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Systemic Risk Network of Chinese Financial Institutions [1]

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Abstract:

The Chinese stock market crash in June 2015 has demonstrated necessary to improve understanding of systemic risk from the perspective of financial network. This study constructs a tail risk network to present overall systemic risk of Chinese financial institutions, given the macroeconomic and market externalities. Employing the Least Absolute Shrinkage and Selection Operator (LASSO) method of high-dimensional models, our results show that firm's idiosyncratic risk can be affected by its connectedness with other institutions. The risk spillover effect from other companies is the main driving factor of firm-specific risk, comparing with macroeconomic state, firm characteristics and historical price movement. The number of connections between institutions significantly increases during June 2014 to June 2016. Moreover, we utilize the Kolmogorov-Smirnov statistic to test significance of systemic risk beta based on tail risk and further rank the systemic risk contribution. Regulators could detect those firms that are most threatening to the stability of system.

Key words: Systemic risk contribution, Tail risk network, Firm-specific risk, VaR

JEL: C30; D85; G20

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Systemic Risk Network of Chinese Financial Institutions

1. Introduction

With the development of financial innovation and globalization over the past few years, the co-movement between financial institutions' assets and credit exposure tends to increase, which gives rise to risk spillover through the networking of firms[2] (Adrian and Brunnermeier, 2016). Since the outbreak of the global financial crisis in 2007, and the dramatic effects of the Lehman collapse in 2008, systemic risk has become a matter of great concern for policy makers and financial institutions. This crisis reminds us that systemic risk can arise through interconnections across the individual firms, and individual firm's failure may have repercussions on the entire financial system (FSB/IMF/BIS, 2009; IOSCO, 2011).

As the second largest market in the world, the Chinese financial system has drawn growing worldwide attention after a series of liberalization policies in China after 2010[3].Many financial institutions are connected by their mutual asset holdings and forming of various financial networks. At present, the cooperation between financial institutions has result in tremendous unprecedented progress both in depth and breadth that also provides more possible risk contagion. Particularly in the Chinese stock market crash of 2015, thousands of A-shares hit either upward or downward price limits, accounting for about one third of the total market. Given this condition, firm-specific risk cannot be appropriately assessed in isolation without accounting for potential risk spillover effects from other firms (Hautsch et al., 2014). Thus, characterization of systemic risk across financial institutions in China is a key

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2 Examples include the 1998 crisis started with losses of hedge funds and spilled over to the trading floors of commercial and investment banks and the 2007/08 crisis spread from SIVs to commercial banks and on to investment banks and hedge funds.

3For example, the RQFII scheme came into effect in August, 2011. The quota for the QFII scheme doubled to 80 billion U.S. dollars in 2012 and almost doubled again in 2013 to 150 billion U.S. dollars. The launch of the Shanghai-Hong Kong Stock Connect Program in November 2014 was a new liberalization milestone (Yu et al., 2017).

problem. Yet to the best of our knowledge, this issue has barely been touched upon in the literature.

This study constructs a tail risk network to investigate the systemic risk across Chinese financial institutions. The firms selected are classified into categories of Commercial Bank, Brokerage, Insurance, and Other categories according to the classification catalogue proposed by the company of Shenyin &Wanguo (SW) Securities. The industry classification of SW Securities, one of the largest research institutions in China, has been unanimously recognized by investors and widely utilized in the Chinese market. From the sample period of January, 2010 to November, 2017, we measure systemic risk contribution using the conditional value-at-risk developed by Adrian and Brunnermeier (2016) when the incremental risk of one firm — that is conditional on another — experiences a crash. Considering the spillover effects, we employ the Least Absolute Shrinkage and Selection Operator (LASSO) method (Belloni and Chernozhukov, 2011), which is a statistical shrinkage technique and standard for high-dimensional models. The potential factors are macroeconomic variables, firm-specific characteristics, lagged return, and the influence of other firms. We further use the Kolmogorov-Smirnov (K-S) statistic extended by Abadie (2002) to test for the significance of systemic risk beta, a measurement based on tail risk and finally rank the systemic risk contributions.

Our work differs from the existing literature in several ways. Compared to the studies that characterize the risk contagion or spillover effect (Cappiello et al., 2006; Girardi and Ergün, 2013), we consider the condition that a single firm can be impacted by many other financial institutions and focus on the tail risk under extreme situations. Studies by Allen and Gale (2010), Leitner (2005), and Wang et al. (2017) employ network models to explore financial risk transmission. Our paper is closely related to Wang et al. (2017), but still differs in several ways. We employ the LASSO method to compute firm-specific VaR, taking into the consideration of the impact of other firms. It enables us to measure the risk of individual firm more specifically. On the other hand, we utilize the Kolmogorov-Smirnov (K-S) statistic extended by Abadie (2002) to test for the significance of systemic risk beta, since not all firms are systemically relevant if an increase in its potential loss position entails significantly higher potential systemic loss. In addition, our sample consists of more firms. It is helpful for exploring the systemic risk of Chinese financial institutions more specifically, and understand how risk propagates in a larger framework. Finally, presenting overall interconnectedness, systemic risk and risk contribution of Chinese financial institutions, we further identify the forward-looking determinants of systemic risk contribution using panel regression. Similar methodology can be found in Barigozzi and Brownlees (2014). In this paper, we investigate the rapidly developing Chinese market and particularly focus on the major turmoil during 2015-2016 to facilitate our understanding of the systemic risk of this emerging market.

Our study contributes to the literature in three aspects: First, to our knowledge, we are the first to illustrate the overall financial risk network in investigating the 2015-2016 Chinese stock market crash. For investors seeking to diversify investment in China, our results aid in monitoring risk across firms and thus better managing risk. Second, we reveal a high degree of tail risk interconnections among Chinese financial institutions and the network effect which serves as a dominant driver of a firm's individual risk. The LASSO method enables us to identify the relevant tail risk factors and build the network topology. Third, we quantify and rank the systemic risk contribution during different periods of the Chinese market. We further identify the determinants of systemic risk contribution using panel regression. A better understanding of how risk contribution responds to firm-specific characteristics and macroeconomic variables will help policymakers formulate more effective policies.

The remainder of the paper is organized as follows: Section 2 gives a brief review of relevant literature. Section 3 and Section 4 describe methodology and data, respectively. We present the results and discuss empirical analysis in Section 5. The paper ends with a brief conclusion.

2. Literature Review

From the perspective of methodology, this paper is closely related to the literature of tail risk network among financial institutions. Using a traditional quantile regression framework, Wang et al. (2017) introduce the concept of CoVaR and present dynamic tail-event driven networks (TENETs) proposed by Härdle et al. (2016), while we employ the LASSO, which is a statistical shrinkage technique and standard for high-dimensional models enabling us to identify the relevant tail risk factors and build the network topology. We compute firm-specific VaR, taking into the consideration of other firms' influence. Our sample consists of more publicly listed Chinese firms, which can help us to examine systemic risk more specifically and understand how risk propagates in a larger framework. In particular, we can also explore the role of small firms in the tail risk network. Barigozzi and Brownlees (2014), using a two-step LASSO procedure to investigate the volatility of 90 blue chip stocks in the U.S. from 2004 to 2015, suggest that financial companies have the greatest risk of spillover effect during the financial crisis. Hautsch et al. (2015) propose a systemic tail risk network of financial firms. They rank a firm's systemic risk contribution to the U.S. financial system, given the network interdependence between firms' tail risk exposures. Differing from these two papers, the Chinese government has made a series of liberalization policies to speed up the opening of the stock market after 2010. It is necessary for us to investigate and quantify systemic risk contribution among Chinese financial institutions within this new environment. Regarding the model structures, we utilize the Kolmogorov-Smirnov statistic by Abadie (2002) to test the significance of systemic risk beta based on tail risk.

Existing literature has employed several methods to characterize the risk contagion across financial markets over the world (Baur and Schulze, 2003; Dimitriou et al., 2013; Girardi and Ergün, 2013). Using an asymmetric multivariate Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) approach, Tai (2007) determined that 1) Asian emerging stock markets become integrated into world capital markets; and 2) there were pure contagion effects between stock and foreign exchange markets for each Asian country (India, Korea, Malaysia, Philippines, Taiwan, and Thailand) during the 1997 Asian crisis. Moreover, the measurement "Value at Risk (VaR)" proposed by J. P. Morgan in 1993 has also been widely used. Adrian and Brunnermeier (2016) introduced the Conditional Value-at-Risk (CoVaR) to investigate the impact of a single financial institution in financial distress upon other institutions. Many scholars have employed the latter method to examine the risk contagion (Roengpitya, 2010; Lopez-Espinosa et al., 2012). However, studies employing the CoVaR approach only take into account the risk contagion between two institutions; furthermore, GARCH models neglect the tail risk. Extending beyond these studies, we utilize financial network to investigate systemic risk, which considers the condition that a single firm can be impacted by other financial institutions and macroeconomic characteristics.

Another strand of literature pays close attention to systemic risk contribution in the framework of financial network models (Diebold et al., 2014; Rönnqvist et al., 2015; Cecchetti et al., 2016; Huang et al., 2016). Allen and Gale (2010) and Freixas et al. (2000) propose the use of network models to study financial risk transmission, pointing out that the risk transmission depends upon the structure of interbank markets. Bluhm et al. (2014) analyze the emergence of systemic risk in a network model of interconnected bank balance sheets and suggest a new macro-prudential risk management approach which builds upon a System Value-at-Risk (SVaR). These networks are usually very large, and their analysis is rather complex. In much of the previous work, specific filtering processes are applied to reduce the complexity, such as the threshold method, Minimum Spanning Tree (MST), and Planar Maximally Filtered Graph (PMFG). However, the economic explanation of the methods identified above is ambiguous. Unlike the complex network models, we combine the LASSO algorithm with the VaR measurement to study the systemic risk between individual institutions. LASSO is a type of compression estimation, which constructs a penalty function to obtain a more refined model. Some coefficients are compressed to zero, which is the foundation of network topology. LASSO not only accurately selects the important variables, but also has the stability of feature selection. Based on the characteristics of LASSO algorithm, we also analyze how the risk propagates while measuring and ranking the systemic risk contribution of financial institutions during different phases of the 2015 Chinese stock market crash. The existing literature rarely considers these aspects, which are the main topics of this study.

3. Methodology

In this analysis, under the framework of Belloni and Chernozhukov (2011) and Hautsch et al. (2015), we construct a tail risk network based on Value at Risk (VaR), which is modeled as a function of firm-specific balance sheet information, macroeconomic variables, and the network position. Our approach is a two-stage quantile regression. First, we estimate the firm-specific VaRs, using the LASSO method (Belloni and Chernozhukov, 2011) to select the relevant factors in advance. In the second stage, we estimate the VaR of market index based on the firm-specific VaRs. The systemic risk contribution is defined as the total increase in the system VaR due to a change in a firm-specific VaR. Finally, we utilize the Kolmogorov-Smirnov (K-S) statistic by Abadie (2002), based on bootstrapping strategy, to test the significance of systemic risk contribution.

3.1 Constructing Financial Networks based on Firm-Specific Risk

The conditional Value-at-Risk defined by Adrian and Brunnermeier (2016) to offer broad flexibility for describing risk spillover effect from one institution to another, or even to the whole financial system. Considering the confidence level q, the effect of tail risk drivers $D_t^{(i)}$, and the return R_t^i of an individual firm i at time t, the tail risk of this company is implicitly defined as the absolute value of q-quantile of the return distribution,

$$\Pr(-R_t^i \geq VaR_{q,t}^i | D_t^{(i)}) = \Pr(R_t^i \leq W_{q,t}^i | D_t^{(i)}) = q \tag{1}$$

Similar to Adrian and Brunnermeier (2016), we take into account both the fundamental factors and market factors. A series of factors including lagged macroeconomic variables M_{t-1}, lagged information of balance sheet Z_{t-1}^i, lagged return R_{t-1}^i of itself and the influence of other firms F_t^j, make up the of tail risk drivers $D_t^{(i)} = (M_{t-1}, Z_{t-1}^i, R_{t-1}^i, F_t^j)'$. Through other institutions' influence $F_t^j = \mathrm{R}_t^j | \left(\mathrm{R}_t^j \leq \hat{W}_{0.1}^j \right)$, where $W_{0.1}^j$ represents the unconditional 10-quantile of R^j, we can construct a tail risk network. Therefore, the conditional VaR of firm i is given as follows:

$$VaR_q^i = D^{(i)'} \xi_q^i \tag{2}$$

Since not all of the drivers have a significant effect on tail risk, we need to pre-select the relevant factors in advance. Belloni and Chernozhukov (2011) adapted the LASSO methods to quantile regression, which are widely used in high-dimensional models. Therefore, we choose the LASSO methods as the factors selection techniques:

$$\xi_q^i = \arg\min_{\xi^i} \frac{1}{T} \sum_{t=1}^{T} \rho_q \left(R_t^i + D_t' \xi^i \right) + \lambda^i \frac{\sqrt{q(1-q)}}{T} \sum_{k=1}^{K} \hat{\sigma}_k \left| \xi_k^i \right| \tag{3}$$

where λ^i is a fixed individual penalty parameter. $\hat{\sigma}_k = \frac{1}{T} \sum_{t=1}^{T} (D_{t,k})^2$ is the variation of potential factors. The loss function is $\rho_q(m) = m(q - I(m<0))$, and the indicator $I(\cdot)$ is 1 for $m<0$ and zero otherwise. The selection criterion is based on the absolute values of their estimated marginal effects $|\xi^i|$ in Equation (3). Specifically, all firms with absolute values below a threshold $\tau = 0.001$ are excluded from D_t in the penalized VaR regression and only the others are reserved. After determining the relevant factors $D^{(i)}$, we run the standard linear quantile regression once again:

$$\hat{\xi}_q^i = \arg\min_{\xi^i} \frac{1}{T} \sum_{t=1}^{T} \rho_q \left(R_t^i + D_t^{(i)'} \xi_q^i \right) \tag{4}$$

where $\hat{\xi}_q^i$ is the final estimated marginal effects. Therefore, we can determine the firm-specific VaR:

$$VaR_{q,t}^{i} = D_t^{(i)'} \hat{\xi}_q^i \tag{5}$$

Comparing Equations (3) and (4), the only difference is that LASSO-quantile regression has a penalty term. The value of penalty parameter λ^i directly determines the process of selecting the regressors. Following Belloni and Chernozhukov (2011), we determine the appropriate value of λ^i from the data in the following two-steps procedure:

First, take T draws from $U[0,1]$, denoted as $M_1,...,M_T$. Conditional on the observations of D, calculate

$$\Lambda^i = T \max_{1 \le k \le K} \frac{1}{T} \left| \sum_{t=1}^{T} \frac{D_{t,k}(q - I(M_t \le q))}{\hat{\sigma}\sqrt{b^2 - 4ac}_k \sqrt{q(1-q)}} \right| \tag{6}$$

Second, repeat the first step for 500 times, generating the empirical distribution of Λ^i. For a confidence level $c = 0.1$ in the selection, set

$$\lambda^i = b \cdot Q(\Lambda^i, 1-c|D_t) \tag{7}$$

where $Q(\Lambda^i, 1-c|W_t)$ is $(1-c)$ -quantile of Λ^i , and $b \leq 2$ is a constant and determined by the backtesting performance of the resulting VaR. In other words, the in-sample predictive ability is maximized.

3.2 Quantifying the Systemic Risk Contribution

Based on the firm-specific VaR on financial risk network, we can further measure the systemic impact of an individual institution, which is defined as the effect of its riskiness on the distress of the entire financial system. Similar to Equation (1), given $VaR^i_{q,t}$, the system return R^s_t and other variables, the system tail risk is measured as the $VaR^s_{p,t}$. Then, systemic risk beta is defined as follows:

$$\frac{\partial VaR^s_{p,t}(X^{(i)}_t, VaR^i_{q,t})}{VaR^i_{q,t}} = \beta^{s|i}_{p,q,t} \tag{8}$$

where $X^{(i)}_t$ is the control variable. The systemic risk contribution is the total increase in the system VaR due to a change in firm-specific VaR, given network and market externalities, which is obtained empirically via

$$\bar{C}^{s|i}_{p,q,t} := \beta^{s|i}_{p,q,t} VaR^i_t \tag{9}$$

To keep the same control variables in Equation (1), for each firm i , we estimate a quantile regression of $VaR^s_{p,t}$ in the following form:

$$VaR^s_{p,t} = X^{(i)'}_t \gamma^s_p + \beta^{s|i}_{p,q,t} VaR^i_{q,t} \tag{10}$$

where the factor $X^{(i)}_t = (1, M^{'}_{t-1}, VaR^{(-i)'}_{q,t})^{'}$. $VaR^{(-i)'}_{q,t}$ comprises the tail risk of all other companies that are selected as relevant risk factors in Equation (4).

Hence, the system return R^s_t is expressed as:

$$R_t^s = -\beta_{0,p,q,t}^{s|i} VaR_{q,t}^{i} - (VaR_{q,t}^{i} \cdot Z_{t-1}^{i})' \eta_{p,q,t}^{s|i} - \hat{X}_t^{(i)'} \gamma_p^s + \varepsilon_t^s$$

(11)

where Z_{t-1}^{i} is the lagged information of the balance sheet. Estimates of all parameters are obtained via a standard quantile regression by minimizing

$$\frac{1}{T}\sum_{t=1}^{T} \rho_q \left(R_t^s + A_t^{(i)'} \xi^s \right)$$

(12)

where $A_t^{(i)} = (VaR_t^i, VaR_t^i * Z_{t-1}^{i\,'}, A_t^{(i)'})'$. Next, the systemic risk beta in Equation (9) is given by

$$\beta_{p,q,t}^{s|i} = \hat{\beta}_{0,p,q,t}^{s|i} + Z_{t-1}^{i} \hat{\eta}_{p,q,t}^{s|i} \tag{13}$$

Finally, we can obtain the systemic risk contribution as $\hat{\hat{C}}_{p,q,t}^{s|t} := \hat{\beta}_{p,q,t}^{s|i} VaR_t^{i}$.

3.3 Testing the Significance of Systemic Risk Contribution

We define a company as systemically relevant if an increase in its potential loss position entails significantly higher potential systemic loss, which requires that its systemic risk beta is significant and nonnegative. As quantile versions of asymptotic t or F -tests are not valid in finite samples, we employ the extended Kolmogorov-Smirnov (K-S) statistic by Abadie (2002), based on bootstrapping strategy, to test the significance of systemic risk beta. The test compares entire cumulative distribution functions (CDFs) rather than mean values which may be sensitive to outliers, as statistical tests based on mean values could indeed lead to false conclusions. This test is asymptotically distribution-free and therefore does not require any assumption concerning the underlying distribution, contrary to statistical tests based on mean values (e.g. student t-test or two-sample z-test).

For the significance test, the two-sample K-S statistic is defined as

$$D_{eq} = (\frac{mn}{m+n})^{1/2} \sup_x \left| F_m(x) - G_n(x) \right| \tag{14}$$

where $F_m(x)$ and $G_n(x)$ are the CDFs of systemic risk beta $\beta_{p,q}^{s|i}$ in Equation (9), and m and n are the size of two samples. In other words, the significance test aims to statistically test whether an institution is systemically relevant. The null hypothesis is

$$H0: \beta_{p,q,t}^{s|i} \leq 0 \tag{15}$$

Kolmogorov-Smirnov type nonparametric distance statistics of D_{eq} generally have good power properties. Unfortunately, the asymptotic distributions of the test statistics under the null hypotheses are generally unknown. We follow Abadie (2002) and use the bootstrap technique to simulate null distribution and make inferences.

4. Data Description

In this paper, we analyze the risk contribution network of publicly traded Chinese financial institutions. The sample covers the period from January 4, 2010, to November 16, 2017, allow us to focus on the firms that went public before 2010. The period covers the Chinese market crash in 2015, thus providing a valuable opportunity to study the risk contributions in terms of extreme market conditions. The institutions, listed in Table 1, include commercial banks, brokerages, insurance, and other financial institutions, which are all financial institutions listed in China before 2010. In addition, we utilize the Shanghai Composite Index as proxy for the Chinese financial system.

Table 1 List of financial institutions in SW industry sectors

Commercial Banks (15)	Hebei BaoShuo Co.,Ltd (HBS)
Agricultural Bank of China (ABC)	Huatai Securities (HTS)
Bank of Beijing (BOB)	Northeast Securities (NS)
Bank of China (BOC)	Pacific Securities (PS)
Bank of Communications (BCM)	Sealand Securities (SS)
Bank of Nanjing (BON)	SDIC Essence (Holdings) Co. Ltd (SDIC)
Bank of Ningbo (BN)	SinoLink Securities (SLS)
China CITIC Bank (CCIB)	Southwest Securities Company, Ltd (SSC)
China Construction Bank (CCB)	**Insurance (5)**

China's Industrial Bank (CIB)	China Life (CL)
China Merchants Bank (CMB)	China Pacific Insurance (CPIC)
China Minsheng Bank (CMSB)	Hubei Biocause Pharmaceutical (HBP)
Huaxia Bank (HXB)	Ping An Insurance (PAI)
Industrial and Commercial Bank of China (ICBC)	Xishui Strong Year (XSY)
Ping An Bank Co (PAB)	**Others (12)**
Shanghai Pudong Development Bank (SPD)	Anhui Xinli Finance (AXF)
Brokerages (18)	An Xin Trust and Investment (AXTI)
China Merchants Securities (CMS)	Bode Energy Equipment (BEE)
Changjiang Securities (CS)	Bohai Financial Investment Holding (BFIH)
China International Trust and Investment Company (CITIC)	Easysight Supply Chain Management (ESCM)
Everbright Securities (ES)	Jingwei Textile Machinery Company (JTMC)
Guangdong Golden Dragon Development (GGDD)	Luxin Venture Capital (LVC)
GF Securities (GFS)	Minmetals Capital Company (MCC)
Guangzhou Yuexiu Financial Holdings Group (GYFHG)	Minsheng Holdings (MSH)
Guoyuan Securities (GS)	Shanghai AJ Group (SAJ)
Harbin Hatou Investment Co. Ltd (HHI)	Shaanxi International Trust (SIT)
Haitong Securities (HS)	Sunny Loan Top (SLT)

Note: This table reports the financial institutions according to the classification catalogue proposed by the company of Shenyin Wanguo Securities (SW). Considering the data integrity, we include all the financial institutions listed before 2010. Letters in parentheses are abbreviations of firms.

All the daily equity price data are obtained from Wind and converted to weekly log returns. All other regressors are also processed into the weekly data. Following Adrian and Brunnermeier (2016), we employ four lagged macroeconomic variables, M_{t-1}^{i}, to account for the general state of the economy, including: (i) volatility, VIX, computed as the average of the daily return square over the weekly frequency; and (ii) liquidity spread, LS, computed as the difference between the three-month collateral repo rate and three-month treasury bill rate; and (iii) spread term, ST, computed as the difference between the ten-year treasury bill rate and three-month treasury bill rate; and (iv) credit spread, CS, which is the change in the ten-year BAA rated bond and ten-year treasury bill rate.

Table 2 The relevant firm-specific tail risk drivers

Driver	Subdivision	Definition

M_{t-1}^{i} : lagged macroeconomic state variables	VIX_{t-1}^{i} : volatility	the average of daily return square over the weekly frequency
	LS_{t-1}^{i} : liquidity spread	difference between three-month collateral repo rate and three-month treasury bill rate
	ST_{t-1}^{i} : spread term	difference between ten-year treasury bill rate and three-month treasury bill rate
	CS_{t-1}^{i} : credit spread	change in ten-year BAA rated bond and Treasury bill rate
Z_{t-1}^{i} : lagged firm-specific characteristic	LEV_{t-1}^{i} : leverage	the value of total assets divided by total equity (in book values)
	BM_{t-1}^{i} : market-to-book value	market value/book value
	$SIZE_{t-1}^{i}$: market capitalization	the logarithm of market valued total assets
	VOL_{t-1}^{i} : equity return volatility	computed from daily equity return data
R_{t-1}^{i} : the lagged return		the firm-specific lagged return
F_{t}^{j} : other firms' return		the return less than unconditional 10% quantile

Note: This table provides the details of all the relevant firm-specific tail risk drivers, including lagged macroeconomic state variables M_{t-1}^{i}, lagged firm-specific characteristics Z_{t-1}^{i},the firm-specific lagged return R_{t-1}^{i} and other firm's influence F_{t}^{j}.All our data including macroeconomic, firm-special and return are estimated weekly.

Figure 1 plots the cumulative return of the main financial institutions and the Shanghai Composite Index. From this figure, it is obvious that Chinese institutions experienced a major turmoil during 2015-2016. Table 3 presents the summary statistics for the returns of financial firms involved in this study. The sample mean of the returns is positive for all sectors, demonstrating that the Chinese stock market grew slowly over the sample years. From the row labelled by $P\{(j|SH) < -VaR(5\%)\}$, we can see the conditional on the circumstance of the Shanghai Composite Index below its $-VaR(5\%)$, and the probabilities of financial sectors below their $-VaR(5\%)$ are 38%, 76%, 52%, and 62%, respectively. In addition, with the unconditional coverage test (Kupiec et al., 1995) and conditional coverage test (Christoffersen et al., 1998), the $P\{(j|SH) < -VaR(5\%)\}$ of the four financial sectors are all statistically significant at the 1% confidence level. This result implies, primarily, risk contribution between system return and financial firms to some extent.

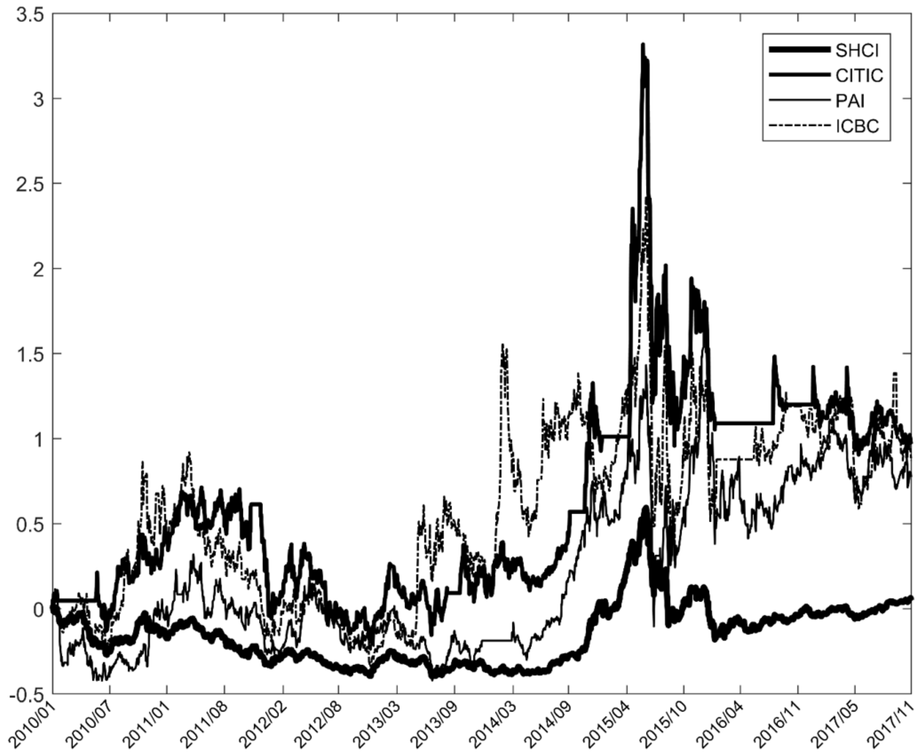

Figure 1 The cumulative return of financial institutions and Shanghai Composite Index

Note: This figure provides the time-series plots of cumulative return for Shanghai Composite Index and main financial institutions. The sample covers the period from January 4, 2010, to November 16, 2017. The four index and institutions are Shanghai Composite Index (SHCI), China International Trust and Investment Company (CITIC), Ping An Insurance (PAI), and Industrial and Commercial Bank of China (ICBC).

Table 3 Descriptive statistics of industry return series

Statistics	Commercial bank	Brokerage	Insurance	Others
Mean (%)	0.1908	0.2686	0.3292	0.3661
Median	-0.0758	0.0557	0.0841	0.6003
Max	14.6584	28.6891	19.5556	17.0758
Min	-11.7981	-14.6975	-12.4422	-25.1407
Std. Dev	3.3906	4.8114	4.1696	4.5888
ADF	-14.1645***	-11.7223***	-13.735***	-13.2621***
PP	-21.147***	-18.1163***	-19.821***	-18.1766***
$P\{(j\|SH) < -VaR(5\%)\}$	38%***	76%***	52%***	62%***

Note: This table reports the descriptive statistics of our sample. The sample period is from January 4, 2010, to November 16, 2017. $P\{(j|SH) < -VaR(5\%)\}$ denotes the probability of j^{th} sector below its VaR(5%) when shanghai Composite Index below its VaR(5%). “*”, “**”, and “***” denote significance at the 10%, 5%, and 1% levels, respectively.

5. Empirical Results

In this section, we use a two-stage quantile procedure to estimate the firm-specific risk and measure the systemic risk contribution of each financial institution. First, we present the results of the LASSO-quantile model, which constructs a tail risk network. Then, we divide the full sample into several periods, thereby allowing us to detect the dynamic evolutionary process of risk contagion during the 2015 Chinese stock market crash. Last, we quantify and rank the systemic risk contribution.

5.1 Tail Risk Network Model and Structure

We construct a tail risk network of the system by using the set of macroeconomic fundamentals, firm-specific characteristics, lagged returns, and loss exceedances of other companies. Figure 2 displays the tail risk network of the Chinese financial institutions. Firms in the system appear as shaded nodes. An arrow pointing from firm j to firm i reflects the impact of extreme returns of j on i when j experiences loss exceedance. The thickness of the line of an arrow reflects the size of the impact. Highly interconnected firms have more arrows including both incoming arrows and outgoing ones.

Figure 3 shows the network according to industry groups to highlight the industry-specific risk spillover effects. From this figure, it is implied that brokerages are most strongly connected with other sectors. The number of average connections between each brokerage and the other sectors is up to 9.67, which means that one brokerage is influenced by almost ten firms in other sectors. Potential reasons are as follows: (i) In recent years, the impact of brokerage firms on the market is growing. One example is that the bull market in China in early 2015 is led by brokerage firms. Moreover, during the first half of 2015, leverage trading provided by brokerages was widespread for financial institutions and investors, strengthening the connections between brokerages and other sectors. (ii) Brokerage firms and commercial banks are more closely connected and share risk. As banks have higher market capitalization and a closer relationship with the other sectors' balance sheets, brokerages are also strongly connected with other sectors. Commercial banks are more than happy to lend to brokerage firms because they are perceived as relatively high-quality firms with little risk. Another potential reason for the close relation is the so-called channel business between banks and brokerages. Brokerages engage in the profitable business of helping banks transfer their loans and notes on the books into off-balance-sheet financial products, and the resulting murky wealth management products (WMPs) of banks and asset management products (AMPs) of securities are the cornerstone of China's shadow banking system and could be a hidden systemic risk (Wang et al., 2017). Commercial banks exhibit the weakest risk inflow connections from others with the number of average inflow connections being 7.4. In addition, commercial banks differ from other industry categories because they display a much more concentrated risk outflow. Their average parameter measuring the size of risk spillover is 0.23, which is the largest among four industries. It is intuitive that commercial banks have the most intricate connections with other sectors in the form of asset and liability exposures or payment flows (Rönnqvist and Sarlin, 2015), which therefore lead to more risk outflow.

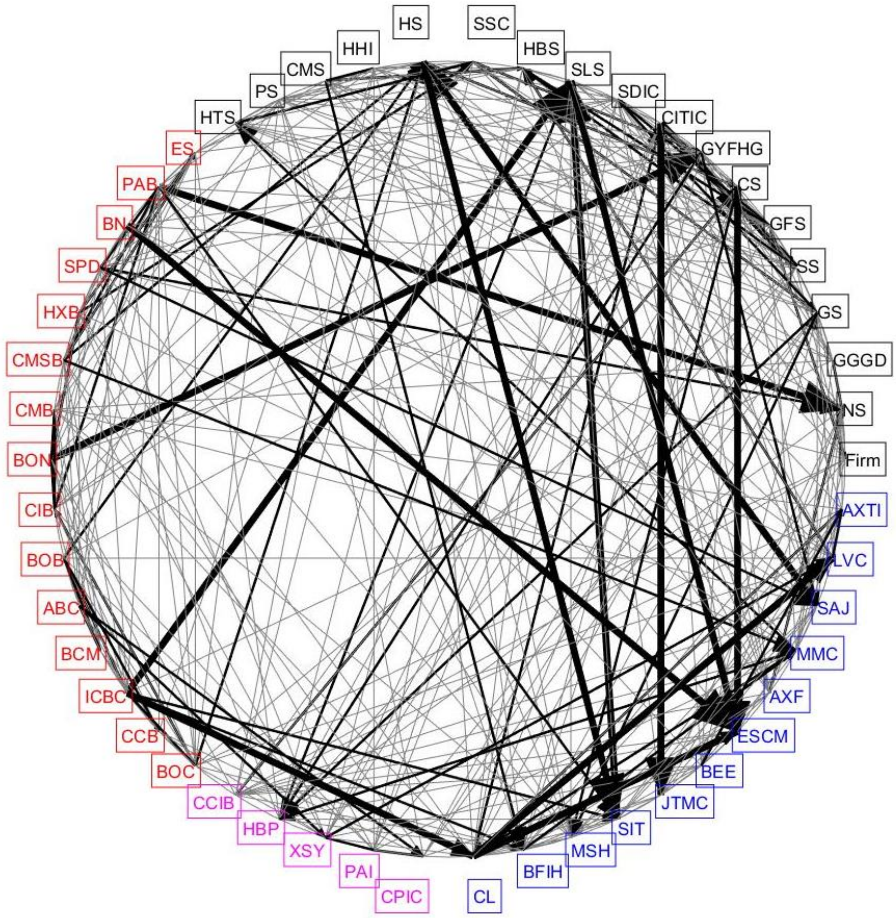

Figure 2. Overall tail risk network graph for fifty financial institutions in China

Note: An arrow pointing from firm j to firm i reflects the impact of extreme returns of j on the VaR. A connection is identified as relevant through LASSO methods. We distinguish the impact into three categories by the thickness of the arrow: (i) thin arrow indicate the absolute value of parameter is up to 0.3; (ii) medium-sized arrow indicate the value of 0.3-0.5; and (iii) thick arrow indicates the value is greater than 0.5. Our sample covers the period from January 2010 to November 2017. The abbreviations are spelled out in full in Table 1.

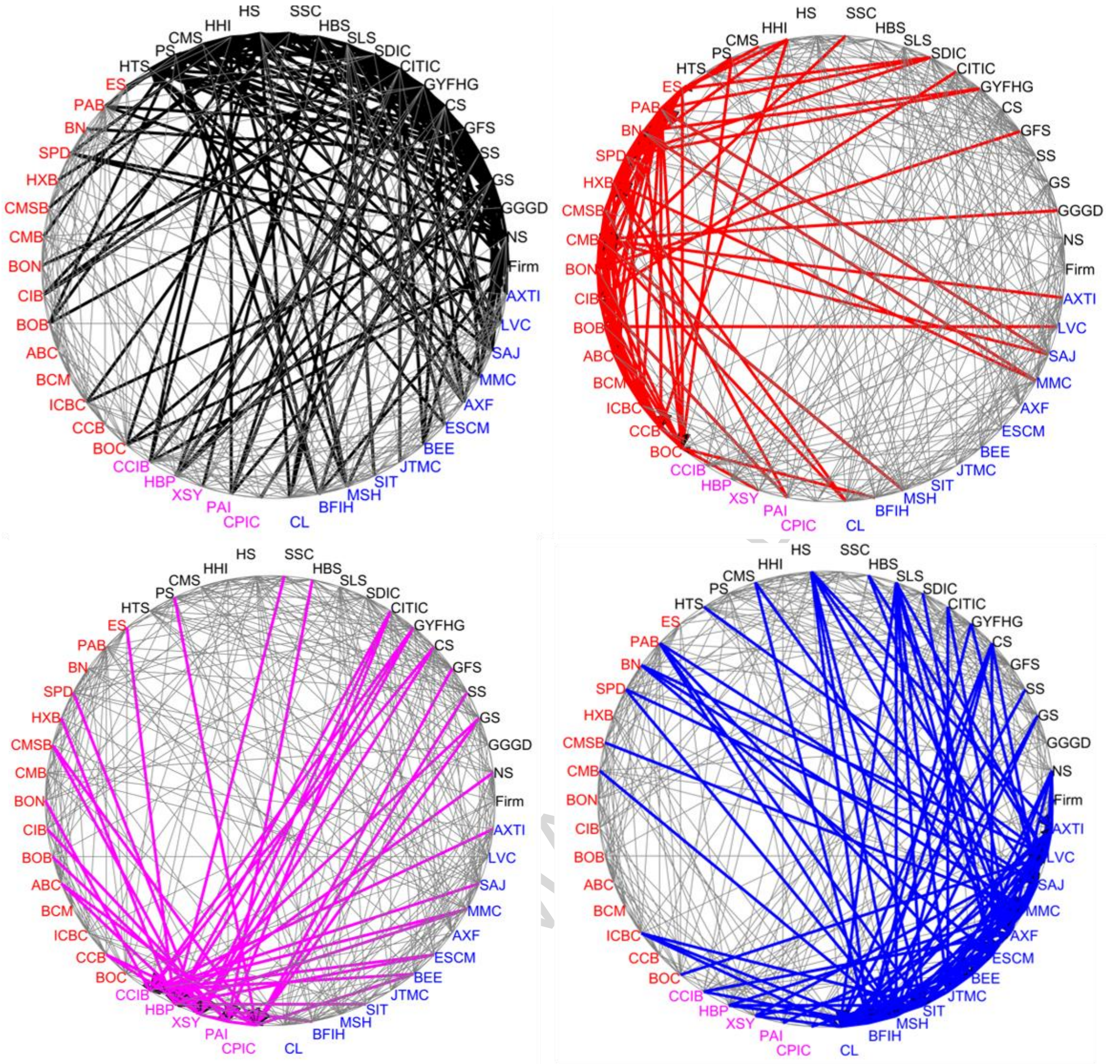

Figure 3 Tail risk network of Industry groups

Note: We arrange the network according to industry groups to highlight the industry-specific risk spillover effects. The four industries are Brokerages (top left), Commercial Banks (top right), Insurance Companies (bottom left), and Other Financial Institutions (bottom right). Our sample covers the period from January, 2010 to November, 2017. The abbreviations are spelled out in full in Table 1.

Next, we employ the LASSO selection procedure described above and the VaR of all individual companies for q=0.05. We choose several representative firms from the four sectors, which are CITIC, BOB, ICBC, PAI and MSH, respectively. Results of the LASSO-quantile regression for firm-specific risk VaR are provided in Table 4. We can see that most macroeconomic variables and firm-specific characteristics have no significant impact and are not selected by the LASSO procedure, while the loss exceedances of other firms predominantly drive the firm-specific risk. For example, VaR specifications for CITIC only contain one firm-specific characteristic of BM, but CITIC is significantly influenced by other firms such as GS and GFS. The implication is that fundamental factors do not play an important role in risk spillover especially during financial crisis. Firm-specific risk mainly comes from the impacts of other companies. The importance of cross-firm effects as drivers of individual tail risk is further confirmed by the failure of Lehman Brothers on September 2008 which leads to a sharp rise in system risk and contributed to market turmoil (Dumontaux and Pop, 2013; Sieczka et al., 2013).

Table 4 LASSO-quantile regressions for firm-specific risk VaR with q=0.05

	Value	**Standard Error**	**t-ratio**	**Pr(>|t|)**
CITIC				
(Intercept)	-0.0772	0.0158	-4.8873	0.0001
BM	-0.0721	0.0241	-2.9918	0.003
GS	-0.1255	0.1056	-1.1883	0.2354
GFS	-0.1054	0.0697	-1.5116	0.1314
CS	-0.131	0.1045	-1.2534	0.2108
SLS	-0.0278	0.0905	-0.3073	0.7588
HS	-0.3727	0.1679	-2.2196	0.0270
CMS	-0.0801	0.1051	-0.7621	0.4464
HTS	-0.1637	0.0971	-1.6852	0.0928
ES	-0.125	0.1177	-1.0619	0.2889
CIB	-0.5098	0.2331	-2.187	0.0293
XSY	-0.1138	0.0449	-2.5326	0.0117
MCC	-0.1	0.0527	-1.8969	0.0586
BOB				
(Intercept)	-0.0285	0.002	-14.3403	0.0001
SDIC	-0.0234	0.0439	-0.5329	0.5944
BON	-0.4218	0.0635	-6.6401	0.0001
CIB	-0.3334	0.0646	-5.159	0.0001
CCIB	-0.3061	0.0876	-3.4958	0.0005
CPIC	-0.1621	0.0658	-2.4643	0.0142
ICBC				
(Intercept)	-0.009	0.0029	-3.12	0.0019
Spread term	0.0057	0.0024	2.3817	0.0177
VOL	0.4323	0.2545	1.6986	0.0902
Lag return	0.1271	0.0461	2.7564	0.0061
CMB	-0.2227	0.0894	-2.4903	0.0132
BON	-0.2064	0.1594	-1.2948	0.1961
ABC	-0.3989	0.1028	-3.8806	0.0001
BCM	-0.2103	0.1075	-1.9559	0.0512
CCB	-0.0885	0.1241	-0.7134	0.476

PAI				
(Intercept)	-0.0554	0.008	-6.9002	0.0001
BM	-0.0539	0.0158	-3.409	0.0007
GYFHG	-0.0694	0.0512	-1.3556	0.1760
CITIC	-0.171	0.082	-2.0852	0.0377
SDIC	-0.1434	0.0621	-2.3083	0.0215
HXB	-0.0374	0.1063	-0.3517	0.7252
CMB	-0.1382	0.0925	-1.4934	0.1361
BCM	-0.4532	0.204	-2.2217	0.0269
BOC	0.1499	0.1539	0.9744	0.3305
CPIC	-0.317	0.0779	-4.0714	0.0001
MSH				
(Intercept)	-0.0274	0.0058	-4.7414	0.0001
VOL	0.5081	0.2778	1.829	0.0682
SS	-0.1691	0.1508	-1.1209	0.2630
GYFHG	-0.2135	0.1501	-1.4227	0.1556
CITIC	-0.2625	0.2644	-0.993	0.3213
HHI	-0.1745	0.1519	-1.1487	0.2514
PC	-0.3973	0.1859	-2.1374	0.0332
CCB	-0.4975	0.259	-1.921	0.0555
HBP	-0.0673	0.1464	-0.4597	0.6460
XSY	-0.2123	0.1206	-1.7594	0.0793
BFIH	-0.1253	0.1304	-0.9603	0.3375
SIT	-0.2455	0.2173	-1.1301	0.2592
BEE	-0.2186	0.0661	-3.3059	0.0010
SAJ	0.0321	0.1239	0.2593	0.7955

Note: This table provides the detailed regressors selected by LASSO-quantile regressions. The representative firms are CITIC, BOB, ICBC, PAI and MSH, respectively. Our sample covers the period from January, 2010 to November, 2017. The abbreviations are spelled out in full in Table 1.

Table 5 provides details about the influenced and influencing institutions for each firm based on the identified tail risk connections between all companies. The number of risk connections varies substantially between different companies.

We divided the firms into three categories: The first group contains companies usually influencing but less influenced by other firms. Therefore, these firms are risk drivers in the system. Once they experience loss exceedance, they shall have significant impacts on other institutions and warrant close supervision. As companies are becoming increasingly interconnected, adverse shocks occurring in one or several financial institutions are spread not only to the entire financial system but also to the real economy, as was illustrated by the dotcom and subprime crises (Bernal et al., 2014). The second group consists of companies that mainly act as risk takers. These companies, like some growth stocks, are vulnerable to external shocks but have less influence on other firms. We can notice that JTMC is impacted by ten different institutions while having an effect on only five firms. The third group is the largest category. It contains companies that serve as both risk recipients and risk transmitters. The finding is consistent with Hautsch et al. (2015) who suggest that these firms amplify tail risk spillovers and increase market volatility on extreme conditions. Such firms are like CS, CITIC, BN and BFIH.

Table 5 Influenced and influencing institutions of tail risk network

Firm	Influenced firm	Influencing Firm
Brokerages		
NS	GGDD, SS, GFS, CS, HXB, CCIB, HBP, MSH	GFS, CS, SLS, HS, SAJ
GGDD	GS, BN, HXB, MMC, SAJ, LVC, SLT	NS, GS, SLS, HHI, HTS, XSY, BEE, ESCM, MMC, AXTI, SLT
GS	GGDD, SS, CS, CITIC, SLS, CCB, SAJ	GGDD, SS, CS, GYFHG, CITIC, SLS, PS, ES, BON
SS	GS, SDIC, SLS, SSC, HS, XSY, CPIC, SIT, ESCM, LVC, AXTI	NS, GS, GFS, SLS, HS, CMS, HTS, ES, XSY, CL, MSH, SIT
GFS	NS, SS, CS, SDIC, HBS, PS, HTS, ES, SPD, CCIB, XSY, CL	NS, CITIC, SDIC, SSC, HS, ES, CL, BFIH
CS	NS, GS, CITIC, SSC, HHI, CMS, PS, ES, BN, SAJ	NS, GS, GFS, CITIC, SDIC, SLS, HBS, SSC, CMS, PS, CIB, CL
GYFHG	GS, SDIC, HHI, ABC, HBP, MSH, ESCM, LVC, SLT	SDIC, SLS, HHI, HBP, PAI, BFIH, MSH, SIT, AXF, LVC
CITIC	GS, GFS, CS, SLS, HS, CMS, HTS, ES, CIB, XSY, MMC	GS, CS, HS, CMS, HTS, SPD, HXB, HBP, XSY, PAI, MSH, LVC
SDIC	GFS, CS, GYFHG, HBS, BOB, CPIC, BFIH, BEE, ESCM, LVC	SS, GFS, GYFHG, BOB, XSY, PAI, CPIC, BEE, MMC
SLS	NS, GGDD, GS, SS, CS, GYFHG, SSC, HHI, HTS, BOB, CPIC, BFIH, MMC, LVC	GS, SS, CITIC, HTS, PAB, BN, HXB, AXF
HBS	CS, CCB, XSY, JTMC, AXF	GFS, SDIC, SSC, BFIH, SIT, JTMC, BEE, AXF, MMC, AXTI
SSC	GFS, CS, HBS, CMS, PS, ES, PAI, AXTI	SS, CS, SLS, PS, HTS, ES, CPIC, MMC, AXTI
HS	NS, SS, GFS, CITIC, CMS, HTS, ES, CMSB, BOB	SS, CITIC, CMS, HTS, ES, CIB, XSY
HHI	GGDD, GYFHG, PS, HTS, CMB, ABC, CCIB, HBP, BFIH, SIT, MMC, LVC	CS, GYFHG, SLS, MSH, SIT, JTMC, MMC, LVC, SLT
CMS	SS, CS, CITIC, HS, PS, ES, PAB, HXB, HBP,	CS, CITIC, SSC, HS, PS, PAB, HXB, BOC

	CPIC, SIT	
PS	GS, CS, SSC, CMS, PAB, MSH, MMC, SAJ, AXTI	GFS, CS, SSC, HHI, CMS, PAB, MSH, MMC
HTS	GGDD, SS, CITIC, SLS, SSC, HS, ES, BN, BON, ABC, MSH, SIT	GFS, CITIC, SLS, HS, HHI, ES, BN, CCIB, CL
ES	GS, SS, GFS, SSC, HS, HTS, AXF, SAJ, LVC	GFS, CS, CITIC, SSC, HS, CMS, HTS, AXTI
Commercial Banks		
PAB	SLS, CMS, PS, BN, HXB, CMSB, CMB, BON	CMS, PS, BN, CMSB, CMB, CIB, CCIB, XSY
BN	SLS, HTS, PAB, HXB, CMB, BON, BOB, BCM, CCB, LVC	GGDD, CS, HTS, PAB, HXB, BON, ABC, BCM, BOC, CCIB, SIT, JTMC, ESCM, LVC
SPD	CITIC, HXB, CMSB, CMB, CIB, BCM, CCIB, SAJ	GFS, HXB, CMB, BCM, CCIB, AXF, SAJ, AXTI
HXB	CITIC, SLS, CMS, BN, SPD, CMB, BOB, CCB	NS, GGDD, CMS, PAB, BN, SPD, CMSB, CMB, CCB, PAI, SIT, LVC
CMSB	PAB, HXB, CIB, BCM, CPIC, BFIH, SAJ	HS, PAB, SPD, CIB, BCM, XSY
CMB	PAB, SPD, HXB, CIB, BCM	HHI, PAB, BN, SPD, HXB, CIB, BCM, ICBC, CCB, PAI, CL, SAJ
BON	GS, BN, BOB, ICBC, BFIH, SIT, LVC, SLT	HTS, PAB, BN, CIB, BOB, BCM, ICBC, SIT
CIB	CS, HS, PAB, CMSB, CMB, BON, BOB, ICBC	CITIC, SPD, CMSB, CMB, BOB, CCB, CCIB, HBP
BOB	SDIC, BON, CIB, CCIB, CPIC	SDIC, SLS, HS, BN, HXB, BON, CIB, BCM, BOC, CCIB, CPIC
ABC	BN, ICBC, CCB, BOC, CCIB, AXTI	GYFHG, HHI, HTS, BCM, ICBC, CCB, BOC, CPIC
BCM	BN, SPD, CMSB, CMB, BON, BOB, ABC, ICBC	BN, SPD, CMSB, CMB, ICBC, CCB, BOC, PAI, CL
ICBC	CMB, BON, ABC, BCM, CCB	BON, CIB, ABC, BCM, CCB, BOC
CCB	HXB, CMB, CIB, ABC, BCM, ICBC, BOC, CCIB	GS, HBS, BN, HXB, ABC, ICBC, BOC, CCIB, BFIH, MSH, JTMC
BOC	CMS, BN, BOB, ABC, BCM, ICBC, CCB	ABC, CCB, CCIB, PAI, CL
CCIB	HTS, PAB, BN, SPD, CIB, BOB, CCB, BOC, PAI, MSH	NS, GFS, HHI, SPD, BOB, ABC, CCB, AXTI
Insurance companies		
HBP	GYFHG, CITIC, CIB, ESCM, AXF, SAJ, LVC, SLT	NS, GYFHG, HHI, CMS, MSH, MMC
XSY	GGDD, SS, CITIC, SDIC, HS, PAB, CMSB, MSH, JTMC, AXF, SAJ	SS, GFS, CITIC, HBS, MSH, JTMC, SAJ
PAI	GYFHG, CITIC, SDIC, HXB, CMB, BCM, BOC, CPIC	SSC, CCIB, CPIC, BFIH, ESCM, AXTI
CPIC	SDIC, SSC, BOB, ABC, PAI, CL	SS, SDIC, SLS, CMS, CMSB, BOB, PAI, CL, SAJ
CL	SS, GFS, CS, HTS, CMB, BCM, BOC, CPIC, ESCM	GFS, CPIC, ESCM
Other financial institutions		
BFIH	GFS, GYFHG, HBS, CCB, PAI, JTMC, BEE, AXF, SAJ, AXTI, SLT	SDIC, SLS, HHI, CMSB, BON, MSH, SIT, BEE, AXF, SAJ, AXTI, SLT

MSH	SS, GYFHG, CITIC, HHI, PS, CCB, HBP, XSY, BFIH, SIT, BEE, SAJ, SLT	NS, GYFHG, PS, HTS, CCIB, XSY, JTMC, MMC, SAJ, SLT
SIT	SS, GYFHG, HBS, HHI, BN, HXB, BON, BFIH, LVC, AXTI	SS, HHI, CMS, HTS, BON, MSH, ESCM, MMC
JTMC	HBS, HHI, BN, CCB, XSY, MSH, BEE, LVC, AXTI, SLT	HBS, XSY, BFIH, LVC, AXTI
BEE	GGDD, SDIC, HBS, BFIH, ESCM, MMC, LVC	SDIC, BFIH, MSH, JTMC, ESCM, LVC, SLT
ESCM	GGDD, BN, PAI, CL, SIT, BEE, AXF, SLT	SS, GYFHG, SDIC, HBP, CL, BEE, SAJ, SLT
AXF	GYFHG, SLS, HBS, SPD, BFIH, LVC	HBS, ES, HBP, XSY, BFIH, ESCM, LVC
MMC	GGDD, SDIC, HBS, SSC, HHI, PS, HBP, MSH, SIT, SLT	GGDD, CITIC, SLS, HHI, PS, BEE
SAJ	NS, SPD, CMB, XSY, CPIC, BFIH, MSH, ESCM, LVC, SLT	GGDD, GS, CS, PS, ES, SPD, CMSB, HBP, XSY, BFIH, MSH, LVC, SLT
LVC	GYFHG, CITIC, HHI, BN, HXB, JTMC, BEE, AXF, SAJ	GGDD, SS, GYFHG, SDIC, SLS, HHI, ES, BN, BON, HBP, SIT, JTMC, BEE, AXF, SAJ
AXTI	GGDD, HBS, SSC, ES, SPD, CCIB, PAI, BFIH, JTMC, SLT	SS, SSC, PS, ABC, BFIH, SIT, JTMC, SLT
SLT	GGDD, HHI, BFIH, MSH, BEE, ESCM, SAJ, AXTI	GGDD, GYFHG, BON, HBP, BFIH, MSH, JTMC, ESCM, MMC, SAJ, AXTI

Note: This table provides details about influenced and influencing institutions for each firm. The “influenced firms” are loss exceedances selected by LASSO as relevant regressors for VaR^i. The “influencing firms” are firms which appears as relevant in their corresponding VaR^j. The abbreviations are spelled out in full in Table 1.

Overall, we construct a tail risk network of the system and arrange the network according to industry groups. By providing LASSO-quantile regression results for firm-specific risk, we find that most macroeconomic variables and firm-specific characteristics have no significant impact and are not selected by the LASSO procedure. At the same time, the loss exceedances of other firms dominantly drive the firm-specific risk. We divided the firms into three categories of risk driver, risk taker, and risk transmitter, respectively.

5.2 Phasing the Tail Risk Network

According to the three specific points in time, we divide the whole sample period into four sub-periods representing tranquil period, bull market period, stock market crash period, and post-crash period, respectively. The four periods correspond to the dynamic evolution of the Chinese stock market in recent years. More details are provided in Table 6.

Table 6 Specific points in time and sub-sample periods

Specific points in time	Sub-sample period
	Tranquil period: from January 4, 2010 to June 30, 2014
June 30, 2014	Bull market: from June 30, 2014 to June 15, 2015
June 15, 2015	Stock market crash: from June 15, 2015 to June 30, 2016
June 30, 2016	Post-crash period: from June 30, 2016 to November 16, 2017

Note: This table presents three specific points in time, which divides the full sample into four sub-samples. Our full sample covers the period from January, 2010 to November, 2017.

In this paper, we focus on the highly volatile periods of bull market and crash. Figure 4 shows the resulting systemic risk networks for fifty financial institutions, computed based on rolling windows from 2013 to 2016, which cover the bull and crash periods. The result implied that the interconnection network is relatively sparse during the tranquil period, but becomes dense after the bull market period. In addition, the number of connections in the network increases from 288 (top left) to 317 (bottom right) from the tranquil period to the bull market and crash period, which reflects higher risk levels of spillover effects. Losses tend to spread faster across financial institutions, thereby threatening the financial system as a whole during times of financial crisis. The increase of co-movement between financial institutions gives rise to systemic risk and risk spillover (Adrian and Brunnermeier, 2016).

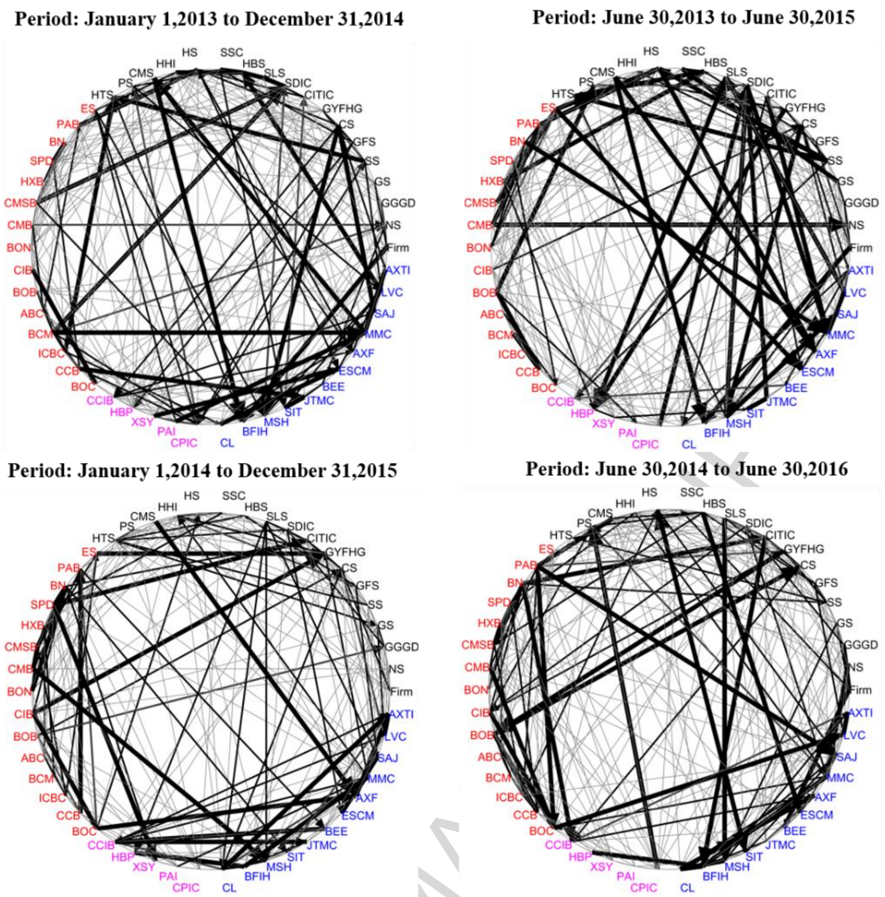

Figure 4 Tail risk network, rolled over from December 2014 to June 2016
Note: Estimates of systemic risk network, rolled over from December 2014 to June 2016, corresponding to the Chinese stock market crash. Abbreviations are spelled out in full in Table 1.

In summary, we divide the whole sample period into four sub-periods to study the evolution of risk spillover in the Chinese stock market. We find higher levels of risk spillover during the volatile periods of bull market and crash.

5.3 Quantifying and Ranking the Systemic Risk Contribution

In this section, we quantify and rank the systemic risk contribution. As described in Section 3.2, the systemic risk beta $\beta^{s|i}_{p,q,t}$ measures the marginal effect of firm i's risk $VaR^{i}_{q,t}$ on the systemic risk $VaR^{s}_{p,t}$. We believe the firm i has significant systemic risk only if $\beta^{s|i}_{p,q,t}$ is significantly positive. As the extended K-S test is asymptotically distribution-free and does not require any assumption concerning the underlying distribution, it may be used to test the significance of systemic risk beta. Table 7 provides the relevant statistics, where a P-value greater than 0.1 means that the company has no significant effect. We select thirty-eight companies out of fifty, indicating that approximately 75% of institutions have a significant systematic risk contribution.

Table 7 Significance test of systemic risk beta by Kolmogorov-Smirnov statistic

Firm	K-S stat	P-value	Firm	K-S stat	P-value
NS	13.3476	0.0001	CIB	0.0000	0.9510
GGDD	2.5424	0.0001	BOB	11.4055	0.0001
GS	14.1598	0.0001	ABC	13.4536	0.0001
SS	6.9563	0.0001	BCM	6.3560	0.0001
GFS	5.7557	0.0001	ICBC	8.8631	0.0001
CS	13.4536	0.0001	CCB	0.0000	0.9595
GYFHG	3.6017	0.0001	BOC	13.7008	0.0001
CITIC	6.7444	0.0001	CCIB	12.9945	0.0001
SDIC	14.1598	0.0001	HBP	3.6017	0.0001
SLS	6.9563	0.0001	XSY	0.5650	0.3695
HBS	7.4860	0.0001	PAI	0.0000	0.9635
SSC	3.1074	0.0001	CPIC	6.2148	0.0001
HS	9.3222	0.0001	CL	10.4874	0.0001
HHI	6.3560	0.0001	BFIH	12.8180	0.0001
CMS	12.0411	0.0001	MSH	13.5948	0.0001
PS	0.4237	0.4855	SIT	13.9126	0.0001
HTS	13.9479	0.0001	JTMC	0.1059	0.9025
ES	0.0000	0.9615	BEE	0.1059	0.8940
PAB	14.1598	0.0001	ESCM	14.1245	0.0001
BN	4.3080	0.0001	AXF	14.1598	0.0001
SPD	6.8151	0.0001	MMC	0.0000	0.9695
HXB	4.5905	0.0001	SAJ	0.1766	0.7630
CMSB	6.0382	0.0001	LVC	14.1598	0.0001
CMB	0.0000	0.9685	AXTI	2.2952	0.0001
BON	14.1598	0.0001	SLT	0.4944	0.4320

Note: This table provides the results of significance test for systemic risk beta. According to the null hypothesis of significance test by KS statistic of D_{eq} in Equation (14), systemic risk beta is less than zero. We exclude firms with insignificant beta from systemic risk contribution ranking. Our sample covers the period from January, 2010 to November, 2017.

Next, we select specific points in time for China's stock market crash and categorize the different systemic risk contributions. Table 8 reports the relevant statistics. Specifically, Panel A reveals the ranking for June 30, 2014, which can be seen as the tranquil time before the bull market. Panel B reports the ranking for June

15, 2015, just at the dusk of the bull market and on the eve of the stock market crash. Panel C provides the ranking for June 30, 2016, which is the tail of the crash. We only list the top 20 rankings for each point in time, respectively, and find some interesting phenomena.

We observe that commercial banks generally have the most systemic risk contribution, which is more prominent in the tranquil period (see Panel A). This observation is in line with common sense, as banks have higher market capitalization and a closer relationship with the other sectors' balance sheets. Essentially, banks play a crucial role in the proper functioning of an economy because they provide the necessary liquidity to the markets and help to promote economic growth (Drakos and Kouretas, 2015). Therefore, they have a higher impact on the systemic risk during a tranquil period. However, other financial institutions such as Luxin Venture Capital (LVC) and Anhui Xinli Finance (AXF) have a top ranking in Panel B. At the apex of the bull market, smaller companies have a larger market capitalization bubble and their prices are highly volatile. The occurrence of a downside will cause a plunge in the stock market.

Furthermore, Panel C shows that brokerages and insurance companies rank higher and banks rank lower. This phenomenon can be attributed to the bailout from government that lowers the systemic risk contribution at this time. Moreover, due to the relative higher market value and high sensitivity to policies and markets, brokerages and insurance companies contribute more risk than other sectors.

Table 8 Rankings of systemic risk contributions

Rank	Name	Systemic risk contribution*10^2	Systemic risk beta	VaR
Panel A: Before the beginning of the bull market, on June 30, 2014				
1	BON	1.5682	0.8267	0.0190
2	HTS	1.4500	0.4034	0.0359
3	GS	1.4382	0.4918	0.0292
4	ICBC	1.3967	0.8031	0.0174
5	ABC	0.8394	0.4560	0.0184
6	NS	0.8340	0.1887	0.0442
7	BOC	0.7848	0.3598	0.0218

8	BOB	0.7474	0.2623	0.0285
9	SDIC	0.7398	0.1482	0.0499
10	SPD	0.6680	0.2233	0.0299
11	PAB	0.6606	0.2572	0.0257
12	SIT	0.6561	0.1500	0.0437
13	LVC	0.5657	0.1138	0.0497
14	BN	0.5410	0.2104	0.0257
15	BCM	0.5303	0.2179	0.0243
16	ESCM	0.5092	0.1688	0.0302
17	CS	0.5089	0.1321	0.0385
18	BFIH	0.4690	0.1388	0.0338
19	CL	0.4658	0.1457	0.0320
20	HS	0.4618	0.1528	0.0302
Panel B: Before the beginning of the crash, on June 15, 2015 (at the end of bull market)				
1	GS	8.8263	0.4066	0.2171
2	LVC	5.6845	0.1328	0.4279
3	BOC	5.2739	0.3386	0.1557
4	CS	3.7027	0.1398	0.2649
5	BON	3.3947	0.2541	0.1336
6	HTS	3.2873	0.1475	0.2228
7	AXF	2.6402	0.0926	0.2850
8	PAB	2.5038	0.1166	0.2148
9	ESCM	2.3169	0.0851	0.2722
10	SDIC	1.8696	0.0587	0.3183
11	CCIB	1.0553	0.0540	0.1954
12	BFIH	0.7753	0.0352	0.2206
13	SIT	0.6773	0.0254	0.2669
14	CL	0.6710	0.0267	0.2513
15	HHI	0.3734	0.0165	0.2268
16	HXB	0.3482	0.0173	0.2010
17	NS	0.3314	0.0138	0.2399
18	SPD	0.1537	0.0090	0.1709
19	SSC	0.0099	0.0003	0.2876
20	GGDD	-0.3539	-0.0115	0.3081
Panel C: End of the crash, on June 30, 2016				
1	GS	2.1279	0.5096	0.0418
2	BON	1.5573	0.5982	0.0260
3	HTS	1.4927	0.3185	0.0469
4	CL	0.6878	0.1834	0.0375
5	ABC	0.6851	0.4380	0.0156
6	BOC	0.6735	0.3088	0.0218
7	SIT	0.6592	0.1508	0.0437

8	SDIC	0.6359	0.1676	0.0379
9	PAB	0.6226	0.2907	0.0214
10	AXF	0.5819	0.0870	0.0669
11	LVC	0.5616	0.1130	0.0497
12	ICBC	0.5122	0.3089	0.0166
13	CMS	0.4357	0.1264	0.0345
14	NS	0.4014	0.0908	0.0442
15	ESCM	0.3854	0.1077	0.0358
16	BFIH	0.3469	0.1536	0.0226
17	BOB	0.3400	0.1193	0.0285
18	CS	0.3049	0.0791	0.0385
19	HS	0.2681	0.0975	0.0275
20	CMSB	0.2663	0.1225	0.0217

Note: According to the systemic risk contributions, we rank the firms at three specific points in time. We exclude firms with insignificant beta from systemic risk contribution ranking. Our sample covers the period from January 2010 to November 2017. The abbreviations are spelled out in full in Table 1.

To illustrate the findings above more specifically, we selected ICBC and LVC as two representative firms and drew their VaR, systemic risk beta, and contribution chart. The average systemic risk beta of ICBC is larger than LVC during the tranquil period, meaning that ICBC extolls higher risk to the system. Due to its huge size and close relationship with many companies, ICBC is a more systemically important firm. However, the average beta of ICBC significantly decreases during market crash. This leads to a fall in systemic risk contribution, although the VaR of itself increases at the same time. Policies introduced by the regulators to protect the systemically important banks make their contribution to systemic risk less obvious, which proves the “too big to fail” theory under this new circumstance. For comparison and verification, we also draw the systemic risk contribution of LVC. Its contribution significantly increases during crisis without the bailout of government, which shows the opposite trend to ICBC.

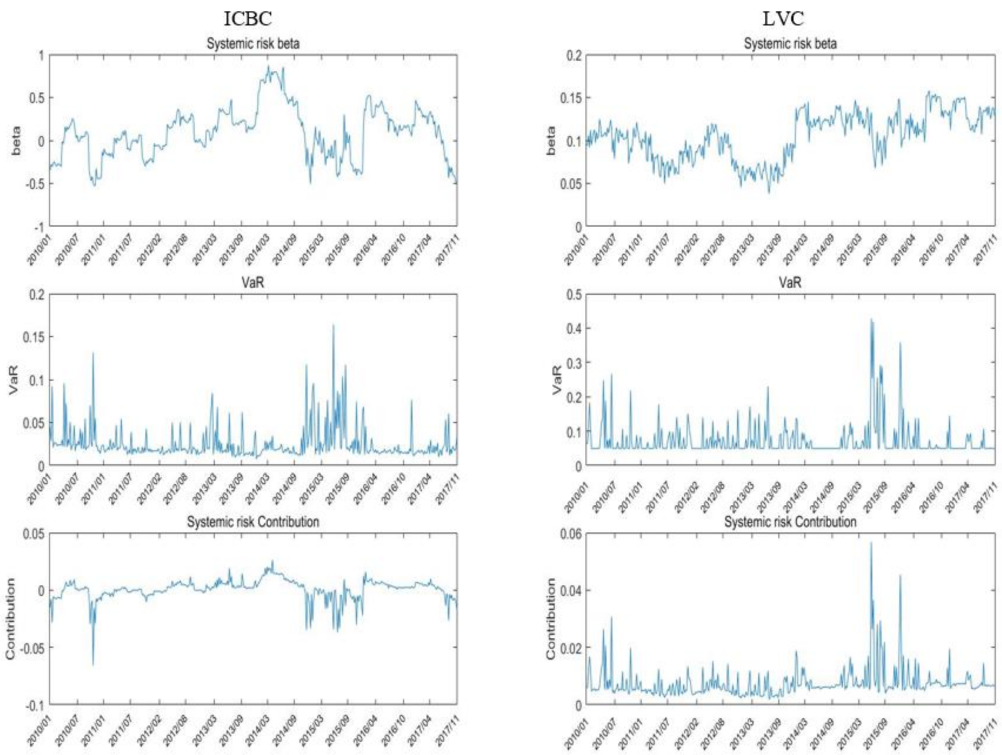

Figure 5 VaR, systemic risk beta, and contribution of two representative institutions

Note: We select two representative institutions to show the time evolution of VaR, systemic risk beta and contribution. Our sample covers the period from January 2010 to November 2017. The two representative institutions are Industrial and Commercial Bank of China (ICBC) and Luxin Venture Capital (LVC), respectively.

In this section, our results show that commercial banks are relatively riskier firms during the tranquil period, because of their huge size and impact on the financial system. However, due to the investor sentiment and government interventions, banks are less risky than other financial institutions during the crisis.

5.4 Testing the determinants of systemic risk contribution

As mentioned above, commercial banks contribute more systemic risk during tranquil periods, which is only a descriptive analysis. In this section, from the perspective of statistical analysis, we further identify the forward-looking determinants of systemic risk contribution using panel regression. Following Adrian and Brunnermeier (2016), the panel regression is specified as:

$$\bar{C}^{s|i}_{p,q,t} * 100 = \alpha^i_0 + \alpha^{'}_1 X^i_{t-1} + \alpha^{'}_2 G^i_{t-1} + \varepsilon^i_t \tag{16}$$

where $\bar{C}^{s|i}_{p,q,t}$ is systemic risk contribution, α^i_0 is the fixed effect of a specific institution, X_{t-1}^{i} represents the determinant variables for risk contribution and G_{t-1}^{i} represents the control variables.

We magnify the systemic risk contribution 100 times to zoom the level of coefficients. To keep in line with Equation (2), we take into account macroeconomic variables and returns of individual stocks as control variables $G_{t-1}^{i}=(VIX_{t-1}^{i},LS_{t-1}^{i},ST_{t-1}^{i},CS_{t-1}^{i},R_{t-1}^{i})'$. The determinant variables are $X_{t-1}^{i}=(crisis*SIZE_{t-1}^{i},SIZE_{t-1}^{i},LEV_{t-1}^{i},BM_{t-1}^{i},VOL_{t-1}^{i})'$. The ranking of systemic risk contribution shows that banks are less risky during the crisis, making $SIZE$ an important factor. Thus, we define a dummy variable $crisis$ to consider the Chinese stock market crash as follows: $crisis=1$ for the crash period (from June 15, 2015 to June 30, 2016), and $crisis=0$ otherwise. The detailed description of regressors is listed in Table 3. We estimate the panel regression of Equation (16) at a weekly frequency, giving us 401 observations for each financial institution.

Table 9 reports the panel regression results of Equation (16). For robustness checks, regressions (1) through (4) incorporate the four determinants one by one and basic controls to account for the macro-economy. While regression (5) includes all measures together, of which all estimated coefficients of determinants are the same signal and significance level with regressions (1) to (4), proving the robustness of our results.

Table 9 Testing the forward-looking determinants of systemic risk contribution

Variables	(1)	(2)	(3)	(4)	(5)
$SIZE_{t-1}$	0.5933***				0.5056***
	(0.0240)				(0.0248)
LEV_{t-1}		0.0180***			0.0065***
		(0.0023)			(0.0023)
BM_{t-1}			-0.5185***		-0.3404***
			(0.0306)		(0.0314)
VOL_{t-1}				3.1649***	2.6500***
				(0.3247)	(0.3197)
$crisis*SIZE_{t-1}$	-0.0057***				-0.0050***

	(0.0018)				(0.0018)
R_{t-1}	0.5281***	0.6034***	0.4764***	0.1536*	0.0712
	(0.0766)	(0.0776)	(0.0775)	(0.0904)	(0.0891)
VIX_{t-1}	12.7023***	12.3285***	10.0393***	8.6391***	7.9501***
	(0.7544)	(0.6762)	(0.6867)	(0.7783)	(0.8540)
LS_{t-1}	-0.0181**	-0.0293***	-0.0250***	-0.0309***	-0.0172**
	(0.0082)	(0.0080)	(0.0080)	(0.0080)	(0.0081)
ST_{t-1}	0.0900***	0.0972***	0.0707***	0.1066***	0.0683***
	(0.0132)	(0.0133)	(0.0134)	(0.01330)	(0.0133)
CS_{t-1}	-0.0346***	-0.0038	0.0162***	-0.0017	-0.0180***
	(0.00330)	(0.0028)	(0.0030)	(0.0028)	(0.00360)
Const	-6.1500***	-0.2542***	-0.0022	-0.1690***	-5.2290***
	(0.2457)	(0.04160)	(0.0398)	(0.0392)	(0.2549)
F-stat	642.32***	620.71***	650.08***	642.32***	626.73***
Observations	401	401	401	401	401

Note: This table provides the panel regression results of Equation (16); the regressors are listed in Table 3. The coefficient on the fixed effect is omitted. The values in parentheses are the estimated standard deviations of the coefficients. All the variables are matched weekly. Our sample covers the period from January, 2010 to November, 2017. "*", "**", and "***" denote significance at the 10%, 5%, and 1% levels, respectively.

As Table 9 indicates, the coefficient of $SIZE_{t-1}$ is significant positive for the non-crash period, meaning that higher market capitalization shall contribute more systemic risk as a whole. However, coefficient of $crisis * SIZE_{t-1}$ is significant negative. Larger firms are adversely less risky when the stock market experiences a crisis. This is due to the fact that during a crash period, governments usually bail out large financial institutions, such as banks or blue chips, and this has led to a lower risk contribution at such times. During financial crises, authorities have an incentive to prevent the failure of a financial institution because such a failure would pose a significant risk to the financial system and, consequently, to the broader economy (Zhou, 2010). A bailout is usually supported by the argument that a financial firm is "too big to fail" (Bernanke, 2009).

Firm-specific volatility is another robust determinant of systemic risk contribution, which is consistent with Zhang et al. (2009). They find that volatility risk alone can predict 50% of the variation in CDS spread levels. Our results imply that the firm-specific lagged volatility is also a robust predictor of its systemic risk contribution to the whole stock market. This implication is intuitive since the riskier the financial institution is, the more risk is propagated to the system.

The book-to-market ratio shows negative effect on the systemic risk contribution, while leverage is the opposite. Adrian and Brunnermeier (2016) and Acharya et al. (2017) show that higher leverage, more maturity mismatch, and smaller book-to-market tend to increase the risk contribution. Lower BM ratio means that the market value is already overvalued relative to the company's book value. Firms with low BM and higher leverage are riskier than others.

Regarding the control variables, a higher VIX and spread term tend to be associated with more systemic risk contribution. In addition, increases in liquidity spread tend to be associated with smaller risk, while lagged returns and credit spread are not robust significant on average.

Overall, leverage and volatility of specific financial institutions are positive, forwarding-looking factors of systemic risk contribution. The risk contribution is predicted to rise when the book-to-market ratio is lower. As a key determinant, size is positively significant on average, indicating that firms with higher market capitalization are more systemically important. However, government tends to bail out large financial institutions that lower the risk contributions during the crisis, proving the "too big to fail" theory under this new circumstance. Finally, some macroeconomic variables are also related with the systemic risk contribution. Thus, we cannot ignore the impact of macroeconomic factors in assessing risks.

6. Conclusion

China has attempted to or has been an indispensable part of the world economy with many achievements in its monetary and financial system, especially with respect to the progress of reforming its stock markets. Due to a series of liberalization policies, the cooperation between China's financial institutions has made tremendous unprecedented progress that has provided opportunities for risk contagion. The Chinese stock market crash in 2015 also demonstrates the need for an improved understanding of systemic risk. Therefore, it is necessary to quantify the systemic risk of the Chinese stock market in this new situation.

With the CoVaR type measure by Adrian and Brunnermeier (2016), we investigate the systemic risk of Chinese stock markets after 2010. Following the framework of Hautsch et al. (2015), we construct a tail risk network of fifty financial institutions to explore firm-specific risk, given the macroeconomic and market externalities. Employing the LASSO method of high-dimensional models, our results show that a firm's idiosyncratic risk can be affected by its connectedness with other institutions. The risk of spillover effect from other companies is the main driver of firm-specific risk, compared with macroeconomic state, firm characteristics, and lagged return. Our results classify the firms into three categories of risk producers, risk transmitters, and risk takers within the network.

Furthermore, we divide the full sample into three sub-sample periods according to specific points in time. The number of connections between institutions significantly increases from June, 2014 to June, 2016. This trend is intuitive since the riskier the stock market is, the more easily firm-specific risk is affected by other companies. Finally, we quantify the systemic risk contribution of each firm, given its role and position in the network. We utilize the Kolmogorov-Smirnov statistic by Abadie (2002) to test the significance of systemic risk beta and further rank the risk contribution. Our results show that commercial banks are the relatively riskier high risky firms during the tranquil period, because of their huge size and impact on the financial system. However, due to the investor sentiment and government interventions, banks are less risky than other financial institutions during the crisis.

Finally, we identify the forward-looking determinants of systemic risk contribution using panel regression. Leverage and volatility of specific financial institutions are positive, forwarding-looking factors of systemic risk contribution. The risk contribution is predicted to rise when the book-to-market ratio is lower. As a key determinant, size is positively significant on average. However, it converts to negative during the 2015-2016 Chinese stock market crash, since government tends to bail out large financial institutions, proving the “too big to fail” theory under this new circumstance. Some macroeconomic variables are also related with the systemic risk contribution. Thus, we cannot ignore the impact of macroeconomic factors in assessing risks.

Our study can be applied to portfolio and risk management. For investors seeking to invest in Chinese stock markets, our results construct a tail risk network in risk propagation and the consequential need to protect these positions from the distress of other firms. The results of our study can help investors monitor risk across firms, and thus better manage risk. Moreover, monitoring the dynamic ranking of firms' systemic risk contributions over time is critical for supervision authorities. Regulators could potentially detect those firms that are most threatening to the stability of the system.

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Highlights:

- This study constructs a tail risk network to present systemic risk in China.
- The results show that a firm’s risk is affected by its connectedness with others.
- The number of connections significantly increases during June 2014 to June 2016.
- We test significance of systemic risk beta and rank the risk contribution further.

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