The Microstructure of the Reinsurance Network among US Property-Casualty Insurers and Its Effect on Insurers' Performance

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Abstract

Reinsurance is the primary source of interconnectedness in the insurance industry and is analogous to inter-bank lending. As such, reinsurance connectivity provides a transmission mechanism for financial shocks and exposes insurers to contagion (and potential systemic) risk. In this paper, connectivity within the U.S. property-casualty (P/C) reinsurance market is modeled as a network. This research is the first detailed empirical analysis of the microstructure of the reinsurance network including both affiliated and unaffiliated insurers. We 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, we 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. We also analyze the resilience of the reinsurance network against contagion risk by simulating economic impacts resulting from failures of one or more strategically networked reinsurers.

Key Words: Reinsurance market, contagion, systemic risk, firm performance, network analysis, property-casualty insurance

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, Bilio 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, we 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, we examine the microstructure of insurer-reinsurer relationships and their main characteristics by adopting a network analysis framework. Second, we investigate the stability of the US P/C insurance industry under our reinsurance network. We determine whether a default cascade can be triggered by reinsurer insolvencies. Third, we empirically analyze the impact of an (re)insurer's network position on its performance.

Our 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. Our 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, we 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, we 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, our 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.

We contribute 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

[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.

for regulatory measures and macroprudential policies. We also provide new empirical evidence that an insurer's position in the reinsurance network affects its loss experience and performance. We 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.

The remainder of this paper is organized as follows. In section 2, we briefly review the literature regarding the application of network analysis in financial markets and related studies for the insurance industry. In section 3, we introduce some basic concepts in network analysis and then explain network centrality measures adopted in this study. In section 4, we develop our hypotheses and discuss the simulation algorithm and empirical models. In section 5, we describe the data and construct the reinsurance network, followed by a detailed analysis of its microstructure. In section 6, we report the results regarding the resilience of the US P/C insurance industry against contagion risk and the effect of an insurer's network position on its performance. Section 7 concludes.

2. Related Literature

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

2.1. Network Literature

In an early and important study, Allen and Gale (2001) 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]

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)

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

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). 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.

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. We therefore address these gaps in this paper.

3. Introduction to Network Analysis

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

3.1. Basic Concepts

A network or graph, denoted by $G \equiv (N, E)$, is defined by two nonempty sets: the set $N = \{1, \ldots, n\}$ 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] We 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), we 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.

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, we 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.

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*).

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. We 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,

$$g_i^{out} = \sum_j A_{ij};\ g_i^{in} = \sum_j A_{ji};\ g_i^{total} = g_i^{out} + g_i^{in}, \tag{1}$$

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, we 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.

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,

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

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]

4. Hypothesis Development and Empirical Methodologies

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

4.1. Hypotheses 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

[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.

and benefits is much 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, we believe the result would not be significantly different if large group affiliated insurers defaulted. We 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.

We next turn our 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.

4.2. Empirical Methodologies

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, we 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. We 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.

Regression Models and Variable Definitions

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

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

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

To test Hypothesis H2, we 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

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

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, we choose the following variables to control for the heterogeneity among insurers. The formal definitions of dependent variables and control variables, along with the predicted signs, are summarized in Table 1.

- *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.

5. Data and the Microstructure of Reinsurance Networks

Our 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.

Our data is from the National Association of Insurance Commissioners (NAIC) annual statements for US P/C insurers during the period of 2000-2011. We 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, we use the NAIC assigned company code and Federal employer identification number (FEIN) for US P/C insurers and their reinsurance counterparties, respectively. We 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, we 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, we 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, we trace 2,901 US P/C insurers and 6,737 non-NAIC regulated reinsurance counterparties with 419,524 reinsurance transaction relationships. On average, our reinsurance network has 4,505 nodes with 1,952 US P/C (re)insurers and 34,960 edges per year.

We 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

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

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 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).

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 6.1.

Figures 2A and 2B 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 2A 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 2B, 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.

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

[10] To save space, we choose not to report parameter estimates and goodness of fit. The results are available from the authors upon request.

[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.

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 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.

A natural question is whether the reinsurance network has a single or several market center(s). We find there is an inverse relationship between the degree distribution and the clustering coefficient.[12] 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.

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. We, therefore, turn to examining contagion risk in the reinsurance network in the next subsection.

[12] To save space, we do not report the figure showing a reverse relationship between node degrees and clustering coefficients. The result is available from the authors upon request.

6. Empirical Results

This section presents our empirical results. We 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, we discuss the results of robustness tests.

6.1. Insolvency Tests

Using the algorithm outlined in Section 4, we 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.

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%. 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%).[13] 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 4. Panel A of Figure 4 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 4 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.

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.

6.2. Reinsurance Network Position and Insurer Performance

This subsection presents regression results of the two-way fixed effects model estimating

[13] To save space, we do not report the results of sensitivity analysis of insolvency tests. The results are available upon request.

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.[14] 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.[15] 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 5 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.

We 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

[14] We remove 2,631, 1,066, and 1,319 observations in step (1)-(3) respectively, resulting in 18,351 observations for the next step – outlier analysis.
[15] 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.

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.

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.

We then test Hypothesis H3 by regressing an insurer's performance measure (*RAROA* and *RAROE*) on the centrality measure. The results are presented in Table 7. 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*).

6.3. Robustness Tests at the Group Level

Previous literature argue that affiliated insurers' reinsurance decisions may be coordinated at the group level (Cummins 2008, Lin, Yu and Peterson 2014). We 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.[16] We 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, we 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

[16] We 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.

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. We observe that US P/C insurers tend to utilize more reinsurance from foreign reinsurers during our sample 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.[17] 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 we construct at the group level, we 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. We 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*).

7. Conclusion

In this paper, we 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, we perform network analysis for the US P/C reinsurance market and describe its basic characteristics. We further examine its stability under some market distress conditions and find that the US P/C reinsurance market is not subject to contagion risk.

[17] 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.

Our 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. Our results also shed light on an insurer's performance based on its network position. We 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, our 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.

For future research, this paper can be extended in several ways. For instance, one can conduct an efficiency study to further examine the interactions between a firm's reinsurance market position and its cost, revenue and profit efficiency. One can also examine how the transactional relationship in the reinsurance network affects a firm's key decisions, such as capital structure and mergers and acquisitions.

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Figure 1: An example of simple networks

This is an example to demonstrate the concept of weakly connected component (WCC) and strongly connected component (SCC) discussed in Section 3. The largest SCC consisting of node a, b, c and f is shaded in green.

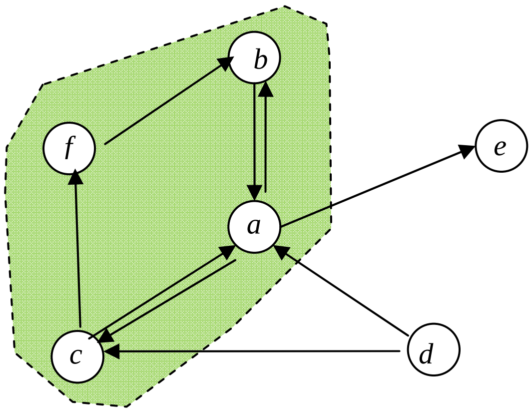

Figure 2A: Graph for the reinsurance networks in year 2011

This figure presents the reinsurance network among US P/C insurers in year 2011, consisting of 1623 nodes and 9429 edges. <u>The size of the node is proportional to the node's in-degree.</u> 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 we label 20 nodes.*)

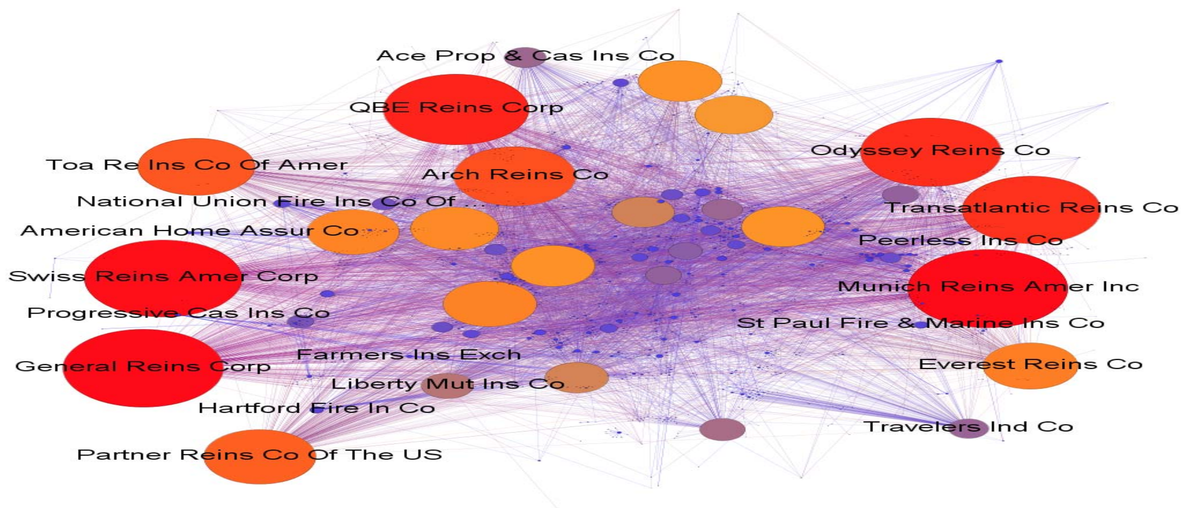

Figure 2B: Graph for the reinsurance networks in year 2011

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

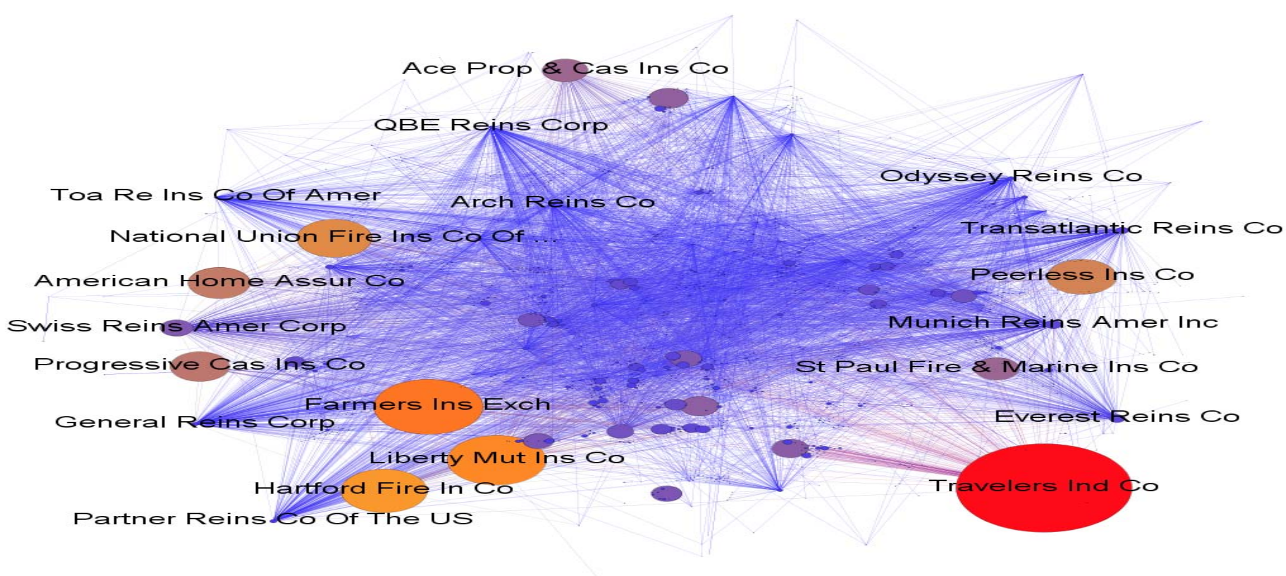

Figure 3: Simulation results for the impact of multiple top insurers' failures

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 (1923) 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.

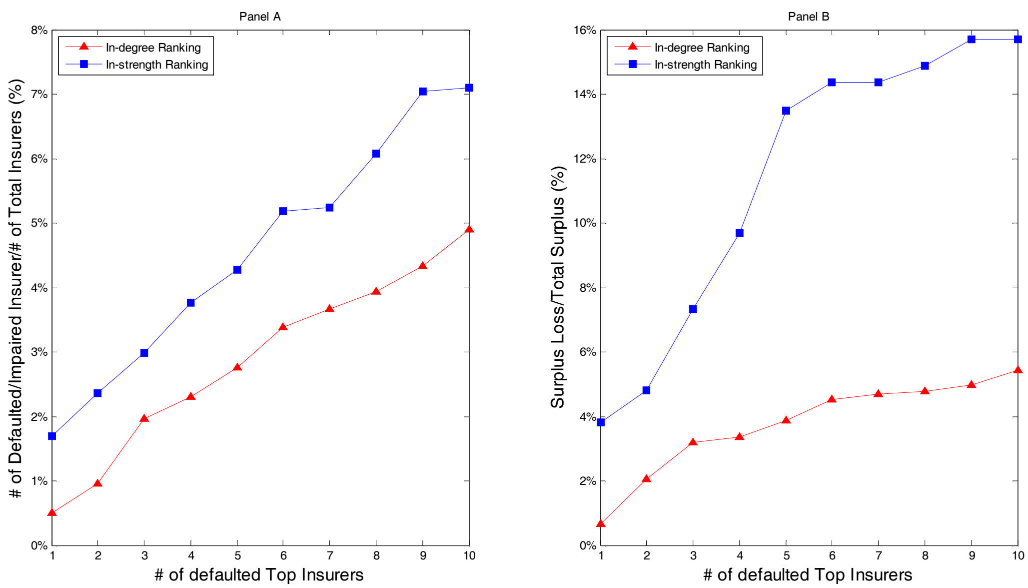

Table 1: Definitions of variables

Variable	Measurement	Expected sign: Combined Ratio	Expected sign: RAROA/ RAROE
Dependent variables			
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 centrality, eigenvalue centrality, betweenness centrality 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	+/-	+/-

Table 2: Reinsurance network density and component analysis

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.

		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 with 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

Table 3: Importance of top (re)insurers in reinsurance networks

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.

	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%

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

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)
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**

Table 5: Summary Statistics

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.

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

Table 6: The effect of an insurer's network position on its combined ratio

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.

	(1)	(2)	(3)	(4)
VARIABLES	Combined Ratio	Combined Ratio	Combined Ratio	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

Table 7: The effects of an insurer's reinsurance network position on its performance

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 performance. 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 variables in models (1)-(4) are *RAROA* defined as the ratio of return on total admitted assets divided by the standard deviation of return on total admitted assets in the previous three years. The dependent variables in models (5)-(8) are *RAROE* defined as the ratio of of return on total surplus divided by the standard deviation of return on total surplus in the previous three years. *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 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.

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