Tail-risk Connectedness Network and Systemic Risk in Chinese Financial Market

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Abstract

This paper studies the tail risk connectedness and the systemic risk in Chinese financial market in the post-crisis period, over 2009-2017. The adopted conditional value-at-risk ($CoVaR$) enables us to characterize precisely the evolution of tail risk connectedness on the institutional, sector and market level. Combined with the complex theory, we construct the tail risk connectedness network and identify the systemically important financial institutions during the Chinese Financial Turbulence. We find that, in normal times, the banking sector contributes most tail risk to the market and the real estate sector contributes least. However, in the crisis period, the real estate sector plays its role and becomes the most significant tail risk emitter. Besides, we identify the SIFIs in Chinese financial market and magnify that the four state-owned commercial banks and two insurance companies dominate. Our results are helpful for policy makers, as well as investors interested in Chinese financial market.

Keywords: systemic risk; CoVaR; tail risk network; systemically important financial institutions.

1. INTRODUCTION

Controlling financial risk, preventing systemic risk and stabilizing the financial market have been stressed consecutively in recent three-years National Congress of China, since the Chinese financial turbulence in 2015-2016. On June 15th, 2015, over one thousand stocks listed in China fell to their limit-down, indicated the onset of the A-share market turbulence. Unimaginably, during the turbulence, more than 1300 stocks dropped to their down limits and another over 1400 stocks saw a suspension in one trading day, on July 8, 2015, to be specific. This phenomenon demonstrates the very strong connectedness between financial institutions in extreme down market. The background makes clear that understanding the systemic risk and the connectedness between financial institutions is key for understanding the Chinese financial turbulence and its evolution.

Identifying the connectedness, especially the tail risk connectedness, between financial institutions is of great theoretical and practical significance to the prevention of the outbreak of the financial crisis, the establishment of effective financial supervision, asset pricing and risk management (Acharya et al., 2012; Ballester et al., 2016; Elyasiani et al., 2015). Studies related to model the connectedness and measure the systemic risk contribution between institutions are twofolds. The first line of research is the economic modeling on financial network models and financial contagion. For example, Allen and Gale (2000), Freixas et al. (2000), Leitner (2005) and so on. Such studies are vast. However, they typically require detailed information on intra-bank asset and liability exposures, and these data are generally not publicly disclosed, and even supervisory authorities can only collect partial information on inter-bank

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linkages. Available empirical studies linked to this literature have to estimate the interbank liability exposures among limited institutions, and can therefore not provide an accurate full picture of institutions' systemic relevance (see, e.g., Furfine, 2003; Upper and Worms, 2004, for Germany and the USA, respectively).

The second line of research is the quantitative modeling. Before the Global Financial Crisis in 2008, financial institutions and regulators heavily relied on financial risk measurement tools, like VaR (Value-at-Risk)(for comprehensive reviews, see Jorion, 2006; Christoffersen, 2009) and ES (Expected Shortfall) (see Yamai and Yoshiba, 2002, 2005; Kerkhof and Melenberg, 2004). These tools have a devastating drawback that they merely consider the risk of an institution in isolation and do not take its connection to other institutions into consideration. They are not capable of capturing tail risk. As a result, the financial institutions failed to depict their tail risk accurately and underestimated the tail risk in the financial market (Du and Escanciano, 2016). The Global Financial Crisis in 2008 also illustrates that inaccurate measurement of the financial risk, especially tail risk connectedness between financial institutions/markets, is responsible for triggering the financial crisis. The conditional value-at-risk, i.e., *CoVaR*, proposed by Adrian and Brunnermeier (2016), can overcome this drawback and capture the tail-dependency between financial institutions and we adopt it to conduct our empirical research.

The objective of this paper is to study the tail risk connectedness in Chinese financial market. The $\Delta CoVaR$ of an institution, calculated from the difference between the $CoVaR$ of it conditional on the distress of the other institution and the $CoVaR$ conditional on the normal state of the other institution, can reflect the directional pairwise tail risk contribution between institutions. We collect weekly stock closing prices of institutions in four sectors, namely, the banking sector, security sector, real estate sector and the other sector comprised by insurance and trust companies. These four sectors are categorized by latest industry classification of CSRC. By estimating the $\Delta CoVaR$ between institutions, we construct the $\Delta CoVaR$ on the sector and the market level to reveal the tail risk connectedness on three scale. Our paper reveal the picture of tail risk connectedness during the Chinese financial turbulence and supplement the existing literature on the systemic risk and risk contagion on global financial market.

We contribute to the literature in three ways. First, we characterize the tail risk connectedness for Chinese financial market on institutional, sector and market level. Even though the recent Chinese financial turbulence caused huge concerns of the investors and, especially, of the government, no study has yet examined how this systemic risk accumulated and how risk was transmitted. We estimate the $\Delta CoVaR$ between institution pairs, construct the tail risk contribution index for sectors and the systemic risk index on the market level. The empirical results show that, in normal times, the banking sector contributes most tail risk to the market and the real estate sector contributes least. However, in the crisis period, the real estate sector plays its role and becomes the most significant tail risk emitter.

Second, we show the evolution of the turbulence and identify the SIFIs in Chinese financial market. Tail risk connectedness is a measure of the extreme risk in the financial market. Through constructing the tail risk connectedness network before, onset, and during the turbulence, we straight-forwardly show how the overall extreme risk evolves with time. Besides, we magnify that the four state-owned commercial banks and two insurance companies dominate as the SISFs.

Third, our conclusion has significant implications for regulators and investors. For regulators, it is often unclear how complex structures eventually translate into dynamic and predictable measures of systemic risk. Since tail risk connectedness can reflect the extreme risk in the market, while the total connectedness is increasing, investors and regulators should be cautions in terms of risk management. Most important, when regulators strengthening the financial supervision system with macro prudential supervision, they should keep their eye on the SISFs, especially on the "too-connected" institutions. Our results can build the premise of effective supervision is to accurately measure systemic risk, and to improve the analysis of cross industry, cross institution risk and risk contagion to improve the macro prudential policy framework.

The rest of the paper is structured as follows. In Section 2, we lay down the background and introduce the data adopted in our work. In Section 3, we outline the basic concepts of systemic risk measurements and estimated method. Section 4 conducts the empirical analysis from three levels. Section 5 concludes the paper.

2. Data

With thousands of stocks listed in China falling to limit-down in 15 June, 2015, the A-share market turmoil caused a panic on the global scale. Since then, the Chinese government and financial risk management departments including China Securities Regulatory Commission (CSRC in short) have been taking measures to stable the financial market. Controlling financial risk, preventing systemic risk and stabilizing the financial market have been stressed consecutively in recent three-years National Congress of China.

Our study focuses on the tail risk connectedness among publicly listed financial institutions in China. According to the latest industry classification of CSRC, we divide the financial institutions listed in China into commercial banks, broke dealers, insurance companies and trust companies. Since the number of insurance companies and trust companies are relatively small, we combine them in the same group and name it as the other firms. Besides, it is known that the Chinese housing sector plays a dominant role in the past decade, we also include it in our analysis as the fourth group. Following Billio et al.(2012), we first select top 20 companies in each category by ranking their market capitalization, and then rule out the companies publicly listed less than 2 years [1]. Finally we come to a sample with 16 banks, 20 security companies, 10 other firms and 20 real estate companies. See Table 1 for the company names and tickers.

[1] Note that there are only 6 insurance companies and 9 trust companies in China, so in the first step, we keep the other firms as 15 companies.

Table 1: Institutions under investigation

Bank		HT	Haitong Securities Co., Ltd.
ICBC	Industrial and Commercial Bank of China Limited	GTJA	Guotai Junan Securities Co., Ltd.
CCB	China Construction Bank Corporation	CS	CITIC Securities Company Limited
ABC	Agricultural Bank of China Limited	Housing	
BOC	Bank of China Limited	CV	China Vanke Co.,Ltd.
CMB	China Merchants Bank Co., Ltd.	POLY	Poly Real Estate Group Co.,Ltd
BCM	Bank of Communications Co.,Ltd.	CFLD	China Fortune Land Development Co.,Ltd.
CIB	Industrial Bank Co.,Ltd.	GHC	Greenland Holdings Corporation Limited
SPDB	Shanghai Pudong Development Bank Co.,Ltd.	LJZ	Shanghai Lujiazui Finance & Trade Zone Development Co.,Ltd.
CITIC	China CITIC Bank Corporation Limited	LZJB	Shanghai Lujiazui Finance & Trade Zone Development Co.,Ltd.
CMBC	China Minsheng Banking Corp., Ltd.	GC	Gemdale Corporation
CEB	China Everbright Bank Company Limited	RRED	Risesun Real Estate Development Co.,Ltd.
PAB	Ping An Bank Co., Ltd.	HNA	Hna Infrastructure Investment Group Co., Ltd
BOB	Bank of Beijing Co., Ltd.	OWH	Oceanwide Holdings Co., Ltd.
HXB	Hua Xia Bank Co.,Limited	XHZB	Xinhu Zhongbao Co.,Ltd.
NBCB	Bank of Ningbo Co.,Ltd	ZTF	Zhongtian Financial Group Company Limited
NJCB	Bank of Nanjing Co.,Ltd.	YINYI	YINYI CO.,LTD.
Security		YG	Yango Group Co.,Ltd
SCS	Soochow Securities Co.,Ltd.	YOG	Youngor Group Co.,Ltd.
SS	Sinolink Securities Co., Ltd.	FSH	Financial Street Holdings Co., Ltd.
GYS	Guoyuan Securities Company Limited	JINKE	Jinke Property Group Co.,Ltd.
WS	Western Securities Co., Ltd	LG	Shanghai Lingang Holdings Co.,Ltd.
DXS	Dongxing Securities Company Limited	BCDH	Beijing Capital Development Co.,Ltd.
CJS	Changjiang Securities Company Limited	WU	Shenzhen Worldunion Properties Consultancy Incorporated
IS	Industrial Securities Co.,Ltd.	Others	
SDIC	SDIC Capital Co., Ltd*	PAIC	Ping An Insurance (Group) Company of China, Ltd.
FS	Founder Securities Co.,Ltd.	LIFE	China Life Insurance Company Limited
EBS	Everbright Securities Company Limited	CPIC	China Pacific Insurance (Group) Co., Ltd.
OSC	Orient Securities Company Limited	NCI	New China Life Insurance Company Ltd.
GS	Guosen Securities Co.,Ltd.	AT	Anxin Trust Co.,Ltd
CMS	China Merchants Securities Co., Ltd	AVIC	AVIC Capital Co.,Ltd.
SHG	Shenwan Hongyuan Group Co.,Ltd.	MIN	Minmetals Capital Company Limited
HTSC	Huatai Securities Co.,Ltd.	HBP	Hubei Biocause Pharmaceutical Co.,Ltd.
GF	GF Securities Company Limited	XSGF	Xishui Strong Year Co.,Ltd Inner Mongolia
CCC	Cnpc Capital Company Limited	AJ	Shanghai AJ Group Co.,Ltd.

[1] SDIC was once named SDIC Essence Co., Ltd before 2017/12/18

2.1. Return series

We collect weekly closing price for each company from Wind Database, with the time span ranging from January, 2009 to December, 2017. The reason for setting the starting point as January, 2009 are mainly twofolds. First, the financial crisis in 2008 brought unexpected shock to global financial market and the Chinese financial market is not immune. On the ground of this historical reason, we eliminate the crisis period to focus our attention on post-crisis risk contagion in Chinese market. Second, some macroeconomic variables are not available before 2009. We will explain this point in more detail later. Table 2 presents the basic information of the institutions under investigation.

The weekly return loss for each stock is calculated as

$$X_t^i = -\,ln\frac{P_t^i}{P_{t-1}^i} \times 100\%, \tag{1}$$

where P_t^i denotes the weekly closing price of company i at time t. One thing need to be noted is that, for those stocks reopening from suspended, we drop their first weekly return to make sure that their return loss series are stationary.

Table 2: Summary of Institutions

Ticker	Assets	Type	Ticker	Assets	Type	Ticker	Assets	Type
ICBC	22694	Bank	IS	460	Security	HNA	436	Housing
CCB	16350	Bank	SDIC	527	Security	OWH	412	Housing
ABC	13163	Bank	FS	528	Security	XHZB	371	Housing
BOC	11631	Bank	EBS	556	Security	ZTF	345	Housing
CMB	7400	Bank	OSC	855	Security	YINYI	336	Housing
BCM	4293	Bank	GS	883	Security	YG	330	Housing
CIB	3717	Bank	CMS	1063	Security	YOG	320	Housing
SPDB	3643	Bank	SHG	1125	Security	FSH	309	Housing
CITIC	2954	Bank	HTSC	1151	Security	JINKE	272	Housing
CMBC	2937	Bank	GF	1176	Security	LG	258	Housing
CEB	2100	Bank	CCC	1261	Security	BCDH	236	Housing
PAB	2052	Bank	HT	1278	Security	WU	221	Housing
BOB	1550	Bank	GTJA	1504	Security	PAIC	12372	Others
HXB	1195	Bank	CS	2075	Security	LIFE	6956	Others
NBCB	1025	Bank	CV	3508	Housing	CPIC	3303	Others
NJCB	767	Bank	POLY	1755	Housing	NCI	1461	Others
SCS	255	Security	CFLD	1061	Housing	AT	581	Others
SS	257	Security	GHC	915	Housing	AVIC	490	Others
GYS	317	Security	LJZ	557	Housing	MIN	402	Others
WS	350	Security	LZJB	557	Housing	HBP	370	Others
DXS	378	Security	GC	551	Housing	XSGF	221	Others
CJS	409	Security	RRED	461	Housing	AJ	197	Others

[1] The market values for companies total assets are in hundred million of RMB, originated from Wind.

2.2. Macroeconomic Variables

Alongside with the stock price series for our investigation objectives, we also collect macro state variables which are accounting for the general state of the Chinese economy. Following Adrian and Brunnermeier (2016), we include a set of macroeconomic state variables with seven macroeconomic variables (see Table 3 for their basic information), which are

(i) The change in the three-month yield Treasury bill rate from ChinaBond v_i;

(i) The change in the slope of the yield curve, denoted as the yield spread between the 10-year and 3-month Treasury bill rate v_2;

(ii) Short-term liquidity spread, calculated as the difference between the three-month interbank repo rate and the three month Treasury bill v_3;

(iii) Credit spread, calculated as the difference between the 10-year A-rated corporate bond and the 10-year Treasury bill rate v_4;

(iv) The weekly CSI 300 index returns v_5;

(v) The weekly real estate index return v_6;

(vi) Equity volatility, calculated as the 22-day rolling standard deviation of the daily SH 50 index return v_7.

Table 3: Macroeconomic Variables Summary

Variable	Start	End	Source
3-month Treasury bill rate	2002/1/4	2017/12/29	Wind
10-year Treasury bill rate	2002/1/4	2017/12/29	Wind
3-month Repo rate	1999/1/4	2017/12/29	Wind
10-year A^+ Corporate bond	2008/8/21	2017/12/29	Wind
CSI300	2002/1/4	2017/12/29	Wind
Estate Index	2001/4/6	2017/12/29	Wind
Financial Index	2001/4/6	2017/12/29	Wind
S&P50	2004/1/2	2017/12/29	Wind

We also present the descriptive statistics of these macro-economic variables, see Table 4. The 1% stress level is the level of each respective variable during the 1% worst weeks for financial system asset returns. For example, the mean of the v_1 during the period is 0.007, as the worst times for v_1 is 0.550. Similarly, the stress level corresponds to a high level of the liquidity spread, a sharp decline in the Treasury bill rate chronologically, sharp increases of the corporate bond and Treasury bill, and large negative equity return in both financial and estate market.

Table 4: Descriptive Statistics of Macro-economic Variables

	Mean	SD	Skew	Min	Max	1% Stress Level
v_1	0.007	0.176	3.406	-1.044	2.015	0.550
v_2	0.925	0.614	0.726	-1.512	2.447	2.412
v_3	1.390	0.720	0.949	0.029	4.681	3.478
v_4	5.309	0.713	-0.572	3.644	6.454	6.379
v_5	0.190	3.457	-0.360	-15.336	15.097	8.053
v_6	0.030	3.303	-0.576	-18.401	11.931	7.282
v_7	1.402	0.706	1.460	0.415	4.386	3.855

3. Methodology

In this section, we lay down the background, some preliminary concepts and estimation models for our systemic risk analysis.

3.1. VaR

Traditionally both academic researchers and practitioners preferably adopt VaR (Value-at-risk) to estimate an institution's risk. VaR is a cardinal instrument to measure the maximum loss of a institution, which is defined as

$$Pr(X_t^i \leq VaR_{q,t}^i) = q, \tag{2}$$

where X_t^i is the log return loss of institution i, and $VaR_{q,t}^i$ corresponds to the maximum loss of institution i at time t based on q% quantile. However, VaR is not capable of measuring the risk contagion and risk spillover between institutions/markets (see Hautsch et al. (2015) for more information). To overcome this drawback, Adrian and Brunnermeier (2016) proposed the conditional VaR model to capture tail risk spillover effects between institutions/markets by taking the macro economic state factors into consideration.

3.2. CoVaR and Network-CoVaR

The risk-taking model established by Adrian and Brunnermeier (2016) is based on the *VaR* model, denoted by *CoVaR*. $CoVaR^{j|i}_{q,t}$ corresponds to the maximum possible loss of institution j conditional on institution i's extreme loss. That is

$$Pr(X^j_t \leq CoVaR^{j|i}_{q,t} | X^i_t = VaR^i_{q,t}) = q \tag{3}$$

Adrian and Brunnermeier (2016) defines $\Delta CoVaR$ as the difference between the *CoVaR* of the financial institution j conditional on the distress of the institution i and the *CoVaR* of the institution j conditional on the normal state of institution i. Therefore, the systemic risk contributed to institution j from institution i at time t is

$$\Delta CoVaR^{j|i}_{q,t} = CoVaR^{j|X_i=VaR^i_{q,t}}_{q,t} - CoVaR^{j|X_i=VaR^i_{50,t}}_{q,t}. \tag{4}$$

In the same way, we can calculate the risk contribution from j to i. Clearly $\Delta CoVaR^{j|i}_{q,t}$ and $\Delta CoVaR^{i|j}_{q,t}$ quantify the directional tail risk transmission between institution i and j and can capture their tail-risk connectedness. We can then build the CoVaR network for all the institutions in the financial system. The Network-CoVaR for a financial system can be represented by the adjacent matrix A_t,

$$A_t = \begin{array}{c} \\ I_1 \\ I_2 \\ I_3 \\ \vdots \\ I_k \end{array} \begin{array}{c} \begin{array}{ccccc} I_1 & I_2 & I_3 & \cdots & I_k \end{array} \\ \begin{pmatrix} 0 & \Delta CoVaR^{1|2}_{q,t} & \Delta CoVaR^{1|3}_{q,t} & \cdots & \Delta CoVaR^{1|k}_{q,t} \\ \Delta CoVaR^{2|1}_{q,t} & 0 & \Delta CoVaR^{2|3}_{q,t} & \cdots & \Delta CoVaR^{2|k}_{q,t} \\ \Delta CoVaR^{3|1}_{q,t} & \Delta CoVaR^{3|2}_{q,t} & 0 & \cdots & \Delta CoVaR^{3|k}_{q,t} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \Delta CoVaR^{k|1}_{q,t} & \Delta CoVaR^{k|2}_{q,t} & \Delta CoVaR^{k|3}_{q,t} & \cdots & 0 \end{pmatrix} \end{array},$$

where A_t's element $A_t(i,j) = \Delta CoVaR^{i|j}_{q,t}$. In this tail risk connectedness network, a node corresponding to an institution, while a directed weighted edge from node i to j corresponding to the tail risk contribution from institution i to institution j.

3.3. Estimation Procedure

Using the macro state variables introduced in Section 2, we estimate the *CoVaR* in two steps through linear quantile regression. The first step starts with modeling the loss return X^i as a function of a set of lagged macro state variables:

$$X^i_t = \alpha^i + \gamma^i v_{t-1} + \varepsilon^i_t \tag{5}$$

$$X^{j|i}_t = \alpha^{j|i} + \gamma^{j|i} v_{t-1} + \beta^{j|i} X^{j|i}_t + \varepsilon^i_t \tag{6}$$

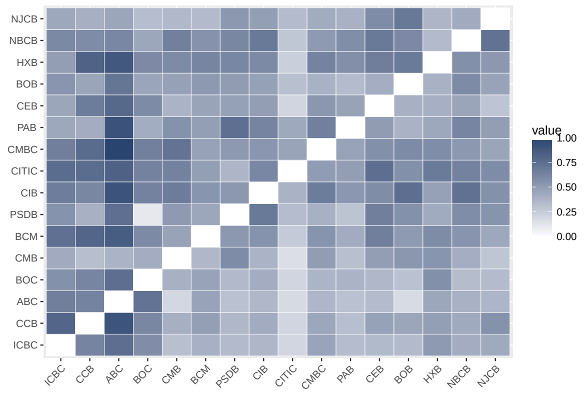
Running these regressions, we obtain $VaR_{q,t}$ and $CoVaR_{q,t}$ for each institution:

$$VaR^i_{q,t} = \widehat{\alpha}^i + \widehat{\gamma}^i v_{t-1} \tag{7}$$

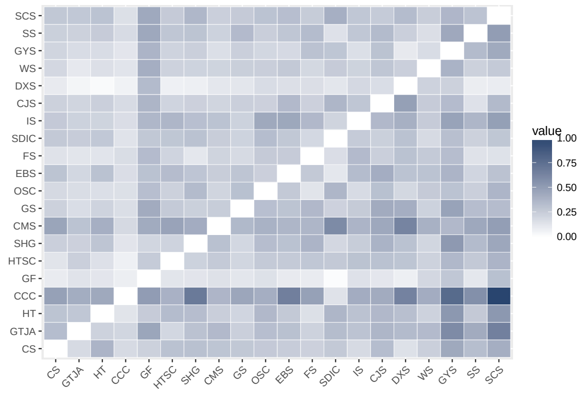
$$CoVaR^{j|i}_{q,t} = \widehat{\alpha}^{j|i} + \widehat{\gamma}^{j|i} v_{t-1} + \widehat{\beta}^{j|i}_q VaR^j_{q,t} \tag{8}$$

In the second step, we calculate $\Delta CoVaR$ according to equation (4)

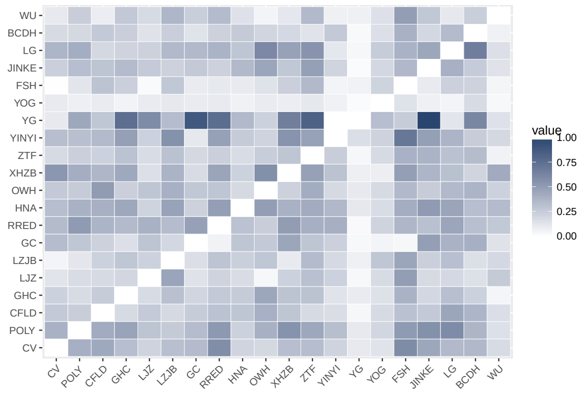
$$\Delta CoVaR^{j|i}_{q,t} = CoVaR^{j|i}_{q,t} - CoVaR^{j|i}_{50,t} = \widehat{\beta}^{j|i}_q (VaR^i_{q,t} - VaR^i_{50,t}) \tag{9}$$



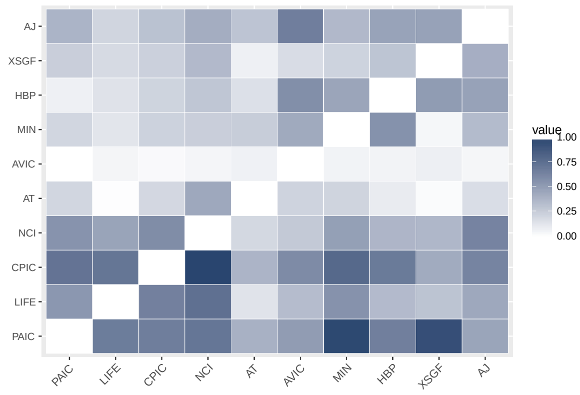
(a) Banks



(b) Security Companies



(c) Real Estate Companies



(d) Others Firms

Figure 1: Tail risk connectedness between institutions within the same sector

4. EMPIRICAL STUDIES

In this section, we use the *CoVaR*, proposed by Adrian and Brunnermeier (2016), together with the complex network theory, to quantify the level of the systemic risk in each group, the tail risk contributions between four groups, and construct the tail risk network.

4.1. Sector Level Analysis

4.1.1. Tail-risk connectedness within sectors

We start our analysis from exploring the the tail-risk connectedness between financial institutions within the same sector, see Figure 1. In Figure 1, each colorful block represents the tail-risk spillover between an institution-pair. The darkness of the blocks corresponds to the scale of the contribution, that is to say, the darker the block is, the more significant impact from the corresponding institution in the column to the institution in the horizon. We present four subgraphs (a), (b), (c) and (d) to illustrate the interaction for institutions in banking, security, real estate, and insurance and trust sector, respectively. For comparison, we normalize the highest contribution in all subgraphs to 1. Clearly, we can find that the tail-risk spillover between banks are most significant in four sectors under consideration, followed by the risk spillover between insurance and trust companies, while the pictures for the other two sectors are different. To further justify this point, we also present the summary statistics of $\beta^{j|i}$ for each sector in Table 5.

Besides, by arranging the institutions decreasingly with respect to their market assets in axes from left (bottom) to right (up), we can find that the tail risk contribution between institution-pairs is asymmetry. This can be verified by the asymmetric of the darkness of the subgraphs. What is more, the market size of the institutions has impact on the spillover between institutions, except the real estate sector. Generally, in the banking sector, banks with larger market size spill more risk, which can be seen from the left-upper triangle in Figure 1(a). In contrast, financial institutions with larger market size receive more risk in the security and the other sectors.

Table 5: $\Delta CoVaR$ across Sectors

	Mean	SD	Min	Max	1% stress level
Banks	4.25	1.22	1.88	10.56	8.248
Securities	4.28	1.38	2.19	9.87	9.429
Real Estate	2.64	3.78	0.11	20.63	17.682
Others	4.30	1.37	0.98	10.54	8.662

We further explore the time-varying overall tail risk connectedness within each sector. The Tail-risk Connectedness Aggregate in the term of IN is defined as $TCA_{i,t}^{IN} = \sum_{j=1}^{k} |\Delta CoVaR_{q,t}^{j|i}|$; The Tail-risk Connectedness Aggregate in the term of OUT is $TCA_{i,t}^{OUT} = \sum_{j=1}^{k} |\Delta CoVaR_{q,t}^{i|j}|$.Considering the number of institutions in the four sectors are not the same, we present the average $\Delta CoVaR_t$ for each sector in Figure 2. It is clear that the tail risk connectedness within four sectors significantly increases during 2015-2016. More notably, the tail risk connectedness in real estate sector, i.e., the green line, is the lowest, approaching to zero, before 2015. However, after that, it soars most significantly to over 20% and remains the highest among the four sectors. In the following section, we will explore this in more detail.

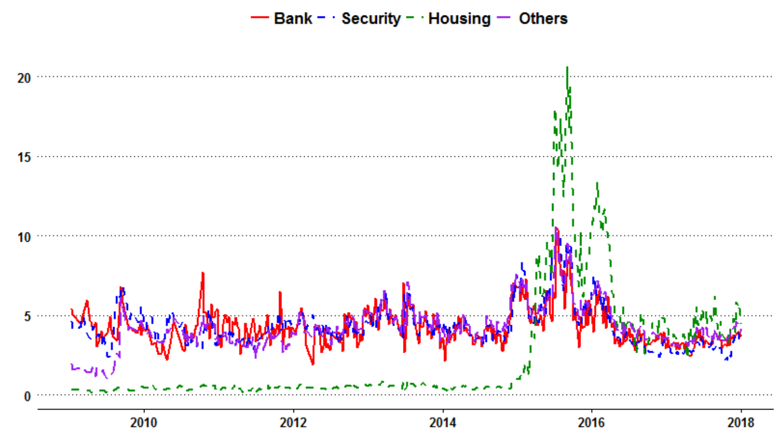


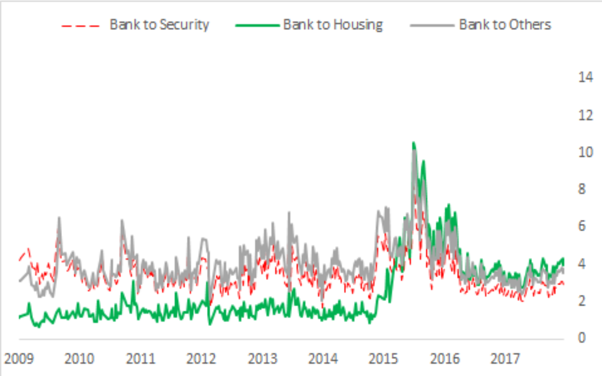
Figure 2: Tail-risk spillover within the same sector

4.1.2. Tail-risk connectedness across sectors

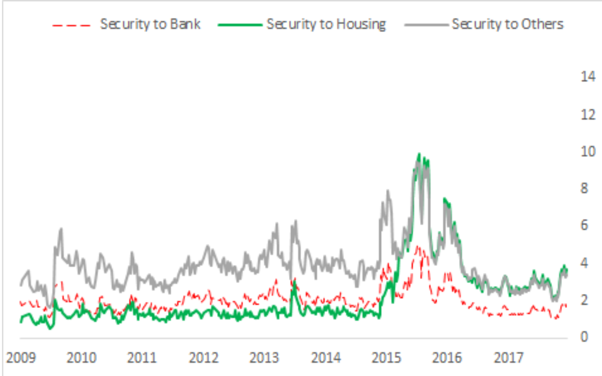
In this subsection, we focus on the tail-risk contribution across the four sectors in Chinese Financial Market. The Figure 3 illustrates the average time-varying tail-risk contribution from one sector to other three sectors. We can draw several conclusions from this figure. First, dynamic tail risk contributions from these four sectors shares the same trend, rising notably during the Chinese Financial Turmoil in 2015 and 2016 and then decreasing afterwards. Second, in normal times before the Chinese Financial Turmoil, the banking sector contributes most tail risk to the financial market, while the real estate sector contributes least, see Figure 3 (e). Moreover, all sectors contribute most tail risk to insurance and trust companies before 2015, indicated by the green line in Figure 3 (a), (b) and (c). However, tail risk contribution from these four sectors are almost in the same scale after the turbulence.

4.2. *System Level Analysis*

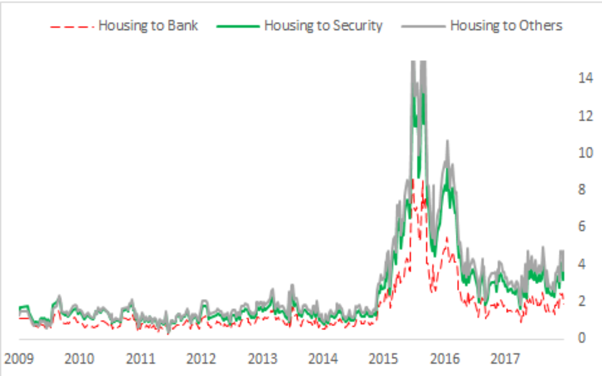
So far, we have analyzed the tail risk connectedness on the sector level. In order to quantify the systemic risk and identify the systemically important financial institutions in Chinese financial market, we proceed to study the tail risk contribution in the system/market level over time. Specifically, we first analyze the time-varying tail risk in the market level, and then we focus on the critical historical days to construct the tail risk network and identify the SIFIs.



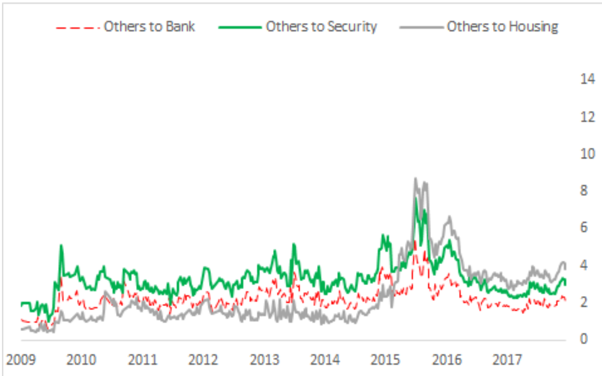
(a) Bank to Others



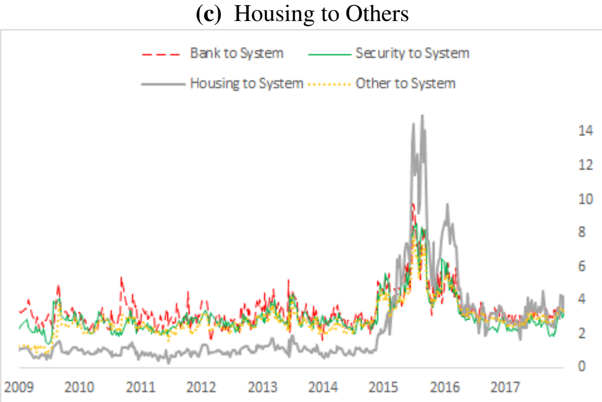
(b) Security to Others



(c) Housing to Others



(d) Others to Others



(e) Total tail risk contribution from each sector

Figure 3: Tail-risk spillover across sectors

4.2.1. *Time-varying tail risk in system level*

Figure 5 plots the total tail risk connectedness over the whole observation window. From a bird's eye view, the total tail risk connectedness has some revealing patterns. Before the end of the 2014, the total risk connectedness in China financial market remains at the 8%-15% band. At the beginning of 2015, the SH500 index increased dramatically. However, the tail risk started to accumulate and rise sharply with thousands of stocks listed in China falling to limit-down, which actually is the beginning of the Chinese financial turmoil. As the financial crisis was unfolding, the total tail risk connectedness soared to around 40% on 10 July, 2015, almost fourfold to the tail risk connectedness in normal times. On 9 July, 2015 and 2 September, 2015, the Shanghai 500 index reached its temporary lowest points to 3373.54 and (具体多少点), respectively. It is worthing noting is that, after the wakeup of the financial turmoil, the Chinese government began to take intervention measurements to stable the financial market, such as, the suspension of IPO, the prohibition of the bare short of the future indices, the increase in the ratio of the margin, the increase holdings from the broke dealers, the reduction of the interest rate for many times, and so forth. We can see from the Figure 5 that the tail risk connectedness also experiences a drop after July and then creates the second highest point in September. Combined with results in Figure 3, the tail risk during this period is mainly attributed to the real estate sector.

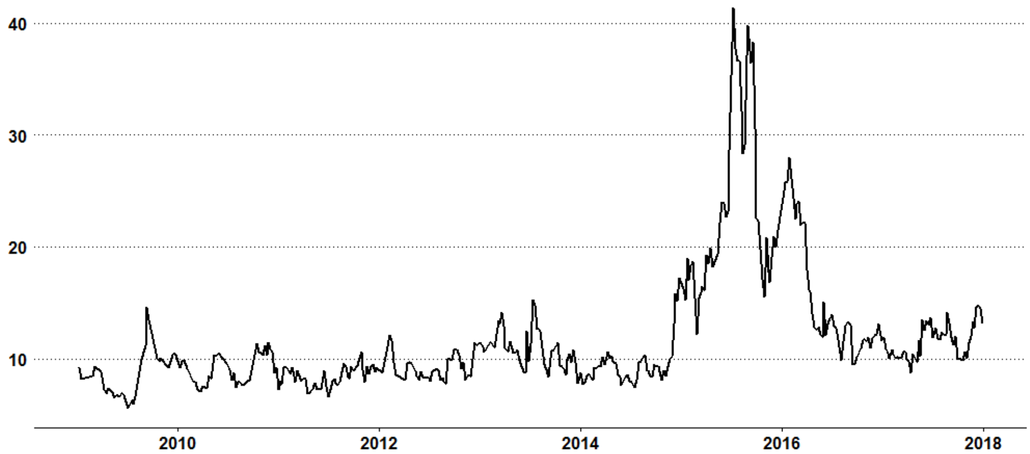


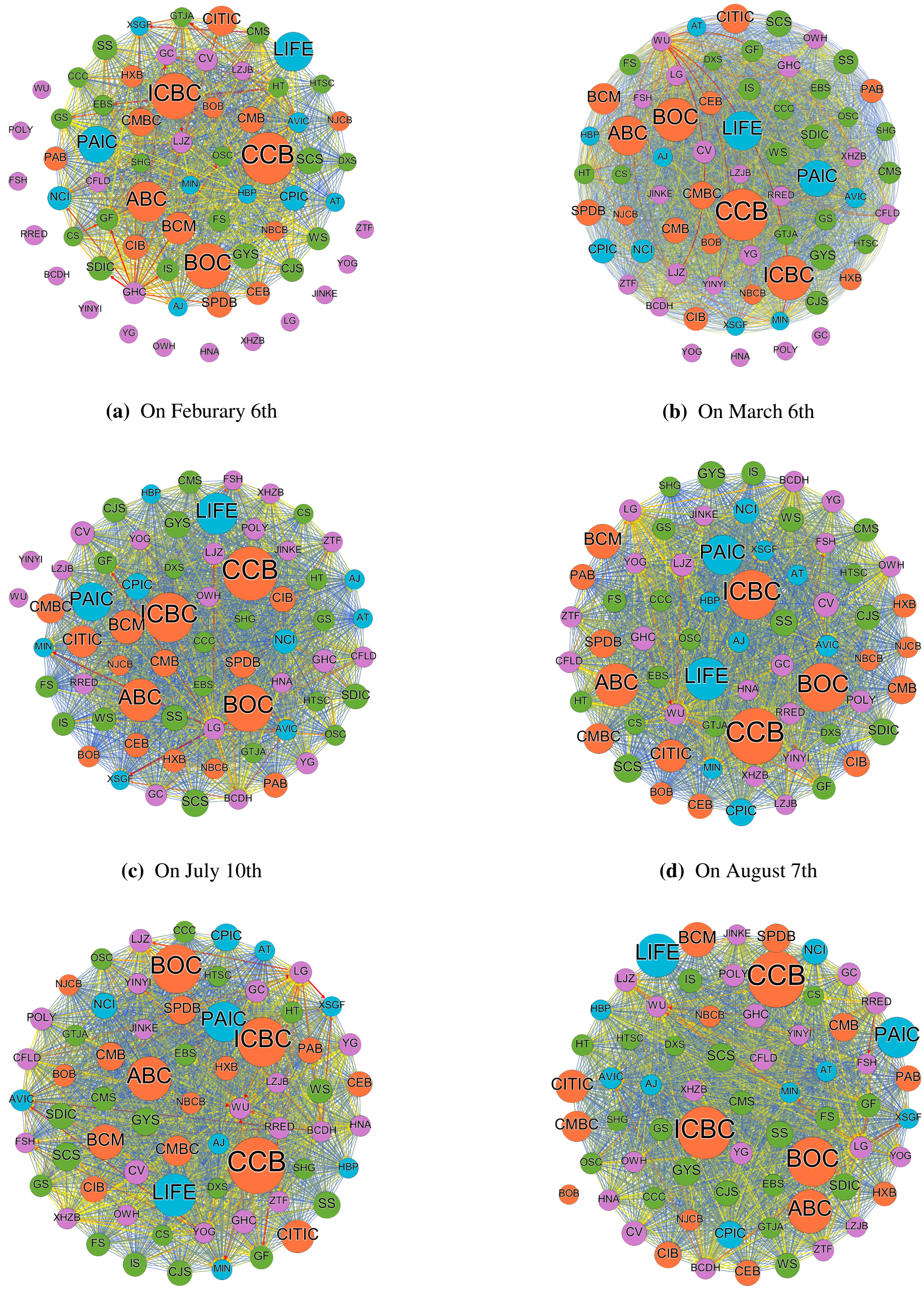
Figure 4: Time-varying tail risk connectedness in the system level

The third highest point appears in the beginning of 2016, which indicates that the institutions are also heavily connected. In the first month of 2016, the China SFC introduced the circuit breakers that impose a brief cooling off period for stocks that move sharply. However, with two circuit breakers triggered on 7 January, 2016, the SFC had to stop the circuit breaker mechanism overnight. Although the SFC insisted that the circuit breaker mechanism was not the main cause of the market plunge, it did not achieve the expected effect, but caused a huge negative effect. Accordingly, we observe an increase of the total tail risk connectedness in January 2016.

4.2.2. Tail-risk connectedness networks during the Chinese Financial Turbulence

The above analysis help to understand the systemic risk in the Chinese financial market over the last decade. We next begin to study the evolution of the tail risk connectedness during the Chinese Stock Turbulence. This part of research will enable us to identify the SISFs during the stressful times.

We start with the build-up stage of the Chinese Financial Turbulence. We select six critical days for our tail risk transmission analysis and the results are presented in Figure 5. In Figure 5, the nodes represent the institutions under investigation, with the orange, green, purple and blue ones corresponding to banks, security companies, real estate companies and other firms (i.e. insurance



(a) On Feburary 6th

(b) On March 6th

(c) On July 10th

(d) On August 7th

(e) On September 2nd

(f) On October 9th

Figure 5: Evolution of the systemic risk during the Chinese Financial Turbulence

and trust companies)[2]. The size of the node indicates its total tail risk receives from the other nodes. Apparently, the bigger size indicated stronger negative effect it receives. The directional lines in Figure 5 represent the directed

[2]The independent nodes represent the institutions whose stocks are closed

tail risk contributions between institutions. In the same way, we use different colors to represent different degrees of connectedness: the red means strong connectedness, followed by the yellow and the blue is the weakest.

The subgraphs (a), (b) and (c) in Figure 5 are the tail risk networks before, on the wake of and the burst of the Chinese Financial Turbulence. It is clear that the blue gets deeper, which magnifies the risk accumulation during this period. However, this trend is stopped temporarily by the government intervention that we analyzed previously, which is illustrated by the lighter blue in Figure 5(d). As time goes by to September 2, more red lines appear and we find the tail risk transmitters are mainly real estate companies.

Further, in order to identify the SISFs during the turbulence, we present the top 10 tail risk transmitters and receivers in Figure 6. The system risk receiver index (SRR) and risk emitter index (SER) for an institution j are defined as follows:

$$SRR_t^j \overset{def}{=} MA_{j,t} \times \sum_{i \in IN} |CoVaR_t^{j|i}| \times MA_{i,t} \tag{10}$$

$$SER_t^j \overset{def}{=} MA_{j,t} \times \sum_{i \in OUT} |CoVaR_t^{i|j}| \times MA_{i,t} \tag{11}$$

Figure 5 (c) presents the specific tail risk network on July 10, 2015, when the systemic risk amounted. We find that the banking sector performs the dominant role both in risk emitting and risk receiving, indicated by the large orange nodes in Figure 6. For more information, we list the top 10 risk emitter and receiver institutions in Table 6 and 7. Both tables show that the four major state-owned commercial banks, i.e. CCB, ICBC, BOC, ABC, are the most significant SIFIs in Chinese financial market. The insurance companies China Life Insurance Company and Ping An Insurance Company are immediate behind and can be marked as the SIFIs as well. This stresses that the regulators should keep an eye on the insurance companies.

Moreover, Figure 6 shows the top 10 $CoVaR^{IN}$ and $CoVaR^{OUT}$. The largest tail risk connectedness between institutions largely relates to the an real estate company LG (Shanghai Lingang Holdings), denoted by the directed red lines.

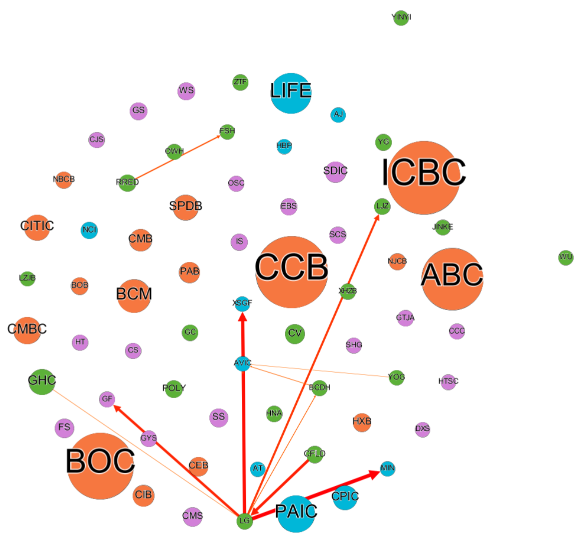


Figure 6: Top 10 tail risk connectedness in the system

Table 6: Top10 directional connectedness

From	To	Weight
LG	MIN	59.39281
LG	XSGF	57.61756
CFLD	LG	55.6398
LG	GF	54.83792
LG	LJZ	52.99849
RRED	FSH	49.66759
LG	BCDH	47.84638
LG	AVIC	47.38036
BCDH	AVIC	47.34707
GHC	LG	46.7519

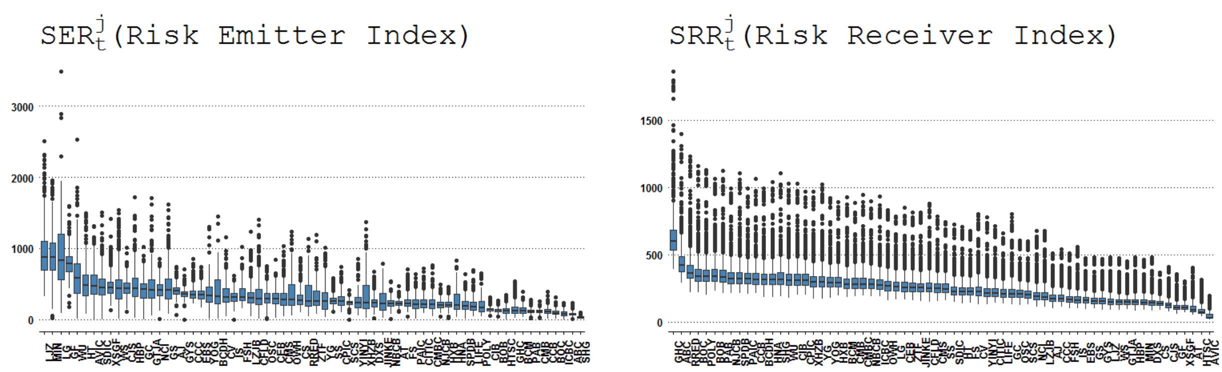
Table 7: Top10 tail risk receivers

Rank	Ticker	IN sum(10^9)	Type
1	CCB(China Construction Bank Corporation)	25.5	Bank
2	ICBC(Industrial and Commercial Bank of China Limited)	22.1	Bank
3	BOC(Bank of China Limited)	20.8	Bank
4	ABC(Agricultural Bank of China Limited)	17.1	Others
5	LIFE(China Life Insurance Company Limited)	16.2	Others
6	PAIC(Ping An Insurance (Group) Company of China,Ltd.)	14.2	Bank
7	BCM(Bank of Communications Co.,Ltd.)	10.8	Bank
8	CITIC(China CITIC Bank Corporation Limited)	9.28	Bank
9	CMBC(China Minsheng Banking Corp., Ltd.)	7.48	Bank
10	SPDB(Shanghai Pudong Development Bank Co.,Ltd.)	6.11	Bank

Table 8: Top10 tail risk emitters

Rank	Ticker	OUT sum(10^9)	Type
1	ICBC(Industrial and Commercial Bank of China Limited)	33.8	Bank
2	CCB(China Construction Bank Corporation)	33.1	Bank
3	BOC(Bank of China Limited)	29.9	Bank
4	ABC(Agricultural Bank of China Limited)	27.1	Bank
5	LIFE(China Life Insurance Company Limited)	15	Others
6	PAIC(Ping An Insurance (Group) Company of China,Ltd.)	13	Others
7	BCM(Bank of Communications Co.,Ltd.)	10.7	Bank
8	CMBC(China Minsheng Banking Corp., Ltd.)	7.19	Bank
9	CITIC(China CITIC Bank Corporation Limited)	6.39	Bank
10	GHC(Greenland Holdings Corporation Limited)	6.34	Housing

5. ESTATE STUDY



(a) Emitter of Tail Risk **(b)** Receiver of Tail Risk

Figure 7: The Receivers and Emitters of tail risk in financial market

In Figure7, we obtain great divergent distribution of the tail risk in terms of receivers and emitters. In the emitter plot, every institution fairly makes different contributions to give the rise to the tail risk increase overall. However, in the receiver part, each institution is of relative similar importance regards their individual magnitude of received risk. Except for GHC, which is housing sector, this particular institution has received a large proportion of the overall risk and worth more attentions.

6. Model Validation

Furthermore, to evaluate the accuracy of the estimated $\Delta CoVaR$, we conduct LASSO-linear regression(See Wolfgang Karl and Weining Wang,2016) compared with our quantile model results to confirm the accuracy.The benchmark linear LASSO model is written as follows:

$$\Delta CoVaR^{j|i}_{\tilde{R}_j,q,t} = CoVaR^{j|X_i=VaR^i_{q,t}}_{\tilde{R}_j,q,t} - CoVaR^{j|X_i=VaR^i_{50,t}}_{\tilde{R}_j,q,t} = \widehat{\beta}^{j|i,\tilde{R}_j}_q (VaR^i_{\tilde{R}_j,q,t} - VaR^i_{\tilde{R}_j,50,t}) \tag{12}$$

$\widehat{\beta}^{j|i,\tilde{R}_j}_q$ is estimated by using linear quantile regression with variable selection and calculate $CoVaR^{j|i}_{\tilde{R}_j,q,t}$

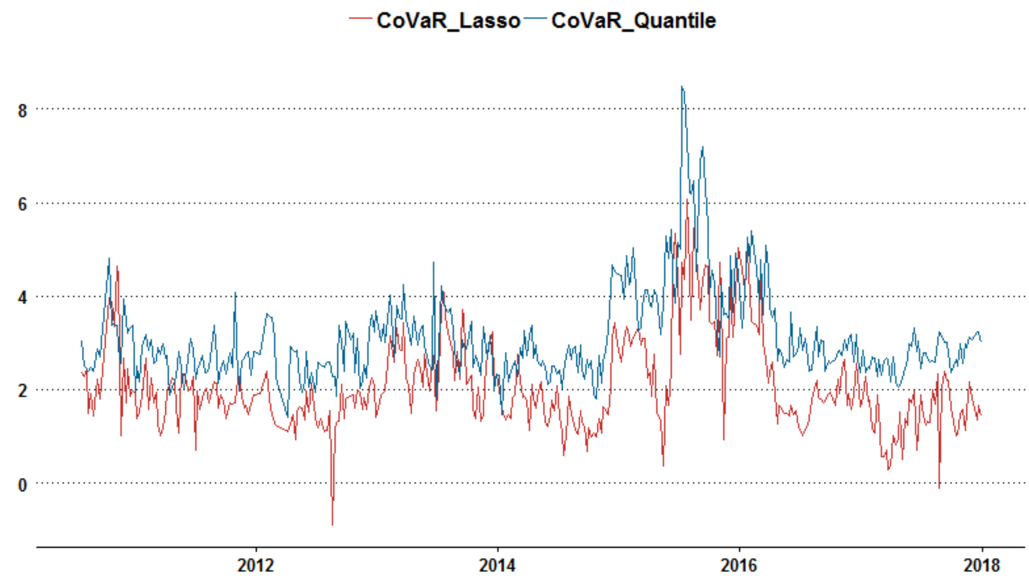


Figure 8: Quantile model and Lasso-linear model

Recall that we denote our estimated $\Delta CoVaR$ as $\Delta CoVaR^{j|i}_{,q,t}$. Now we compare the results of $\Delta CoVaR^{j|i}_{,q,t}$ and $\Delta CoVaR^{j|i}_{\tilde{R}_j,q,t}$ estimated by Lasso. In 8, the red solid line represent the $\Delta CoVaR^{j|i}_{\tilde{R}_j,q,t}$ of the market $\tilde{R}_j$ after model selection. In order to compare with $\Delta CoVaR^{j|i}_{,q,t}$ (blue solid line), We apply the CaViaR test proposed by Berkowitz et al. (2011) to consider the nth-order autoregression

$$I_t = \alpha + \sum_{k=1}^{n} \beta_{1k} I_{t-k} + \sum_{k=1}^{n} \beta_{2k} g(I_{t-k}, I_{t-k-1}, \cdots, R_{t-k}, R_{t-k-1}) + u_t \tag{13}$$

where $g(I_{t-k}, I_{t-k-1}, \cdots, R_{t-k}, R_{t-k-1}) = \Delta CoVaR$. We can then test whether $\alpha = p$(p represent the distress probability of I_t) using standard t-tests. At the condition that n=5, the p-values of $\Delta CoVaR^{j|i}_{\tilde{R}_j,q,t}$ in overall period is 0.31, the p-values of $\Delta CoVaR^{j|i}_{,q,t}$ is only 0.00059. However, in crisis period(from 8 May 2015 to 27 May 2016)$\Delta CoVaR^{j|i}_{,q,t}$

preforms better than $\Delta CoVaR^{j|i}_{\tilde{R}_j,q,t}$. So, all-set quantile regression can obtain more accurate results in the crisis period because of its high p-value (do not reject $\alpha = p$) and low standard deviation. See in the table(9) for more detail.

Table 9: Thep-values of CaViaR test in overall and crisis periods for $\Delta CoVaR^{j|i}_{\tilde{R}_j,q,t}$ and $\Delta CoVaR^{j|i}_{,q,t}$, the standard deviations are given in the brackets

p-value of CaViaR test	$\Delta CoVaR^{j\|i}_{\tilde{R}_j,q,t}$	$\Delta CoVaR^{j\|i}_{q,t}$
The overall period	0.31009(0.03153)	0.00059(0.053077)
The crisis period	0.4708(0.141153)	0.86368(0.139059)

It is reasonable to use Lasso-quantile regression to estimate $CoVaR$ for simplicity in normal period. However, when it comes to the period where the financial market is highly volatile, it is wiser to consider all the institutions in the market to calculate the tail risks more accurately.

7. CONCLUSION AND IMPLICATIONS

With the fast developing of China, the Chinese financial market attracts a lot of investments from domestic and abroad. However, the Chinese Financial Turbulence causes a huge shock and worries the investors and regulators. In order to reveal the systemic risk level in Chinese financial market, we estimated the tail risk connectedness between institution pairs, and construct the tail risk connectedness index on the sector and market level, over the period from January 2009 to December 2017. Our empirical results magnify that the banking sector contributes most tail risk to the market in normal times; whereas in crisis period, the real estate sector plays a dominant role in risk emitting. Moreover, we provide the tail risk connectedness networks on several significantly historical days. By identifying the SIFIs in Chinese financial market, we state that the four state-owned commercial banks and two insurance companies dominate.

Our findings are meaningful for policy makers, as well as investors interested in Chinese financial market, in terms of the prevention of the outbreak of the financial crisis, the establishment of effective financial supervision, asset pricing and risk management. Regulators and investors should take care of the sharp increase of the total tail risk in the market wide and keep a close eye on the SIFIs to avoid huge loss.

Appendix A

The market value of the institutions under investigation on July 10, 2015 are listed in Table 9 for reference.

Table 10: Institutions' market values on 2015/7/10

Bank		Security		Housing		Other	
ICBC	19744.91	SCS	3358.807	CV	1653.894	PAIC	7512.265
CCB	17800.78	SS	2388.15	POLY	1217.204	LIFE	10197.91
ABC	12796.89	GYS	2563.729	CFLD	613.287	CPIC	2820.094
BOC	16279.64	WS	1752.73	GHC	1912.834	NCI	1741.331
CMB	4789.249	DXS	28.78267	LJZ	772.4741	AT	255.5721
BCM	6312.332	CJS	1685.022	LZJB	68.86991	AVIC	605.0704
CIB	3223.32	IS	1550.772	GC	653.5079	MIN	39.61267
SPDB	3368.453	SDIC	2329.538	RRED	606.5782	HBP	91.23196
CITIC	4575.801	FS	2084.44	HNA	377.6093	XSGF	140.928
CMBC	3798.125	EBS	1481.529	OWH	321.1077	AJ	240.4335
CEB	2126.269	OSC	830.574	XHZB	312.941		
PAB	2702.72	GS	963.9791	ZTF	408.9744		
BOB	1386.553	CMS	1397.128	YINYI	384.9812		
HXB	1438.278	SHG	677.04	YG	772.4741		
NBCB	683.1139	HTSC	625.5315	YOG	163.2969		
NJCB	622.0286	GF	914.1513	FSH	102.2574		
		CCC	621.7432	JINKE	209.5741		
		HT	512.2373	LG	342.8037		
		GTJA	519.75	BCDH	253.286		
		CS	501.4388	WU	275.8459		

[1] Market assets are in hundred million of RMB, originated from Wind. t=282.

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