Tail Risk Spillover and Its Contribution to Systemic Risk:

A Network Analysis for Global Reinsurers

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Abstract

Measuring and monitoring tail risk has important implications to financial contagion and systemic risk. This paper analyzes the short-run tail risk dependence among global reinsurers and studies its relationship with systemic risk in the reinsurance industry. We measure the tail risk of each reinsurer by the Value-at-Risk and construct the tail risk network among global reinsurers based on Granger causality tests. We then explore the general property of the proposed tail risk network and investigate its contribution to systemic risk. Our results show that the tail risk interconnectedness among global reinsurers is subject to the impacts of both an insurance industry-wide shock and economy-wide shocks, where the former seems to have a larger effect than the latter. Moreover, we 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 network position will cause a higher level of systemic risk. We also find that there is a threshold effect of tail risk connectedness to systemic risk, i.e. when the daily network density is below its median state, the increase in the tail risk connectedness will cause a decrease in systemic risk possibly through risk diversification; when the daily network density is above its median state, the increase in the tail risk connectedness will cause the increase in reinsurer's systemic risk.

Keywords: reinsurance, Granger Causality, network analysis, tail risk, systemic risk

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 a 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 Motohiro, 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, we 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. We aim at filling these gaps in this paper.

The rest of the paper is organized as follows. In section 2, we briefly review the literature. In section 3, we introduce the empirical methodologies regarding the estimation of tail risks of global reinsurers, the construction of the tail risk network based on Granger causality tests, and the measure of interconnectedness of the tail risk network. In section 4, we describe our sample. In section 5, we provide the empirical results and discussions. We conclude in section 6.

2. Related Literature

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; Brownless 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. 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[1] 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[2]. Based on their network, they use the PageRank algorithm that take into account a firm's

[1] They use the interconnectedness measure proposed in Billio et al. (2012), which is based on the principle component analysis on insurers' standardized stock returns.
[2] The sample in Dungey, Luciani and Veredas (2014) includes 20 insurance companies and 18 deposit-taking institutions, all of whom were recipients from TARP.

network position and other characteristics (size, leverage, and liquidity) to determine systemic risk of individual firms. They find that their 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 paper, 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.

3. Empirical Methodology

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.

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 VaR as

$$\Pr(r_{it} \leq -VaR_{it}^{\tau}) = \tau \tag{1}$$

where VaR_{it}^{τ} is the τ -quantile of r_{it} . Here we define VaR_{it}^{τ} 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.,

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

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

$$-VaR_{it}^{\alpha} = \hat{\mu}_{it} + \hat{\sigma}_{it} F_{\varepsilon_i}^{-1}(\alpha) \tag{3}$$

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. Specifically, we choose the Skewed t distribution as the distribution for 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.,

$$\begin{aligned} r_{m,t} &= \sigma_{m,t}\varepsilon_{m,t} \\ \sigma_{mt}^2 &= \omega_m + \beta_m \sigma_{m,t-1}^2 + \alpha_m \varepsilon_{m,t-1}^2 + \gamma_m \varepsilon_{m,t-1}^2 1_{[\varepsilon_{m,t-1}\le 0]} \end{aligned} \tag{4}$$

and,

$$-VaR_{mt}^{\alpha} = \hat{\mu}_{mt} + \hat{\sigma}_{mt} F_m^{-1}(\alpha) \tag{5}$$

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.[3]

3.2 Construction of the Tail Risk Network

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:

$$\begin{aligned} y_t^1 &= a_0 + a_1 y_{t-1}^1 + ... + a_p y_{t-p}^1 + b_1 y_{t-1}^2 + ... + b_p y_{t-p}^2 + e_t^1 \\ y_t^2 &= c_0 + c_1 y_{t-1}^2 + ... + c_p y_{t-p}^2 + d_1 y_{t-1}^1 + ... + d_p y_{t-p}^1 + e_t^2 \end{aligned} \tag{6}$$

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, 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

[3] 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%. We 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 VaR back testing results are available upon request from the authors.

conditions, we augment the VAR model in equation (6) by including lagged market tail risk measures,

$$\begin{aligned} VaR^{\alpha}_{it} &= a_0 + \sum_{k=1}^{p} a_k VaR^{\alpha}_{i,t-k} + \sum_{l=1}^{q} b_l VaR^{\alpha}_{j,t-l} + \sum_{s=1}^{n} g_l VaR^{\alpha}_{m,t-s} + e_{it} \\ VaR^{\alpha}_{jt} &= c_0 + \sum_{k=1}^{p} c_k VaR^{\alpha}_{j,t-k} + \sum_{l=1}^{q} d_l VaR^{\alpha}_{i,t-l} + \sum_{s=1}^{n} h_l VaR^{\alpha}_{m,t-s} + e_{jt} \end{aligned} \tag{7}$$

Our null hypothesis that reinsurer *j*'s tail risk will not Granger cause reinsurer *i*'s tail risk is thus formulated as $H_0 : b_1 = ... = b_p = 0$, which can be tested using the standard Wald statistics. Following Billio et al. (2012), we select the optimal lags in equation (7) 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

$$A_{(j,i)} = (j \to i) = \begin{cases} 1, & \text{if j Granger causes i} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

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 (7) 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.[4] We then perform the Granger-causality

[4] 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.

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.

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 *N(N-1)* pairs of connections for *N* reinsurers:

$$Density = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} A_{(i,j)}}{N(N-1)} \tag{9}$$

(2) *Degree* counts the number of connections that each reinsurer $i = 1, \ldots, N$ 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 edges that point to a reinsurer from all other reinsurers.

$$\begin{aligned} \#out_i &= \sum_{j=1}^{N} A_{(i,j)} \Big/ (N-1) \\ \#in_i &= \sum_{j=1}^{N} A_{(j,i)} \Big/ (N-1) \\ \#total_i &= \#out_i + \#in_i \end{aligned} \tag{10}$$

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.,

$$\lambda v = Av \tag{11}$$

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.

3.4. Regression Models

To gauge a reinsurer's systemic risk, we use Marginal Expected Shortfall (MES, Archaya, Engle and Richardson 2012), Δ CoVaR (Adrian and Brunnermeier, 2014) and modified Δ CoVaR (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,

$$SR_{i,t} = \alpha + \beta Net_{i,t} + \gamma X_{i,t} + v_i + \varepsilon_{i,t} \tag{12}$$

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.[5] Additionally, we

[5] 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.

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:

$$SR_{it} = \alpha + \beta_1 Net_{it} + \beta_2 Net_{it} I(D_t \geq D_q) + \beta X_t + v_i + e_{it} \tag{12}$$

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 (13), 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.

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.[6] Table 1 provides

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

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).[7]

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 2 provides definitions for systemic risk measures, network-based measures for interconnectedness and data sources for economic state variables used in the regression analysis.

5. Empirical Results

We begin our analysis with the overall connectedness of our constructed tail risk network measured by the network density. Figure 1 provides the comparison between the density of the tail risk network and an equally-weighted return index[8] for the sampled global reinsurers. The mean (median) of the daily tail network density is around 0.28 (0.25). That is, on average only 28% of all possible edges, or Granger causal relationships that are statistically significant at 5% level, are

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

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 add reference lines that represent the top 5 events in terms of insured losses (Swiss Re 2014).[9]

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[10], 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[11], 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, we examine the role of global reinsurers in the tail risk network based on their

[9] 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).

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

[11] 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%.

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 2 (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.

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 2 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.

We now examine the systemic risk measures for global reinsurers during our sample period of 1999-2013. Figure 4 provides a comparison of historical market returns, proxied by the return of the DataStream Insurance Index, and the average estimated daily MES, Δ CoVaR and modified Δ CoVaR across our sampled reinsurers. Figure 3 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 as a result of 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.

Table 3 provides the summary statistics of reinsurers' tail risk interconnectedness (measured by total degree and eigenvector centrality) and the estimated systemic risk measures (Table 3 Panel A), along with the daily tail risk network density and economy state variables (Table 3 Panel B). Table 4 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 Δ CoVaR and modified Δ CoVaR, 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.

We formally examine the contribution of a reinsurer's tail risk network position to its systemic risk using regression analysis. Table 5a 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 5a 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 5b and Table 5c report the regression results using Δ CoVaR and modified Δ CoVaR as the dependent variable, respectively. Unlike the case of MES where a higher positive value indicates a higher exposure to systemic risk, a lower Δ CoVaR or modified Δ CoVaR means a higher contribution to systemic risk. In general, the results in Table 5b and 5c are consistent with those reported in Table 5a. That is, a higher degree of interconnectedness is associated with a higher level contribution to systemic risk. For instance, in Table 5b where the dependent variable is a reinsurer’s Δ CoVaR, 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 5c where we use the modified Δ CoVaR as the measure of systemic risk contribution.

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 Δ CoVaR and modified Δ CoVaR 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 (Δ CoVaR and modified Δ CoVaR) 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 Δ CoVaR and modified Δ CoVaR, 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 6 reports the firm-fixed effect regression results using in-degree (out-degree) as the explanatory variable when the dependent variable is MES (Δ CoVaR or modified Δ CoVaR). 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 Δ CoVaR (model 3-4 in Table 6) and modified Δ CoVaR (model 5-6 in Table 6).

Lastly, we turn to the question of whether there exists a threshold effect of interconnectedness on systemic risk. Table 7a 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 7a, 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 7a, and when we use Δ CoVaR and modified Δ CoVaR to measure systemic risk contribution, as shown in Table 7b and Table 7c.

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 20^{th} percentile to the 60^{th} 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.

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.

For future study, our framework can be easily extended to examine the tail risk spillover among primary insurers and reinsurers, or to study the inter-industry connectedness between insurers and banks, which would provide us more insights regarding the co-movement of tail risk among different financial sectors and its effects on the stability of the financial sector.

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Figure 1: Tail Risk Network Density and Equally-weighted Return

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 the tail risk network are determined by Granger-causal relationships that are statistically significant level at 5% level. Reinsurer's tail risk is measured by VaR with loss exceedence level of 5%. We also add the top 5 most costly natural catastrophes (Swiss Re 2014) during the sample period.

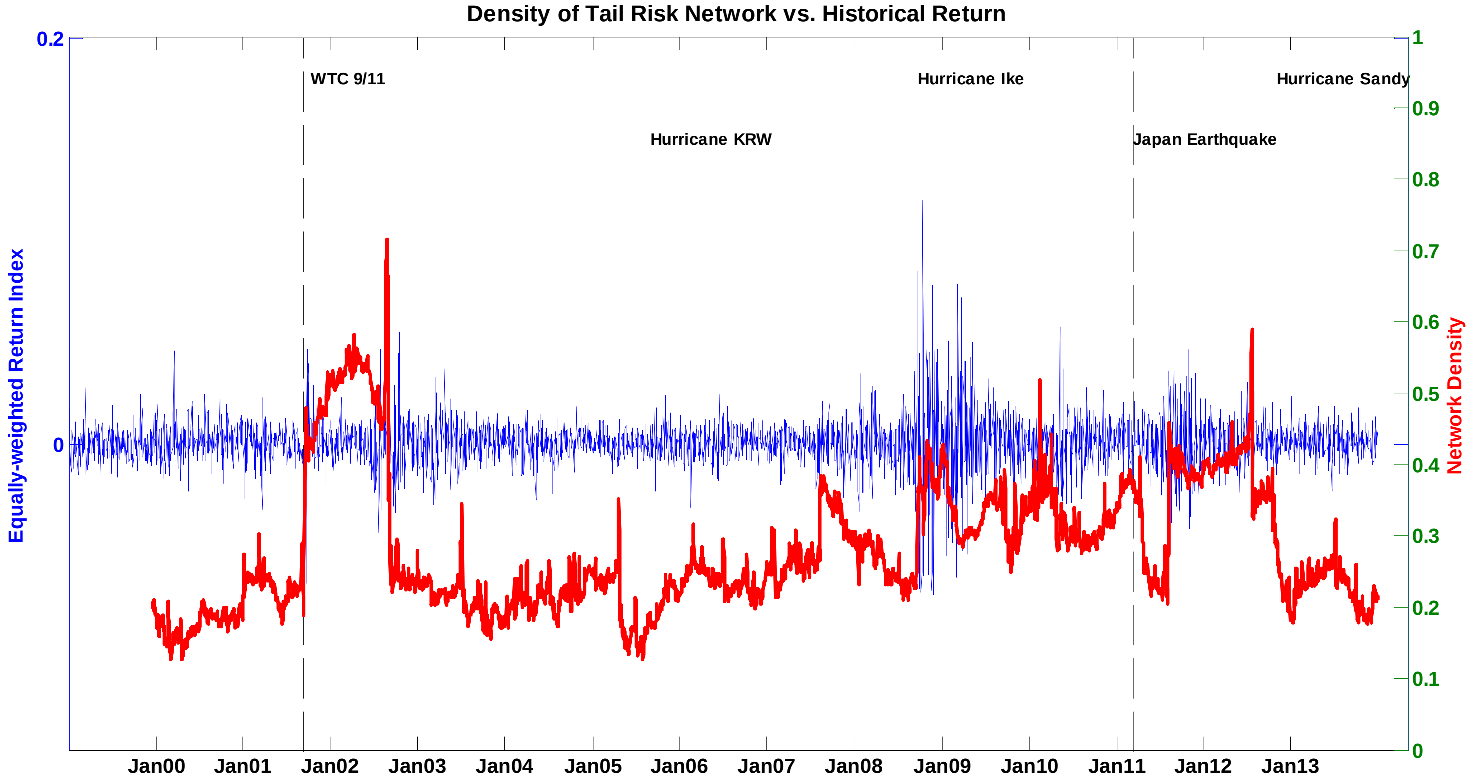
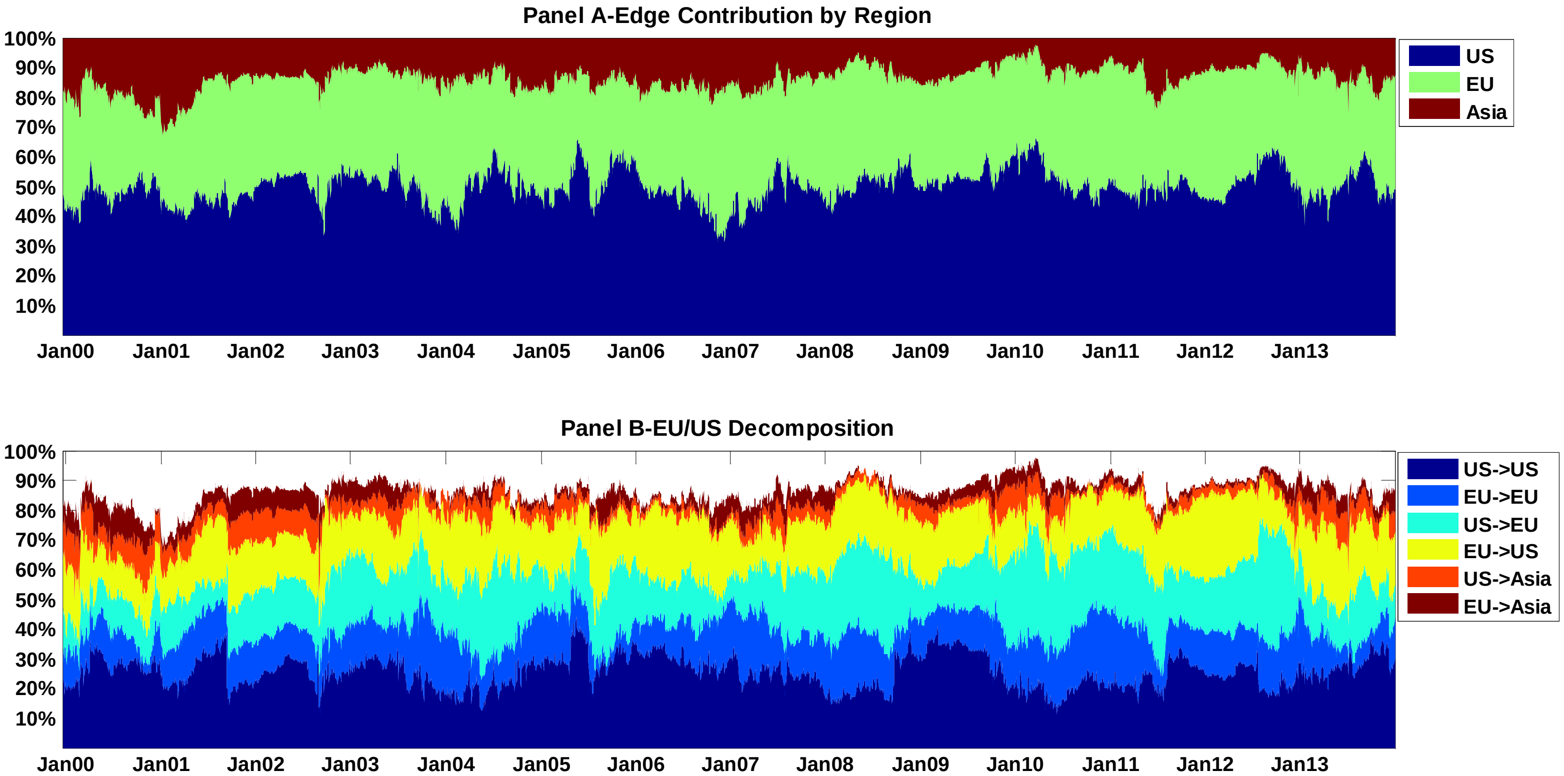


Figure 2: Edge Contributions to Tail Risk Network



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, 2013; (4) the edges in tail risk network are determined by Granger-causal relationships that are statistically significant at the 5% level based on reinsurers' VaR with loss exceedence level of 5%.

Figure 3: Plots for Market Return and Systemic Risk Measures

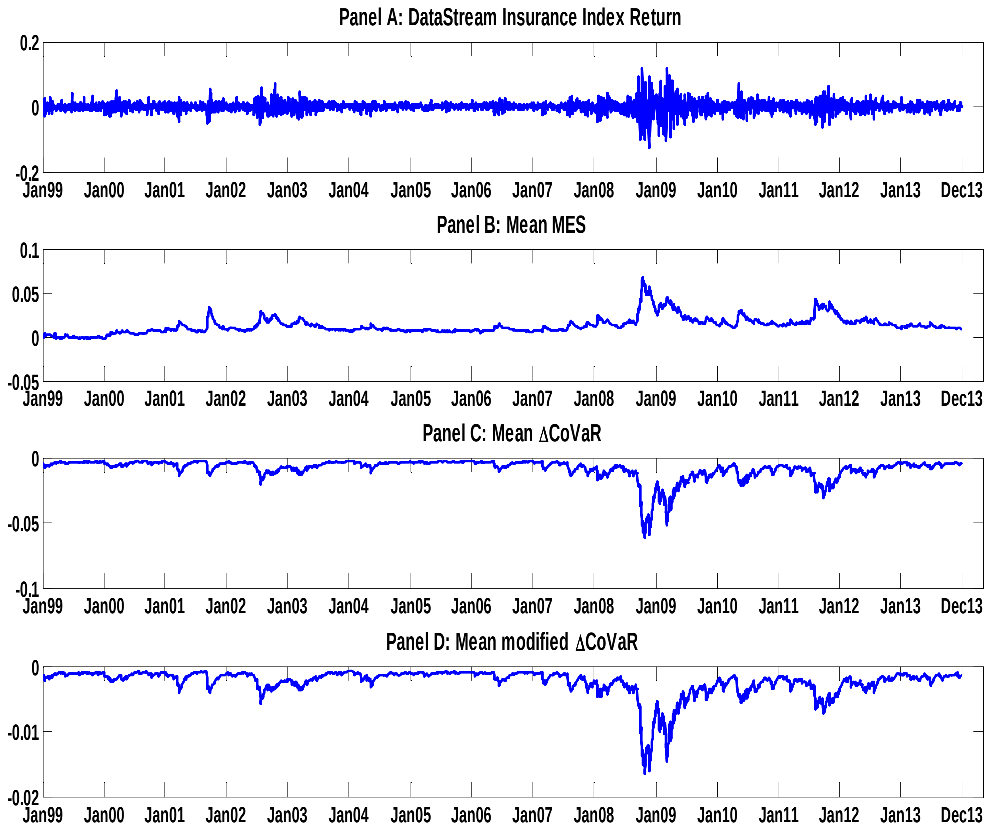


Table 1: Company Information of Sampled Global Reinsurers

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.

Table 2: Variable Definitions

This table provides the variable name, definition for the variables and the data source for the construction of variables used in our regression analysis.

Variables	Definition	Data Source
MES	Marginal Expected Shortfall, calculated as in Brownlees and Engle (2012), 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

Table 3: Summary Statistics

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.

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

Table 4: Correlation Matrix

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.

	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

Table 5a: Firm-Fixed Effect Regression Model between Tail Risk Network Position and MES

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 tail risk network state variable ('netdens') and 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	mes	mes	mes	mes	mes	mes	mes	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

Table 5b: Firm-Fixed Effect Regression Model between Tail Risk Network Position and ΔCoVaR

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.

	(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

Table 5c: Firm-Fixed Effect Regression Model between Tail Risk Network Position and modified Δ CoVaR

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 Δ CoVaR. 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.

	(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

Table 6: Tail Risk Network Position and Exposure and Contribution to Reinsurer's Systemic Risk

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 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 Δ CoVaR ('covar') and modified Δ CoVaR ('mcovar') 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 tail risk network density ('netdens') and 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.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	mes	mes	covar	covar	mcovar	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

Table 7a: Threshold Regression Models between Tail Risk Network Position and MES

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. 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 50th percentile and 0 otherwise. The other independent variables are tail risk network density ('netdens') and 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.

	(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

Table 7b: Threshold Regression Models between Tail Risk Network Position and ΔCoVaR

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 ΔCoVaR ('covar'). 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 50th 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.

	(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

Table 7c: Threshold Regression Models between Tail Risk Network Position and modified ΔCoVaR

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 . 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.

	(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