009. They investigate the impact of reinsurance downgrades on the stock prices of ceding insurers. Lin, Yu and Peterson (2014) find an insurer's reinsurance network position affects its reinsurance decisions in a non-linear manner. This study differs from theirs in several major ways. First, Park and Xie (2014) do not employ network analysis to measure interconnectivity among insurers, but rather use more standard accounting measures such as reinsurance premiums ceded.[1] Second, I

---

[1] Park and Xie (2014) study US P/C insurers' dependence on reinsurance and the diversification of reinsurance portfolios. They analyze the composition of US P/C insurers' reinsurance premiums ceded and reinsurance recoverables by reinsurers' domicile and group affiliation. They find that US P/C insurers depend mostly on group affiliated reinsurance transactions. Moreover, they use the Herfindahl index to measure the diversification of reinsurance portfolios. They find that US insurers are not diversified.

provide a much more complete analysis of the microstructure of the reinsurance market which is not explicitly addressed in Lin, Yu and Peterson (2014). Based on the constructed reinsurance network, I examine its resilience in the face of highly connected reinsurers' insolvency. Third, the empirical results provided in Lin, Yu and Peterson (2014) are based on group-level data instead of firm-level data. By utilizing firm-level data, my analysis allows us to examine the interrelationships among insurers in much more detail, shedding light on both affiliated and non-affiliated reinsurance transactions. Lastly, Lin, Yu and Peterson (2014) do not explore the effect of an insurer's network position on its loss experience and firm performance.

This study contributes to the literature in several ways. A detailed analysis of the topology of the reinsurance network, along with the individual insurer's characteristics, not only helps us better understand the interconnectedness created by reinsurance transactions but also has implications for regulatory measures and macroprudential policies. I also provide new empirical evidence that an insurer's position in the reinsurance network affects its loss experience and performance. I find an inverse U-shaped relationship between an insurer's network position and its combined ratio and a U-shaped relationship between an insurer's reinsurance network position and its performance.

1.2. Related Literature

In this section recent network and financial market resilience literature is reviewed. Following this, P/C insurance related studies are discussed.

1.2.1. Financial Network Literature

In an early and important study, Allen and Gale (2000) examine inter-linkages in the credit market and show that increasing connectivity monotonically increases financial stability through risk sharing. They argue that a more equal distribution of interbank claims increases the resilience of the system against the insolvency of any individual bank. However, this view has been challenged after the recent financial crisis.

The current, general consensus seems to be that a nonlinear relationship exists between interconnectedness and the stability of the financial market, which can be termed as the "robust-yet-fragile" property of a connected network (Haldane, 2009) or "phase transition" (Acemoglu, Ozdaglar and Tahbaz-Salehi, 2013). Below a certain threshold, connectivity among financial institutions serves as a shock-absorber, allowing the system to function as a mutual insurance device and disperse exogenous shocks. Connectivity therefore improves the robustness of the system through risk sharing and diversification. Above the threshold, however, interconnections can serve as shock-amplifiers that channel and enhance the propagation of losses through the system and lead to more fragility.

In addition to connectedness, other network characteristics are found to be important. For instance, many financial markets share the property that the total number of counterparties of market participants follows a power law distribution. In addition, a core-periphery market structure, combined with the well-known "small world" property, can result in the "too-interconnected-to-fail" phenomenon (Borgatti and Everett, 1999, Markose, Giansate and Shaghaghi, 2012).[2, 3]

---

[2] In the financial network literature, the core-periphery structure can be viewed as a two-class partition of

Another strand of the financial economics literature focuses on the strategic interactions of financial firms in a particular network and the implications for a firm's decision-making, acquisitions, and firm performance (Ahern and Harford, 2014; Li and Schurhoff, 2012; Cohen-Cole, Kirilenko and Patacchini, 2014). Generally, a central position in a financial network comes with both benefits and costs. From the benefits perspective, a central network position can provide information advantages that (1) facilitate risk management and develop expertise; (2) increase operational efficiency; (3) reduce transactions costs and achieve economies of scale; and (4) gain market power, allowing firms to charge above-average market prices for their services. However, the costs associated with contagion risk, such as counterparty risk, may also increase when a firm becomes more central in a financial network (Li and Schurhoff, 2012; Cohen-Cole, Kirilenko and Patacchini, 2014).

Thus, network theory can provide a conceptual framework within which the intricate structure of linkages and various patterns of connections formed among financial institutions can be described and analyzed in a meaningful way (Allen and Babus, 2009). It is therefore not surprising that there is a fast growing literature concerning market structure and its implications for financial stability for various financial markets using network analysis. Among these studies the banking system has been most extensively analyzed (European Central Bank, 2010; also see Hasman (2013) for a recent survey).

nodes, where nodes refer to financial institutions in the network. Nodes in the core have higher connectivity and financial flows than nodes in the periphery; usually periphery nodes only connect to the core nodes and barely connect with each other. Many financial markets are found to have the core-periphery structure. See Markose, Giansate and Shaghaghi (2012) for a brief review.

[3] Small world networks exhibit a small average shortest path length between nodes and a large clustering coefficient (see Watts and Strogatz, 1998). In other words, in a small world most nodes are not neighbors of one another, but most nodes can be reached from every other node by a small number of steps. Haldane (2009) suggests that the "small world" property tends to increase the likelihood of local disturbances having global effects over the network.

This strand of literature has extended from banking to other financial systems, such as the credit default swaps (CDS) market (Kaushik and Battiston, 2012; Markose, Giansate and Shaghaghi, 2012), the global banking market (Minoiu and Reyes, 2012), and the global derivatives market (Markose, 2012). Empirically, Upper (2011) reviews network analysis and systemic risk with an emphasis on simulation-based methods. Hasman (2013) provides a recent survey in the area of contagion risk and the banking system. On the theoretical side, Chinazzi and Fagiolo (2013) compare various economic models in the network structure and financial stability. One important message from these studies is that the microstructure of a particular financial market has important economic implications for financial stability.

1.2.2. Insurance Related Studies

The aforementioned literature provides a rationale for documenting the network properties of the reinsurance market and the resilience of (re)insurers with respect to reinsurer insolvencies. This subsection reviews the limited insurance literature on network analysis and insurance market resilience.

Lelyveld et al. (2011) provides an empirical analysis of the effect of reinsurer failures on the stability of Dutch insurers. They model the contagion risk from the direct linkage between insurers and reinsurers through a reinsurance matrix and conduct scenario analysis to test the resilience of the Dutch insurance industry to the failure of reinsurers. They find no evidence of systemic risk due to reinsurance failure in the Dutch insurance market.

Park and Xie (2014) examine the interconnectedness in the US P/C insurance industry using a sample period of 2003 to 2009. They study both the direct contagion effect due to the failure of top reinsurers and an information-based indirect contagion effect via reinsurer downgrading. Based on their simulation study, they conclude that the likelihood of systemic risk caused by the failure of the top 3 reinsurer groups (Swiss Re, Munich Re and Berkshire Hathaway) is small for the US P/C insurance industry. They also find that primary insurers' stock prices react negatively to their reinsurer's downgrade. Such negative effects can spill over to insurers that are not directly exposed to downgraded reinsurers.

Only one insurance study, Lin, Yu, and Peterson (2014), investigates the relationship between a reinsurer's network position and reinsurance decisions in the US P/C insurance industry. Lin, Yu, and Peterson (2014) build an optimal reinsurance model for the insurer and posit that there is a nonlinear trade-off between the costs and benefits of reinsurance. As an insurer conducts business with more reinsurance counterparties, an insurer's reinsurance loadings decrease. At the same time, its search and monitoring costs increase. When its network centrality is below a certain threshold, the decrease in reinsurance loadings outweighs the increase in costs, resulting in an increasing usage of reinsurance. When its network centrality is above this threshold, the costs associated with contagion risk and search/monitoring costs dominate, leading to a decrease in the usage of reinsurance. They also provide empirical evidence that supports such a curvilinear (i.e., inverse U-shaped) relationship between an insurer's network position and its reinsurance decisions. They, however, do not analyze the relationship between an insurer's network position and its performance. In addition, their analysis is conducted at the group level, i.e., they do not consider group affiliated reinsurance transactions in the reinsurance network.[4] They do not study P/C insurers' network characteristics in detail, either. I therefore address these gaps in this study.

1.3. Introduction To Network Analysis

In this section, I introduce basic concepts used in network analysis. The focus is on the network density and network centrality measures.

1.3.1. Basic Concepts

A network or graph, denoted by $G \equiv (N, E)$, is defined by two nonempty sets: the set $N = \{1, ..., n\}$ of nodes or vertices and the set $E = \{(i, j)\}, \forall i, j \in N$ of pairs of distinct elements which are called links or edges that represent the connections between the nodes. The size of the set N is the number of nodes in the network and the size of E is the total number of direct links established in the network. Every graph can be represented as a $N \times N$ binary adjacency matrix, $A = \{a_{ij}\}$, where $a_{ij} = 1$ if a node i has a direct link with node j and $a_{ij} = 0$ otherwise. If there is an edge between nodes i and j, then i and j are neighbors.

A graph is *directed* (*or undirected*) if the edges are formed by ordered (or unordered) pairs of nodes.[5] For instance, in a directed graph, an edge originating from node i and terminating at node j does not necessarily imply there is another edge from node j to node i.

---

[4] I investigate the relationship between an insurer's network position and its reinsurance utilization using both firm-level and group-level data. Similar to Lin, Yu and Peterson (2014), I find that there is an inverse U-shaped relationship between an insurer's network centrality measure and its reinsurance utilization at the group level. Such relationships hold at the firm level, too.

[5] In a directed graph, edges can be defined by ordered pairs of nodes where each ordered pair of nodes represents the originating and terminating node of an edge. In an undirected graph, edges do not have directions.

In a graph, two nodes can be connected not only by a direct link but also by indirect link(s). A key concept in network theory is a *path*: two nodes i and j are connected if there is a path from i to j. A path of length k from i to j is defined as an ordered sequence of nodes $[i_0, i_1, ..., i_k]$ starting from i and ending at j (i.e., $i_0 = i, i_k = j$). That is, a path is an ordered sequence of nodes where node i_s and i_{s+1} are directly connected. There may be several paths connecting two nodes. A *geodesic* path is the shortest path between two nodes. The *distance*, denoted by d_{ij}, is the length of the shortest path between node i and node j.

1.3.2. Connected Sub-graphs: Network Component

A network is *connected* if there is a path from each node to every other node, i.e., every pair of nodes in the network is reachable. Conversely, a network may be *disconnected*. Figure 1 presents a disconnected network, where node *e* cannot reach other nodes. A disconnected graph can be partitioned into two or more components. A *component* is a subset of the nodes in a network such that there exists at least one path from each member of that subset to each other member and such that no other nodes in the network can be added to the subset while preserving this property.

Components are classified into two types according to whether the nodes in the subset are reachable via directed or undirected edges. A *strongly connected component* (SCC) is a maximal subset of nodes such that there is a directed path between every pair of nodes. A *weakly connected component* (WCC) is a maximal subset of nodes such that any two nodes are connected by one or more paths, where paths are allowed to go either direction along any edge (i.e., ignoring the direction of the edge). The SCCs of a network might be subsets of the largest and any of the smaller WCCs of the same network.

Using the directed graph in Figure 1 as an example, I can find three SCCs. The largest SCC includes four nodes: *a*, *b*, *c* and *f*. Although node *d* is connected to node *a* and *c* via direct links and to *b* and *f* via indirect links, node *d* does not belong to the largest SCC because it only has outgoing edges and thus cannot be reached by node *a, b, c* and *f*. By definition, single nodes *d* and *e* each represents a SCC. The network itself is weakly connected. That is, by ignoring the direction of edges, all nodes are connected with each other. Clearly, the largest SCC consisting of node *a*, *b*, *c* and *f* is a subset of the largest WCC, including all nodes in the graph.

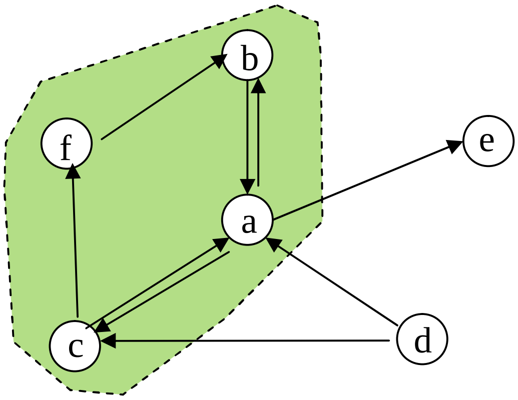

Figure 1. An Example Of Simple Network

Note: this is an example to demonstrate the concept of weakly connected component (WCC) and strongly connected component (SCC) discussed in Section 1.3.2. The largest SCC consisting of node a, b, c and f is shaded in green.

Component analysis is important to our reinsurance network analysis because it can provide an alternative measure of interconnectedness of the network. For instance, the network presented in Figure 1 is not complete (i.e., not all nodes can be reached by all other nodes) but all nodes are connected in the same WCC. Moreover, it helps us identify the active risk sharing community (as measured by SCC) that might be subject to contagion risk. In Figure 1, if a shock hit node *f*, it could spread to other nodes in the largest SCC (i.e., node *a*, *b* and *c*) and nodes that are not in the largest SCC but are connected to it (i.e., node *d*).

1.3.3. Network Centrality Measures

One of the most prominent questions in network analysis is how to identify the most "influential" or "central" nodes in a graph. I choose three commonly used centrality measures (i.e., degree centrality, eigenvalue centrality and betweenness centrality) to characterize an insurer's reinsurance network position.

Degree centrality measures the connectivity of an insurer in the network (a local property) by computing the number of counterparties to which an insurer is directly connected through reinsurance transactions. In a directed reinsurance network where we differentiate the direction of the reinsurance transactions (i.e., ceding or assuming), both the out-degree and in-degree are used for a node: out-degree, g_i^{out}, counts the number of insurers to which insurer i cedes reinsurance; in-degree, g_i^{in}, is the number of the insurers from which insurer i assumes reinsurance. The total degree, g_i, of node i is the sum of its out-degree and in-degree. Formally,

$$g_i^{out} = \sum_j A_{ij};\ g_i^{in} = \sum_j A_{ji};\ g_i^{total} = g_i^{out} + g_i^{in} \qquad (1)$$

where A denotes the (directed) binary adjacency matrix.

Moreover, a node's *strength* (or weighted degree) can be computed by using proper transactional measures to weight the links with the other nodes. In particular, I choose two measures of transactional exposures: reinsurance premium and net reinsurance recoverable. Calculations of the total strength, in-strength and out-strength are similar to calculations of the total degree, in-degree and out-degree by using a properly weighted adjacency matrix. For instance, node i's reinsurance premium weighted strengths can be calculated as

$$g_i^{out-strength} = \sum_j W_{ij};\ g_i^{in-strength} = \sum_j W_{ji};\ g_i^{total-strength} = g_i^{out-strength} + g_i^{in-strength} \tag{2}$$

where W denotes the reinsurance premium weighted adjacency matrix. Note that an insurer's reinsurance premium weighted out-strength and in-strength are its total reinsurance premiums ceded and assumed, respectively. Also note at the reinsurance network level, the total reinsurance premiums ceded is equal to the total reinsurance premiums assumed because $\sum_i \sum_j W_{ij} = \sum_j \sum_i W_{ij}$.

Eigenvector centrality measures the importance of an insurer in the network (a global property) by assigning relative scores to all insurers in the network based on the principle that connections to high-scoring insurers contribute more to the score of the insurer than equal connections to low-scoring insurers.

While degree centrality only considers a node's direct links, eigenvector centrality takes into account not only direct links of a node but also the links of its neighbors and the links of the neighbors of the neighbors, etc. The defining equation of an eigenvector in a matrix form is

$$\lambda v = Av \tag{3}$$

where A is the binary adjacency matrix, λ is the eigenvalue, and v is the corresponding eigenvector. The standard convention is to use the eigenvector associated with the largest eigenvalue. Such a measure can also be applied to a weighted and/or directed network by using a proper adjacency matrix.

Betweenness centrality measures a node's absolute position (a global property) by taking into account the connections beyond the immediate neighbors. Betweenness is computed by counting the number of shortest paths linking any two insurers in the network that pass through the insurer. Like eigenvector centrality, betweenness captures an insurer's overall importance. Formally, the normalized betweenness centrality for a directed network is defined as

$$btw_i = \frac{\sum_{j,l} \frac{a_{jl,i}}{a_{jl}}}{(n-1)(n-2)} \tag{4}$$

where $a_{jl,i}$ denotes the number of shortest paths between j and l that pass through node i, and a_{jl} denotes the total number of shortest paths between node j and l.

1.3.4. Network Density and Clustering

Network density is defined as the number of actual links formed in a network, denoted by m, divided by the total number of possible links. Formally,

$$density = \frac{m}{2n(n-1)} \tag{5}$$

This indicator ranges from 0 to 1 as a network gets "denser." In the limiting case of a complete graph where each node is directly connected with all other nodes, the density is 1.

It is very common in many real world networks (for instance, social networks) that there is a high probability that nodes having the same neighbors are connected with each other. Such a tendency is measured by the local clustering coefficient, defined as the number of connected pairs of neighbors divided by the total number of pairs of neighbors. That is, the local clustering coefficient measures the average probability that two neighbors of a node are themselves neighbors. Formally, the clustering coefficient, c_i, of node *i* is defined as

$$c_i = \frac{\sum_j \sum_k g_{jk,i}}{g_i(g_i - 1)} \tag{6}$$

where g_i denotes the degree of node i, $g_{jk,i}$ equals one for all j,k that are connected with each other and are both neighbors to node i and zero otherwise.[6]

1.4. Hypothesis Development And Empirical Methodologies

In this section, I posit the hypotheses about the financial stability of reinsurance networks and the impact of an insurer's network position on its performance. I then describe the empirical methodologies that I employ to test these hypotheses, including the algorithm of simulations, regression models and variable definitions.

1.4.1. Hypothesis Development

The reinsurance market is vulnerable to a *retrocession spiral* whereby the failure of major reinsurers triggers the failure of their reinsurance counterparties, who in turn default on their obligations to primary insurers, resulting in a crisis permeating the insurance industry on a worldwide scale (Cummins and Weiss, 2014). In 2008, US P/C insurers ceded $412.5 billion in reinsurance premiums, representing 83.7% of direct premiums written and 86.8% of surplus. Although P/C insurers' equity is not seriously exposed to counterparty risk in terms of current receivables (8.4% of equity), the reinsurance counterparty exposure for estimated future losses and benefits is much

[6] In order to calculate the clustering coefficient, the node's degree has to be greater than or equal to 2. If a node has a degree of 1 (i.e., it only has one neighbor), its clustering coefficient is defined as 0.

higher. For example, the net reinsurance recoverable from non-affiliated reinsurers is 32.5% of surplus and that from affiliated reinsurance is 128.9% of surplus. Cummins and Weiss (2014) argue that "at least one-fourth of property-casualty insurers would be seriously at risk if several large reinsurers were to fail."

Nevertheless, the evidence associated with the aftermath the 2007-2008 financial crisis suggests that the insurance industry is not subject to systemic risk due to reinsurance (IAIS, 2012). Park and Xie (2014) consider multiple scenarios where top global reinsurers become insolvent. They find that under an extreme assumption of a 100 percent reinsurance recoverable default by one of the top three global reinsurers, only about 2 percent of insurers would be downgraded, and 1 percent of insurers would become insolvent. The chain effect that insolvent primary insurers caused via affiliated and non-affiliated reinsurance transactions was minimal too. Though their analysis is limited to hypothetical defaults of global reinsurers, I believe the result would not be significantly different if large group affiliated insurers defaulted. I therefore posit:

H1: The US P/C insurance industry is not subject to contagion risk resulting from insolvency of either global reinsurers or group affiliated insurers.

I next turn my attention to the economic implications of an insurer's network position to its performance. A central reinsurance network position comes with both benefits and costs. Burt (1992) argues that firms can obtain significant performance advantages, such as heterogeneous sources of information and diverse business opportunities, when exploiting relationships with their partners in an industrial network. In line with this view, a central reinsurance network position might provide insurers with several benefits that might potentially enhance their performance. First, it can facilitate insurers exploring business opportunities that are not viable in the primary insurance market, such as participation in global risk-diversification. Second, insurers with a central network position have easy access to information in the reinsurance market, such as reinsurance price, quality of services, and financial status of reinsurance counterparties. These information advantages, in turn, can help insurers increase bargaining power in the reinsurance market and obtain coverages and rates that otherwise would not be available. Third, a central reinsurance network position might allow insurers to develop knowledge and expertise in their reinsurance operations, which may further improve their performance in the primary insurance market. Fourth, centrality can help insurers improve operational efficiency in the reinsurance market and benefit from economies of scale.

On the cost side, there are at least three types of costs associated with an insurer’s reinsurance network positions: coordination costs, cost related to counterparty risk, and cost associated with contagion risk. Coordination costs include the direct costs for managing an insurer’s reinsurance counterparty relationships, such as search and monitoring costs. Costs may also arise due to the need to effectively allocate an insurer’s internal resources between the primary insurance and reinsurance markets. As an insurer becomes more central, its coordination costs inevitably increase because of the increasing complexity of its reinsurance operations. In the meantime, costs from counterparty risk increase with an insurer’s network centrality. The level of counterparty risk may depend on the extent of information asymmetries in the reinsurance market. Garven, Hilliard, and Grace (2014) find that a long-term and focused cedant-reinsurer relationship helps reduce information asymmetries between reinsurance counterparties. As a result, the ceding insurer’s reinsurance utilization, profitability, and credit quality will increase as the reinsurance tenure increases. Lastly, we should take into account costs associated with contagion risk. Park and Xie (2014) have provided evidence that the downgrading of reinsurers can have a spillover effect to the stock prices for insurers even if they do not have direct transactions with downgraded reinsurers.

Thus benefits and costs associated with an insurer's network position are complicated, with non-linear manner tradeoffs as a possibility. In fact, Lin, Yu and Peterson (2014) find a non-linear relationship between reinsurance utilization and reinsurance network position. As an insurer plays a more central role in the reinsurance network, both the costs and benefits increase. Up to some point, the costs from coordination, counterparty risk and contagion risk may dominate the benefits from risk-diversification, information advantages, reinsurance expertise and economies of scale, resulting in a deterioration in loss experience and firm performance. Beyond this point, the benefits may outweigh the costs, leading to an improvement in loss experience and firm performance. This discussion suggests the following two hypotheses:

H2: An insurer's reinsurance network position is non-linearly related to its underwriting experience.

H3: An insurer's reinsurance network position is non-linearly related to its firm performance.

1.4.2. Empirical Methodologies

1.4.2.1. Simulation Algorithm For Insolvency Tests

To test Hypothesis H1, i.e., the resilience of the reinsurance network against contagion risk caused by the failure of central insurers, we perform several simulation studies using the reinsurance network constructed in year 2011. The simulation algorithm is designed as follows.

Step 1: Initialize simulation parameters: reinsurance net recoverable matrix, denoted by $R_{N\times N}$ (where column *i* of R represents insurer *i*'s net reinsurance recoverable payable to its reinsurance counterparties); and total surplus vector, denoted by $S_{N\times 1}$ (where *N* denotes the total number of insurers).

Step 2: Given insurer *i*'s default, update the total surplus vector as $S' = S - R_{N,i} \times LGD$, where *LGD* is the ratio of loss (of the net reinsurance recoverable) given default.

Step 3: Based on the updated total surplus vector, S', find the insurers whose total surplus after reduction of the loss of net reinsurance recoverable is below 0. These insurers are considered to be insolvent (or defaulted insurers)

- If the number of defaulted insurers is greater than 0, update the total surplus vector as $S' = S' - \sum_{j \in D} R_{N,j} \times LGD$, where *D* denotes the set of defaulted insurers and repeat step 3.
- If no insurers are found to default, then go to step 4.

Step 4: Based on the updated total surplus vector, S', find the number of impaired insurers, defined as insurers with a risk-based capital (RBC) ratio (i.e., the total surplus divided by risk-adjusted capital) after surplus deduction of less than 200%. [7]

Step 5: Calculate the total number of defaulted insurers and impaired insurers. Calculate the total surplus losses of defaulted insurers and impaired insurers.

In the above algorithm, I assume that once an insurer defaults, it cannot pay its net reinsurance recoverable to its reinsurance counterparties, resulting in immediate surplus reductions at the counterparties. I assume the same LGD ratio in all calculations of surplus reductions. This algorithm allows us to trace the possible "default cascade" in the reinsurance network and can be easily adapted to the scenario where several insurers default at the same time.

1.4.2.2. Regression Models And Variable Definitions

[7] I choose 200% as a conservative capital requirement for the RBC ratio since the NAIC starts to monitor insurers closely when this ratio is below 200%.

To test Hypotheses H2 and H3, I specify a two-way fixed effect regression model as follow:[8]

$$DependentVariable_{i,t} = \alpha_0 + \theta_1 \text{Centrality}_{i,t} + \theta_2 \text{Centrality}_{i.t}^2 + X_{i,t}\beta + v_i + \eta_t + \varepsilon_{i,t} \quad (7)$$

where v_i represents the firm fixed effect for insurer *i* and η_t is the time fixed effect for year *t*.

To test Hypothesis H2, I choose the combined ratio, defined as the sum of the loss ratio and the expense ratio for insurer *i* in year *t*, as the dependent variable in equation (7). For Hypothesis H3, we use risk adjusted return on assets (*RAROA*) or risk adjusted return on equity (*RAROE*) as the dependent variable. We define an insurer's return as net income before dividends to policyholders and federal/foreign income taxes. An insurer' *RAROA* (*RAROE*) is then defined as the ratio of the return on total admitted assets (total surplus) to its standard deviation in the previous three years.

The key variable of interest, $\text{Centrality}_{i,t}$, measures insurer *i*'s reinsurance network position in year *t*. We include its square term, $\text{Centrality}_{i.t}^2$ to test for a non-linear effect. For simplicity, we choose two measures of the reinsurance network position in our regression analysis: $Degree_{i,t}$, defined as insurer *i*'s total degree in year *t*, and $Net_{i,t}$, defined as the first principal component of insurer *i*'s total degree centrality, eigenvalue centrality, betweenness centrality, and clustering coefficient in year *t* (see Li and Schurhoff, 2012). $X_{i,t}$ is a vector of insurer *i*'s characteristics in year *t*. Specifically, I choose the following variables to control for the heterogeneity among insurers. The

[8] Two way fixed effects models are chosen after conducting the Hausman test to determine whether fixed or random effects should be used.

formal definitions of dependent variables and control variables, along with the predicted signs, are summarized in Table 1.

Table 1. Definitions Of Variables

Variable	Measurement	Expected sign	
Dependent variables		Combined Ratio	RAROA RAROE
Combined Ratio	The sum of the loss ratio and the expense ratio, where the loss ratio is defined as the sum of loss incurred and loss adjustment expenses divided by net premium earned, and the expense ratio is defined as expenses divided by net premium written.		
RAROA	Risk adjusted return on assets, defined as return on assets divided by the standard deviation of return on assets in the previous 3 years, where return on assets is calculated as net income before dividends to policyholders and before federal and foreign income taxes divided by total admitted assets.		
RAROE	Risk adjusted return on equity, defined as return on equity divided by the standard deviation of return on equity in the previous 3 years, where return on equity is calculated as net income before dividends to policyholders and before federal and foreign income taxes divided by total surplus.		
Independent variables			
Degree	An insurer's total degree centrality in the reinsurance network	+/-	+/-
Degree2	The square term of Degree	+/-	+/-
Net	The first principal component of an insurer's reinsurance network position measured by degree, eigenvalue, betweenness and clustering coefficient.	+/-	+/-
Net2	The square term of Net	+/-	+/-
Ln(asset)	The logarithm of total admitted assets	-	+
Leverage	The ratio of total liabilities to total admitted assets	-	+
HHI_geo	Herfindahl index of direct premium written across geographic areas	+/-	+/-
HHI_line_npw	Herfindahl index of net premium written across all business lines		
Percent_lp_npw	The percentage of net premium written in long-tail personal lines to total direct premium written	+/-	+/-
Percent_sc_npw	The percentage of net premium written in short-tail commercial lines to total direct premium written	+/-	+/-
Percent_lc_npw	The percentage of net premium written in long-tail commercial lines to total direct premium written	+/-	+/-
Dummy_Stock	1 for stock insurers, 0 otherwise	+/-	+/-
Dummy_Group	1 for group affiliated insurers, 0 otherwise	+	+
Dummy_Reinsurer	1 for an insurer satisfying the A.M. Best definition for professional reinsurer, 0 otherwise	+/-	+/-

- *Size*: Size may play an important role in influencing an insurer's risk-taking behavior and performance through its effect on investment opportunities and access to capital markets. Large insurers are usually more diversified by line and geographical location; they benefit from economies of scale in risk management and have greater ability to raise capital than small insurers. Previous studies have found firm size positively affects P/C insurers' performance (Cummins and Nini, 2002). Size is measured as the natural logarithm of an insurer's total admitted assets.

- *Organizational form*: There are two main types of insurers in the insurance industry – stock insurers, owned by stockholders, and mutual insurers, owned by policyholders. Generally speaking, stock firms have better access to the capital market and can raise capital more easily than mutual insurers. The effect of organizational form on insurers' underwriting experience and performance is ambiguous. For instance, Cummins et al. (1999) and Liebenberg and Sommer (2008) find that mutuals have higher costs than stocks because the former have more difficulties in controlling managerial perquisite consumption. By contrast, Greene and Segal (2004) find no significant difference in accounting profitability between mutual and stock life insurers. We use a dummy variable, *Dummy_stock*, which is equal to one if an insurer is a stock insurer and zero otherwise.

- *Group affiliation*: Reinsurance transactions can occur among group affiliated insurers or between (re)insurers that are not part of the group. Previous studies consider group affiliated transactions as internal capital market activities that help affiliated insurers stabilize their performance and maintain a target capital structure (Powell and Sommer, 2007; Fier et al., 2013). Park and Xie (2014) also find that group affiliated transactions account for a major portion of reinsurance market activities in terms of reinsurance premiums ceded. We therefore expect that group affiliated insurers obtain better underwriting experience and performance. We use a dummy variable, *Dummy-group*, to denote insurers that belong to an insurance group.

- *Leverage*: Leverage can be an indicator of an insurer's insolvency risk which tends to affect returns and losses. A high debt ratio can worsen the underinvestment problem and increase bankruptcy costs. We expect leverage to be negatively associated with an insurer's underwriting experience and performance. We define *Leverage* as the ratio of the total liabilities to total admitted assets.

- *Business concentration*: In addition to using reinsurance, an insurer can diversify its underwriting risk across different lines of business or geographic regions. The predicted effect of business concentration on firm performance is undetermined. On the one hand, the pro-conglomeration arguments suggest that geographically diversified insurers face lower risk and can thus charge higher prices. On the other hand, pro-focus arguments suggest that geographically focused insurers can avoid monitoring costs associated with operations across different areas and gain efficiencies through market specialization (Cummins et al., 2010). The degree of an insurer's diversification is measured by the Herfindahl index by lines of business and by geographical areas based on net premium written.

- *Business mix*: Business mix is the degree of concentration in an insurer's core business. Following Cummins et al. (2008) and Lin, Yu and Peterson (2014), we classify an insurer's lines of business into four categories: short-tail personal, long-tail personal, short-tail commercial and long-tail commercial. We use the percentage of net premiums written for each line to indicate an insurer's business mix. The variable defined as the short-tail personal line is omitted in the regression.

1.5.Data And The Microstructure Of Reinsurance Networks

The main analysis is conducted at the individual firm level, i.e., including all affiliated and non-affiliated insurers, for several reasons. First, by recognizing the intra- and inter- group reinsurance transactions, we gain a better understanding of interconnectedness among insurers, both affiliated and non-affiliated, and thus present a more detailed microstructure of the reinsurance network than previous research. Second, certain analyses, such as the insolvency tests for the reinsurance network, are not permissible if we use group-level data. Third, it is meaningful for each insurer to understand its network position in order to achieve better performance. It is also crucial for regulatory authorities to make and implement macroprudential policies for each insurer. We perform additional analysis as robustness tests using group-level data, i.e., the network is constructed using insurance groups and nonaffiliated single insurers.

The data is from the National Association of Insurance Commissioners (NAIC) annual statements for US P/C insurers during the period of 2000-2011. I require the insurers included in our sample to have positive total assets, surplus, and net premiums written in each sample year. The reinsurance networks are constructed based on our sample insurers' reinsurance transactions extracted from Schedule F, Part 3 of the NAIC annual statement. In order to uniquely identify and trace each insurer and its reinsurance counterparties, I use the NAIC assigned company code and Federal employer identification number (FEIN) for US P/C insurers and their reinsurance counterparties, respectively. I manually clean the firm-level reinsurance transactions by excluding reinsurance transactions with negative reinsurance premium ceded or negative net reinsurance recoverable and transactions without enough information for us to identify the counterparties. In this way, I can measure all types of reinsurance transactions, especially those between US P/C insurers and non-US domiciled reinsurance counterparties. The final sample represents more than 98% of total P/C industry net premiums written.

For each sample year, I construct three reinsurance networks: (1) an equally-weighted network, i.e., each existing edge is weighted by 1; (2) a value-weighted network, weighting by reinsurance premiums ceded; and (3) a value-weighted network, weighting by net reinsurance recoverables. In total, I trace 2,901 US P/C insurers and 6,737 non-NAIC regulated reinsurance counterparties with 419,524 reinsurance transaction relationships. On average, the reinsurance network has 4,505 nodes with 1,952 US P/C (re)insurers and 34,960 edges per year.

I use the network measures introduced in Section 3 to characterize the structure of the reinsurance market. Table 2 Panel A repots the reinsurance network density over the sample years. For example, the network density is 0.0014 in 2011.[9] We conclude that the reinsurance network is sparse with a low degree of density. Although the overall network density is low, the component analysis reveals that most of the US P/C insurers are still connected in one risk-sharing community as defined by the largest WCC. In 2011, the largest WCC consists of 89% of the total US P/C insurers (1,717 out of 1,923), and it

[9] For comparisons, the density for a complete graph where all nodes are directly connected with each other is 1.

generates 78% of total reinsurance premiums ceded (Table 2 Panel B). Moreover, there is a sizeable risk-sharing community as defined by the largest SCC where insurers actively trade reinsurance with each other. In 2011, 26% (491 out of 1,923) of US P/C insurers belong to the largest SCC, generating 55% of total reinsurance premiums ceded (Table 2 Panel C). The last column of Table 2 documents an increasing trend in the number of SCCs with size (i.e., the number of insurers included in the SCC) greater than 2. It suggests that the reinsurance market is slowly moving toward "decentralized" risk-sharing. We conjecture that this is because the increasing amount of catastrophe losses drives US P/C insurers into different local markets where insurers share risks with those who have similar exposures (Swiss Re, 2012).

Table 2. Reinsurance Network Density And Component Analysis

		Panel A	**Panel B: Largest WCC**			**Panel C: Largest SCC**			**Panel D**
Year	No. of total insurers	Network Density	Size	No. of insurers (%)	Premium (%)	Size	No. of insurers (%)	Premium (%)	# of SCC size >2
2000	1991	0.0024	1933	97	84	828	42	75	19
2001	1978	0.0021	1902	96	82	806	41	69	19
2002	1917	0.0019	1840	96	81	715	37	69	25
2003	1923	0.0017	1820	95	81	654	34	64	28
2004	1903	0.0017	1786	94	81	593	31	65	30
2005	1883	0.0017	1661	88	79	492	26	59	41
2006	1975	0.0017	1792	91	81	552	28	68	44
2007	1972	0.0016	1770	90	80	468	24	56	46
2008	2017	0.0016	1824	90	80	511	25	57	46
2009	1981	0.0015	1778	90	79	515	26	63	42
2010	1963	0.0015	1748	89	79	511	26	55	47
2011	1923	0.0014	1717	89	78	491	26	55	52

Note: Panel A reports the overall reinsurance network density. Panel B (Panel C) reports the size (i.e., the number of insurers) in the largest WCC (SCC), the percentage of insurers in the largest WCC (SCC) to the total number of insurers in our sample and the percentage of reinsurance premium ceded in the largest WCC (SCC). Panel D reports the number of SCCs with size bigger than 2.

IAIS (2012, p. 9) concludes that "the insurance market does not contain the feedback mechanisms that would make it fully interconnected and therefore prone to potentially systemic events akin to the systemic events observed in the interbank market and recently seen between banks and shadow banks." This conclusion has to be interpreted with caution given the evidence we present here. As shown above, the majority of the reinsurance market is weakly connected, and more importantly, a large portion of (re)insurers is strongly connected with each other. Each SCC can be viewed as a risk-sharing community subject to contagion risk. When a shock hits one or more insurers within an SCC it can spread to the insurers within the SCC and those connected to the SCC. It suggests that "feedback" mechanisms may exist and thus result in contagion risk in the reinsurance network. This incentivizes us to investigate the resilience of the reinsurance market against contagion risk in section 1.6.1.

Figures 2 and 3 provide us a visualization of the reinsurance network that we construct using our sample in 2011, revealing the fact that all insurers do not play an equal role. We can see from Figure 2 that top nodes ranked by in-degree are the conventional professional reinsurers, such as Munich Re America and Swiss Re America. However, if we rank insurers by their in strength weighted by reinsurance premium ceded as shown in Figure 3, top nodes become large group affiliated P/C insurers, such as Travelers (Travelers), Liberty Mutual Insurance (Liberty Mutual), and National Union Fire Insurance Company of Pittsburgh (AIG group), which are heavily engaged in intra-group reinsurance transactions.

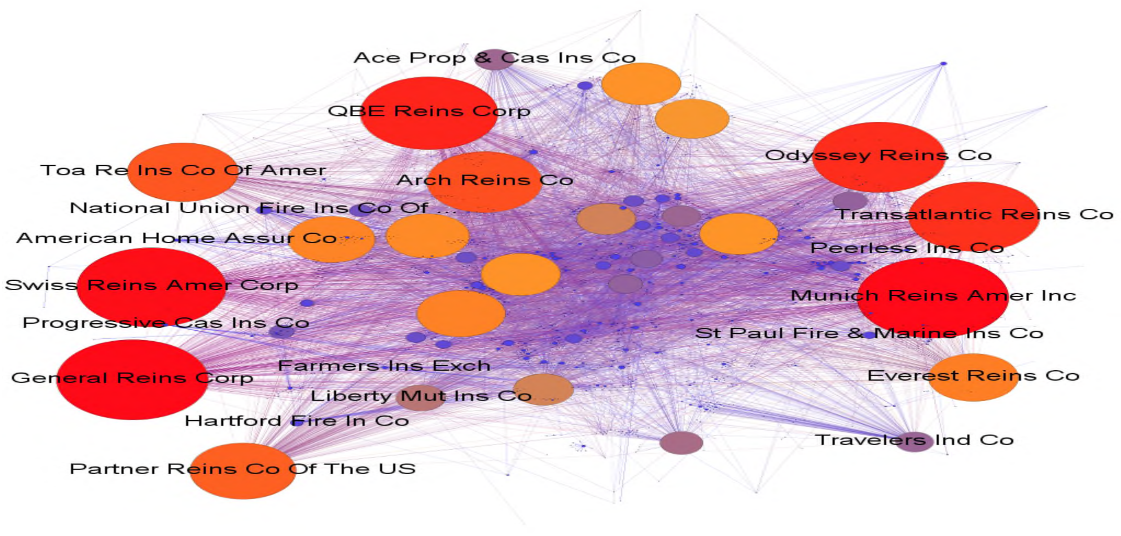

Figure 2. Graph For The Reinsurance Network In 2011 (Degree Rank)

Note: this figure presents the reinsurance network among US P/C insurers in year 2011, consisting of 1623 nodes and 9429 edges. The size of the node is proportional to the node's in-degree. Top 10 insurers ranked by in-degree and in-strength are labeled. (Note: we label top 10 for in-degree ranking and top 10 for in-strength ranking, so that in total I label 20 nodes.)

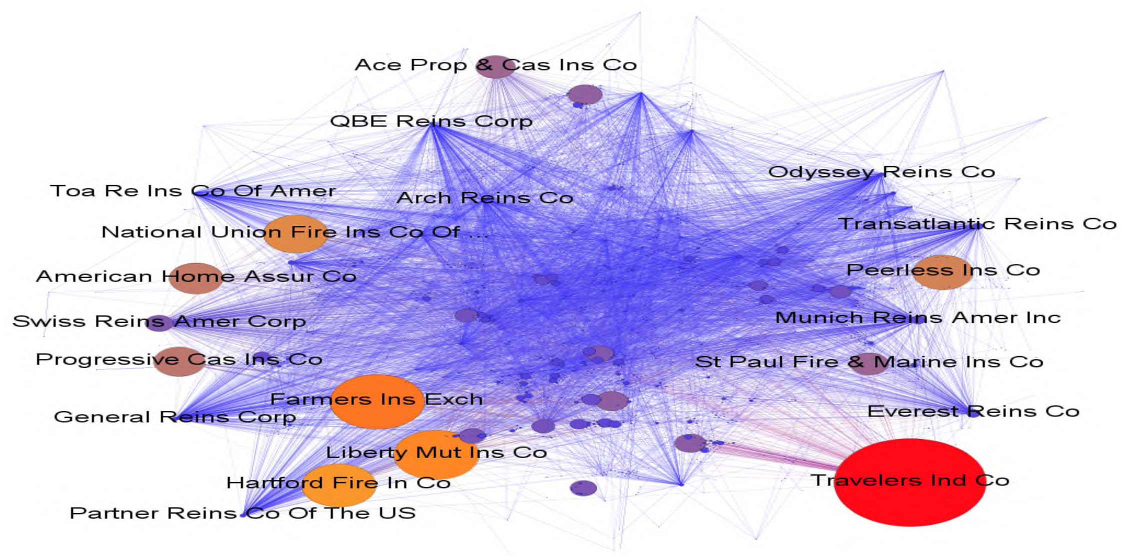

Figure 3. Graph For The Reinsurance Network In 2011 (Strength Rank)

Note: this figure presents the reinsurance network among US P/C insurers in year 2011, consisting of 1623 nodes and 9429 edges. The size of the node is proportional to the node's in-strength. Top 10 insurers ranked by in-degree and in-strength are labeled.

Empirical evidence from other financial networks suggests that the degree distribution follows a power-law distribution (see, e.g., Markose, Giansate and Shaghaghi, 2012; Li and Schurhoff, 2012), i.e., the degree density function is $f(x) \propto x^{-\alpha}$, where x denotes the degree of the node in the financial network and α is the power-law exponent. We, therefore, fit the nodes' total degree, in-degree and out-degree to a power-law distribution. Not surprisingly, we find that the power-law distribution provides a good fit and the estimated exponent is highly significant.[10] This result has two economic implications. First, the reinsurance network is far from a random network which would yield a Poisson distribution of node degrees.[11] In other words, instead of randomly choosing their reinsurance counterparties, insurers tend to cede reinsurance to "core" (re)insurers. Second, a power-law distribution is heavy-tailed, implying that the reinsurance network may be subject to "targeted" shocks that hit "core" (re)insurers (Haldane, 2009).

Table 3 further documents the importance of the "core insurers" (top 10, 20, and 30) in terms of the percentage of links formed with other insurers to total links in the reinsurance network and the percentage of reinsurance premiums assumed to total premiums assumed in the network. Although none of the top insurers dominates the reinsurance market, the top insurers as a group have important market influence. For

[10] To save space, I choose not to report parameter estimates and goodness of fit.

[11] In a random network where connectivity between any two nodes is uncorrelated, the probability distribution of a node with k degrees is given by $\Pr(k) = \binom{N-1}{k} p^k (1-p)^{N-k-1} \cong \frac{p^k e^{-p}}{k!}$, where p denotes the probability of a node to connect with other nodes. In this case, the degree distribution would not exhibit a long tail. In a regular network, the degree of each node will be the same. See Markose (2012) for a brief comparison of the properties of regular, random and scale-free networks.

instance, in 2011 the top 10 insurers ranked by in-degree account for 37% of total links formed in the reinsurance network, and the top 10 insurers ranked by in-strength account for 36% of reinsurance premiums assumed.

Table 3. Importance Of Top (Re)insurers In Reinsurance Networks

	Panel A: Ranked by node in-degree						**Panel B: Ranked by node in-strength**					
	Percentage of Total Connected P/C Insurers			**Percentage of Reins. Premiums Assumed**			**Percentage of Total Connected P/C Insurers**			**Percentage of Reins. Premiums Assumed**		
Year	Top10	Top20	Top30	Top10	Top20	Top30	Top10	Top20	Top30	Top10	Top20	Top30
2000	27%	44%	58%	13%	16%	17%	9%	19%	23%	32%	45%	54%
2001	26%	44%	57%	14%	17%	19%	12%	19%	24%	33%	47%	57%
2002	26%	45%	59%	11%	16%	21%	10%	22%	24%	34%	48%	57%
2003	27%	46%	60%	8%	16%	23%	7%	21%	29%	36%	49%	58%
2004	30%	50%	63%	7%	11%	23%	8%	18%	28%	37%	50%	59%
2005	30%	52%	63%	5%	14%	16%	7%	16%	23%	39%	52%	60%
2006	33%	55%	66%	5%	10%	20%	7%	14%	23%	38%	50%	59%
2007	37%	58%	68%	5%	14%	34%	7%	16%	23%	39%	52%	60%
2008	37%	58%	68%	5%	14%	24%	6%	15%	21%	37%	50%	59%
2009	37%	58%	68%	4%	13%	22%	6%	14%	21%	38%	51%	59%
2010	36%	57%	68%	5%	7%	21%	6%	12%	17%	36%	49%	57%
2011	37%	59%	69%	5%	8%	23%	5%	13%	21%	36%	50%	58%

Note: this table reports the importance of top (re)insurers in the reinsurance networks as measured by (1) the percentage of links formed to total links in the reinsurance network; (2) the percentage of reinsurance premiums assumed to total premiums in the reinsurance network.

A natural question is whether the reinsurance network has a single or several market center(s). Figure 4 depicts the scatter plot of reinsurer’s in-degree/out-degree and clustering coefficient in year 2011. I find there is an inverse relationship between the degree distribution and the clustering coefficient. On the one hand, periphery insurers with low degrees tend to cede reinsurance to only a few (re)insurers (i.e., local market centers) that are connected with each other to form a highly clustered local risk-sharing community, resulting in larger clustering coefficients. On the other hand, reinsurance transaction flows among those local market centers are only maintained by a few (re)insurers, resulting in low clustering coefficients for nodes with high degrees. The negative relationship between the clustering coefficient and the degree distribution, together with the power-law degree distribution, reveals a core-periphery reinsurance market structure.

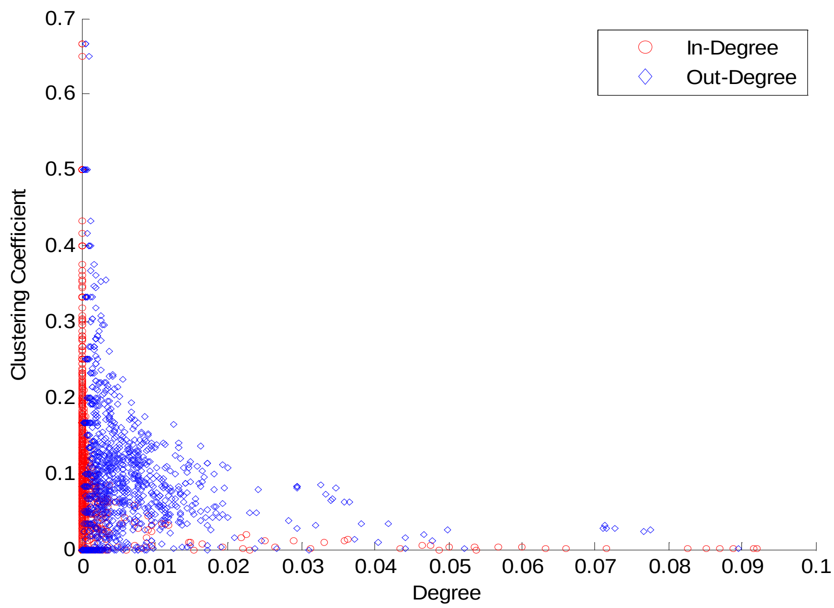

Figure 4. Scatter Plot Of Degree And Clustering Coefficient In 2011

To summarize, the reinsurance networks are sparse with decentralized risk-sharing, i.e., a few insurers play active risk-taking roles in the market. Concentration of reinsurance premium flows to a few reinsurers in the reinsurance network comes with both benefits and costs. On the one hand, such concentration may lead to more efficient risk diversification and yield economies of scale in risk management for assuming insurers. On the other hand, concentration may reduce the reinsurance network's stability and resilience to shocks, increasing contagion risk and costs associated with counterparty risk for ceding insurers. I, therefore, turn to examining contagion risk in the reinsurance network in the next subsection.

1.6. Empirical Results

This section presents the empirical results. I first report the simulation results from insolvency tests and then provide the regression results regarding the impact of an insurer's network position on its performance. Lastly, I discuss the results of several robustness tests.

1.6.1. Insolvency Tests

Using the algorithm outlined in Section 1.4, I choose top reinsurers ranked by in-degree (the number of incoming links) or in-strength (weighted by the total reinsurance premium assumed) to conduct our simulation study. Table 4 reports the results. The LGD ratio for the net reinsurance recoverables is assumed to be 100%, i.e., when an insurer defaults, its counterparties will lose 100% of reinsurance recoverables. Overall, the results suggest that the failure of any top insurer is unlikely to lead to systemic risk in the US P/C insurance industry. If one of the top insurers ranked by in-degree defaulted, on average 6 insurers (0.3% of 1,923 sampled US P/C insurers) would become either insolvent or impaired with a total loss of $181 million (0.016% of the industry surplus). If one of the top insurers ranked by reinsurance premiums assumed defaulted, on average 15 insurers (0.8% of 1,923 sampled US P/C insurers) would be either insolvent or impaired resulting in a loss of $ 8,787 million (0.77% of the industry surplus). The last column of Table 4 further reports the loss attributed to the affiliated insurers. The failure of top insurers ranked by in-degree results in the failures of non-affiliated insurers, whereas the failure of insurers ranked by in-strength mostly impacts intra-group insurers.

Table 4. Simulation Results For The Impact Due To The Failure Of An Individual Top Insurer To The Reinsurance Network

Panel A: Ranked by the insolvent insurer's in-degree

Company Name	# of Defaulted Insurers	# of Impaired Insurers	Loss of Defaulted Insurers ($ mn)	Loss of Impaired Insurers ($ mn)	Total Loss ($ mn)	Percentage of Total US P/C Insurers (%)	Percentage of Total Surplus (%)	Loss of Affiliated Insurers ($ mn)
Munich Reins. Amer Inc	4	4	36.14	68.73	104.87	0.45	0.02	0.00
General Reins. Corp	2	5	5.63	18.57	24.20	0.39	0.00	0.00
Swiss Reins. Amer Corp	11	5	608.69	297.65	906.34	0.90	0.14	410.55
QBE Reins. Corp	0	2	0.00	25.69	25.69	0.11	0.00	0.00
Odyssey Reins. Co	2	2	149.06	9.46	158.51	0.23	0.02	137.99
Transatlantic Reins. Co	5	4	43.26	28.42	71.68	0.51	0.01	0.00
Arch Reins. Co	0	2	0.00	5.45	5.45	0.11	0.00	0.00
Toa Re Ins. Co Of Amer	0	2	0.00	28.16	28.16	0.11	0.00	28.16
Partner Reins. Co Of The US	2	3	28.48	15.94	44.42	0.28	0.01	0.00
Everest Reins. Co	3	3	302.65	137.25	439.91	0.34	0.07	179.70
Average	**3**	**3**	**117.39**	**63.53**	**180.92**	**0.34**	**0.027**	**75.64**
Panel B: Ranked by the insolvent insurer's in-strength								
Travelers Ins. Co	27	2	14505.24	3786.00	18291.24	1.63	2.77	18184.54
Farmers Ins. Exch	9	1	2621.54	51.67	2673.21	0.56	0.41	2673.21
Liberty Mut Ins. Co	9	0	3002.07	0.00	3002.07	0.51	0.45	3002.07
Hartford Fire Ins. Co	9	2	2551.88	353.22	2905.09	0.62	0.44	2725.98
National Union Fire Ins. Co Of Pitts	6	1	10921.41	1465.47	12386.88	0.39	1.88	12386.12
Peerless Ins. Co	13	1	3141.14	915.08	4056.22	0.79	0.61	4050.17
American Home Assur Co	6	1	17868.11	1465.47	19333.58	0.39	2.93	19332.83
Progressive Cas Ins. Co	12	1	1776.58	323.64	2100.22	0.73	0.32	2100.22
Ace Prop & Cas Ins. Co	8	5	2660.31	912.17	3572.48	0.73	0.54	3457.63
St Paul Fire & Marine Ins. Co	27	2	15766.90	3786.00	19552.91	1.63	2.96	19446.20
Average	**13**	**2**	**7481.52**	**1305.87**	**8787.39**	**0.80**	**1.33**	**8735.90**

The key assumption that the LGD ratio of net reinsurance recoverables equals 100% upon an insurer's default may be too restrictive. We conduct sensitivity analysis by changing the LGD ratio to 80%, 50%, and 30% and report the simulation results in Table 5. When the LGD ratio decreases, the numbers of defaulted insurers and impaired insurers also decrease. For instance, the possible failure of Munich Reinsurance America, the top reinsurer by in-degree ranking, would trigger 3 (or 0) insurers' default when the LGD ratio is 80% (or 30%). These results further confirm that the default of a single top reinsurer is unlikely to cause systemic risk in the US P/C insurance industry.

The next question is then what would happen if multiple top insurers defaulted at the same time. We illustrate our simulation results in Figure 5. Panel A of Figure 5 shows the impacts of simultaneous failures of top insurers on the US P/C insurance industry in terms of the percentage of the number of defaulted and impaired insurers to the total number of insurers in our sample and Panel B of Figure 5 demonstrates the impacts in terms of the percentage of the total surplus loss to the total surplus of our sampled insurers. For instance, if the top 10 insurers ranked by in-degree defaulted at the same time, less than 5% of our sampled insurers would either default or become impaired with surplus losses accounting for less than 6% of total surplus. The failures of top insurers ranked by in-strength (weighted by reinsurance premiums assumed) have a relatively big impact in terms of the total surplus losses. If the top 10 insurers ranked by in-strength defaulted simultaneously, nearly 7% of our sampled insurers would become either insolvent or impaired and about 16% of total surplus would be wiped out.

Table 5. Simulation Results For Different Loss Given Default

Panel A:Ranked by Node in-degree

	LGD=0.3			LGD=0.5			LGD=0.8		
Company Name	**# Defaulted Insurers**	**# Impaired Insurers**	**Total Loss ($ mn)**	**# Defaulted Insurers**	**# Impaired Insurers**	**Total Loss ($ mn)**	**# Defaulted Insurers**	**# Impaired Insurers**	**Total Loss ($ mn)**
Munich Reins Amer Inc	0	1	3.49	0	1	5.82	3	4	38.35
General Reins Corp	0	4	3.88	0	6	11.30	2	5	20.48
Swiss Reins Amer Corp	1	2	40.22	4	6	215.92	8	5	402.33
QBE Reins Corp	0	0	0.00	0	0	0.00	0	2	20.55
Odyssey Reins Co	0	0	0.00	1	0	11.06	2	1	149.97
Transatlantic Reins Co	0	2	17.90	2	1	25.87	3	3	50.57
Arch Reins Co	0	1	0.26	0	2	2.72	0	2	4.36
Toa Re Ins Co Of Amer	0	1	0.99	0	1	1.65	0	2	22.53
Partner Reins Co Of The US	0	0	0.00	1	0	6.05	1	1	6.47
Everest Reins Co	2	2	265.94	3	1	313.89	3	2	322.28

Panel B: Ranked by Node in-strength

	LGD=0.3			LGD=0.5			LGD=0.8		
Company Name	**# Defaulted Insurers**	**# Impaired Insurers**	**Total Loss ($ mn)**	**# Defaulted Insurers**	**# Impaired Insurers**	**Total Loss ($ mn)**	**# Defaulted Insurers**	**# Impaired Insurers**	**Total Loss ($ mn)**
Travelers Ind Co	11	6	3317.94	16	6	5099.74	22	6	14196.00
Farmers Ins Exch	6	0	2289.55	7	0	2466.06	7	2	2608.70
Liberty Mut Ins Co	6	1	2733.28	9	0	3002.07	9	0	3002.07
Hartford Fire In Co	7	0	2440.92	8	0	2492.81	9	1	2695.17
National Union Fire Ins Co Of Pitts	2	3	4154.57	5	1	9446.61	6	1	12093.78
Peerless Ins Co	5	5	1891.53	10	1	2754.14	12	2	3872.55
American Home Assur Co	0	0	0.00	0	1	10580.95	6	1	19040.49
Progressive Cas Ins Co	5	4	876.31	10	0	1027.86	10	1	1286.77
Ace Prop & Cas Ins Co	3	1	2210.34	4	5	2570.65	6	5	2682.86
St Paul Fire & Marine Ins Co	0	0	0.00	0	1	5784.33	23	5	16225.81

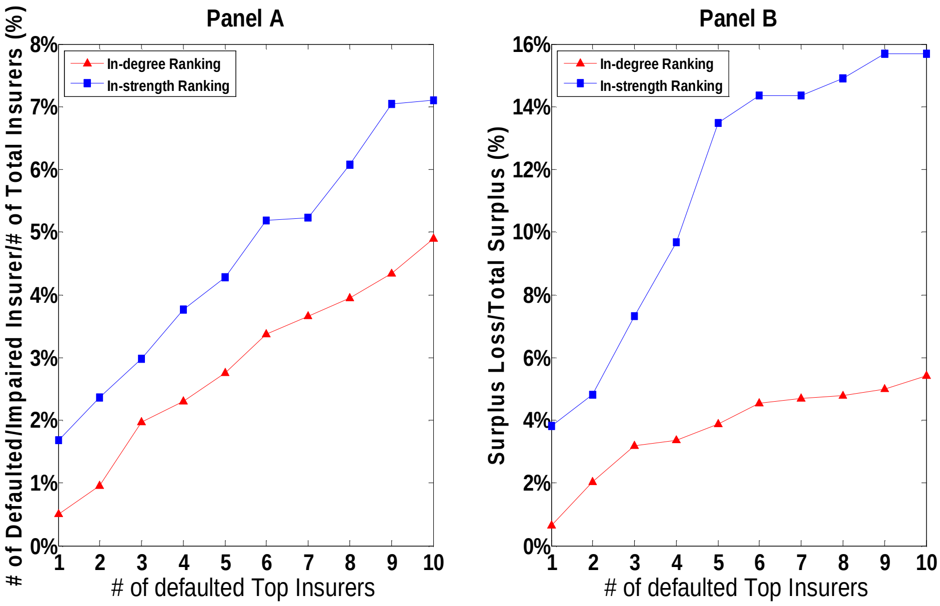

Figure 5. Simulation Results For The Impact Of Multiple Top Insurers' Failures

Note: this figure reports the simulation results for the impact of multiple top insurers' failures at the same time based on the reinsurance network in year 2011. The horizontal axis is the number of failed top insurers. The vertical axis in panel A represents the percentage of defaulted insurers (i.e. total surplus<=0) and impaired insurers (i.e. RBC ratio<200%) to the total number of insurers (1, 923) in year 2011. The vertical axis in panel B represents the percentage of surplus wiped out to total surplus of sampled insurers in year 2011. We compare the losses of top insurers ranked by in-degree (i.e., in-coming links ranking) and those ranked by in-strength (i.e., reinsurance premium assumed ranking). The loss given default ratio for net reinsurance recoverable is assumed to be 100% in all scenarios considered here.

To summarize, we cannot reject Hypothesis H1, i.e., the US P/C insurance industry is not subject to contagion risk resulting from intra-company reinsurance transactions, under extreme scenarios when one or more top insurers ranked by in-degree (mostly traditional reinsurers) or in-strength (mostly group affiliated insurers) default. This is consistent with the conclusion in Park and Xie (2014). While they only focus on the defaults of top professional reinsurers, we provide a more comprehensive study by taking into account defaults of top group affiliated insurers that account for a large portion of transactions in terms of reinsurance premium assumed.

1.6.2. Reinsurance Network Position And Insurer Performance

This subsection presents regression results of the two-way fixed effects model estimating the impact of an insurer's network position on its performance. Our original sample includes 23,367 firm-year observations. We remove observations with (1) missing values for the geographic Herfinahl index; (2) negative combined ratio or negative incurred losses; and (3) missing values for risk adjusted ROA/ROE.[12] We then perform outlier detection by running the pooled ordinary least squared (OLS) regression on equation (7) and calculate the Cook's distance for each observation. We then remove the outliers determined by the Cook's distance.[13] Our final sample is an unbalanced panel with 17,746 firm-year observations, which account for 83% (86%) of the entire US P/C insurance market in terms of total assets in year 2000 (2011). After removing the outliers, we find that all variables, except for the combined ratio, have reasonable distributions. We therefore winsorize the combined ratio at the 5 and 95 percentiles.

Table 6 reports the summary statistics for the dependent variables and independent variables. The mean value for the centrality measure, *Degree*, is 0.005 and that for *Net* is 0.0033. The mean values for our main dependent variables, *Combined Ratio*, *RAROA*, and *RAROE*, are 1.021, 2.090, and 1.871, respectively. Moreover, 69.7% of insurers are stock insurers and 67.2% of insurers are group affiliated insurers.

[12] I remove 2631, 1066, and 1319 observations in step (1)-(3) respectively, resulting in 18,351 observations for the next step – outlier analysis.

[13] We consider the observations whose Cook's distance is greater than 4/N as outliers, where N denotes the number of observations in the regression model (Fox 1997). In total, we identify and remove 605 outliers.

Table 6. Summary Statistics

Variable	# of obs	Mean	Std Dev	p5	Median	p95
Combined Ratio	17746	1.021	0.195	0.693	0.993	1.536
RAROA	17746	2.090	3.423	-1.539	1.344	8.353
RAROE	17746	1.871	2.973	-1.599	1.306	7.451
Degree	17746	0.005	0.012	0.000	0.002	0.020
Net	17746	0.033	1.481	-0.615	-0.421	1.904
Ln(asset)	17746	18.368	1.948	15.296	18.287	21.725
Leverage	17746	0.571	0.182	0.195	0.609	0.804
HHI_line_npw	17746	0.489	0.302	0.124	0.407	1.000
HHI_geo	17746	0.567	0.385	0.055	0.536	1.000
Percent_npw_lp	17746	0.279	0.302	0.000	0.169	0.802
Percent_npw_lc	17746	0.451	0.394	0.000	0.427	1.000
Percent_npw_sc	17746	0.154	0.266	0.000	0.042	1.000
Dummy_stock	17746	0.697	0.460	0.000	1.000	1.000
Dummy_group	17746	0.672	0.469	0.000	1.000	1.000
Dummy_reinsurer	17746	0.031	0.173	0.000	0.000	0.000

Note: this table reports the summary statistics for the variables used in the regression analysis. *Degree* is an insurer's normalized total degree; *Net* is the first principal component of degree centrality, eigenvalue centrality, betweenness centrality and clustering coefficient; *RAROA* is the ratio of return on total admitted assets divided by the standard deviation of return on total admitted assets in the previous three years; RA*ROE* is the ratio of return on total surplus divided by the standard deviation of return on total surplus in the previous three years; *Ln(asset)* is defined as the natural logarithm of total admitted assets; *Leverage* is the total liabilities to total admitted assets; *Combined Ratio* is the sum of the loss ratio and expense ratio; *HHI_geo* is the geographic Herfindahl index;*HHI_line_npw* is the business line Herfindahl index based on net premium written; *Percent_npw_lp*, *Percent_npw_sc*, *Percent_npw_lc*) is the percentage of net premium written in long-tail personal lines, short-tail commercial lines and long-tail commercial lines, respectively; *Dummy_stock* is equal to 1 if the firm is a stock insurer and 0 otherwise; *Dummy_group* is equal to 1 if the firm is affiliated with an insurance group and 0 otherwise; *Dummy_reinsurer* is equal to 1 if the insurer satisfies the A.M. Best definition of reinsurer and 0 otherwise.

I first test Hypothesis H2 using the combined ratio as a measure of an insurer's loss experience and report the regression results in Table 6. We observe that the combined ratio is positively associated with the centrality measure (degree or Net) but negatively related to its squared term, and both are statistically significant at the 1% level. That is, when an insurer becomes more connected with other (re)insurers in the reinsurance network, its loss experience deteriorates at first. We conjecture that this occurs because the search and monitoring costs outweigh the benefits of risk diversification below a certain threshold. However, when the insurer plays a more important role in the reinsurance network such that this threshold is passed, it can diversify the risk in a more efficient way and thus its loss experience starts to improve (the combined ratio decreases) with the centrality measure.

Table 7. The Effect Of Reinsurance Network Position On Combined Ratio

VARIABLES	(1) Combined Ratio	(2) Combined Ratio	(3) Combined Ratio	(4) Combined Ratio
Intercept	2.0991***	2.1218***	2.1112***	2.1401***
	(0.1386)	(0.1394)	(0.1397)	(0.1412)
Degree	0.8984**	3.4591***		
	(0.3834)	(0.7383)		
Degree2		-22.7237***		
		(5.1957)		
Net			0.0075***	0.0216***
			(0.0028)	(0.0052)
Net2				-0.0012***
				(0.0003)
Ln(asset)	-0.0633***	-0.0654***	-0.0636***	-0.0652***
	(0.0077)	(0.0078)	(0.0077)	(0.0078)
Leverage	0.2318***	0.2307***	0.2327***	0.2317***
	(0.0277)	(0.0277)	(0.0277)	(0.0278)
Percent_npw_lp	-0.0315	-0.0312	-0.0304	-0.0304
	(0.0471)	(0.0469)	(0.0470)	(0.0468)
Percent_npw_lc	-0.0687*	-0.0684*	-0.0685*	-0.0689*
	(0.0412)	(0.0411)	(0.0411)	(0.0409)
Percent_npw_sc	-0.0817*	-0.0794*	-0.0814*	-0.0806*
	(0.0462)	(0.0459)	(0.0461)	(0.0457)
HHI_geo	-0.0153	-0.0140	-0.0164	-0.0148
	(0.0187)	(0.0187)	(0.0187)	(0.0187)
HHI_line_npw	0.0738***	0.0790***	0.0732***	0.0762***
	(0.0261)	(0.0260)	(0.0261)	(0.0260)
Dummy_stock	-0.0282*	-0.0266*	-0.0286*	-0.0282*
	(0.0158)	(0.0159)	(0.0158)	(0.0159)
Dummy_group	0.0193*	0.0189	0.0194*	0.0186
	(0.0116)	(0.0116)	(0.0116)	(0.0116)
Dummy_reinsurer	0.0256	0.0243	0.0272	0.0262
	(0.0192)	(0.0193)	(0.0193)	(0.0192)
Observations	17,746	17,746	17,746	17,746
R-squared	0.091	0.093	0.091	0.092
Number of cocode	2,502	2,502	2,502	2,502
Adj R-squared	0.0898	0.0917	0.0898	0.0908
Chi2 Stat	288.65	286.72	285.86	284.22
Hausman p-value	0.0000	0.0000	0.0000	0.0000

Note: this table reports the regression results of a two-way fixed effects model to investigate the effect of an insurer's network position on its combined ratio. The clustered standard errors based on insurers are reported in parentheses. The last two rows report test statistics and p-values for the Hausman test for random effects vs. fixed effects. We omit the time dummy variables to save space. The symbol ***, **, * denote the statistical significance at the level of 0.01, 0.05 and 0.1, respectively. The dependent variable is *Combined Ratio* which is defined as the sum of the loss ratio and expense ratio. *Degree* is an insurer's normalized total degree; *Degree2* is the squared value of *Degree*; *Net* is the first principal component of degree centrality, eigenvalue centrality, betweenness centrality and the clustering coefficient; *Net2* is the squared value of *Net*; *Ln(asset)* is the natural logarithm of total admitted assets; *Leverage* is the total liabilities to total admitted assets; *HHI_geo* is the geographic Herfindahl index; *HHI_line_npw* is the business line Herfindahl index based on net premium written; *Percent_npw_lp*, *Percent_npw_sc*, *Percent_npw_lc* are the percentages of net premium written in long-tail personal lines, short-tail commercial lines and long-tail commercial lines, respectively; *Dummy_Stock* is equal to 1 if the firm is a stock insurer and 0 otherwise; *Dummy_Group* is equal to 1 if the firm is affiliated with an insurance group and 0 otherwise; *Dummy_Reinsurer* is equal to 1 if the insurer satisfies the A.M. Best definition of reinsurer and 0 otherwise.

The regression results also show that size is negatively related to the combined ratio, suggesting that larger insurers may enjoy economies of scale in risk diversification which can lead to better underwriting performance. There is a statistically significant, positive relationship between an insurer's leverage and combined ratio. Intuitively, an insurer with higher leverage faces higher insolvency risk, which can drive up transactions costs in acquiring new business in the primary market and lead to an increase in the expense ratio; in the meantime, the insurer with higher insolvency risk may have to reduce premiums in order to compete with other insurers in the market, resulting in an increase in its loss ratio. Moreover, stock insurers tend to have a better underwriting performance than mutual insurers, consistent with the fact that stock insurers have easier access to the capital markets which can lower their capital costs. We also find that the business line Herfindahl index is positively related to an insurer's combined ratio, i.e., an insurer with more concentrated business may incur higher costs and suffer larger losses. Lastly, it is interesting to note that the percentage of net premium written in long-tail personal, short-tail commercial and long-tail commercial lines are all negatively related with the combined ratio, with short-tail and long-tail commercial lines significant at the 10% level. This can be explained by the high level of losses associated with short-tail personal lines (the omitted category) which contains homeowners insurance; homeowners insurance is subject to catastrophe risk.

I then test Hypothesis H3 by regressing an insurer's performance measure (*RAROA* and *RAROE*) on the centrality measure. The results are presented in Table 8. The linear models show a statistically significant negative impact of an insurer's network position on its performance. In the non-linear models, the coefficient of *Degree* or *Net* is negative and that of the squared term is positive, and both are statistically significant at the 1% level. These coefficients indicate a U-shaped curve for an insurer's performance against its centrality in the reinsurance network. This result is consistent with the inverse U-shaped curve of the insurer's combined ratio reported in Table 6. Among other explanatory variables, an insurer's size and leverage are statistically significant in the performance models. That is, insurers with larger size and lower leverage ratios tend to have better performance. Moreover, the coefficient of *Dummy_reinsurer* is significantly negative in both the *RAROA* and *RAROE* regressions. This could possibly result from the fact that multiple catastrophic events occurred during the sample period which caused more volatile *ROA* (R*OE*) for reinsurers and thus lower *RAROA* (*RAROE*).

Table 8. The Effect Of Reinsurance Network Position On Performance

VARIABLES	(1) RAROA	(2) RAROA	(3) RAROA	(4) RAROA	(5) RAROE	(6) RAROE	(7) RAROE	(8) RAROE
Intercept	-10.8171***	-11.1354***	-11.13***	-11.6031***	-8.486***	-8.7317***	-8.743***	-9.1870***
	(2.0284)	(2.0357)	(2.042)	(2.0579)	(1.790)	(1.7971)	(1.802)	(1.8156)
Degree	-26.4176***	-62.3738***			-22.23***	-49.9733***		
	(6.0784)	(11.8631)			(5.552)	(10.9495)		
Degree2		319.0722***				246.1864***		
		(74.3718)				(68.3268)		
Net			-0.207***	-0.4372***			-0.172***	-0.3887***
			(0.0531)	(0.0957)			(0.0531)	(0.0868)
Net2				0.0189***				0.0179***
				(0.0049)				(0.0049)
Ln(asset)	0.8796***	0.9090***	0.886***	0.9118***	0.705***	0.7281***	0.710***	0.7346***
	(0.1103)	(0.1111)	(0.111)	(0.1116)	(0.0974)	(0.0981)	(0.0979)	(0.0986)
Leverage	-5.4906***	-5.4749***	-5.517***	-5.5015***	-4.531***	-4.5184***	-4.552***	-4.5381***
	(0.3507)	(0.3509)	(0.351)	(0.3508)	(0.319)	(0.3199)	(0.319)	(0.3205)
Percent_npw_lp	-0.9823	-0.9875	-1.014	-1.0136	-1.086*	-1.0904*	-1.113*	-1.1122*
	(0.7467)	(0.7470)	(0.748)	(0.7496)	(0.622)	(0.6227)	(0.623)	(0.6246)
Percent_npw_lc	0.2960	0.2915	0.285	0.2927	0.400	0.3964	0.390	0.3974
	(0.6351)	(0.6365)	(0.636)	(0.6385)	(0.545)	(0.5461)	(0.545)	(0.5472)
Percent_npw_sc	0.3667	0.3337	0.356	0.3444	0.393	0.3673	0.384	0.3728
	(0.6544)	(0.6554)	(0.655)	(0.6570)	(0.554)	(0.5559)	(0.555)	(0.5573)
HHI_geo	0.4032	0.3857	0.437	0.4103	0.307	0.2937	0.336	0.3108
	(0.3001)	(0.3003)	(0.299)	(0.2998)	(0.264)	(0.2642)	(0.264)	(0.2638)
HHI_line_npw	-0.2075	-0.2817	-0.187	-0.2373	-0.157	-0.2145	-0.140	-0.1867
	(0.3561)	(0.3568)	(0.357)	(0.3585)	(0.307)	(0.3079)	(0.307)	(0.3080)
Dummy_stock	0.3546	0.3325	0.367	0.3603	0.181	0.1642	0.192	0.1852
	(0.3207)	(0.3210)	(0.322)	(0.3230)	(0.240)	(0.2404)	(0.241)	(0.2424)
Dummy_group	-0.0629	-0.0564	-0.0671	-0.0539	0.0729	0.0778	0.0692	0.0817
	(0.1882)	(0.1880)	(0.188)	(0.1881)	(0.155)	(0.1547)	(0.155)	(0.1545)
Dummy_reinsurer	-0.9502***	-0.9322***	-0.998***	-0.9808***	-0.712***	-0.6979***	-0.752***	-0.7359***
	(0.2600)	(0.2601)	(0.261)	(0.2592)	(0.237)	(0.2374)	(0.238)	(0.2365)
Observations	17,746	17,746	17,746	17,746	17,746	17,746	17,746	17,746
R-squared	0.085	0.086	0.085	0.086	0.089	0.090	0.089	0.090
Number of cocode	2,502	2,502	2,502	2,502	2,502	2,502	2,502	2,502
Adj R-squared	0.0844	0.0853	0.0842	0.0849	0.0883	0.0891	0.0881	0.0890
Chi2 Stat	101.08	81.71	103.25	101.47	69.09	66.31	70.23	68.93
Hausman p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Note: The clustered standard errors based on insurers are reported in parentheses. The last two rows report test statistics and p-values for the Hausman test for random effects vs. fixed effects. Iomit the time dummy variables to save space. The symbol ***, **, * denote the statistical significance at the level of 0.01, 0.05 and 0.1, respectively.

1.6.3. Robustness Tests At The Group Level

Previous literature argue that affiliated insurers' reinsurance decisions may be coordinated at the group level (Cummins et al.,2008; Cummins, Feng and Weiss, 2012; Lin, Yu and Peterson, 2014). I therefore construct the reinsurance networks at the group level during our sample period. In the group-level reinsurance network, the nodes represent US P/C insurance groups, single non-affiliated US P/C insurers and their reinsurance counterparties, and the edges represent non-affiliated reinsurance counterparty relationships.[14] I find that the reinsurance networks at the group level exhibit similar properties to those at the firm level, i.e., the group-level reinsurance network is sparse with a low network density and the degree distributions follow a long-tailed distribution.

The analyses at the group level reveal some interesting facts that are not shown at the firm level. First, I find that US P/C insurance groups are highly connected at the group level. E.g., out of a total of 381 sampled insurance groups in 2011, 362 (141) insurance groups are connected in the largest WCC (SCC) of the network. Second, the dominant reinsurance counterparty relationships at the firm level are intra-group reinsurance transactions among US domestic affiliated insurers, which on average account for 70% of total reinsurance premiums ceded. At the group level, when the US domestic affiliated reinsurance transactions are eliminated, the reinsurance relationships between US P/C insurers and foreign reinsurers become important. I observe that US P/C insurers tend to utilize more reinsurance from foreign reinsurers during our sample

[14] I treat all affiliated insurers, both domestic and foreign, under the same insurance group as a single node. In this way, we remove all the intra-group reinsurance transactions at the group level.

period. E.g., the percentage of reinsurance premiums ceded to foreign reinsurers increased from 35% in 2000 to 60% in 2011. This increase is most likely due to the trend for US P/C insurers to utilize more reinsurance from their foreign affiliated reinsurers.[15] The percentage of reinsurance premiums ceded to foreign affiliated reinsurers to total reinsurance premiums ceded increased from 12% in 2000 to 37% in 2011. The increasing utilization of foreign affiliated reinsurance transactions could be driven by tax considerations.

Based on the reinsurance networks constructed at the group level, I calculate the network centrality measures for each insurer and run the regressions again to study the effect of an insurer's network position on its loss experience and performance. I find that the previous results still hold at the group level, i.e., there is an inverse U-shaped (U-shaped) relationship between an insurer's network position and its combined ratio (*RAROA* and *RAROE*).

1.7. Conclusions

In this study, I analyze the microstructure of the reinsurance network for US P/C insurers and investigate the impact of an insurer's reinsurance network position on its loss experience and firm performance. Using detailed reinsurance transaction data at the individual firm level, I perform network analysis for the US P/C reinsurance market and describe its basic characteristics. I further examine its stability under some market distress conditions and find that the US P/C reinsurance market is not subject to contagion risk.

---

[15] In reinsurance premium ceded flow analysis, we keep the foreign affiliated reinsurers for comparison purposes. When we calculate the network centrality measures to perform regression analysis at the group level, we eliminate foreign affiliated reinsurers.

This empirical analysis has important policy implications. Currently adopted conventional measures related to reinsurance, such as those proposed in IAIS (2013), may not be adequate to capture the complexity of the reinsurance market and interconnectedness among insurers through reinsurance transactions. In order to effectively address the issues relevant to contagion risk and financial stability from the regulator's perspective, the introduction of new regulatory measures based on new methodologies such as network analysis seems to be necessary. The results also shed light on an insurer's performance based on its network position. I find that there is an inverse U-shaped (U-shaped) relationship between an insurer's reinsurance network position and its combined ratio (*RAROA* and *RAROE*) due to the tradeoff between the benefits and costs associated with its network position.

As with all research, some limitations exist. For instance, the resilience tests on the reinsurance market are conducted based on relatively strict assumptions which might be quite different from real world conditions. Moreover, an important part of the reinsurance network is still missing due to the lack of the reinsurance transaction data among non-state regulated insurers, which could further increase the complexity of the reinsurance network. Therefore, my analysis can be viewed as preliminary and the results need to be interpreted with caution. This data limitation also calls for regulatory cooperation in information disclosure at an international level in order to effectively regulate the US reinsurance market.

CHAPTER 2

TAIL RISK SPILLOVER AND ITS CONTRIBUTION TO SYSTEMIC RISK: A NETWORK ANALYSIS FOR GLOBAL REINSURERS

2.1. Introduction

Over the last few years, network analysis has become increasingly popular in economics and finance research. Network analysis aims at representing the complex interactions within a large system as a graph and then using the graph to examine the properties of the system. Because network analysis can provide a rigorous way to analyze interactions, we have seen an increasing growth of the number of studies adopting this framework to investigate the relationship between interconnectedness and systemic risk. Examples include Billio et al. (2012), Hautsch, Schaumburg, and Schienle (2013) and Dungey, Luciani and Veredas (2014).

In the aftermath of the 2007-2008 financial crisis, systemic risk of financial institutions has gained much attention from both academia and policy makers. Among various systemic risk analytics that have been proposed, the Marginal Expected Shortfall (MES, Acharya et al., 2010), ΔCoVaR (Adrian and Brunnermeier, 2014), and SRISK (Acharya, Engle and Peterson, 2012) have been extensively used in empirical studies of systemic risk. One advantage of these metrics is that they can provide an indication of systemic risk at both the system level and an individual firm level when the market is in distress. However, it is arguable that these systemic risk measures might not fully capture the richness of the interconnectedness among financial institutions that could be of interest to regulatory authorities. For instance, these systemic risk indicators measure the interconnectedness in a bivariate manner, i.e., “interconnectedness” between each individual firm and the general market is analyzed, while the connectedness among individual firms with each other receiving little attention.

Financial risk propagation mechanisms can also be an important consideration for regulatory authorities. Ideally, in a financial system that is exposed to possible contagion risk, the firms that are the “creators” of the contagion risk, along with those who transfer the contagion risk, should receive more regulatory attention than that are the recipients (or victims) of the contagion risk. However, such “casual effect” cannot be directly captured by commonly-used systemic risk measures.

The objective of this study is threefold. First, we intend to construct a Granger-causal tail risk network among global reinsurers from the US, European and Asian-Pacific regions where the tail risk is measured by an individual reinsurer’s Value-at-Risk (VaR). Second, we aim at examining the topological property of the proposed downside risk networks, such as the interconnectedness of global reinsurers and possible contagion risk channels under adverse market conditions. Third, we investigate the contribution of an individual reinsurer’s tail network position to its systemic risk exposure.

We put our focus on global reinsurers for several reasons. First, as the insurance for insurers, reinsurance plays a fundamental role in the global risk transfer market. For instance, three hurricanes, Katrina, Rita, and Wilma (KRW), struck the US Gulf Coast in the fall of 2005. Among the total payments of 2005 KRW claims, the payments from US insurers only accounted for 41% while those from foreign reinsurers accounted for 59% , including 27% from Bermuda, 22% from Europe, and 10% from Lloyd’s of London. Without access to global reinsurance capacity, the claims arising from 2005 KRW would have fallen on US insurers (IAIS, 2012). Moreover, reinsurance contributes significantly to capital management of primary insurers by allowing risk transfer. Such a role can be vital to the operation of certain line of insurance business (Koijen and Yogo, 2013). Second, global diversification is a common strategy for global reinsurers to manage natural catastrophes, which could increase the connectedness among these reinsurers if they were exposed to the same event and also increase the systemic risk of global reinsurers as a whole. For instance, 26 out of the 40 most costly insured events since 1970 occurred between 2001 and 2013. Due to this distinct risk profile inherent in global reinsurers' operation, we are interested in answering the question: if natural catastrophes did increase the interconnectedness among global reinsurers and thus their systemic risk, should more regulatory attention/requirements be imposed on them because of the risks that they are dealing with? Third, previous studies of systemic risk (e.g., Weiss, Bierth and Felix, 2014) do not separate primary insurers from reinsurers, which might not be appropriate because primary insurers and reinsurers have different risk profiles and business models.

This study is related to the fast growing literature in financial network analysis. We extend the network analysis framework proposed in Billio et al. (2012) to examine the interconnectedness of global reinsurers due to extreme risk spillover where the extreme risk is measured by the VaR of their stock returns. In this way, we are able to investigate the dependence structure among global reinsurers under extremely adverse market conditions. This research is also related to the literature studying systemic risk in the insurance sector (IAIS, 2012; Chen et al., 2014; Weiss and Mühlnickel, 2013; Weiss, Bierth and Felix, 2014; and Dungey, Luciani and Veredas, 2014). Although a few studies have examined the drivers of systemic risk in the insurance industry, I find very limited empirical evidence on systemic risks of global reinsurers. It is not clear how their distinct risk profiles (i.e., exposures to natural catastrophes) affect their interconnectedness, and how contagion risk is transmitted among different regions. I aim at filling these gaps in this study.

2.2. Related Literature

2.2.1. Literature On The Financial Network

Network theory provides a general framework that enables us to study the various connections among financial institutions in a meaningful way. In a nutshell, network analysis represents a complex system as a graph which is a collection of nodes and edges (or links). Nodes can represent the financial institutions; edges can represent various types of connections among these financial institutions. Examples of connections include capital market risk (return or volatility connectedness), asset and liability risk (common exposures to certain classes of assets or liabilities), credit risk (default connectedness), and counterparty risk (bilateral and multilateral contractual connectedness). The properties of the graph and the characteristics of the nodes and edges can in turn be examined by a wide range of well-developed network measures.

In finance literature, Allen and Gale (2000) and Freixas, Parigi and Rochet (2000) first introduce the network analysis to study the risk diversification and the stability of banking system. Allen and Babus (2009) provide a general review of the application of network analysis in finance studies. Because network analysis can better explain certain economic phenomena by directly modeling the interactions among financial institutions, there is a fast growing number of literature that study the relationship between the connectedness and the systemic risk and the financial stability aftermath the recent US financial crisis. For instance, Chinazzi and Fagiolo (2013) and Bougheas and Kirman (2014) provide recent surveys of the studies on the complex financial network, the financial stability and the systemic risk.

The most common type of connectedness among financial institutions are the co-movements of the stock returns and volatilities (i.e. return spillover and volatility spillover), which will become more evident in the market downturn. These risk spillover effects can be modeled by different econometric methods, such as correlation (Huang, Zhu and Zhou, 2009; Brownlees and Engle, 2012; Dungey, Luciani and Veredas, 2014), principle component analysis (Billio et al., 2012), Granger causality (Billio et al., 2012), copula (Oh and Patton, 2014) and network-based model (Billio et al., 2012; Diebold and Yilmaz, 2013; Diebold and Yilmaz, 2014). Billio et al. (2012) first propose the construction of a financial network among various financial institutions using pairwise Granger-causality tests. A link between two financial institutions represents a statistically significant "Granger causal" effect between their stock returns. Specifically, Billio et al. (2012) use linear and nonlinear Granger-causality tests to capture the return and volatility spillover, respectively. They find that institutions from different financial sectors (banks, insurers, hedge funds and broker/dealer) have become increasingly connected with each other through a complex and time-varying network between 1994 and 2008. Moreover, their proposed Granger-causality network based measures have out-of-sample predictive power in identifying the institutions that were affected by the US financial crisis.

Volatility spillover has been examined extensively in the finance literature. Diebold and Yilmaz (2013) argue that volatility connectedness can be viewed as "fear connectedness" of market participants and that volatility is particularly crisis-sensitive.

They introduce a directed network based on H-step ahead forecast error variances using Generalized Variance Decomposition. Barigozzi and Brownlees (2014) propose a long-run partial correlation network that can capture the volatility spillover based on a two-step least absolute shrinkage and selection operator (LASSO) regression. Dungey, Luciani and Veredas (2014) construct a risk network based on correlations of the realized daily volatility estimated from high-frequency data for S&P 500 firms with a focus on the dynamics of the systemic risk of deposit-institutions and insurers.

Financial networks can also be constructed based on a downside risk measure, such as VaR or the spread of Credit Default Swaps (CDS), aiming to capture extreme risk spillover. Hautsch, Schaumburg and Schienle (2013) propose a conditional type VaR model in order to capture the individual firm's time-varying tail risk, conditional on other firms' performance within a system, firm characteristics, and macroeconomic variables. Mutual firm dependence is captured by the LASSO selection procedure. That is, there is a link between firm *i* and firm *j* if firm *j*'s VaR can have a statistically significant influence on firm *i*'s VaR and vice versa. In their empirical study with 57 US financial firms, they find that the main drivers of company-specific VaRs are the loss exceedances of other firms, while macroeconomic and firm characteristics often do not have a statistically significant influence. Billio et al. (2013) construct the Granger-causal network based on the spread of CDS to study the changes in sovereign risk of European countries and credit risk of major European, U.S., and Japanese banks, brokerages, and insurance companies between January 2001 and March 2012. They find that the system of financial institutions (banks and insurers) and countries is dynamically connected. The connections and the associated network measures may be useful to quantify the asset-liability mismatch within and across these financial institutions and countries.

2.2.2. Literature On The Insurance Industry

For the insurance industry, the general consensus among academic researchers and regulatory authorities is that traditional insurance operations do not result in systemic risk (IAIS, 2012; Cummins and Weiss, 2014). See also Eling and Pankoke (2014) for a comprehensive survey of these studies.

Weiss and Mühlnickel (2013) study the drivers of an insurer's systemic risk (measured by MES and ΔCoVaR) using a sample of 89 publicly listed US life and non-life insurers. They find that insurer size, ratio of investment income to net revenues, and non-policyholder liabilities before the crisis are positively associated with the probability of becoming severely exposed to systemic risk during the subprime crisis between July 2007 and December 2008. As to an insurer's contribution to systemic risk, they find that insurer size is the only relevant driver. They find no evidence to support the regulator's point of view that leverage, global diversification, and short-term funding increase an insurer's contribution to systemic risk. This study only focuses on the relationships between insurers' characteristics and systemic risk without taking into the interconnectedness among insurers.

In another study using a sample of 253 life and non-life insurers in the world between 2000 and 2012, Weiss, Bierth and Felix (2014) find that systemic risk in the international insurance sector is small compared to banks, but insurers did contribute to the instability of the financial system during the financial crisis. Interestingly, they find that an insurer's interconnectedness[16] and leverage have statistically significant predictive power on its exposure to systemic risk, but insurer size is not a fundamental driver of its contribution to systemic risk. The insurance sector, as a whole, predominantly suffers from being exposed to systemic risk rather than contributing to the financial system's fragility.

So far there are only a few studies addressing the interconnectedness of insures and its relation with systemic risk. Chen et al. (2014) examine the interconnectedness between US banks and insurers with linear and nonlinear Granger causality tests. They use the distress insurance premium proposed by Huang, Zhu and Zhou (2009) as a systemic risk measure and study 22 US banks and 11 US insurers between 2002 and 2008. They find that the impact of distress in banks on insurers is stronger and of longer duration than the impact of distress in insurers on banks after adjusting for heteroskedasticity. They also conduct stress testing and find that banks create significant systemic risk for insurers but not vice versa. Therefore, they suggest that US insurers are victims rather than propagators of systemic risk.

Dungey, Luciani and Veredas (2014) construct a risk network among S&P 500 firms using the correlation of realized daily volatility during the period 2003 - 2011, with a focus on banks and insurers[17]. Based on their network, they use the PageRank algorithm that take into account a firm's network position and other characteristics (size, leverage, and liquidity) to determine systemic risk of individual firms. They find that their

[16] They use the interconnectedness measure proposed in Billio et al. (2012), which is based on the principle component analysis on insurers' standardized stock returns.

[17] The sample in Dungey, Luciani and Veredas (2014) includes 20 insurance companies and 18 deposit-taking institutions, all of whom were recipients from TARP.

constructed systemic risk indices for the financial sector, banks and insurers declined after October 2008. However, the systemic risk index of insurers started to increase in 2010 and was higher than the financial sector as a whole and higher than for banks by December 2011, due to insurers' large exposure to the CDS market. In addition, they find that insurance companies are clustered immediately behind banks in the systemic threat posed to the economy. They suggest that the insurance sector displays substantial systemic risk via interconnectedness with the financial sector and the real economy.

Slijkerman, Schoenmaker, and De Viries (2013) study the systemic risk and risk diversification between European banks and insurers (10 largest banks and 10 largest insurers) during the period 1992 - 2003. Under the extreme value theory framework, they develop a non-parametric systemic risk measure that captures the downside dependence among banks and insurers. They empirically demonstrate that cross-sector dependences are usually lower than the dependences within the same sector, suggesting that banks and insurers may have different risk profiles. They also argue that by forming a cross-industry conglomerate each firm can benefit from risk diversification.

In this study, we focus on the tail risk (i.e. the left tail of the stock return distribution) spillover effect and its relationship to global reinsurers' systemic risk by extending Billio et al. (2012) and Chen et al. (2014). We would argue that tail risk connectedness may be more relevant and suitable for the examination of systemic risk, because systemic risk is a concept tied to the condition that the market is in distress state, and because the common return and volatility spillover measures fail to distinguish the market conditions. Moreover, although the systemic risk of insurance industry has been examined numerous studies (i.e. Archaya et al., 2012; Billio et al., 2012; Weiss and

Mühlnickel, 2013; Chen et al. 2014; Weiss, Bierth and Felix, 2014), there is little empirical study examine the connectedness and systemic risk in global reinsurance industry. Global reinsurers have distinct risk profiles that are different with these of banks and of primary insurers and thus deserve separate examinations.

2.3. Empirical Methodologies

In this section, we describe the method that we use to estimate global reinsurers' downside risk. We then discuss how to construct the tail risk network based on Granger causality tests and introduce some network-based measures for interconnectedness. We develop our hypotheses and specify regression models that test the relationship between interconnectedness and systemic risk of global reinsurers.

2.3.1. Estimation Of Downside Risk

Denote r_{it} the equity return for reinsurer *i* at time *t*. We measure the downside risk (i.e., the left tail of its equity return distribution) of a reinsurer by its Value-at-Risk (VaR) as

$$\Pr(r_{it} \leq -VaR_{it}^{\alpha}) = \alpha \tag{8}$$

where VaR_{it}^{α} is the α-quantile of r_{it}. Here we define VaR_{it}^{α} as a positive number which be interpreted as a loss position.

There are several approaches that we can use to estimate the VaR, including historical return simulations, simulations based on the standardized residuals of an ARMA-GARCH models, and the method based on the extreme value theory and quantile regressions. See Kuester, Mittnik, and Paolella (2006) for a survey. In this study, we choose the standard ARMA-GARCH models to estimate a reinsurer's VaR based on its daily stock returns. We choose AR(1) and GJR-GARCH (1,1,1) (Glosten, Jagannathan and Runkle,1993) as the conditional mean model and the conditional volatility model, respectively, i.e.,

$$
\begin{aligned}
r_{it} &= \phi_{0i} + \phi_{1i} r_{i,t-1} + \sigma_{it}\varepsilon_{it} \\
\sigma_{it}^2 &= \omega_i + \beta_i \sigma_{i,t-1}^2 + \alpha_i \varepsilon_{i,t-1}^2 + \gamma_i \varepsilon_{i,t-1}^2 1_{[\varepsilon_{i,t-1} \le 0]}, \varepsilon_{it} \sim F(\varepsilon_i)
\end{aligned} \tag{9}
$$

where ε_{it} and $F(\varepsilon_i)$ denote the standardized innovation and its cumulative probability density function (CDF) respectively; $1_{[\varepsilon_{i,t-1} \le 0]}$ is an indicator function, which equals 1 when the innovation $\varepsilon_{i,t-1}$ is negative and 0 otherwise. This term captures the leverage effect, i.e., a negative shock usually causes a higher volatility than does a positive one. To choose an appropriate distribution for standard innovations, we compare the Gaussian distribution with some heavy-tailed distributions - the Student-t distribution and the Skewed t distribution (Hansen, 1994) - using the Bayesian Information Criterion (BIC). After we estimate the AR(1)-GJR-GARCH(1,1,1) model for a reinsurer, its VaR at a level of α is then approximated by

$$
-VaR_{it}^{\alpha} = \hat{\mu}_{it} + \hat{\sigma}_{it} F_{\varepsilon_i}^{-1}(\alpha) \tag{10}
$$

where $\hat{\mu}_{it}$ and $\hat{\sigma}_{it}$ denote the estimated conditional mean and conditional volatility at time *t* respectively; $F_{\varepsilon_i}^{-1}(\bullet)$ denotes the inverse CDF of the standard innovation. We measure an individual reinsurer's VaR at the level of $\alpha = 5\%$.

Similarly, we can also estimate the VaR for the market, i.e.,

$$
\begin{aligned}
r_{m,t} &= \sigma_{m,t}\varepsilon_{m,t} \\
\sigma_{mt}^2 &= \omega_m + \beta_m \sigma_{m,t-1}^2 + \alpha_m \varepsilon_{m,t-1}^2 + \gamma_m \varepsilon_{m,t-1}^2 1_{[\varepsilon_{m,t-1} \le 0]}
\end{aligned} \tag{11}
$$

and,

$$
-VaR_{mt}^{\alpha} = \hat{\mu}_{mt} + \hat{\sigma}_{mt} F_m^{-1}(\alpha) \tag{12}
$$

where $\hat{\mu}_{mt}$ and $\hat{\sigma}_{mt}$ denote the estimated conditional mean and conditional volatility of the market return at time *t* respectively; $F_m^{-1}(\bullet)$ is the inverse CDF of the standard innovation of the market index return. Here we choose Skewed t distribution as the distribution of the standard innovation of the market index return based on the BIC.

In order to evaluate the accuracy of the VaR estimation method, we perform the back testing on the estimated VaR for each individual reinsurers and the market return, using the unconditional coverage test, the independence test and the conditional coverage test (Christoffersen, 1998). The overall VaR back testing results confirm the validity of our VaR estimation method.[18]

2.3.2. Construction Of The Tail Risk Networks

Granger causality defined by Granger (1969) is inferred when the lagged values of a variable y_t^1 have explanatory power on another variable y_t^2 (Greene, 2005). Specifically, let y_t^1 and y_t^2 be two stationary time series. Granger causality can be tested with the following vector autoregression (VAR) models:

$$\begin{aligned} y_t^1 &= a_0 + a_1 y_{t-1}^1 + ... + a_p y_{t-p}^1 + b_1 y_{t-1}^2 + ... + b_p y_{t-p}^2 + e_t^1 \\ y_t^2 &= c_0 + c_1 y_{t-1}^2 + ... + c_p y_{t-p}^2 + d_1 y_{t-1}^1 + ... + d_p y_{t-p}^1 + e_t^2 \end{aligned} \tag{13}$$

where e_t^1 and e_t^2 are uncorrelated White noise processes, $a_i, c_i (i = 0, ..., p)$, $b_j, d_j (j = 1, ..., p)$ are the coefficients of the model, and p is the lag number. Time series y_t^2 Granger-causes y_t^1 if we can reject the null hypothesis $H_0 : b_1 = ... = b_p = 0$. Similarly,

---

[18] The estimated VaR for the market return is not rejected by all three tests. For the estimated individual reinsurer's VaR, only one reinsurer (out of twenty sampled reinsurers) is rejected by the conditional coverage test at a statistical significance level of 1%. I also compare the VaRs estimated using ARMA-GJR-GACH approach with those estimated by the CAViaR model proposed by Engle and Manganelli (2004). The results are quite similar.

the test of $H_0 : d_1 = ... = d_p = 0$, against $H_A : Not\ H_0$ will determine if y_t^1 Granger-causes y_t^2 or not.

Given the estimated individual reinsurer's VaR, we apply the pair-wise Granger-causality test to detect the direction of tail risk spillover. In order to control for the change in general market conditions, I augment the VAR model in equation (14) by including lagged market tail risk measures,

$$\begin{aligned} VaR_{it}^{\alpha} &= a_0 + \sum_{k=1}^{p} a_k VaR_{i,t-k}^{\alpha} + \sum_{l=1}^{q} b_l VaR_{j,t-l}^{\alpha} + \sum_{s=1}^{n} g_l VaR_{m,t-s}^{\alpha} + e_{it} \\ VaR_{jt}^{\alpha} &= c_0 + \sum_{k=1}^{p} c_k VaR_{j,t-k}^{\alpha} + \sum_{l=1}^{q} d_l VaR_{i,t-l}^{\alpha} + \sum_{s=1}^{n} h_l VaR_{m,t-s}^{\alpha} + e_{jt} \end{aligned} \tag{14}$$

The null hypothesis that reinsurer *j*'s tail risk will not Granger cause reinsurer *i*'s tail risk is thus formulated as $H_0 : b_1 = ... = b_q = 0$, which can be tested using the standard Wald statistics. Following Billio et al. (2012), we select the optimal lags in equation (14) using the BIC.

The tail risk network is represented by a binary adjacency matrix A. Define the indicator of causality for a pre-specified statistical significance level as

$$A_{(j,i)} = (j \rightarrow i) = \begin{cases} 1, & \text{if j Granger causes i} \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

where $A_{(j,i)}$ denotes the input for the element (j, i) in the adjacency matrix. For sure, the pre-specified significance level affects the number of edges (i.e., Granger causal relationships): a larger value of the pre-specified significance level will lead to more edges in the tail risk network, and vice versa.

Our Granger-causal tail risk network is constructed at daily levels. At date t, for each possible pair of sampled reinsurers, we first determine the optimal lags for the VAR model specified in equation (14) with a rolling window length of 250 trading days (i.e., about one year). Specifically, we test different VAR models by setting $p = q = n = 1$ up to 10 lags and choose the optimal VAR model associated with the minimum BIC.[19] We then perform the Granger-causality tests based on the optimal VAR model. The tail risk network is then represented as a binary adjacency matrix, denoted by A_t, in which the edges (the direction of causality) are determined at a pre-specified statistical significance level $\alpha = 0.05$. Our sample period is from January 1, 1999 to December 31, 2013 with 3,912 trading days. We begin to construct the daily tail risk network on December 20, 1999 and end up having 3,662 daily tail risk networks.

2.3.3. Network-based Measures For Interconnectedness

The interconnectedness of the tail risk network can be measured by a wide range of well-developed network statistics. Denote A as the binary adjacency matrix and *N* as the number of reinsurers within the network, we define some interconnectedness measures as follows.

(1) *Network Density* represents the number of statistically significant Granger-causality relationships among all possible 2*N(N-1)* pairs of connections for *N* reinsurers:

$$Density = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} A_{(i,j)}}{2N(N-1)} \tag{16}$$

(2) *Degree* counts the number of connections that each reinsurer $i = 1, ..., N$ has formed with other reinsurers within the network. Moreover, the *out-degree* counts the number of edges that a reinsurer points to all other reinsurers; the *in-degree* counts the number of

[19] We make this choice to reduce the computational cost. In this way, we compare 10 VAR models for each pair of reinsurers for each trading day. Taking all possible pairs of reinsurers into account, we evaluate 20,90 (=190x11) VAR models for each trading day.

edges that point to a reinsurer from all other reinsurers.

$$\begin{aligned}
\#out_i &= \sum_{j=1}^{N} A_{(i,j)} \Big/ (N-1) \\
\#in_i &= \sum_{j=1}^{N} A_{(j,i)} \Big/ (N-1) \\
\#total_i &= \#out_i + \#in_i
\end{aligned} \tag{17}$$

Degree measures only take into account a reinsurer's direct linkages formed with other reinsurers and can thus be viewed as "local" measures of a reinsurer's network position. (3) *Eigenvector centrality* measures the importance of a reinsurer in a network by assigning a score based on how connected it is to the rest of the network. Eigenvector centrality is calculated as the eigenvector *v* of the adjacency matrix associated with the largest eigenvalue, i.e.,

$$\lambda v = Av \tag{18}$$

where λ is the eigenvalue, and v is the corresponding eigenvector. Unlike degree centrality, eigenvector centrality takes into account both the direct and indirect connections formed with other reinsurers, and thus could be viewed as a "global" measure of a reinsurer's network position.

2.3.4. Regression Models

To gauge a reinsurer's systemic risk, we use Marginal Expected Shortfall (MES, Archaya, Engle and Richardson 2012), ΔCoVaR (Adrian and Brunnermeier, 2014) and modified ΔCoVaR (Girardi and Ergün, 2013). We adopt the firm-fixed effect regression model to examine the relationship between interconnectedness of a reinsurer in the network and its systemic risk,

$$SR_{i,t} = \alpha + \beta Net_{i,t} + \gamma X_{i,t} + v_i + \varepsilon_{i,t} \tag{19}$$

where $SR_{i,t}$ is the systemic risk measure of reinsurers *i* at time *t*, $Net_{i,t}$ measures reinsurer *i*'s interconnectedness in the tail risk network at time *t* (either degree or eigenvector centrality), $X_{i,t}$ is the vector of economic state variables, and v_i represents the firm fixed effect for insurer *i*.

Following Adrian and Brunnermeier (2014), we include the following economic state variables: (1) yield spread between 10-year and 3-month US treasury bonds; (2) the relative change in the VIX index calculated by the Chicago Board Options Exchange; (3) the US real estate sector return proxied by the Willshire US Real Estate Securities Total Market Index.[20] Additionally, we include the daily return and volatility of the DataStream Insurance Sector Index to control for insurance industry specific shocks. We also include the estimated daily network density as the state variable that measures the overall connectedness of these global reinsurers as a whole.

It is shown in the literature that connectivity might have some threshold effect on the stability of a financial system (Acemogulu, Ozdaglar and Tahbaz-Salehi, 2013). That is, below a certain threshold, interconnectedness could increase the stability of a financial system via risk diversification; however, a further increase in connectivity above that threshold could cause financial instability via channeling and amplifying exogenous shocks through the system. In order to examine whether such a threshold effect exists in our tail risk network, we adopt the following regression model:

$$SR_{it} = \alpha + \beta_1 Net_{it} + \beta_2 Net_{it} I(D_t \geq D_q) + \beta X_t + v_i + e_{it} \tag{20}$$

[20] Because there are Europe-based reinsurers in our sample, we also examine the explanatory power of variables that are related to European stock market, such as return of EuroStoxx 600 and volatility index VStoxx. We find that these variables do not add much explanatory power to the regression models. We therefore do not include them in the following regression analysis.

where $I(D_t \geq D_q)$ is an indicator function that equals to 1 if the tail risk network density at time *t* is below its q-th percentile and 0 otherwise. In equation (20), the coefficient β_1 ($\beta_1 + \beta_2$) captures the effect of reinsurer *i*'s network connectedness on its systemic risk if the tail network density is below (above) the threshold D_q. In our baseline threshold regression model, we set q=50, i.e., we use the median of the daily tail risk network density as the threshold. We consider other threshold values in the robustness tests.

2.4. Sample Data

In order to identify global reinsurers, we rely on the reinsurers listed in the A.M. Best Global Reinsurer Index (AMBGR). Originally, the AMBGR index contains 36 global reinsurers. After eliminating the reinsurers listed after January 1, 1999, our sample consists of 10 US reinsurers, 7 European reinsurers, and 3 reinsurers from the Asia-Pacific region.[21] Table 8 provides the company name, country domicile and stock tickers for the sample reinsurers. Our relative small sample size is due to the fact that the reinsurance market is a rather concentrated international market. The reinsurance market concentration measured by premiums ceded to the top 10 reinsurers to total reinsurance premiums ceded for non-life and life businesses between 2000 and 2010 is 50% and 90%, respectively (IAIS, 2012). The global reinsurers included in our sample represent 73% of the reinsurance market in terms of net reinsurance premiums written (Standard & Poor's 2013).[22]

---

[21] I treat the firms that are not domiciled in US but listed on the stock exchanges in the US as the US reinsurers.

[22] Specifically, our sample includes 9 out of the top 10 largest global reinsurers except for Lloyd's London in 2012.

Table 9. Company Information Of Sampled Global Reinsurers

Company Name	Ticker	Country	Region
Korean Reinsurance Co. Ltd.	003690.KS	Korea	Asia-Pacific
QBE Insurance Group Ltd.	QBE.AX	Australia	Asia-Pacific
Singapore Reinsurance Corp. Ltd.	T:REIN	Singapore	Asia-Pacific
Aegon N.V.	H:AGN	Netherland	Europe
Amlin PLC	AML.L	Great Britain	Europe
Hannover Rueckversicherungs AG	D:HNR1	Germany	Europe
Mapfre S.A.	E:MAP	Spain	Europe
Muenchener Rueckversicherungs-Gesellschaft AG	D:MUV2	Germany	Europe
Scor S.E.	F:SCO	France	Europe
Swiss Reinsurance Co.	RUKN.VX	Switzerland	Europe
Arch Capital Group Ltd.	ACGL	Bermuda	US
Argo Group International Holdings Ltd.	AGII	United States	US
Berkshire Hathaway Inc.	BRK-A	United States	US
Everest Re Group Ltd.	RE	United States	US
PartnerRe Ltd.	PRE	United States	US
Reinsurance Group of America Inc.	RGA-A	United States	US
RenaissanceRe Holdings Ltd.	RNR	United States	US
W.R. Berkley Corp.	WRB	United States	US
White Mountains Insurance Group Ltd.	WTM	United States	US
XL Group PLC	XL	United States	US

Note: (1) the ticker in the second column is extracted from DataStream; (2) the fourth column reports our area classification for sampled reinsurers. We classify Arch Capital Group as US, because it is listed on NASDAQ.

Our sample period is between January 1, 1999 and December 31, 2013 with 3,912 trading days. We obtain the sampled reinsurers' historical stock price data from Thomson DataStream. To avoid potential bias, we use the stock prices reported in US dollars (see also White, Kim and Manganelli, 2013; Weiss, Bierth and Felix, 2014) to calculate reinsurers' daily stock returns. In order to calculate the systemic risk measures for reinsurers, we choose the DataStream Insurance index as the benchmark index for the market. Table 9 provides definitions for systemic risk measures, network-based measures for interconnectedness and data sources for economic state variables used in the regression analysis.

Table 10. Variable Definitions

Variables	Definition	Data Source
MES	Marginal Expected Shortfall, calculated as in Brownlees and Engle (2011), conditional on the return of the DataStream Insurance Index.	DataStream, Own calculation
Δ CoVaR	Calculated as in Adrian and Brunneimier (2014) by assuming bivariate Normal distribution between market return and individual return, where the conditional correlation is estimated using DCC model (Engle 2002).	DataStream, Own calculation
Modified Δ CoVaR	Calculated as in Girardi and Ergün (2013) by assuming bi-variate Gaussian distribution between market return and individual return, where the conditional correlation is estimated using DCC model (Engle 2002).	DataStream, Own calculation
Netdens	Daily tail risk network density	Own calculation
totaldeg	A reinsurer's total degree in constructed daily tail risk network.	Own calculation
eigcen	A reinsurer's eigenvector centrality in constructed daily tail risk network	Own calculation
mkt_ret	Market return where market is proxied by DataStream Insurance Index	DataStream Own calculation
mkt_vol	Estimated market return volatility where market return is proxied by the return of the DataStream Insurance Index	DataStream Own calculation
yield	Yield spread between interest rate of 10-year US treasury bond ant 3-month US treasury bond	FRED, Fed Reserve of St. Louis
VIX_chg	Relative change of VIX index as computed by the Chicago Board Options Exchange	CRSP, own calculation
usre_ret	Relative change of Willshire US Real Estate Securities Total Market Index	FRED, Fed Reserve of St. Louis

2.5. Empirical Results

I begin our analysis with the overall connectedness of our constructed tail risk network measured by the network density. Figure 6 provides the comparison between the density of the tail risk network and an equally-weighted return index[23] for the sampled global reinsurers. The mean (median) of the daily tail network density is around 0.28

[23] I choose the equally-weighted index in order to avoid the potential distortion caused by the heterogeneous market capitalizations of sampled reinsurers. For instance, Berkshire Hathaway accounted for 44.3% of total market capitalization of 20 sampled global reinsurers on December 31, 2013.

(0.25). That is, on average only 28% of all possible edges, or Granger causal relationships that are statistically significant at 5% level, are found in the tail risk network over the entire sample period. In addition, the degree of interconnectedness among global reinsurers varies over time. Because global reinsurers are exposed to natural catastrophes which could be a driving force of reinsurers' short-run tail risk dependence, we also add reference lines that represent the top 5 events in terms of insured losses (Swiss Re, 2014).[24]

Interestingly, the highest network density appeared immediately after the attack on the World Trade Center in 2001. The tail risk network density increased to 0.35 and remained at a relatively high level until it reached its peak (0.72) at the end of August 2002. Hurricanes Katrina, Rita and Wilma (KRW) did not seem to affect the interconnectedness of global reinsurers at all, while the other three big insured loss events (Hurricane Ike, Japan tsunami, and Hurricane Sandy) occurred during the time period of the global financial crises (for example, 2007-2009 US financial crisis, 2011 US debt-ceiling crisis,[25] and 2010-2012 European sovereign debt crisis) so their effects were hard to tell. During this period, the network density increased to some extent but not comparable to the degree caused by the 9/11 attack. One possible reason is that the 9/11 terrorism attack in 2001, as an unprecedented loss event for the reinsurance industry,[26]

[24] The top 5 most costly insured loss events during our sample period are 2005 Hurricane Katrina (80.3 billion USD) , 2011 Japan tsunami (37.7 billion USD), 2012 Hurricane Sandy (36.9 billion USD), 2001 terrorism attack on WTC(25.7 billion USD) and 2008 Hurricane Ike (22.8 billion USD) (Swiss Re, 2014).

[25] Standard & Poor's downgraded the US federal government credit-rating from AAA to AA+ on August 5, 2011.

[26] Note that the 2001 9/11 terrorism attack also caused significant impact on the US stock market. On September 17 2001 when the US stock market reopened, the Dow Jones Industrial Average dropped by 7.13%, and the CRSP valued-weighted index dropped by 5.27%.

greatly changed reinsurers' loss expectations and resulted in a high level of risk contagion. In contrast, during the period of the US financial crisis or the European debt crisis, global reinsurers did not play as a pivotal role as banks, thus the degree of tail risk spillover was increased by a relatively small percentage only.

Next, I examine the role of global reinsurers in the tail risk network based on their domicile regions. We first measure the contribution of reinsurers in each region (US, European and Asia-Pacific) as the percentage of edges formed by each region to the total number of edges in the tail risk network. Figure 7 (Panel A) shows that US reinsurers contribute most to tail risk spillovers, accounting for 50% of total edges formed in the tail risk network, followed by the European reinsurers taking up 36% of edges. Asia-Pacific reinsurers on average only contribute 14% of edges in the tail risk network. When we look into the change in contributions over time, European reinsurers contributed more to the tail risk spillover (about 50%) than US reinsurers (about 40%) in the post-World Trade Center attack period. This could be due to the fact that European reinsurers as a group played a more important role in the global reinsurance market in terms of reinsurance premiums assumed.

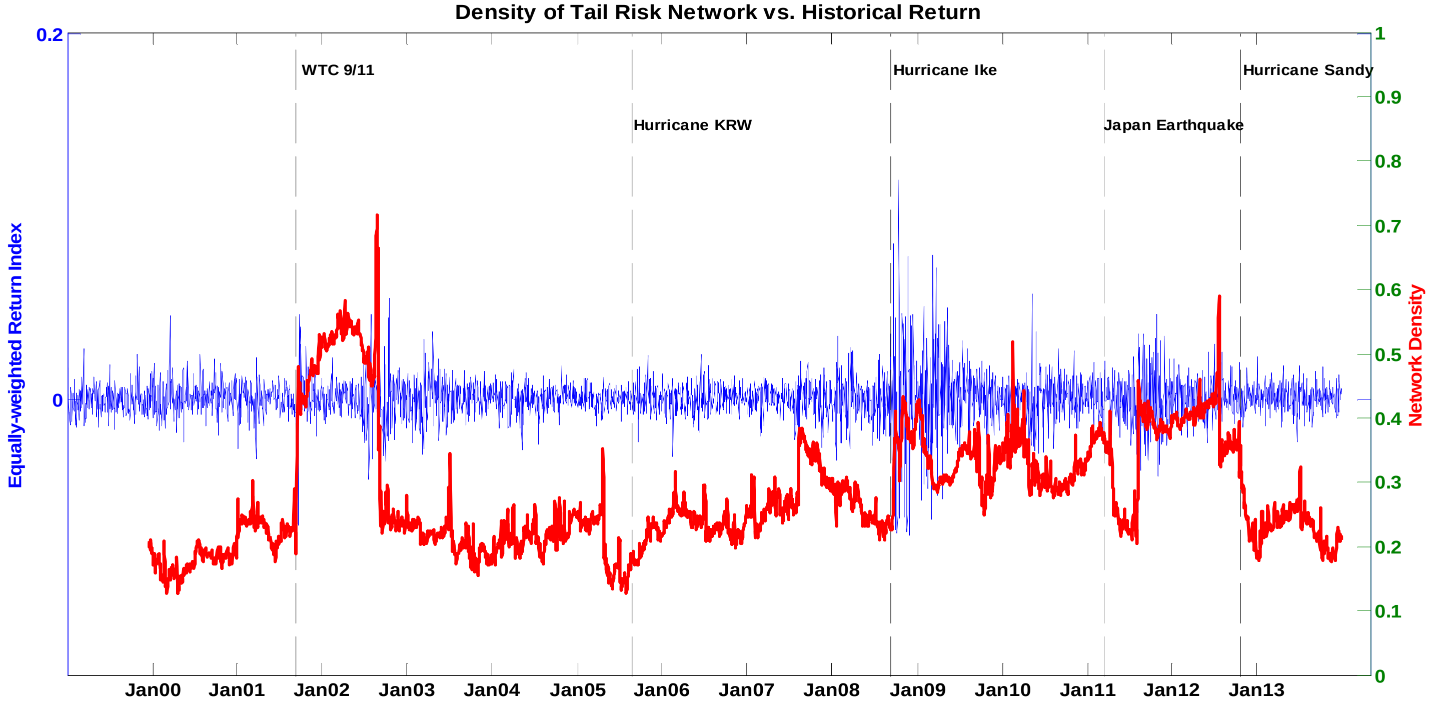

Figure 6. Tail Risk Network Density And Equally-weighted Return

Note: this figure provides the density of the tail risk network of global reinsurers. The left y-axis provides the equally weighted return index of sampled global reinsurers (blue line). The right y-axis provides the density (red line) of the Granger-causality network. The edges in tail risk network are determined by Granger-causal relationships that are statistically significant level at 5% based reinsurers' VaR with loss exceedence level of 5%. We also add the top 5 most costly natural catastrophes (Swiss Re 2014) during the sample period.

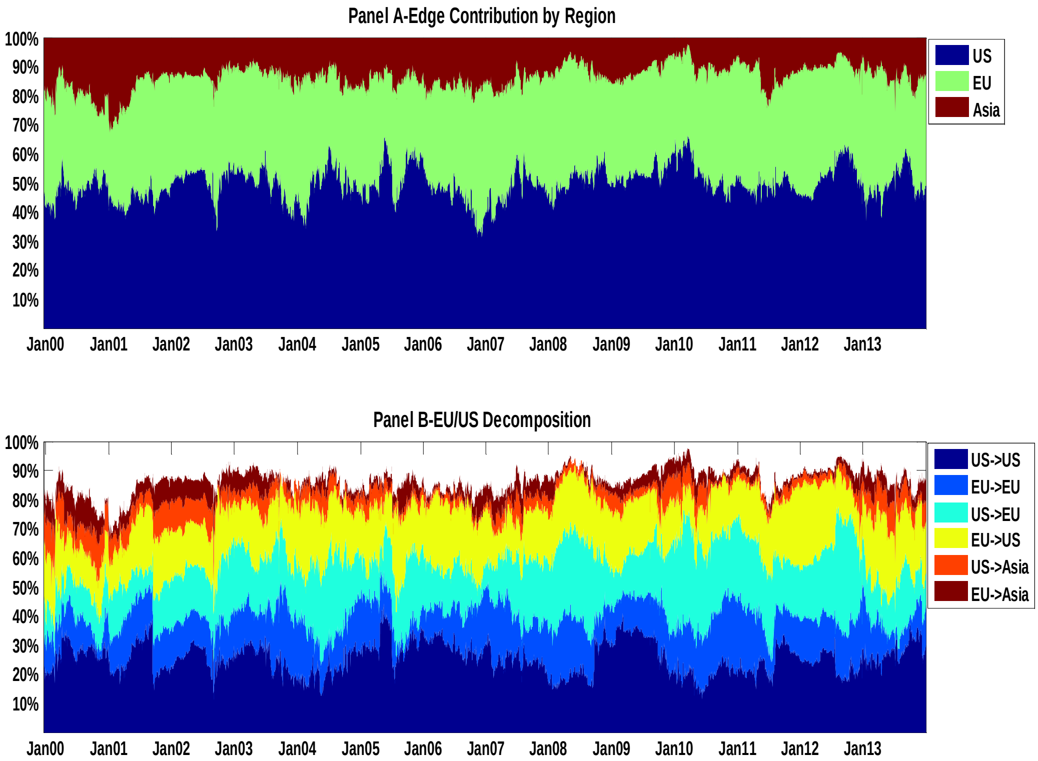

Figure 7. Edge Contributions To Tail Risk Network

Note: (1) this figure provides the edge contributions by each region (US,EU and Asia-Pacific); (2) for each region, we calculate the total number out-edges pointed to reinsures within the same region and to reinsurers within the other two regions, then normalized by the total number of edges in the tail risk network; (3) the sample period is from December 20,1999 to December 31, 2011.

To further explore the interconnectedness in the tail risk network contributed by US-based and Europe-based reinsurers, we decompose the outgoing edges formed by reinsurers in these two regions as (1) US-to-US (i.e. US reinsurer granger causes US reinsurer); (2) EU-to-EU; (3) US-to-EU; (4) EU-to-US; (5) US-to-Asia and (6) EU-to-Asia. Figure 7 Panel B shows that the average contribution of 'US-to-US' and 'EU-to-EU' are 26% and 14% respectively, suggesting that US reinsurers are more likely to connect with each other. The average contributions of 'US-to-EU' and 'EU-to-US' are

19% and 18% respectively, suggesting that European reinsurers are more likely to connected with US reinsurer than connecting with each other. Moreover, the combined average contribution between US and EU (i.e. 'US-to-EU'+ 'EU-to-US') equals 37%, which is comparable the combined average contribution within US and within EU (i.e. 'US-to-US'+ 'EU-to-EU') of 39%. Lastly, the average contribution of 'US-to-Asia' and 'EU-to-Asia' are 5% and 4% respectively. The above results reveal that US and European reinsurers play dominant roles in the tail risk network and that there is a relatively strong cross-region tail risk spillover between EU and US reinsurers.

I now examine the systemic risk measures for global reinsurers during our sample period of 1999-2013. Figure 8 provides a comparison of historical market returns, proxied by the return of the DataStream Insurance Index, and the average estimated daily MES, ΔCoVaR and modified ΔCoVaR across our sampled reinsurers. Figure 8 Panel A shows that historical market returns experienced significantly clustered volatility during the US financial crisis, followed by another volatile period in the second half of 2011 and the first half of 2012, which is possibly due to the European sovereign debt crisis. Consistently, all three systemic risk measures demonstrate sharp increases (in absolute values) during these market downturn periods. The highest peak of the systemic risk measures appeared between 2008 and 2009 which may be due to the 2007-2009 US financial crises. Second highest peak appears to happen between 2011 and 2012, which may be due to the Euro zone debt crisis. We also observe that these systemic risk measures are also active between 2002 and 2003 with larger humps than these in 2001, which may be due to the credit market deterioration (Huang, Zhu and Zhou, 2009). However, economy-wide shocks (such as the US financial crisis) apparently caused higher levels of systemic risk to the global reinsurance industry than insurance industry shocks (such as the 9/11 attack). This is because systemic risk measures are driven by the bivariate correlation between the market distress and firm distress. The stock market as a whole absorbed the insurance industry shock quickly after 9/11, but was heavily affected by the financial crises.

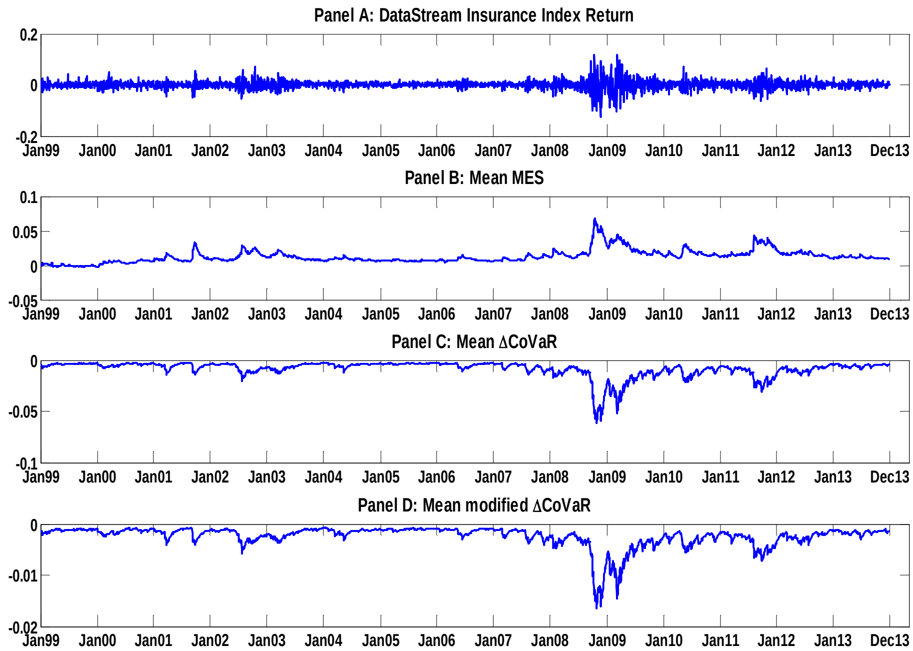

Figure 8. Plots For Market Return And Estimated Systemic Risk Measures

Table 11 provides the summary statistics of reinsurers' tail risk interconnectedness (measured by total degree and eigenvector centrality) and the estimated systemic risk measures (Table 11 Panel A), along with the daily tail risk network density and economy state variables (Table 11 Panel B). Table 12 reports the linear correlation matrix among these variables. At the individual firm level, we can see that a high level of tail risk measures is associated with a higher level of systemic risk. For instance, reinsurers' total degree ('totaldeg') and eigenvector centrality ('eigcen') are positively correlated with MES, and negatively correlated with ΔCoVaR and modified ΔCoVaR, and is statistically significant at the 1% level. In addition, the measures of tail risk spillovers are positively correlated with the insurance sector market return volatility ('mkt_vol') and yield spread between US 10-year and 3-month Treasury bonds ('yield'). Similarly, a higher level of the daily tail risk network density ('netdens') is associated with a higher level of reinsurers' systemic risk. For instance, the linear correlation coefficient between the daily tail risk network density and reinsurer's MES is 0.21, and is statistically significant at the 1% level.

Table 11. Summary Statistics

Variable	**N**	**Mean**	**Std Dev**	**p5**	**Median**	**p95**
Panel A: firm level systemic risk measure and tail risk network position						
mes	73240	0.0208	0.0199	0.0036	0.0157	0.0541
covar	73240	-0.0058	0.0050	-0.0148	-0.0046	-0.0012
mcovar	73240	-0.0017	0.0013	-0.0040	-0.0014	-0.0004
totaldeg	73240	0.2810	0.1434	0.0789	0.2632	0.5526
eigcen	73240	0.2125	0.0697	0.0871	0.2186	0.3152
indeg	73240	0.2810	0.1989	0.0526	0.2632	0.6842
outdeg	73240	0.2810	0.1576	0.0526	0.2632	0.5790
Panel B: tail risk network density and economic state variables						
netdens	3662	0.2810	0.0930	0.1711	0.2474	0.4737
mkt_ret	3662	0.0000	0.0155	-0.0229	0.0006	0.0214
mkt_vol	3662	0.0002	0.0005	0.0000	0.0001	0.0007
yield	3662	0.0183	0.0129	-0.0035	0.0206	0.0352
vix_chg	3662	-0.0001	0.0622	-0.0902	-0.0023	0.1040
usre_ret	3662	0.0004	0.0199	-0.0246	0.0000	0.0232

Note: this table reports the summary statistics for the variables used in our regression analysis. Our sample period for the construction of daily tail risk network is between December 20, 1999 and December 31, 2013 with 3,662 trading days. In Panel A, we report the summary statistics economic state variables and tail risk network density. In Panel B, we report the summary statistics for the estimated daily systemic risk measures and tail risk network position measures for sampled reinsurers.

Table 12. Correlation Matrix

	totaldeg	eigcen	netdens	mes	covar	mcovar	mkt_ret	mkt_vol	yield	vix_chg	usre_ret
totaldeg	1										
eigcen	0.6849										
	(0.0000)	1									
netdens	0.6489	0.0434									
	(0.0000)	(0.0000)	1								
mes	0.1841	0.0725	0.2103								
	(0.0000)	(0.0000)	(0.0000)	1							
covar	-0.2778	-0.1122	-0.3233	-0.7607							
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	1						
mcovar	-0.2632	-0.0949	-0.3270	-0.7091	0.9730						
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	1					
mkt_ret	-0.0191	-0.0008	-0.0295	-0.0202	0.0319	0.0352					
	(0.0000)	(0.8254)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	1				
mkt_vol	0.1561	0.0143	0.2406	0.5489	-0.7366	-0.7962	-0.0074				
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0457)	1			
yield	0.2247	0.0129	0.3462	0.1631	-0.2203	-0.2273	-0.0042	0.1914			
	(0.0000)	(0.0005)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2522)	(0.0000)	1		
vix_chg	-0.0023	0.0002	-0.0035	-0.0212	0.0435	0.0471	-0.5102	-0.0393	-0.0126		
	(0.5378)	(0.9527)	(0.3424)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0007)	1	
usre_ret	-0.0060	-0.0007	-0.0092	-0.0110	0.0042	0.0049	0.5381	0.0154	0.0065	-0.4889	
	(0.1062)	(0.8573)	(0.0128)	(0.0003)	(0.2549)	(0.1887)	(0.0000)	(0.0000)	(0.0805)	(0.0000)	1

Note: this table reports the Person correlation coefficients among the tail risk network density (‘netdens’), the individual reinsurer’s network position measured by total degree (‘totaldeg’) and eigenvector centrality (‘eigcen’), the estimated individual reinsurer’s systemic risk measured by MES (‘mes’), ΔCoVaR(‘covar’) and modified ΔCoVaR(‘mcovar’), and economic state variables. We report the p-values for Person correlation coefficients in parenthesis.

We formally examine the contribution of a reinsurer's tail risk network position to its systemic risk using regression analysis. Table 13 reports the results for the firm-fixed effect regression models which regress a reinsurer's MES on its connectivity measures. Model (1) and (4) in Table 13 are our baseline models where the only explanatory variable is a reinsurer's tail risk network position measured by its total degree ('totaldeg') or eigenvector centrality ('eigcen'). In model (1), the coefficient on total degree is positive and statistically significant at the 1% level, suggesting that an increase in a reinsurer's direct connections with other reinsurers will lead to an increase in its MES. The adjusted R^2 for model (1) is about 26.9%. Similarly, we observe a positive and statistically significant relationship between a reinsurer's eigenvector centrality and its MES with an adjusted R^2 of 24.7% in model (5), implying that an increase in a reinsurer's direct and indirect connections with other reinsurers will lead to an increase in its MES. When we include the daily tail risk network density and other economic state variables into our regression models, this positive relationship between interconnectedness and MES remains unchanged and statistically significant at the 1% level. Particularly, the coefficients of daily tail risk network density are positive and statistically significant at the 1% in model (1) to (8), suggesting that a high level of tail risk spillover among all reinsurers is associated with a higher level of systemic risk as measured by MES. We also find that the insurance sector return ('mkt_ret'), the change of VIX ('vix_chg') and the US real estate sector performance ('usre_ret') are negatively related to MES while the volatility of the insurance sector return ('mkr_ret') and the yield spread ('yield') positively contribute to MES.

Table 13. Firm-Fixed Effect Regression Model Between Tail Risk Network Position And MES

VARIABLES	(1) mes	(2) mes	(3) mes	(4) mes	(5) mes	(6) mes	(7) mes	(8) mes
Intercept	0.0238***	0.0166***	0.0189***	0.0187***	0.0281***	0.0160***	0.0185***	0.0182***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0004)	(0.0004)	(0.0003)	(0.0003)
totaldeg	0.0218***	0.0018**	0.0018***	0.0018***				
	(0.0006)	(0.0007)	(0.0006)	(0.0006)				
eigcen					0.0056***	0.0026***	0.0019***	0.0019***
					(0.0009)	(0.0009)	(0.0007)	(0.0007)
netdens		0.0433***	0.0160***	0.0133***		0.0450***	0.0177***	0.0150***
		(0.0010)	(0.0008)	(0.0008)		(0.0008)	(0.0006)	(0.0006)
mkt_ret			-0.0179***	-0.0143			-0.0179***	-0.0143
			(0.0069)	(0.0089)			(0.0069)	(0.0089)
mkt_vol			22.7048***	22.5055***			22.7036***	22.5042***
			(0.3530)	(0.3531)			(0.3531)	(0.3531)
yield				0.0590***				0.0590***
				(0.0033)				(0.0033)
vix_chg				-0.0049***				-0.0049***
				(0.0012)				(0.0012)
usre_ret				-0.0203***				-0.0203***
				(0.0074)				(0.0074)
Observations	73,240	73,240	73,240	73,240	73,240	73,240	73,240	73,240
R-squared	0.270	0.292	0.555	0.557	0.248	0.292	0.555	0.557
Adj R-squared	0.269	0.291	0.555	0.557	0.247	0.291	0.555	0.557

Note: this table reports the firm-fixed effect regression model between individual reinsurer' tail risk network position and its systemic risk. The dependent variable is reinsurers' estimated MES. The main independent variables are reinsurers' tail risk network positions as measured by its total degree ('totaldeg') and eigenvector centrality ('eigcen'). The other independent variables are economy state variables including the return of DataStream Insurance Index ('mkt_ret'), the estimated conditional volatility of DataStream Insurance Index return ('mkt_vol'), yield spread between US 10-year and 3-month Treasury bond ('yield'), the relative change of VIX index ('VIX_chg') and the US real estate sector return proxied by Willshire US Real Estate Securities Total Market Index ('usre_ret'). We omit the firm dummy variables to conserve space. We report the robust standard errors in parenthesis and mark the regression coefficients that are statistically significant at the level of 0.01, 0.05 and 0.1 as ***, ** and * respectively.

Table 14 and Table 15 report the regression results using ΔCoVaR and modified ΔCoVaR as the dependent variable, respectively. Unlike the case of MES where a higher positive value indicates a higher exposure to systemic risk, a lower ΔCoVaR or modified ΔCoVaR means a higher contribution to systemic risk. In general, the results in Table 14 and 15 are consistent with those reported in Table 13. That is, a higher degree of interconnectedness is associated with a higher level contribution to systemic risk. For instance, in Table 14 where the dependent variable is a reinsurer's ΔCoVaR, the coefficient of total degree (or eigenvector centrality) is negative and statistically significant at the 1% level across all models. Similar results can be found in Table 15 where we use the modified ΔCoVaR as the measure of the contribution to systemic risk.

Table 14. Firm-Fixed Effect Regression Model Between Tail Risk Network Position And ΔCoVaR

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
VARIABLES	**covar**	**covar**	**covar**	**covar**	**covar**	**covar**	**covar**	**covar**
Intercept	-0.0050***	-0.0022***	-0.0030***	-0.0029***	-0.0064***	-0.0017***	-0.0026***	-0.0025***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
totaldeg	-0.0086***	-0.0009***	-0.0009***	-0.0009***				
	(0.0001)	(0.0002)	(0.0001)	(0.0001)				
eigcen					-0.0034***	-0.0022***	-0.0020***	-0.0020***
					(0.0002)	(0.0002)	(0.0001)	(0.0001)
netdens		-0.0166***	-0.0074***	-0.0067***		-0.0174***	-0.0083***	-0.0076***
		(0.0003)	(0.0002)	(0.0002)		(0.0002)	(0.0001)	(0.0001)
mkt_ret			0.0072***	0.0114***			0.0072***	0.0114***
			(0.0013)	(0.0016)			(0.0013)	(0.0016)
mkt_vol			-7.5901***	-7.5281***			-7.5889***	-7.5267***
			(0.0665)	(0.0664)			(0.0665)	(0.0664)
yield				-0.0147***				-0.0148***
				(0.0007)				(0.0007)
vix_chg				0.0033***				0.0033***
				(0.0003)				(0.0003)
usre_ret				0.0037***				0.0037***
				(0.0013)				(0.0013)
Observations	73,240	73,240	73,240	73,240	73,240	73,240	73,240	73,240
R-squared	0.169	0.219	0.680	0.682	0.116	0.219	0.680	0.683
Adj R-squared	0.168	0.219	0.680	0.682	0.116	0.219	0.680	0.683

Note: this table reports the firm-fixed effect regression model between individual reinsurer' tail risk network position and its systemic risk. The dependent variable is reinsurers' estimated ΔCoVaR. The main independent variables are reinsurers' tail risk network positions as measured by its total degree ('totaldeg') and eigenvector centrality ('eigcen'). The other independent variables are tail risk network state variable ('netdens') economy state variables including the return of DataStream Insurance Index ('mkt_ret'), the estimated conditional volatility of DataStream Insurance Index return ('mkt_vol'), yield spread between US 10-year and 3-month Treasury bond ('yield'), the relative change of VIX index ('VIX_chg') and the US real estate sector return proxied by Willshire US Real Estate Securities Total Market Index ('usre_ret'). We omit the firm dummy variables to conserve space. We report the robust standard errors in parenthesis and mark the regression coefficients that are statistically significant at the level of 0.01, 0.05 and 0.1 as ***, ** and * respectively.

Table 15. Firm-Fixed Effect Regression Model between Tail Risk Network Position And Modified ΔCoVaR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**mcovar**	**mcovar**	**mcovar**	**mcovar**	**mcovar**	**mcovar**	**mcovar**	**mcovar**
Intercept	-0.0014***	-0.0007***	-0.0009***	-0.0009***	-0.0018***	-0.0006***	-0.0008***	-0.0008***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
totaldeg	-0.0021***	-0.0001**	-0.0001***	-0.0001***				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
eigcen					-0.0008***	-0.0005***	-0.0004***	-0.0004***
					(0.0001)	(0.0001)	(0.0000)	(0.0000)
netdens		-0.0043***	-0.0018***	-0.0017***		-0.0044***	-0.0019***	-0.0018***
		(0.0001)	(0.0000)	(0.0000)		(0.0001)	(0.0000)	(0.0000)
mkt_ret			0.0021***	0.0033***			0.0021***	0.0033***
			(0.0003)	(0.0004)			(0.0003)	(0.0004)
mkt_vol			-2.0807***	-2.0651***			-2.0805***	-2.0648***
			(0.0142)	(0.0141)			(0.0142)	(0.0142)
yield				-0.0036***				-0.0036***
				(0.0002)				(0.0002)
vix_chg				0.0009***				0.0009***
				(0.0001)				(0.0001)
usre_ret				0.0010***				0.0010***
				(0.0003)				(0.0003)
Observations	73,240	73,240	73,240	73,240	73,240	73,240	73,240	73,240
R-squared	0.120	0.175	0.722	0.724	0.069	0.175	0.722	0.724
Adj R-squared	0.120	0.174	0.722	0.724	0.0687	0.175	0.722	0.724

Note: this table reports the firm-fixed effect regression model between individual reinsurer' tail risk network position and its systemic risk. The dependent variable is reinsurers' estimated modified ΔCoVaR ('mcovar'). The main independent variables are reinsurers' tail risk network positions as measured by its total degree ('totaldeg') and eigenvector centrality ('eigcen'). The other independent variables are economy state variables including the return of DataStream Insurance Index ('mkt_ret'), the estimated conditional volatility of DataStream Insurance Index return ('mkt_vol'), yield spread between US 10-year and 3-month Treasury bond ('yield'), the relative change of VIX index ('VIX_chg') and the US real estate sector return proxied by Willshire US Real Estate Securities Total Market Index ('usre_ret'). We omit the firm dummy variables to conserve space. We report the robust standard errors in parenthesis and mark the regression coefficients that are statistically significant at the level of 0.01, 0.05 and 0.1 as ***, ** and * respectively.

The logical designs of the systemic risk measures are usually different with each other. MES is defined as a financial institution's expected equity loss under the condition that the market is in distress state. An institution that is more affected by the market thus has a higher MES. In contrast, the ΔCoVaR and modified ΔCoVaR are defined as the difference of the CoVaRs, i.e. the market's VaRs conditioned on an institution being distress and normal respectively. These two measures measure an institution's systemic risk by its impact to the market. By design our daily tail risk networks are directed networks, i.e., a link represents directional causal relationship between two reinsurers. This property enables us to better examine the effect of tail risk spillover to a reinsurer's exposure to systemic risk (i.e., MES) or its contribution to systemic risk (ΔCoVaR and modified ΔCoVaR) by choosing more appropriate measures of interconnectedness. For MES, we consider a reinsurer's in-degree would be a better proxy of the market's effect on its expected loss rather than its total degree. With respect to ΔCoVaR and modified ΔCoVaR, a reinsurer's impact to the market can be better measured by its out-degree. We then examine the explanatory powers of these refined tail risk network measures tailored to different systemic risk measures. Table 16 reports the firm-fixed effect regression results using in-degree (out-degree) as the explanatory variable when the dependent variable is MES (ΔCoVaR or modified ΔCoVaR). Model (1) and (2) suggest that a high value of a reinsurer's in-degree, i.e., more exposed to tail risk spillovers, is associated with a high level of MES. We also find that a reinsurer with a higher out-degree, i.e., the one "Granger" cause more tail risk spillovers to others, has a higher level of ΔCoVaR (model 3-4 in Table 16) and modified ΔCoVaR (model 5-6 in Table 16).

Table 16. Regression Results Of Tail Risk Network Position And Exposure /Contribution To Reinsurer's Systemic Risk

VARIABLES	(1) mes	(2) mes	(3) Covar	(4) covar	(5) mcovar	(6) mcovar
Intercept	0.0264***	0.0188***	-0.0052***	-0.0029***	-0.0014***	-0.0009***
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0000)	(0.0000)
indeg	0.0007***	0.0002***				
	(0.0000)	(0.0000)				
outdeg			-0.0003***	-0.0000***	-0.0001***	-0.0000***
			(0.0000)	(0.0000)	(0.0000)	(0.0000)
netdens		0.0119***		-0.0074***		-0.0017***
		(0.0007)		(0.0002)		(0.0000)
mkt_ret		-0.0143		0.0114***		0.0033***
		(0.0089)		(0.0016)		(0.0004)
mkt_vol		22.5055***		-7.5281***		-2.0651***
		(0.3520)		(0.0664)		(0.0142)
yield		0.0590***		-0.0147***		-0.0036***
		(0.0033)		(0.0007)		(0.0002)
vix_chg		-0.0049***		0.0033***		0.0009***
		(0.0012)		(0.0003)		(0.0001)
usre_ret		-0.0203***		0.0037***		0.0010***
		(0.0073)		(0.0013)		(0.0003)
Observations	73,240	73,240	73,240	73,240	73,240	73,240
R-squared	0.263	0.557	0.154	0.682	0.109	0.724
Adj R-squared	0.263	0.557	0.154	0.682	0.109	0.724

Note: this table reports the firm-fixed effect regression model between individual reinsurer' tail risk network position and its systemic risk. In model (1) and (2), the dependent variable is estimated reinsurers' MES ('mes') as a measure of reinsurer's exposure to systemic risk; the independent variable is reinsurer's in-degree ('indeg') in tail risk network as a measure of exposure to tail risk spillover. In model (3)-(6), the dependent variables are ΔCoVaR and modified ΔCoVaR respectively as measure of reinsurer's contribution to systemic risk; the independent variable is reinsurer's out-degree ('outdeg') as a measure of contribution to tail risk spillover. The other independent variables are economy state variables including the return of DataStream Insurance Index ('mkt_ret'), the estimated conditional volatility of DataStream Insurance Index return ('mkt_vol'), yield spread between US 10-year and 3-month Treasury bond ('yield'), the relative change of VIX index ('VIX_chg') and the US real estate sector return proxied by Willshire US Real Estate Securities Total Market Index ('usre_ret'). We omit the firm dummy variables to conserve space. We report the robust standard errors in parenthesis and mark the regression coefficients that are statistically significant at the level of 0.01, 0.05 and 0.1 as ***, ** and * respectively.

Lastly, we turn to the question of whether there exists a threshold effect of interconnectedness on systemic risk. Table 17 reports the panel regression results between a reinsurer's network position and its MES. Particularly, in addition to total degree (or eigenvector centrality), we include the interaction term between total degree (or eigenvector centrality) and an indication function using the median network density as the threshold. In model (1)-(3) of Table 17, the coefficients of total degree are all negative while the coefficients on the interaction terms are all positive with larger magnitudes. Therefore, when the daily network density is below its median, an increase in total degree will result in a decrease in MES due to the effect of risk diversification; when the network density is above its median, a higher interconnectedness among reinsurers can propagate the spread of systemic risk. This observed threshold effect is robust when we use eigenvector centrality as an alternative measure of interconnectedness, as shown in model (4)-(8) in Table 17, and when we use ΔCoVaR and modified ΔCoVaR to measure systemic risk contribution, as shown in Table 18 and Table 19.

We perform other robustness tests on the observed threshold effect. First, we change the threshold level to different percentiles of the daily network density. We find that such a threshold effect exists when the threshold changes from the 20th percentile to the 60th percentile of the daily network density. Second, we examine the threshold effect in a sub-sample period between September 30 2002 and December 31 2013, removing the impact of the 9/11 attack. We find the threshold effect still holds.

Table 17. Threshold Regression Models Between Tail Risk Network Position And MES

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**mes**	**mes**	**mes**	**mes**	**Mes**	**mes**	**mes**	**mes**
Intercept	0.0279***	0.0231***	0.0205***	0.0203***	0.0276***	0.0226***	0.0206***	0.0204***
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)
totaldeg	-0.0109***	-0.0112***	-0.0013**	-0.0014**				
	(0.0007)	(0.0007)	(0.0006)	(0.0006)				
totaldeg_nd50	0.0271***	0.0192***	0.0045***	0.0047***				
	(0.0005)	(0.0007)	(0.0005)	(0.0005)				
eigcen					-0.0117***	-0.0081***	-0.0016**	-0.0017**
					(0.0009)	(0.0008)	(0.0007)	(0.0007)
eigcen_nd50					0.0411***	0.0295***	0.0097***	0.0101***
					(0.0006)	(0.0008)	(0.0006)	(0.0006)
netdens		0.0215***	0.0110***	0.0080***		0.0192***	0.0094***	0.0064***
		(0.0014)	(0.0011)	(0.0011)		(0.0010)	(0.0008)	(0.0008)
mkt_ret			-0.0184***	-0.0152*			-0.0188***	-0.0161*
			(0.0069)	(0.0089)			(0.0069)	(0.0089)
mkt_vol			22.5862***	22.3756***			22.4554***	22.2377***
			(0.3536)	(0.3537)			(0.3544)	(0.3546)
yield				0.0603***				0.0616***
				(0.0033)				(0.0033)
vix_chg				-0.0049***				-0.0050***
				(0.0012)				(0.0012)
usre_ret				-0.0198***				-0.0193***
				(0.0074)				(0.0074)
Observations	73,240	73,240	73,240	73,240	73,240	73,240	73,240	73,240
R-squared	0.296	0.299	0.556	0.557	0.301	0.304	0.557	0.558
Adj R-squared	0.296	0.299	0.556	0.557	0.300	0.304	0.556	0.558

Note: this table reports the threshold regression model between individual reinsurer' tail risk network position and its systemic risk controlled for firm-fixed effect. The dependent variable is reinsurers' estimated MES ('MES'). The main independent variables are (1) reinsurers' tail risk network positions as measured by its total degree ('totaldeg') and eigenvector centrality ('eigcen'); (2) the interaction terms (i.e. 'totaldeg_nd50', 'eigcen_nd50') between reinsurer's network positions and an indicator function that equals 1 when the tail risk network density is above its 50^{th} percentile and 0 otherwise. The other independent variables includes the return of DataStream Insurance Index ('mkt_ret'), the estimated conditional volatility of DataStream Insurance Index return ('mkt_vol'), yield spread between US 10-year and 3-month Treasury bond ('yield'), the relative change of VIX index ('VIX_chg') and the US real estate sector return proxied by Willshire US Real Estate Securities Total Market Index ('usre_ret'). We omit the firm dummy variables to conserve space. We report the robust standard errors in parenthesis and mark the regression coefficients that are statistically significant at the level of 0.01, 0.05 and 0.1 as ***, ** and * respectively.

Table 18. Threshold Regression Models Between Tail Risk Network Position And ΔCoVaR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**covar**	**covar**	**covar**	**covar**	**Covar**	**covar**	**covar**	**covar**
Intercept	-0.0067***	-0.0053***	-0.0045***	-0.0044***	-0.0062***	-0.0047***	-0.0041***	-0.0040***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
totaldeg	0.0052***	0.0053***	0.0020***	0.0021***				
	(0.0002)	(0.0002)	(0.0001)	(0.0001)				
totaldeg_nd50	-0.0115***	-0.0092***	-0.0044***	-0.0044***				
	(0.0001)	(0.0002)	(0.0001)	(0.0001)				
eigcen					0.0037***	0.0026***	0.0005***	0.0005***
					(0.0002)	(0.0002)	(0.0001)	(0.0001)
eigcen_nd50					-0.0169***	-0.0134***	-0.0069***	-0.0070***
					(0.0001)	(0.0002)	(0.0001)	(0.0001)
netdens		-0.0061***	-0.0026***	-0.0018***		-0.0057***	-0.0025***	-0.0017***
		(0.0004)	(0.0002)	(0.0002)		(0.0003)	(0.0002)	(0.0002)
mkt_ret			0.0078***	0.0123***			0.0079***	0.0127***
			(0.0013)	(0.0016)			(0.0013)	(0.0016)
mkt_vol			-7.4743***	-7.4056***			-7.4140***	-7.3422***
			(0.0669)	(0.0669)			(0.0673)	(0.0673)
yield				-0.0160***				-0.0166***
				(0.0007)				(0.0007)
vix_chg				0.0033***				0.0033***
				(0.0003)				(0.0003)
usre_ret				0.0033***				0.0030**
				(0.0013)				(0.0013)
Observations	73,240	73,240	73,240	73,240	73,240	73,240	73,240	73,240
R-squared	0.243	0.247	0.686	0.689	0.255	0.261	0.691	0.694
Adj R-squared	0.242	0.246	0.686	0.689	0.255	0.260	0.691	0.694

Note: this table reports the results of the firm-fixed effect threshold regression model between individual reinsurer' tail risk network position and its systemic risk. The dependent variable is estimated ΔCoVaR ('covar'). The main independent variables are (1) reinsurers' tail risk network positions as measured by total degree ('totaldeg') and eigenvector centrality ('eigcen'); (2) the interaction terms (i.e. 'totaldeg_nd50', 'eigcen_nd50') between network positions and an indicator function that equals 1 when the tail risk network density is above its 50^{th} percentile and 0 otherwise. The other independent variables include the return of DataStream Insurance Index ('mkt_ret'), the estimated conditional volatility of DataStream Insurance Index return ('mkt_vol'), yield spread between US 10-year and 3-month Treasury bond ('yield'), the relative change of VIX index ('VIX_chg') and the US real estate sector return proxied by Willshire US Real Estate Securities Total Market Index ('usre_ret'). The firm dummy variables are omitted to conserve space. We report the robust standard errors in parenthesis and mark the regression coefficients that are statistically significant at the level of 0.01, 0.05 and 0.1 as ***, ** and * respectively.

Table 19. Threshold Regression Models Between Tail Risk Network Position And Modified ΔCoVaR

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	**mcovar**	**mcovar**	**mcovar**	**mcovar**	**Mcovar**	**mcovar**	**mcovar**	**mcovar**
Intercept	-0.0018***	-0.0014***	-0.0012***	-0.0012***	-0.0017***	-0.0013***	-0.0011***	-0.0011***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
totaldeg	0.0013***	0.0014***	0.0005***	0.0005***				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
totaldeg_nd50	-0.0029***	-0.0022***	-0.0009***	-0.0009***				
	(0.0000)	(0.0000)	(0.0000)	(0.0000)				
eigcen					0.0010***	0.0007***	0.0001***	0.0001***
					(0.0001)	(0.0001)	(0.0000)	(0.0000)
eigcen_nd50					-0.0042***	-0.0032***	-0.0014***	-0.0014***
					(0.0000)	(0.0001)	(0.0000)	(0.0000)
netdens		-0.0018***	-0.0009***	-0.0007***		-0.0016***	-0.0007***	-0.0005***
		(0.0001)	(0.0001)	(0.0001)		(0.0001)	(0.0000)	(0.0000)
mkt_ret			0.0022***	0.0034***			0.0022***	0.0035***
			(0.0003)	(0.0004)			(0.0003)	(0.0004)
mkt_vol			-2.0580***	-2.0410***			-2.0444***	-2.0266***
			(0.0143)	(0.0142)			(0.0143)	(0.0143)
yield				-0.0038***				-0.0040***
				(0.0002)				(0.0002)
vix_chg				0.0009***				0.0009***
				(0.0001)				(0.0001)
usre_ret				0.0009***				0.0009***
				(0.0003)				(0.0003)
Observations	73,240	73,240	73,240	73,240	73,240	73,240	73,240	73,240
R-squared	0.193	0.199	0.725	0.728	0.206	0.213	0.729	0.732
Adj R-squared	0.193	0.199	0.725	0.728	0.206	0.212	0.729	0.732

Note: this table reports the threshold regression model between individual reinsurer' tail risk network position and its systemic risk controlled for firm-fixed effect. The dependent variable is reinsurers' estimated modified ΔCoVaR ('mcovar'). The main independent variables are (1) reinsurers' tail risk network positions as measured by its total degree ('totaldeg') and eigenvector centrality ('eigcen'); (2) the interaction terms (i.e. 'totaldeg_nd50', 'eigcen_nd50') between reinsurer's network positions and an indicator function that equals 1 when the tail risk network density is above its 50^{th} percentile and 0 otherwise. The other independent variables are economy state variables including the return of DataStream Insurance Index ('mkt_ret'), the estimated conditional volatility of DataStream Insurance Index return ('mkt_vol'), yield spread between US 10-year and 3-month Treasury bond ('yield'), the relative change of VIX index ('VIX_chg') and the US real estate sector return proxied by Willshire US Real Estate Securities Total Market Index ('usre_ret'). We omit the firm dummy variables to conserve space. We report the robust standard errors in parenthesis and mark the regression coefficients that are statistically significant at the level of 0.01, 0.05 and 0.1 as ***, ** and * respectively.

2.6. Conclusions

Based on the concept of Granger causality of tail risks, we construct the short-run tail risk network among a group of global reinsurers and examine tail risk spillover and its effect on global reinsurers' systemic risk between 1999 and 2013. Our main results show that the tail risk spillover among global reinsurers is time-varying and appears to be driven both by reinsurance industry shocks (such as the 2001 terror attack on the World Trade Center) and by economy-wide shocks (such as the US financial crisis and the European sovereign debt crisis). Interestingly, the unprecedented reinsurance industry-wide shock seems to create a larger effect on the tail risk spillover than do economy-wide shocks.

Through examining the tail risk Granger-causal relationships, we also find that the detected Granger causal tail risk relationships differ by reinsurers' domicile region. For instance, US reinsurers tend to be more connected with each other and European reinsurers tend to more connected with US reinsurers, while Asia-Pacific reinsurers do not play a very important role in the tail risk network. More importantly, we also find evidence of the significant tail risk spillover between US and European reinsurers. These findings could be explained by reinsurers' market share in the global reinsurance market. For instance, European reinsurers in general have a larger market share in terms of reinsurance premiums assumed than US and Asia-Pacific reinsurers. And European and US reinsurers as a whole are dominant in the reinsurance market.

The panel regression analysis results first reveal that tail risk spillover among global reinsurers contributes to their systemic risk. We also find that Granger-causality based tail risk network can offer finer risk spillover measures among global reinsurers.

Moreover, the network measures have sizeable explanatory power to reinsurer's exposure and contribution to systemic risk. More importantly, we also provide the first empirical evidence that there exists threshold effect of tail risk connectedness to reinsurer's systemic risk.

Our empirical results have at least two policy implications. First, we provide new empirical evidence that complement recent studies on the reinsurance and financial stability (e.g., IAIS, 2012). That is, the short-run tail risk connectedness among global reinsurers is more likely driven by specific reinsurance industry-wide shocks. One source of increasing tail risk connectedness among global reinsurers could be similar loss exposures that they face through reinsurance operations and global risk diversification. From the regulatory point of view, it would be appropriate for the insurance regulator to focus more on the solutions for the "next-big" one (such as cyber risk) for the reinsurance industry instead of penalizing risk diversification due to the concern of financial contagion. After all, global reinsurers have survived the 2001 World Trade Center attack and other major insurance loss events. Secondly, even though the tail risk connectedness does contribute to a reinsurer's systemic risk, it appears that economy-wide shocks contribute more significantly than insurance industry shocks. Insurance regulators should focus on the regulation of inter-industry contagion channels, such as non-core activities of insurers to enhance the financial stability of the reinsurance industry.

REFERENCE CITED

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi, 2013, "Systemic Risk and Stability in Financial Networks," Working Paper No. 18727, National Bureau of Economic Research,Cambridge, MA.

Acharya, V. V., L. H. Pedersen, T. Philippon, and M. Richardson, 2010, "Measuring Systemic Risk," working paper, Federal Reserve Bank of Cleveland, Cleveland, OH.

Acharya, V. V., R. F. Engle, and M. Richardson, 2012, "Capital shortfall: A New Approach to Ranking and Regulating Systemic Risks," *American Economic Review: Papers & Proceedings*, 102: 59-64.

Adrian, T. and M. Brunnermeier, 2014, "CoVaR," Staff Reports, No.348, Federal Reserve Bank of New York, New York.

Ahern, K. R. and J. Harford, 2014, "The importance of Industry Links in Merger Waves," *Journal of Finance*, forthcoming.

Allen, F. and A. Babus, 2009, "Networks in finance," in P, Kleindorfer and J. Wind (Eds.), *Network-based Strategies and Competencies*, 367-382, Philadelphia, Wharton School Publishing.

Allen, F. and D. Gale, 2000, "Financial contagion," *Journal of Political Economy*, 108: 1-33.

Barigozzi, M. and C. Brownlees, 2014, "Nets: Network Estimation for Time Series," working paper, available at SSRN: http://ssrn.com/abstract=2249909.

Battiston, S., D.D. Gatti, M. Gallegati, B. Greenwald, and J. Stiglitz, 2009, "Liaisons Dangereuses: Increasing Connectivity, Risk Sharing, and Systemic Risk," Working paper No. 15611, National Bureau of Economic Research, Cambridge, MA.

Battiston, S., D.D. Gatti, M. Gallegati, B. Greenwald, and J. Stiglitz, 2012, "Default cascades: When does risk diversification increase stability?" *Journal of Financial Stability*, 8: 138-149.

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

Billio, M., M. Getmansky, D. Gray and A. W. Lo, 2013, "Sovereign, Bank and Insurance

Credit Spreads: Connectedness and System Networks," Working paper, MIT.

Bisias, D., M. Flood, A. W. Lo and S. Valavanis, 2012, "A Survey of Systemic Risk Analytics," *Annual Review of Financial Economics*, 4: 255-296.

Brownlees, T. C. and R. F. Engle, 2012, "SRISK: A Conditional Capital Shortfall Index for Systemic Risk Measurement," working paper, available at SSRN: http://ssrn.com/abstract=1611229.

Borgatti, S. P. and M.G. Everett, 1999, "Models of Core/Periphery Structures," *Social Networks*, 21: 375-395.

Bougheas, S. and A. Kirman, 2014, "Complex Financial Networks and Systemic Risk: A Review," CESifo Working Paper Series, No. 4756, available at SSRN: http://ssrn.com/abstract=2436826.

Burt, R., 1992, *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press.

Chen, H., J. D. Cummins, K. S. Viswanathan and M. A. Weiss, 2014, "Systemic Risk and the Interconnectedness between Banks and Insurers: An Econometric Analysis," *Journal of Risk and Insurance*, 81: 623-652.

Chinazzi, M. and G. Fagiolo, 2013, "Systemic Risk, Contagion, and Financial Networks: A Survey," available at SSRN: http://ssrn.com/abstract=2243504.

Christoffersen, P. F., 1998, "Evaluating Interval Forecast," *International Economic Review*, 39: 841-862.

Cohen-Cole, E., A. Kirilenko, and E. Patacchini, 2014, "Trading networks and liquidity provision," *Journal of Financial Economics,* 113: 235-251.

Cole, C.R. and K.A. McCullough, 2006, "A Reexamination of the Corporate Demand for Reinsurance," *Journal of Risk and Insurance,* 73: 169-192.

Cummins, J. D., M.A. Weiss, and H. Zi, 1999, "Organizational Form and Efficiency: The Coexistence of Stock and Mutual Property-Liability Insurers," *Management Science*, 45:1254-1269.

Cummins, J. D., G. Dionne, R. Gagne and A. Nouira, 2008, "The Costs and Benefits of reinsurance," working paper, HEC Montreal, Montreal, Canada.

Cummins, J. D., Z. Feng, and M. A. Weiss, 2012, "Reinsurance Counterparty Relationships and Firm Performance in the U.S. Property-Liability Insurance Industry," working paper, Temple University.

Cummins, J. D. and G. Nini, 2002, "Optimal Capital Utilization by Financial Firms: Evidence from the Property-Liability Insurance Industry," *Journal of Financial Services Research*, 21: 15-53.

Cummins, J. D. and M.A. Weiss, 2009, "Convergence of Insurance and Financial Markets: Hybrid and Securitized Risk Transfer Solutions," *Journal of Risk and Insurance*, 76:493-545.

Cummins, J. D. and M.A. Weiss, 2014, "Systemic Risk and U.S. Insurance Sector," *Journal of Risk and Insurance*, 81: 489-527.

Cummins, J.D., M. Weiss, X. Xie, and H. Zi, 2010, "Economies of Scope in Financial Services: A DEA Efficiency Analysis of the US Insurance Industry," *Journal of Banking and Finance*, 34: 1525-1539.

Diebold, F. X. and K. Yilmaz, 2012, "Better to give than receive: predictive directional measurement of volatility spillovers," *International Journal of Forecast*, 28: 57-66.

Diebold, F. X. and K. Yilmaz, 2014, "On the Network Topology of Variance Decompositions: Measuring the connectedness of financial firms," *Journal of Econometrics*, 182: 119-134.

Dungey, M., M. Luciani and D. Veredas, 2013, "Googling SIFIs," working paper, available at SSRN: http://ssrn.com/abstract=2166504.

Dungey, M., M. Luciani and D. Veredas, 2014, "The Emergence of Systemically Important Insurers," Center for International Finance and Regulation, Working paper No. WP038, available at SSRN: http://ssrn.com/abstract=2494030.

Eling, M. and D. Pankoke, 2014, "Systemic Risk in the Insurance Sector-What Do We Know?" Working papers on Risk Management and Insurance, No. 124, University of St. Gallen.

Engle, F. R., 2002, "Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models," *Journal of Business & Economic Statistics*, 20: 339-350.

Engle, F. R. and S. Manganelli, 2004, "CAViaR: Conditional Autoregressive Value at

Risk by Regression Quantiles," *Journal of Business and Economic Statistics*, 22: 367-381.

European Central Bank, 2010, "Recent advances in modeling systemic risk using network analysis," (Frankfurt: European Central Bank).

Fier, S., K.A. McCullough, and J.M. Carson, 2013, "Internal capital markets and the partial adjustment of leverage," *Journal of Banking and Finance*, 37: 1029-1039.

Freixas, X., B. M. Parigi and J. Rochet, 2000, "Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank," *Journal of Money, Credit and Banking*, 32: 611-638.

Fox, J., 1997, *Applied regression analysis, linear models, and related models*, Sage publications, Inc.

Garven, J.R., J.I. Hilliard, and M.F. Grace, 2014, "Adverse Selection in Reinsurance Market," working paper, Georgia State University.

Geneva Association, 2010, "Systemic Risk in Insurance-An Analysis of Insurance and Financial Stability," Geneva, Switzerland. http://www.genevaassociation.org.

Glosten, L. R., R. Jagannathan, and D. E. Runkle, 1993, "On The Relation Between The Expected Value and The Volatility of Nominal Excess Return on Stocks", *Journal of Finance*, 48: 1779-1801.

Granger, C. W. J., 1969, "Investigating Causal Relations by Econometric Methods and Cross-Spectral Methods," Econometrica, 34: 424-438.

Girardi, G. and A. T. Ergün, 2013, "Systemic risk measurement: Multivariate GARCH estimation of CoVaR," *Journal of Banking and Finance*, 37: 3169-3180.

Greene, W. H., 2003, Econometric Analysis (5th edition), Prentice Hall, Upper Saddle River NJ.

Greene, W.H. and D. Segal, 2004, "Profitability and Efficiency in the U.S. Life Insurance Industry," *Journal of Productivity Analysis*, 21: 229-247.

Haldane, A.G., 2009, "Rethinking the Financial Network," Speech delivered at the Financial Student Association, Amsterdam, the Netherlands.

Hansen, B. E., 1994, "Autoregressive Conditional Density Estimation," *International*

Economic Review, 35: 705-730.

Hasman, A., 2013, "A Critical Review of Contagion Risk in Banking," *Journal of Economic Surveys*, 27: 978-995.

Hautsch, N., J. Schaumburg and M. Schienle, 2014, "Financial Network Systemic Risk Contributions," *Review of Finance*,1-54.

Huang, X., H. Zhou, and H. Zhu, 2009, "A Framework for Assessing the Systemic Risk of Major Financial Institutions," *Journal of Banking and Finance*, 33: 2036-2049.

International Association of Insurance Supervisors (IAIS), 2011, "Insurance and Financial Stability," Basel, Switzerland.

IAIS, 2012, "Reinsurance and Financial Stability," Basel, Switzerland.

IAIS, 2013, "Global Systemically Important Insurers: Initial Assessment Methodology," Basel, Switzerland.

Kaushik, R. and S. Battiston, 2012, "Credit Default Swaps Drawup Networks: Too Tied To Be Stable?" ETH Risk Center Working Paper 12-013, Swiss Federal Institute of Technology, Zurich, Switzerland.

Koijen, R. S. J. and M. Yogo, 2013, "Shadow Insurance," National Bureau of Economic Research, Working Paper No. 19568, Cambridge, MA.

Kuester, K., S. Mittnik and M. S. Paolella, 2006, "Value-at-Risk Prediction: A Comparison of Alternative Strategies," *Journal of Financial Econometrics*, 4: 53-89.

Lelyveld, I., F. Leidorp, and M. Kampman, 2011, "An Empirical Assessment of Reinsurance Risk," Jou*rnal of Financial Stability*, 7: 191-203.

Li, D. and N. Schurhoff, 2012, "Dealer Network: Market Quality in Over-The-Counter Markets," working paper.

Lienbenberg, A.P. and D.W. Sommer, 2008, "Effects of Corporate Diversification: Evidence from the Property-Liability Insurance Industry," *Journal of Risk and Insurance*, 75:893-919.

Lin, Y., J. Yu, and M.O. Peterson, 2014, "Reinsurance Networks and Their Impact on Reinsurance Decisions: Theory and Empirical Evidence," *Journal of Risk and Insurance*, forthcoming.

Markose,S., 2012, “Systemic Risk from Global Financial Derivatives: A Network Analysis of Contagion and Its Mitigation with Super-Spreader Tax,” Working Paper No. 12/282, Washington DC, International Monetary Fund.

Markose, S., S. Giansante, and A. Shaghaghi, 2012, “’Too Interconnected to Fail’ Financial Network of US CDS Market: Topological Fragility and Systemic Risk,” *Journal of Economic Behavior & Organization*, 83: 627-646.

Minoiu, C. and J.A. Reyes, 2012, “A Network Analysis of Global Banking: 1978-2010,” *Journal of Financial Stability*, Forthcoming.

Oh, D. and A. Patton, 2014, “Modelling Dependence in High Dimensions with Factor Copulas,” working paper, Duke University.

Parke, S.C. and X. Xie, 2014, “Reinsurance and Systemic Risk: The Impact of Reinsurer Downgrading on Property-Casualty Insurers,” *Journal of Risk and Insurance*, forthcoming.

Powell, L.S. and D.W. Sommer, 2007, “Internal Versus External Capital Markets in the Insurance Industry: The Role of Reinsurance”, *Journal of Financial Service Research*, 31: 173-188.

Powell, L.S., D.W. Sommer, and D.L. Eckles, 2008, “The Role of Internal Capital Markets in Financial Intermediaries: Evidence from Insurance Groups,” *Journal of Risk and Insurance*, 75: 439-461.

Slijkerman, J. F., D. Schoenmaker, and C. G. de Viries, 2013, “Systemic Risk and Diversification Across European Banks and Insurers,” *Journal of Banking and Finance*, 37: 773-785.

Standard & Poor, 2013, *Global Reinsurance Highlights 2013*, McGraw-Hill Companies, Inc., New York.

Swiss Re, 2003, Reinsurance – A Systemic Risk? *Sigma* No. 5/2003 (Zurich, Switzerland).

Swiss Re, 2012, “Natural Catastrophes and Man-made Disasters in 2011: Historical Losses Surface from Record Earthquakes and Floods,” *Sigma* No. 2/2012 (Zurich, Switzerland).

Swiss Re, 2014, “Natural Catastrophe and Man-made Disasters in 2013,” *Sigma*, No.1/2014 (Zurich, Switzerland).

Upper, C., 2011, "Simulation methods to assess the danger of contagion in interbank markets," *Journal of Financial Stability,* 7: 111-125.

Watts, D.J. and S. H. Strogatz, 1998, "Collective dynamics of 'small-world' networks", *Nature*, 393: 440-442.

Weiss, G. N.F. and J. Mühlnickel, 2013, "Why do some insurers become systemically relevant? " Journal *of Financial Stability*, 13:95-117.

Weiss, G. N. F., C. Bierth and F. Irresberger, 2014, "Systemic Risk of Insurers Around the Globe," working paper, available at SSRN: http://ssrn.com/abstract=2419508.

White, H., T. Kim and S. Manganelli, 2013, "VAR for VaR: Measuring Tail Dependence Using Multivariate Regression Quantiles," working paper, available at http://www.simonemanganelli.org/Simone/Research_files/var_for_var.pdf.