Systemic risk and financial regulation

Huang, Qiubin

CHAPTER 2

Systemic Risk in the Chinese Banking System*

Abstract

We examine systemic risk in the Chinese banking system by estimating the change in conditional value at risk (ΔCoVaR), the marginal expected shortfall (MES), the systemic impact index (SII) and the vulnerability index (VI) for 16 listed banks in China for the 2007–2014 period. We find that these measures show different patterns, capturing different aspects of systemic risk of Chinese banks. However, rankings of banks based on these measures (except MES) are significantly correlated. The time series results for the ΔCoVaR and MES measures suggest that systemic risk in the Chinese banking system decreased after the Global Financial Crisis but started rising in 2014.

*This chapter is based on Huang et al. (2017) which was one of the Pacific Economic Review's top 20 most downloaded recent papers.

2.1 Introduction

Macro-prudential regulation, which aims to reduce systemic risk and achieve financial stability, has been one of the most important policy innovations after the Global Financial Crisis (GFC) (Kim and Chey, 2010; and Blinder et al., 2017). However, to implement such regulation, policymakers need to identify systemic risk in the banking system. This chapter analyzes systemic risk in the Chinese banking system. China has achieved remarkable progress in reforming its banking system. There were 117 Chinese banks in the 2015 Top 1000 World Banks ranking;[1] three of them (the Bank of China, the Industrial and Commercial Bank of China, and the Agricultural Bank of China) were rated as global systemically important banks.[2] Chinese banks made $292 billion in aggregate pretax profit in 2013, or 32% of total earnings of the world's top 1,000 banks, outperforming US banks (with a share of 20%), according to The Banker magazine.[3]

However, the Chinese banking system faces numerous challenges. Economic growth in China has been slowing down since the GFC and its export-led growth path does not seem sustainable (Aizenman, 2015), overcapacity in some sectors is becoming increasingly serious, and there seems to be a bubble in the real estate market, whose financing mainly depends on banking loans. No doubt, these challenges may affect the stability of the banking system.[4] Furthermore, the rapid expansion of China's shadow-banking sector may pose a threat to banking stability (Li, 2014), as illustrated by the default (or near-default) of several trusts exposed to the coal-mining sector in 2014.[5] Banks are not immune to the risks of the shadow-banking sector, as many of them distribute wealth

[1] See the report published on 29 June, 2015 in The Banker, available at `www.thebanker.com/Top-1000-World-Banks/Top-1000-World-Banks-China-s-banks-show-no-signs-of-slowdown`.

[2] See the 2014 update of the list of global systemically important banks (G-SIBs), 6 November 2014, available at `www.financialstabilityboard.org/2014/11/2014-update-of-list-of-global-systemically-important-banks`.

[3] The report is available at `www.reuters.com/article/2014/06/29/us-banks-rankings-china-idUSKBN0F411520140629`.

[4] As Fenech et al. (2014) point out, loan quality of the Chinese banking system is directly linked to real estate and government supported infrastructure projects. Koetter and Poghosyan (2010) also find that house price fluctuations contribute to bank instability. Pasiouras and Kosmidou (2007) and Athanasoglou et al. (2008) find that macroeconomic conditions have a significant effect on banks' performance.

[5] See `www.thebanker.com/Top-1000-World-Banks/Top-1000-World-Banks-2014-Back-on-track`.

management products or refinance trust companies.

A banking crisis in China would create enormous problems not only in China but also in other countries, see Feldkircher and Korhonen (2014) and Qiu and Zhan (2016) for evidence on China's increasing influence on the global economy. It therefore seems wise to nip the risk in the bud. And for this we need to analyze systemic risk timely and objectively. According to official reports, the ratio of non-performing loans was about 1% for the vast majority of banks, indicating a good health of the banking system. However, China's official figures are often of questionable reliability, as argued by Krugman (2011). Moreover, data from bank balance sheets are typically backward-looking and less accessible. Therefore, our research resorts to stock market data which is publicly accessible and typically forward-looking.

We investigate systemic risk via several measures. More specifically, we apply the change in conditional value at risk (ΔCoVaR) measure of Adrian and Brunnermeier (2016), the marginal expected shortfall (MES) measure of Acharya et al. (2017), and the systemic impact index (SII) and the vulnerability index (VI) of Zhou (2010) to 16 listed banks in China for the 2007–2014 period.[6] The former two are widely used to monitor financial institutions by central bankers and bank regulators and have a high impact in academia (Benoit et al., 2013). The latter two are based on a different estimation method (i.e., Extreme Value Theory). These measures, calculated using daily equity returns, are used to capture individual banks' systemic risk contributions.

We find that the four systemic risk measures diverge in the cross section, as they capture different aspects of systemic risk in the banking system. However, the rankings of banks based on these measures (except MES) are significantly correlated. Moreover, the time series results for the ΔCoVaR and MES measures suggest that systemic risk in the Chinese banking system decreased after the GFC but started rising in 2014.

Our research contributes to the academic literature on the Chinese banking system. In the past decade, several papers have been published, analyzing different aspects of the Chinese banking system. To name a few, Hasan et al. (2015) investigate the Chinese banking structures and their effect on small business development; García-Herrero et al. (2006), Fu and Heffernan (2009), Lin

[6] We also consider the SRISK approach of Brownlees and Engle (2017), but we find that this approach may not applicable to Chinese banks because the results are zero for all banks considered in the 2007-2010 period, which seems counter intuitive. See Appendix 2.A for related results.

and Zhang (2009), and Dong et al. (2016) focus on the reform and performance of the Chinese banking system; Berger et al. (2009), Ariff and Luc (2008), and Asmild and Matthews (2012) investigate the efficiency of Chinese banks; while Bailey et al. (2011) and Fenech et al. (2014) investigate the quality of bank loans and some other characteristics of the Chinese banking system. However, only a few studies investigate systemic risk in the Chinese banking system. Chen et al. (2014) apply an indicator-based approach proposed by the Basel Committee to identify domestic systemically important banks (D-SIBs) and analyze their correlation with non-D-SIBs. Wang et al. (2015) employ a Merton model to estimate the default probability of banks to construct a systemic risk index of banks. Gang and Qian (2015) examine the impact of China's monetary policy on systemic risk, using CoVaR. To the best of our knowledge, this is the first study that constructs multiple measures of systemic risk for Chinese banks.

The rest of this chapter is organized as follows. Section 2.2 reviews the Chinese banking system. Section 2.3 introduces the systemic risk measures and describes the data. Section 2.4 provides the results. Section 2.5 concludes and discusses.

2.2 A brief review of the Chinese banking system

In the 1990s, the banking system in China was dominated by four large state-owned banks. In addition, there were 13 joint-stock banks and 18 city commercial banks. However, the four state-owned big banks faced serious problems, such as high non-performing loans and inefficient operation and management. The Chinese authorities learned their lessons from the Asian financial crisis, initiating a series of reforms of the banking system in 2003; the first step was the restructuring of the state-owned commercial banks.

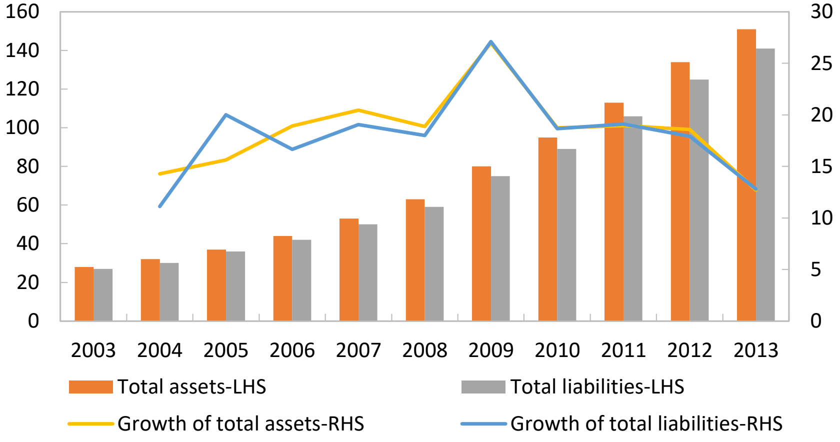
The successful reform of the Bank of China (BOC) and the China Construction Bank (CCB), two of the four state-owned banks, which consisted of disposing of non-performing assets, establishing modern corporate governance frameworks and introducing strategic investors, was followed by reform of the other two state-owned banks, the Industrial and Commercial Bank of China (ICBC) and the Agricultural Bank of China (ABC). The four state-owned banks became joint-stock commercial banks and they have been listed on the Shanghai Stock Exchange since 2006. Reforms were also implemented in other small and medium-sized commercial banks and rural credit cooperatives since 2003.[7]

After the reform, the Chinese banking system became more and more comprehensive and diversified, playing a dominant role in the Chinese financial system. At the end of 2013, it comprised of three development banks, five large-scale commercial banks, 12 joint-stock commercial banks, 145 city commercial banks, 468 rural commercial banks, 122 rural cooperative banks, 1803 rural credit cooperatives, 1134 new rural financial institutions, one postal savings bank, and 92 branches of foreign banks or non-bank financial institutions, according to the classification and statistics of the China Banking Regulatory Commission (CBRC) and the People's Bank of China (PBC).[8] According to the Chinese Financial Stability Reports (2009–2014), the banking system accounted for more than 90% of total asset of all financial intermediation since 2008. Besides, total assets, liabilities and profits of the Chinese banking system grew rapidly since 2003. Total assets and total liabilities grew from 28 trillion Yuan and 27 trillion Yuan in 2003 to 151 trillion Yuan and 141 trillion Yuan in 2013 with an average growth rate of 18% (see Figure 2.1). Profits before taxes of the banking system grew from 32 million Yuan in 2003 to 338 million Yuan in 2006 with an average growth rate of 119%, while the profit after tax of the banking system grew from 447 million Yuan in 2007 to 1744 million Yuan in 2013, with an average growth rate of 25% (see Figure 2.2).

Although the Chinese banking system had become more diversified, it was still dominated by several large banks. For example, five large-scale commercial banks accounted for 43% of total assets of the Chinese banking system at the end of 2013 and 12 joint-stock commercial banks for 18% (see Figure 2.3). The after-tax profits of the Chinese banking system had a similar distribution as banking assets. In 2013, the five large-scale commercial banks accounted for 48% of total after-tax profits and the 12 joint-stock commercial banks for 17% (see Figure 2.4).

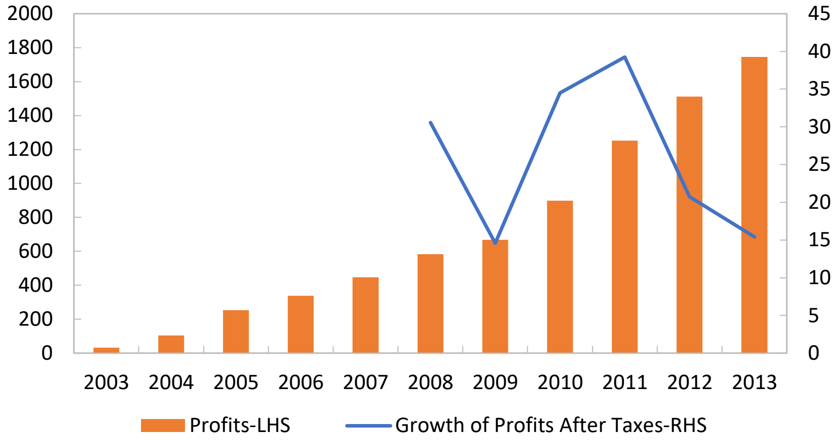
[7] For further details of the reform process of Chinese banks we refer to García-Herrero and Santabárbara (2004), García-Herrero et al. (2006), Podpiera (2006), Fu and Heffernan (2009), and Lin and Zhang (2009).

[8] Data sources: "The Agenda of Regulatory Statistical Information in 2014, Scope of Institutions and Indicator's Explanation", `http://www.cbrc.gov.cn/chinese/home/docView/DF50505B98DF45E1916AEC2BBCD55E1E.html`; "China Banking Regulatory Commission Annual Report 2013", `http://www.cbrc.gov.cn/chinese/home/docView/3C28C92AC84242D188E2064D9098CFD2.html`; and "China Financial Stability Report 2014", `http://www.pbc.gov.cn/publish/jinrongwendingju/369/index.html`.



Assets and liabilities are in trillion Yuan. Growth rate is in percent. Source: China Banking Regulatory Commission Annual Report 2013; and authors' calculation.

Figure 2.1. Assets and liabilities of the Chinese banking system

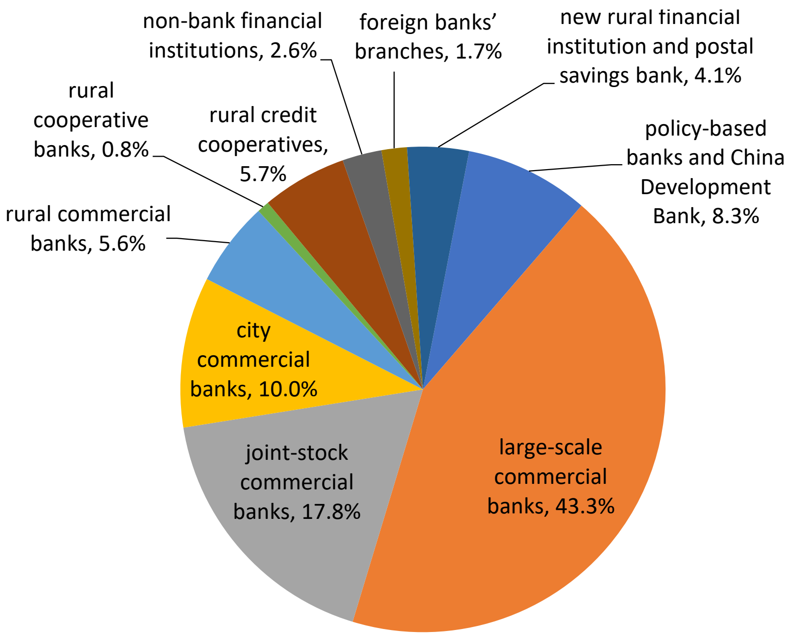


Profits are in million Yuan. Growth rate is in percent. Profits before taxes are shown for 2003–2006 and after taxes for 2007–2013 due to a change in statistical standard. Source: China Banking Regulatory Commission Annual Report 2013; and authors' calculation.

Figure 2.2. Profits of the Chinese banking system

2.3 Methodology and data

Several measures of systemic risk have been developed since the GFC, see Bisias et al. (2012) for a detailed overview of 31 quantitative measures of systemic risk. These measures mainly rely on market data, as they are believed to effectively re-

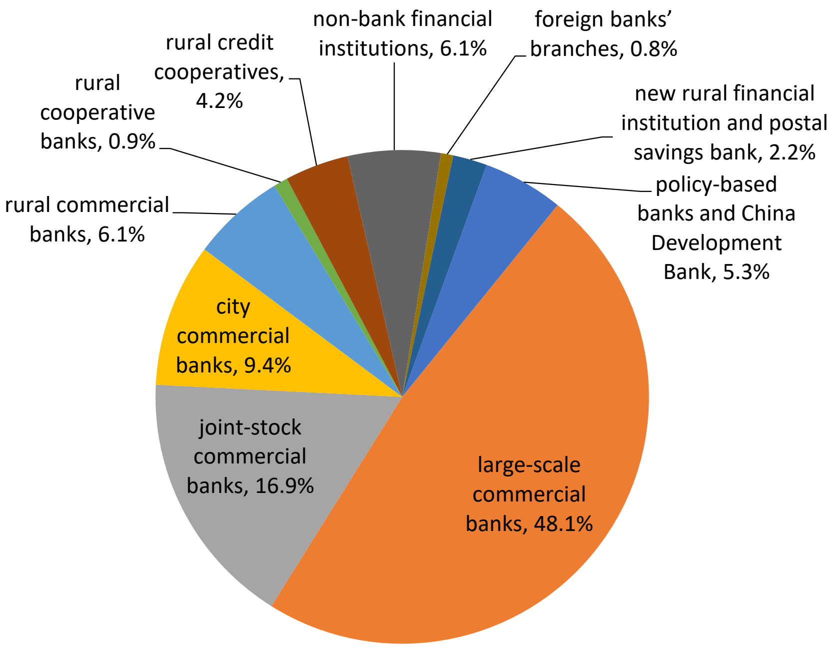


Source: China Banking Regulatory Commission Annual Report 2013; and authors' calculation.

Figure 2.3. Distribution of banking assets in 2013

flect information about publicly traded firms. Lo (2008) and Bisias et al. (2012) suggest to analyze systemic risk based on multiple measures rather than on a single measure, because the banking system is complex and dynamic, while no single measure is able to capture all aspects of systemic risk. Following this suggestion, we employ the conditional value at risk (CoVaR) measure, the marginal expected shortfall (MES), the systemic impact index (SII) and the vulnerability index (VI) to capture systemic risk contributions of Chinese banks.[9] Below we introduce the definition and estimation of these measures and describe the sample used, followed by some reflections on the application of these measures to the Chinese banking system and their comparability.

[9] We focus on measures relying on stock returns. Measures based on data from the CDS market are not considered in this chapter because China's CDS market is still under development and there is not enough data for our purposes. In September 2016, the Chinese government approved trading of CDS by financial institutions in the nation's interbank market (See `http://www.bloomberg.com/news/articles/2016-09-22/china-said-to-allow-trading-of-cds-in-nation-s-interbank-market-ite5sevj`).



Source: China Banking Regulatory Commission Annual Report 2013; Authors' calculation.

Figure 2.4. Distribution of banking profits after taxes in 2013

2.3.1 CoVaR: Definition and estimation

CoVaR, short for value at risk of the financial system conditional on institutions being under distress, has been proposed by Adrian and Brunnermeier (2016). They define an institution's contribution to systemic risk as the difference between the CoVaR conditional on the institution being under distress and the CoVaR conditional on the institution being in a normal state. Note that the value at risk of institution i (VaR_q^i) can be defined as:

$$P(r^i \leq VaR_q^i) = q, \tag{2.1}$$

where r^i is the return of institution i and VaR_q^i is the Value-at-Risk of institution i at quantile q in a given time horizon. As a result, the $CoVaR_q^{s|i}$ can be expressed as the q-quantile of the conditional probability distribution:

$$P(r^s \leq CoVaR_q^{s|i} | r^i = VaR_q^i) = q, \tag{2.2}$$

where $CoVaR_q^{s|i}$ is denoted by the VaR of system s conditional on the institution i being in its VaR. Thus, the contribution of institution i to the risk of system

s is denoted by

$$\Delta CoVaR_q^{s|i} = CoVaR_q^{s|r^i=VaR_q^i} - CoVaR_q^{s|r^i=Median^i}, \tag{2.3}$$

where $\Delta CoVaR_q^{s|i}$ is the contribution of institution i to the systemic risk of the system. Adrian and Brunnermeier (2016) use the median return of institution i as a proxy for the normal state of institution i.

Girardi and Ergün (2013) modify Adrian and Brunnermeier's CoVaR through assuming that the conditioning financial distress event refers to the return of institution i being at most at its VaR ($R^i \leq VaR^i$) as opposed to being exactly at its VaR ($R^i = VaR^i$). Thus, Equation (2.2) is replaced by:

$$P(r^s \leq CoVaR_q^{s|i} | r^i \leq VaR_q^i) = q, \tag{2.4}$$

This specification has three advantages over Adrian and Brunnermeier's CoVaR. First, it allows to consider more severe distress events of institution i that are further away in the tail (beyond its VaR). In addition, it improves the consistency of CoVaR with respect to the conditional dependence of the system on individual institutions (Mainik and Schaanning, 2014). Lastly, due to the time-varying correlation between an institution and the system in Girardi and Ergün's (2013) CoVaR, it allows the linkage to be changing over time while this is assumed to be constant in Adrian and Brunnermeier (2016).

Therefore, we adopt the version of Girardi and Ergün (2013) and calculate the CoVaR metric following their three-step procedure. Firstly, we calculate the VaR of each bank i based on a GARCH(1,1) model and secondly, using the DCC(1,1) model we estimate the bivariate density of each bank and the system.[10] After these two steps, we can calculate CoVaR at the distressed state ($q = 0.05$)[11] and at the benchmark state ($\mu_t^i - \sigma_t^i \leq r_t^i \leq \mu_t^i + \sigma_t^i$) from the dual

[10] We choose the GARCH(1,1) and DCC(1,1) specifications following Engle's suggestion that these best fit most financial time series. The dynamic conditional correlation (DCC) model has been introduced by Engle (2002). We adopt this model to obtain the time-varying correlation between returns of the system and the institution. Notice that we estimate their correlation rather than their causal relationship, and the DCC model has taken into account the variables' autocorrelation. Thus, ΔCoVaR is just a tail-dependency measure and does not necessarily reflect causality (Adrian and Brunnermeier, 2016). This argument also holds for the MES measure as discussed in Section 2.3.2.

[11] In practice, the quantiles of 0.05 and 0.01 are widely used to weigh the extreme risk of a bank. We adopt the quantile of 0.05 because banking crises have not occurred in China, so that there are too few observations in the tail distributions of banks' return at quantile 0.01.

integral Equations (2.5) and (2.6):

$$\int_{-\infty}^{CoVaR_{q,t}^{s|t}} \int_{-\infty}^{VaR_{q,t}^{i}} pdf_t(x,y)\,dy\,dx = q^2, \tag{2.5}$$

$$\int_{-\infty}^{CoVaR_{q,t}^{s|t}} \int_{\mu_t^i-\sigma_t^i}^{\mu_t^i+\sigma_t^i} pdf_t(x,y)\,dy\,dx = p_t^i q, \tag{2.6}$$

where $pdf_t(x, y)$ is the joint probability density function of x and y at time t, and $p_t^i = P(\mu_t^i - \sigma_t^i \leq r_t^i \leq \mu_t^i + \sigma_t^i)$.

Finally, ΔCoVaR is the percentage difference between the CoVaR at the distressed state and at the benchmark state, as defined in Equation (2.7):

$$\Delta CoVaR_{q,t}^{s|i} = 100 \times (CoVaR_{q,t}^{s|i} - CoVaR_{q,t}^{s|b^i})/CoVaR_{q,t}^{s|b^i} \tag{2.7}$$

Thus, ΔCoVaR reflects the spillover effect from a bank to the system, indicating the percentage change of the system's VaR when the bank is in distress and in the normal state.

2.3.2 MES: Definition and estimation

Acharya et al. (2017) consider a financial institution's contribution to systemic risk as its expected loss when the market declines substantially. Under the definition of VaR in Equation (2.1), the expected shortfall (ES), which is the expected loss conditional on something bad happening, can be defined as follows:

$$ES_\alpha = E[R|R \leq VaR_\alpha]. \tag{2.8}$$

In order to get a bank's marginal expected shortfall (MES), define R as the total return of the banking system and decompose it into the sum of each bank's return (r_i), that is $R = \sum_i y_i r_i$, where y_i is the weight of bank i in the banking system. Then we have:

$$ES_\alpha = \sum_i y_i E[r_i|R \leq VaR_\alpha], \tag{2.9}$$

and

$$MES_\alpha^i = \frac{\partial ES_\alpha}{\partial y_i} = E[r_i|R \leq VaR_\alpha]. \tag{2.10}$$

Thus, MES_α^i measures bank i's average equity return on days when the return of the entire banking system drops below a threshold (i.e. VaR_α).

In Acharya et al. (2017), a bank's MES is the average return of its equity (R_b) during the 5% worst days for the overall market return (R_m), where the market is presented by the CRSP Value Weighted Index or the financial subsector's index:

$$MES_i = \frac{\sum\limits_{t:\ system\ is\ in\ its\ 5\%\ tail} R_{i,t}}{number\ of\ the\ 5\%\ worst\ days}. \tag{2.11}$$

This method is simple but it may not get sound results when there are few extreme events in the tail of the return distribution. Furthermore, Acharya et al. (2017) assume the probability of observing a conditioning event to be constant, which is somewhat far from reality as it is more probable to observe losses beyond a given threshold when the volatility is higher. Brownlees and Engle (2017) propose an alternative method to calculate MES which might overcome these shortcomings. Therefore, we adopt Brownlees and Engle's method to calculate MES via the following three steps: 1) Modeling volatilities by GARCH models to obtain conditional volatility and standardized residuals; 2) Resorting to a DCC specification to obtain conditional correlation and the standardized idiosyncratic firm residual; 3) Inference on the model innovations is based on the GARCH/DCC residuals. The one period ahead MES can be expressed as:

$$\begin{aligned} MES^{i|s}_{t-1} = \{&\sigma_{i,t}\rho_{is,t}E_{t-1}(\epsilon_{s,t}|\epsilon_{s,t} \leq VaR_{s,t}/\epsilon_{s,t}) \\ &+ \sigma_{i,t}\sqrt{1-\rho^2_{is,t}}E_t - 1(\epsilon_{i,t}|\epsilon_{s,t} \leq VaR_{s,t}/\epsilon_{s,t})\} \end{aligned} \tag{2.12}$$

where, $E()$ is the tail expectation of the standardized innovations distribution, $\rho_i s$ is the dynamic conditional correlation between bank i and system s, σ_i and σ_s are time-varying conditional standard deviations. We only need to estimate the tail expectations of the standardized innovations distribution because the dynamic conditional correlation and conditional standard deviations have been calculated from the GARCH/DCC model in the previous sub-section. Following Brownlees and Engle (2017), we resort to a non-parametric kernel estimation approach to compute the tail expectations. Let

$$K_h(t) = \int_{-\infty}^{t/h} k(u)\,du, \tag{2.13}$$

where $k(u)$ is a kernel function and h is a positive bandwidth. Then

$$\hat{E}_h(\epsilon_{s,t}|\epsilon_{s,t} \leq k) = \frac{\sum_{i=1}^{n}\epsilon_{s,t}K_h(\epsilon_{s,t}-k)}{n\hat{p}_h}, \tag{2.14}$$

and

$$\hat{E}_h(\varepsilon_{i,t}|\epsilon_{s,t} \leq k) = \frac{\sum_{i=1}^{n} \varepsilon_{i,t} K_h(\epsilon_{s,t} - k)}{n\hat{p}_h}, \tag{2.15}$$

where $\hat{p}_h = \frac{\sum_{i=1}^{n} K_h(\epsilon_{s,t}-k)}{n}$. Thus, MES reflects the vulnerability of individual banks, indicating the expected loss of individual banks conditional on the system being in distress.

2.3.3 SII and VI: Definition and estimation

We introduce the SII and the VI measures together in this section because they have some common backgrounds and estimation methods. The SII and VI measures have been developed by Zhou (2010) through extending the concept of the "probability that at least one bank becomes distressed" (PAO) in Segoviano and Goodhart (2009). According to Zhou (2010), SII measures the expected number of bank failures in the banking system given that one particular bank fails, whereas VI measures the probability that a particular bank fails when there is at least one other failure in the system. Thus, SII and VI are defined by Equation (2.16) and Equation (2.17), respectively:

$$SII_i(p) = E\left(\sum_{j=1}^{d} 1_{X_j > VaR_j(p)} | X_i > VaR_i(p)\right) \tag{2.16}$$

where 1_A is the indicator function that is equal to 1 when A holds, and is 0 otherwise; and

$$VI_i(p) = P\Big(X_i > VaR_i(p) | \{\exists j \neq i, s.t. X_j > VaR_j(p)\}\Big) \tag{2.17}$$

Zhou (2010) uses extreme value theory (EVT) to compute the SII and the VI. Suppose $(X_1, X_2, \cdots, X_d)$ follows the multivariate EVT setup, then we have

$$SII_i = \lim_{p \to 0} SII_i(p) = \sum_{j=1}^{d} (2 - L_{i,j}(1,1)) \tag{2.18}$$

and

$$VI_i = \lim_{p \to 0} VI_i(p) = \frac{L_{i \neq 1}(1,1,\cdots,1) + 1 - L(1,1,\cdots,1)}{L_{i \neq 1}(1,1,\cdots,1)} \tag{2.19}$$

where $L(1,1,\cdots,1)$ is the L function characterizing the tail dependence of $(X_1, X_2, \cdots, X_d)$, and $L_{\neq i}(1,1,\cdots,1)$ is the L function capturing the tail dependence of $(X_1, \cdots, X_{i-1}, X_{i+1}, \cdots, X_d)$. More details about the L function and the derivation of Equation (2.18) and Equation (2.19) are provided in De Haan and Ferreira (2007) and Zhou (2010). Before obtaining the results of SII and VI, we need to estimate the L function. According to Zhou (2010), a counting measure can be applied to estimate the $L(1, 1, \cdots, 1)$,[12] then we have

$$\hat{L}(1, 1, \cdots, 1) = \frac{1}{k} \sum_{s=1}^{n} 1_{\exists 1 \leq i \leq d},\ s.t. X_{is} > X_{i,n-k}. \tag{2.20}$$

2

In Equation (2.20), a critical issue is the choice of the value of k. Zhou (2010) suggests to calculate the estimator of $L(1, 1, \cdots, 1)$ under different k values and draw a line plot against the k values, then picking the first stable part of the line plot starting from low k, which balances the trade-off between the variance arising from low k values and the bias arising from high k values. Following this procedure, we finally choose $k = 60$, which corresponds to a p of 3.4%. Thus, SII reflects the spillover effect from a bank to other banks, indicating the expected number of distressed banks when a particular bank becomes distressed. The VI mirrors a bank's capacity to cope with shocks due to bank failures by calculating the probability of failure of a particular bank.

2.3.4 Sample and data summary

We investigate systemic risk of Chinese banks employing the different measures introduced above using time series data of 14 commercial banks' equity prices during September 25, 2007- December 31, 2014. We focus on 14 banks because there are only 16 banks listed in China's stock exchange and two of them have been listed only since 2010 (the Agricultural Bank of China and the China Everbright Bank). The chosen period depends on data availability and our goal to use a long time period in order to observe the dynamics of banks' systemic risk before and after the GFC. We also compute systemic risk of the other two banks during September 1, 2010 to December 31, 2014. Although there are only 16 (14) banks investigated, they capture a substantial part of the banking system in China in view of their dominant position. The 16 banks include five large-scale commercial banks, eight national joint-stock commercial banks and three city joint-stock commercial banks according to the classification of the China Banking Regulatory Commission. Their combined assets account for more than 79% of all commercial banks.

[12] For more details about the counting measure, see Van Oordt and Zhou (2012).

Data for equity prices of banks is obtained from TDX, as are data of the banking sector index (BSI).[13] The summary statistics for the banks and the BSI are listed in Table 2.1. As Table 2.1 shows, average equity returns of all banks nearly equal 0, which indicates that our assumption of zero mean return is valid for the data set employed. We also observe that all daily returns exhibit high kurtosis and skewness compared with the kurtosis and skewness from the normal distribution, which are 3 and 0, respectively.

Table 2.1. Descriptive statistics of daily log-returns of 16 Chinese banks during 9/25/2007–12/31/2014

Notes: Sector is Banking Sector Index. ICBC: Industrial and Commercial Bank of China; CCB: China Construction Bank; ABC: Agricultural Bank of China; BOC: Bank of China; BCM: Bank of Communications; CMB: China Merchants Bank Co., Ltd; CNCB: China CITIC Bank; CIB: Industrial Bank Co., Ltd; SPDB: Shanghai Pudong Development Bank; CMBC: China Minsheng Banking Co., Ltd; CEB: China Everbright Bank; PAB: Ping An Bank; HB: Huaxia Bank; BOB: Bank of Beijing; BON: Bank of Nanjing; NBCB: Bank of Ningbo. Sample period is from 9/26/2007 to 12/31/2014 for all banks except for ABC and CEB, for which the sample period is from 9/1/2010 to 12/31/2014. Banks listed in the first column are sorted in descending order of their average assets during the sample period. Source: authors' calculations using data provided by TDX.

Banks	Mean (%)	Std. (%)	Max (%)	Min (%)	Skew.	Kurt.	Obs.
ICBC	-0.001	0.021	0.139	-0.156	0.08	11.40	1765
CCB	0.000	0.022	0.139	-0.152	0.06	9.87	1765
ABC	0.051	0.014	0.104	-0.097	0.83	12.40	1050
BOC	-0.005	0.019	0.127	-0.125	0.44	10.82	1765
BCM	-0.018	0.023	0.108	-0.115	0.10	7.13	1765
CMB	-0.015	0.023	0.097	-0.105	0.02	6.27	1765
SPDB	0.005	0.031	0.154	-0.157	0.04	7.34	1765
CNCB	-0.004	0.025	0.104	-0.111	0.18	6.20	1765
CIB	0.002	0.028	0.107	-0.116	-0.03	5.56	1765
CMBC	0.023	0.027	0.130	-0.140	0.06	6.85	1765
CEB	0.017	0.019	0.107	-0.098	0.75	9.01	1050
HB	-0.002	0.030	0.127	-0.137	-0.10	6.33	1765
PAB	0.004	0.029	0.102	-0.112	0.10	5.46	1765
BOB	-0.012	0.026	0.120	-0.132	-0.08	6.64	1765
NBCB	-0.016	0.028	0.120	-0.130	-0.04	6.24	1765
BON	0.012	0.023	0.106	-0.107	0.17	5.96	1765
Sector	-0.004	0.019	0.096	-0.104	-0.01	7.77	1765

[13] TDX (also called Tong Da Xin Financial Terminal) is software provided for analyzing the Chinese stock market. All equity price data can be downloaded from TDX. To exclude the effect of dividend, we employ adjusted closing prices from TDX.

2.3.5 Reflections on the application of systemic risk measures

We choose the above four measures of systemic risk, because they have been widely used in recent years, both in academia and regulatory institutions (Benoit et al., 2013). In addition, they capture systemic risk from different angles. As suggested by Lo (2008) and Bisias et al. (2012), analyzing systemic risk based on multiple measures is necessary, because the banking system is complex and dynamic, while no single measure is able to capture all aspects of systemic risk. Because different systemic risk measures may indicate different degrees of banks' systemic risk contributions, it is important to apply several indicators of systemic risk and compare their performance, as done in this chapter.[14] CoVaR and SII aim to detect the spillover effects from a bank's distress to the banking system whereas MES and VI reflect a bank's ability to withstand shocks from other banks' distress. Despite the difference among these measures, they all attempt to capture the tail-dependency between stock returns of banks. Previous research has suggested that these measures are appropriate indicators of systemic risk (see Adrian and Brunnermeier, 2016; Acharya et al., 2017; and Zhou, 2010).

Notice that these measures were originally proposed for US banks with the underlying premise that US bank stock prices fully reflect all available information.[15] A potential concern when applying these measures to Chinese banks is whether this premise also holds for the Chinese stock market, which is less mature than its US counterpart. To address this concern, we discuss the efficiency of the Chinese stock market and examine market liquidity of bank stocks.

Several earlier studies document that the Chinese stock market was inefficient (e.g., see Groenewold et al., 2004; Seddighi and Nian, 2004; and Chen and Li, 2006), but a series of reforms of the Chinese stock have made it more

[14] To make an analogy, there are also different indicators of market concentration, like the Herfindahl index (HHI) and the concentration ratios (CRn), which emphasize a different dimension of concentration and may also give different answers to the question of how concentrated a particular market is. Therefore, the HHI and CRn measures have been widely used, often jointly, to examine market concentration, also in research on banking (e.g., see Berger et al., 2004).

[15] Some have expressed doubts whether markets are efficient. After all, the market cannot price what the market cannot see. If OTC market structures or varying overlapping portfolios are unobserved and are important in understanding systemic risk (cf. Glasserman and Young, 2016) then market prices can only provide a noisy signal. This potential critique, which is a general criticism on market-based measures, is beyond the scope of our analysis. However, it is important to keep it in mind when interpreting our results.

efficient. One of the remarkable reforms was the 2005 non-tradable share reform which aimed to eliminate non-tradable shares by the end of 2006. These shares belonged to the State or to domestic financial institutions ultimately owned by central or local governments. About two thirds of the Chinese stock market was composed of non-tradable shares at the beginning of 2005 (Beltratti et al., 2012). By the end of 2006, more than 90% of Chinese firms had successfully reformed their share structure (Chong et al., 2012). Beltratti et al. (2016) study the reaction of stock returns and trading volumes to the non-tradable share reform and conclude that their results do not suggest gross valuation errors in the Chinese stock market. Chong et al. (2012) evaluate eleven trading rules derived from the self-exciting threshold autoregressive model, the autoregressive model and the moving average model for the Composite Indices of the Chinese stock market. They find that none of the trading rules can consistently generate abnormal profits for investors after the non-tradable share reform. Their results support the Efficient Market Hypothesis for the Chinese stock market. Carpenter et al. (2015) find that Chinese investors price risk and other stock characteristics remarkably similar to investors in other large economies. They also find that the informativeness of stock prices about future corporate earnings has increased steadily over the last decade, reaching levels that compare favorably with those in the US. They conclude that the Chinese stock market appears to be aggregating diffuse information and generating useful signals for managers. Overall, these studies suggest that the Chinese stock market has been fairly efficient during our sample period, so that it makes sense to estimate systemic risk measures based on bank stock returns as has been done for many other countries than the US.

Another potential concern is that some banks are partially owned by the government and therefore have a low free float rate, which might affect the representativeness of their stock prices in measuring banks' systemic risk. In our sample, the eight national joint-stock commercial banks and the three city joint-stock commercial banks are not owned by the government. Hence, our discussion focuses on the five large-scale commercial banks (ICBC, CCB, ABC, BOC and BCM), which are partially owned by the Chinese government (represented by the Ministry of Finance and Central Huijin Investment Co Ltd).

The government holds about 70%, 57%, 79%, 67% and 26.5% of stocks of ICBC, CCB, ABC, BOC and BCM, respectively. And the government-owned proportions hardly changed during our sample period, even during the 2015 stock market crash. In addition, even excluding the proportions owned by the government, the rest of the negotiable market capitalizations (hereafter, adjusted Cap) of ICBC, ABC, BOC and BCM were 360 billion, 196 billion, 239 billion and 164 billion Yuan in 2016, respectively. These four banks, in terms of their adjusted Cap, still ranked in the Top 20 out of 2969 stocks in the Chinese stock market. Their significant roles in the stock market and their improved stocks' liquidity (see Appendix 2.B) along with the improved market efficiency, imply that these banks' stock prices provide useful information.

Still, these banks' ownership structures (and/or their potential too-big-to-fail status) may result in investors' expectations of government guarantees when banks are in distress. Such expectations might bias the estimates of our systemic risk measures when the government guarantees are not correctly expected or the expectations are not correctly priced in the stock market. Currently, we have no direct evidence to verify this possibility. In fact, the potential presence of government guarantees for banks is a general issue that not only applies to China, but also to advanced economies. This has not deterred numerous scholars from using market-based indicators of systemic risk in empirical analyses. We leave the influence of government guarantee and bank ownership structure on estimating systemic risk of banks for future study. In this chapter, the goal is to compare the performance of different systemic risk measures for the same sample of banks. In this context, the concern about the influence of ownership structure, at least to some extent, can be relieved.

A related potential concern is whether Chinese bank stocks are sufficiently liquid after the 2005 non-tradable share reform. A liquid stock is one that investors can easily buy and sell without the price running off. Only when bank stocks are sufficiently liquid can they be priced efficiently, so that we can exploit information contained in bank stock returns to estimate systemic risk. To examine whether market liquidity of bank stocks has improved significantly after the 2005 non-tradable share reform, we apply the illiquidity measure of Amihud (2002) to examine the liquidity of bank stocks over time. Details about the illiquidity measure and our results and analyses are provided in Appendix 2.B. Overall, our results suggest that bank stocks have been highly liquid during our sample period 2007–2014 compared with their liquidity before 2007. Therefore, the improved efficiency of the Chinese stock market reported by previous studies and our results concerning the improved liquidity of bank stocks lead us to conclude that it is meaningful to estimate market-based systemic risk measures for the Chinese banking system, as has been done for banking systems in several other countries.

2.4 Results and analyses

This section first presents the results for the four measures of systemic risk and examines the rankings based on these measures over time. Then we compare the rankings of banks under these four measures.

2.4.1 Results for ΔCoVaR

Table 2.2 shows the dynamic conditional correlation (DCC) between each bank and the banking system, the value at risk (VaR) at the 5% quantile of each bank and the ΔCoVaR of each bank during the whole sample period. The average DCC of all banks is above 0.8 (see Column 7 in Table 2.2), indicating strong links between each bank and the banking system, which implies that distress in one bank will easily propagate to other banks. Corresponding to the strong links, we find that the ΔCoVaR is associated with the DCC while the VaR (5%) is not. The cross-section correlation coefficient between banks' average ΔCoVaR and their average DCC is as high as 0.99, while it is negative (-0.11) for banks' VaR (5%) with their average DCC.

We find that SPDB has the highest mean of ΔCoVaR among the 16 banks, indicating the highest systemic risk contribution. The value of its ΔCoVaR tells us that distress of SPDB (when its return is below 5% VaR) on average increases the VaR of the banking system by 166.9% compared to a normal situation for the SPDB.

Table 2.3 shows the ranking of banks according to their ΔCoVaR for different periods. We separate the whole sample period into two periods (2007-2010 and 2011-2014), because the equity price data of ABC and CEB are only available since September 2010. Thus, the rankings for the first and second period are not completely comparable. The rankings of most of banks hardly change during 2007 to 2010 while they change dramatically between 2011 and 2014. This suggests that the banking system has undergone some changes since the GFC (e.g., see Cheung et al., 2016).

Furthermore, we consider the relation of ΔCoVaR with bank size (measured by assets). We calculate Spearman rank correlations between the banks' yearly average ΔCoVaR and their assets and do the same for the different periods. The last row of Table 2.3 shows the results. The correlation between the ranking based on average ΔCoVaR and that based on asset size drops from

Table 2.2. Descriptive statistics of ΔCoVaR, DCC and VaR

Notes: See Table 2.1 for abbreviations for the banks. The sample period is from 9/26/2007 to 12/31/2014 for all banks except for ABC and CEB, whose sample period is from 9/1/2010 to 12/31/2014. Banks listed in the first column are sorted in descending order of their average assets during the sample period. VaR (5%) denotes the value at risk at 5% quantile of a bank's stock return. DCC Ave. and VaR (5%) Ave. are average DCC and average VaR (5%) across the sample period, respectively.

Banks	Mean (%)	Std. (%)	Max (%)	Min (%)	DCC Ave.	VaR (5%) Ave. (%)
ICBC	156.59	11.68	193.71	88.14	0.88	-3.05
CCB	147.53	18.18	191.67	68.66	0.86	-3.21
ABC	138.32	18.34	187.67	78.45	0.83	-2.12
BOC	148.90	11.07	194.94	106.35	0.86	-2.82
BCM	157.32	7.07	198.30	64.00	0.89	-3.50
CMB	164.87	15.75	194.98	112.67	0.90	-3.55
SPDB	166.85	13.40	196.86	120.18	0.91	-4.64
CNCB	139.28	18.45	176.34	75.21	0.83	-3.89
CIB	160.42	10.43	184.55	120.35	0.89	-4.41
CMBC	152.59	20.32	194.97	78.01	0.87	-4.17
CEB	136.41	20.22	203.72	24.44	0.82	-2.83
HB	142.95	17.41	182.63	50.25	0.84	-4.58
PAB	136.51	26.54	193.72	17.54	0.81	-4.42
BOB	143.95	13.94	166.67	52.86	0.85	-3.93
NBCB	132.36	13.69	161.54	69.57	0.81	-4.30
BON	143.83	15.92	183.03	66.85	0.85	-3.71

0.57 in first period to 0.34 in the second period. The yearly correlation tends to decrease between 2009 and 2013, suggesting that bank size plays a smaller role in determining banks' systemic risk contribution during the post-crisis years, but it increases dramatically in 2014. Still, the coefficients are lower than 0.5 in most years, indicating that the link between bank size and ΔCoVaR is not very strong. For example, the coefficient is only 0.06 in 2013. This result suggests that a relatively small bank can also exert a significant effect on the banking system's stability.

Finally, we divide the banks into three groups according to the classification of the China Banking Regulatory Commission and calculate their average ΔCoVaR. The Big-5 includes five large-scale commercial banks, the National-8 includes eight national joint-stock commercial banks and the City-3 includes three city joint-stock commercial banks. As shown in Table 2.4, we find that the Big-5's average ΔCoVaR ranks first in both the first period (2007-2010) and in the second period (2011-2014). The mean values of ΔCoVaR for the Big-5

Table 2.3. Ranking of banks based on yearly average ΔCoVaR of each bank

Notes: See Table 2.1 for abbreviations for the banks. The sample period is from 9/26/2007 to 12/31/2014 for all banks except for ABC and CEB, whose sample period is from 9/1/2010 to 12/31/2014. Banks listed in the first column are sorted in descending order of their average assets during the sample period. The last row shows the Spearman correlation between bank size and systemic risk.

ΔCoVaR	2007–10	2011–14	2007	2008	2009	2010	2011	2012	2013	2014
ICBC	5	5	5	8	4	4	5	3	9	5
CCB	7	11	9	6	5	7	9	13	14	8
ABC	–	12	–	–	–	–	13	16	11	6
BOC	8	6	8	12	8	9	6	11	7	7
BCM	6	3	4	7	7	5	2	4	3	4
CMB	1	4	1	1	1	1	3	1	12	3
SPDB	2	1	3	2	2	3	1	2	1	1
CNCB	9	14	10	9	12	10	15	8	8	16
CIB	4	2	2	4	3	6	4	5	2	2
CMBC	3	10	6	3	6	2	11	10	4	11
CEB	–	13	–	–	–	–	16	12	13	12
HB	12	8	12	10	9	12	10	7	6	9
PAB	13	15	7	5	14	14	14	14	16	10
BOB	11	7	14	13	10	8	7	6	10	13
NBCB	14	16	13	14	13	13	12	15	15	15
BON	10	9	11	11	11	11	8	9	5	14
Spearman Correlation	0.57	0.34	0.47	0.37	0.58	0.46	0.32	0.14	0.06	0.58

and the National-8 decrease in the second period compared to the first period, whereas that of City-3 basically remains the same in the second period. As a result, the average ΔCoVaR for City-3 ranks second in the second period. ΔCoVaR is the highest in 2008 for all three groups and tends to decrease slowly in the following four years.

Table 2.4. Yearly average ΔCoVaR of different bank groups

Notes: Big-5 includes ICBC, CCB, ABC, BOC and BCM; National-8 includes CMB, SPDB, CNCB, CIB, CMBC, CEB, HB and PAB; City-3 includes BOB, NBCB and BON. Numbers are in percent.

Groups	2007–2010	2011–2014	2007	2008	2009	2010	2011	2012	2013	2014
Big-5	155.1	148.4	145.5	157.2	156.1	147.3	146.7	142.8	150.7	153.3
National-8	154.4	144.3	141.3	166.4	153.3	142.3	139.4	144.7	149.7	143.7
City-3	146.9	146.6	106.2	153.6	150.9	146.6	147.0	144.3	152.5	143.0

However, the average ΔCoVaR of the Big-5 tends to increase in 2013 and 2014, becoming almost as high as in 2008. In contrast, the average ΔCoVaR of the National-8 and City-3 are lower, both compared to their own past levels and to the Big-5. Finally, we perform a t-test for equality of means of different groups' ΔCoVaR and find that the differences of means among different groups are not always statistically significant. For example, there are no significant differences for the three groups in 2013, but in 2014 the Big-5's mean of ΔCoVaR is significantly bigger than those of the National-8 and City-3. This suggests that systemic risk of banks may be changing over time.

2.4.2 Results for MES

Table 2.5 shows the dynamic conditional correlations (DCC) between each bank and the banking system, the value at risk (VaR) at the 5% quantile of each bank, and the MES of each bank during the whole sample period. We find that NBCB has the highest mean of MES among the 16 banks. Equity returns of NBCB drop on average by 1.02% when the banking system's return is below its VaR (5%). It should be noted that large banks, such as ICBC and ABC, have a relatively small MES, which means that their marginal contributions to systemic risk are relatively low. In addition, we find that there is not a high cross-sectional correlation between MES and DCC (the correlation coefficient is 0.106), or between VaR and DCC (the correlation coefficient is -0.109). However, the correlation coefficient between MES and the absolute value of VaR is as high as 0.877. This suggests that banks with high VaR may suffer more from the distress of the banking system.

To observe the change in the banks' rankings based on MES over time, Table 2.6 shows their rankings during different periods. The last row of Table 2.6 presents the Spearman rank correlation between MES and bank size, both on an annual basis and for different periods. It appears that most rankings hardly change over time. For example, NBCB ranks first in all years but 2008, when it came out second. The five large-scale banks rank last since 2010, suggesting their relatively strong ability to avoid losses in case of banking system distress. Spearman rank correlations between bank size and MES vary between -0.78 and -0.66 since 2009, indicating a relatively high negative correlation between bank size and MES. In other words, a bigger bank tends to have a lower MES, contributing less to systemic risk of the banking system.

Table 2.5. Descriptive statistics of MES, DCC and VaR

Notes: see Table 2.1 for abbreviations for the banks. The sample period is from 9/26/2007 to 12/31/2014 for all banks except for ABC and CEB, whose sample period is from 9/1/2010 to 12/31/2014. Banks listed in the first column are sorted in descending order of their average assets during the sample period. VaR (5%) denotes the value at risk at 5% quantile of a bank's stock return. DCC Ave. and VaR (5%) Ave. are average DCC and average VaR (5%) across the sample period, respectively.

Banks	Mean (%)	Std. (%)	Max (%)	Min (%)	DCC Ave.	VaR (5%) Ave. (%)
ICBC	0.56	0.34	2.84	0.20	0.88	-3.05
CCB	0.63	0.38	2.95	0.23	0.86	-3.21
ABC	0.32	0.11	1.14	0.15	0.83	-2.12
BOC	0.56	0.31	2.20	0.20	0.86	-2.82
BCM	0.60	0.28	2.10	0.26	0.89	-3.50
CMB	0.72	0.31	1.86	0.32	0.90	-3.55
SPDB	0.83	0.46	2.78	0.29	0.91	-4.64
CNCB	0.68	0.23	1.84	0.35	0.83	-3.89
CIB	0.85	0.33	2.07	0.39	0.89	-4.41
CMBC	0.84	0.40	2.56	0.31	0.87	-4.17
CEB	0.35	0.16	1.23	0.18	0.82	-2.83
HB	0.92	0.39	2.40	0.40	0.84	-4.58
PAB	0.71	0.31	1.76	0.09	0.81	-4.42
BOB	0.92	0.38	2.66	0.43	0.85	-3.93
NBCB	1.02	0.38	2.65	0.46	0.81	-4.30
BON	0.76	0.27	1.77	0.33	0.85	-3.71

Table 2.7 shows the results for the three groups of banks according to the classification of the China Banking Regulatory Commission. It is clear that the MES of all three groups has decreased significantly in the second period compared to the first period. MES was the highest for all three groups in 2008; it decreased in the following four years, but rose again in 2013. In 2014, the MES of the three groups has declined to nearly half the average level of 2007-2010. The Big-5 banks have the smallest MES and the City-3 banks have the highest MES in all years except 2007. The t-tests show that the differences of the means among the different groups are statistically significant in all years except 2007. In other words, the City-3 banks have a significantly higher MES than the other two groups, which again reminds us to pay close attention to the systemic risk of small(er) banks.

Table 2.6. Ranking of banks based on yearly average of MES

Notes: See Table 2.1 for abbreviations for the banks. The sample period is from 9/26/2007 to 12/31/2014 for all banks except for ABC and CEB, whose sample period is from 9/1/2010 to 12/31/2014. Banks listed in the first column are sorted in descending order of their average assets during the sample period. ** indicates the significance at the 0.01 level. The last row shows the Spearman correlation between bank size and systemic risk.

Banks	2007–2010	2011–2014	2007	2008	2009	2010	2011	2012	2013	2014
ICBC	11	14	2	11	14	13	13	13	15	14
CCB	10	12	8	9	9	12	11	12	12	13
ABC	–	16	–	–	–	–	16	15	16	16
BOC	14	13	5	12	11	14	14	14	13	12
BCM	13	11	12	13	12	11	12	11	11	11
CMB	7	10	9	7	7	9	8	9	10	10
SPDB	4	8	6	1	5	7	7	8	7	9
CNCB	12	7	14	14	13	6	9	7	9	3
CIB	6	4	3	6	6	4	4	5	2	6
CMBC	5	5	4	5	4	8	6	6	3	5
CEB	–	15	–	–	–	–	15	16	14	15
HB	3	3	7	3	2	3	2	2	5	4
PAB	9	9	10	8	10	10	10	10	6	8
BOB	2	2	11	4	3	2	3	3	4	2
NBCB	1	1	1	2	1	1	1	1	1	1
BON	8	6	13	10	8	5	5	4	8	7
Spearman Correlation	-0.68**	-0.75**	0.09	-0.46	-0.66**	-0.78**	-0.73**	-0.71**	-0.69**	-0.71**

Table 2.7. Yearly average MES of different bank groups

Notes: Big-5 includes ICBC, CCB, ABC, BOC and BCM; National-8 includes CMB, SPDB, CNCB, CIB, CMBC, CEB, HB and PAB; City-3 includes BOB, NBCB and BON. Numbers are in percent.

Groups	2007–2010	2011–2014	2007	2008	2009	2010	2011	2012	2013	2014
Big-5	0.81	0.39	0.95	1.09	0.76	0.54	0.39	0.33	0.41	0.42
National-8	0.99	0.57	0.9	1.35	0.93	0.72	0.55	0.47	0.73	0.55
City-3	1.13	0.68	0.92	1.54	1.04	0.86	0.68	0.61	0.81	0.62

2.4.3 Results for SII

We employ the SII approach to 14 listed banks in China for the full sample period.[16] Table 2.8 reports the results. To understand our findings, let's take ICBC as an example. The estimated systemic impact index of ICBC is almost 9, which suggests that almost 9 banks would fail if ICBC failed. We find that the most and the least systemically important banks are not the biggest or

[16] We exclude ABC and CEB, because these two banks were only listed in 2010 so that there are not enough observations to calculate the SII and VII measures.

the smallest banks, but are medium-sized banks. SPDB and CNCB, which rank sixth and seventh places in terms of bank size, are the most and the least systemically important banks according to the SII measure, respectively. This suggests that bank size is not a key element for banks' systemic importance under this measure. Indeed, the Spearman rank correlation between bank size and SII is not significant (shown in the last row of Table 2.8).

Table 2.8. Results for SII

Notes: SII is the systemic importance index, defined as the number of expected banks failures given a particular bank fails. See Table 2.1 for abbreviations for the banks. The sample period is from 9/26/2007 to 12/31/2014 for all banks. Banks listed in the first column are sorted in descending order of their average assets during the sample period. The last row shows the Spearman correlation between bank size and systemic risk.

Banks	SII	Systemic Importance Ranking
ICBC	8.9789	8
CCB	9.0737	5
BOC	8.6316	12
BCM	9.3263	3
CMB	9.4105	2
SPDB	9.4842	1
CNCB	8.5684	14
CIB	9.2211	4
CMBC	8.9895	7
HB	8.9053	9
PAB	8.6526	11
BOB	9.0421	6
NBCB	8.6105	13
BON	8.6842	10
Spearman Correlation	-0.35	

There is little variation among results of banks' SII, and all banks' SII show a relatively high systemic impact. This may be explained by their high correlations with the banking system, where their correlations are all higher than 0.8 (see the last second column in Table 2.2). We expect that SII values would show more dispersion if we had more banks and their correlations with the banking system would have been lower. For example, Zhou (2010) shows that SII values of 28 U.S. banks range from 6.53 to 12.44.

2.4.4 Results for VI

We apply the VI approach to 14 listed banks in China for the full sample period. Table 2.9 presents the rankings as well as the Spearman rank correlation between the VI and bank size. To understand the results, let's take ICBC as an example. The value of the vulnerability index (VI) of ICBC is 35.8%, indicating that the probability of ICBC being distressed would be 35.8% if at least one other bank becomes distressed. We find that there is little variation of VI across different banks, and all VI values are higher than 33% showing a relatively high vulnerability. Furthermore, the Spearman rank correlation between bank size and VI is not statistically significant, as shown in the last row of Table 2.9, suggesting that large banks are not the most systemically important banks.

Table 2.9. Results for VI

Notes: VI is the vulnerability index, defined as the probability of failure given there exists at least another bank failure in the system. See Table 2.1 for abbreviations for the banks. The sample period is from 9/26/2007 to 12/31/2014 for all banks. Banks listed in the first column are sorted in descending order of their average assets during the sample period. The last row shows the Spearman correlation between bank size and systemic risk.

Banks	VI (%)	Systemic Importance Ranking
ICBC	35.80	3
CCB	35.04	8
BOC	33.73	12
BCM	36.05	2
CMB	36.29	1
SPDB	35.55	5
CNCB	33.73	12
CIB	35.55	5
CMBC	34.52	11
HB	35.80	3
PAB	33.20	14
BOB	35.29	7
NBCB	35.04	8
BON	35.04	8
Spearman Correlation		-0.28

2.4.5 Comparing rankings under the four systemic risk measures

As the measures used capture different dimensions of systemic risk, it is important to account for all of them when addressing the question of which banks have the highest systemic risk and to examine whether the different measures provide a different answer. Because these measures are indicators of systemic risk with higher values indicating greater systemic importance, we compare the rankings of banks' systemic importance based on different measures[17] (see Table 2.10) and compute the pairwise correlations among the rankings (see Table 2.11). The comparison focuses on 14 banks for the full sample period (from 09-25-2007 to 12-31-2014).[18]

Table 2.10. Systemically important banks' rankings in the full sample period

Banks	ΔCoVaR	MES	SII	VI
ICBC	5	13	8	3
CCB	8	11	5	8
BOC	7	13	12	12
BCM	4	12	3	2
CMB	2	8	2	1
SPDB	1	6	1	5
CNCB	12	10	14	12
CIB	3	4	4	5
CMBC	6	5	7	11
HB	11	2	9	3
PAB	13	9	11	14
BOB	9	2	6	7
NBCB	14	1	13	8
BON	10	7	10	8

Table 2.10 shows that there is no bank having the same rank under the four measures. For instance, ICBC ranks fifth according to the ΔCoVaR, while it ranks 13th, eighth and third according to the MES, the SII and the VI, respec-

[17] Recent studies on systemic risk (measures) are more interested in the ranking rather than the exact degree of banks' systemic risk contributions. In particular, studies like Zhou (2010) and Yun and Moon (2014) compare rankings of banks' systemic importance based on several systemic risk measures. We follow these studies in comparing the outcomes of the systemic risk measures used in this chapter.

[18] We cannot estimate the SII and the VI for these two banks due to the limited number of observations for ABC and CEB, so the comparison of these four measures is based on 14 banks.

Table 2.11. Pearson correlations among rankings of systemically important banks

Notes: ** indicates the significance at the 0.01 level. * indicates the significance at the 0.05 level.

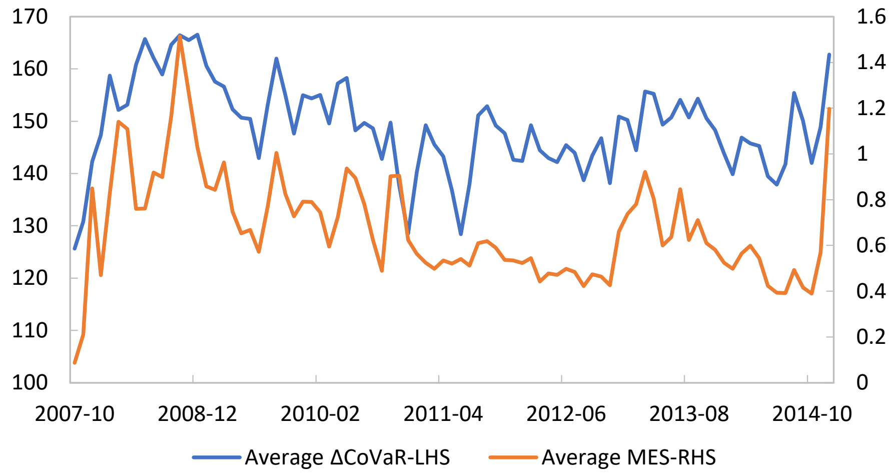
	ΔCoVaR	MES	SII	VI
ΔCoVaR	1.00			
MES	-0.24	1.00		
SII	0.85**	0.03	1.00	
VI	0.61*	0.08	0.70**	1.00

tively. Still, the pairwise correlations of the rankings based on the ΔCoVaR, the SII and the VI are all above 0.6 and are significant at the 5 percent level, but all of them only have very weak relations with the ranking based on the MES measure (see Table 2.11). Our finding that the rankings based on ΔCoVaR and MES have no significant relationship for Chinese banks differs from those of Yun and Moon (2014) who find that rankings based on these two measures are highly correlated for Korean banks. The different findings could be due to some fundamental differences in both countries, such as the differences of banking structure, bank regulation, government policies, and stock market structure, efficiency and regulation. Though the exact reasons are not clear, these different findings suggest that supervisory authorities should examine the suitability of these measures before using them.

To examine developments over time, we show average ΔCoVaR and average MES of all banks in Figure 2.5.[19] In general, the movements of results of both measures are roughly aligned, indicating that systemic risk in the Chinese banking system tended to increase before the GFC and reached a peak in October 2008. After the GFC, systemic risk was relatively low. However, it began to rise in 2014, arriving at a relatively high level at the end of 2014.

It is not surprising that different measures show similarities and differences as they have something in common but are not the same. Firstly, both ΔCoVaR measure and SII are used to gauge the spillover effects from a bank to the banking system, while both MES and VI are used to capture banks' capacity to cope with negative shocks in the banking system. Secondly, both ΔCoVaR and MES weigh the magnitude of a loss, whereas both SII and VI emphasize the probability of distress. These two reasons may partly explain the similarities

[19] Here we do not provide time series results of the SII and the VI because there are no time series results for these two measures.



Note: The units of the average ΔCoVaR and the average MES are percent. Source: Authors' calculation.

Figure 2.5. Average ΔCoVaR and average MES of all banks

and the differences among the results of the measures. In addition, they may be associated with some bank-specific factors, such as the dynamic correlation between returns of banks and the market, as shown by Benoit et al. (2013).

Overall, our findings have important policy implications that financial regulators should acknowledge the different meaning of different systemic risk measures, and that they should not rely on one single measure to identify systemic risk of banks.

2.5 Conclusion

In this chapter, we review the development of Chinese banks since the 1990s and study their systemic risk since the GFC by employing the CoVaR, MES, SII and VI measures to listed Chinese banks. The CoVaR and the MES are calculated based on Engle's (2002) DCC model which allows for capturing time-varying nature of the systemic risk exposures of individual banks, a merit not shared by the quantile regression method also used to estimate the original CoVaR measure in Adrian and Brunnermeier (2016). The SII and the VI measures have been derived using the extreme value theory framework, which can overcome the problem of the scarcity of crisis observations (Zhou, 2010).

We find that these four systemic risk measures yield different rankings for the banks considered, but correlations among rankings based on the ΔCoVaR, the SII and the VI measures are significant. We also find that these similarities and differences are time-varying. Despite the difference of ΔCoVaR and MES with respect to the ranking of banks based on their systemic risk, both measures yield the same finding that systemic risk in the Chinese banking system tended to increase during the GFC and was relatively low after the crisis. However, systemic risk began to rise in 2014, arriving at a relatively high level at the end of 2014. An important policy implication is that financial regulators should acknowledge the different meaning of (changes in) ΔCoVaR, MES, SII and VI, and that they should not rely on one single measure.

Appendix 2.A Application of the SRISK measure

This appendix performs analysis for Chinese banks based on the SRISK measure of Brownlees and Engle (2017). We show that the SRISK measure might be not applicable to Chinese banks.

2.A.1 SRISK: Definition and estimation

Based on the MES approach, Brownlees and Engle develop a new measure, called SRISK, which combines market information and balance sheet. They define the capital shortfall of firm i on day t as

$$CS_{it} = kA_{it} - W_{it} = k(D_{it} + W_{it}) - W_{it}, \tag{2.A.1}$$

where W_{it} is the market value of equity, D_{it} is the book value of debt, A_{it} is the value of quasi assets and k is the prudential capital fraction. Then SRISK is defined as the expected capital shortfall conditional on a systemic event

$$\begin{aligned} SRISK_{it} &= E_t(CS_{it} \mid R_{mt} < C) \\ &= kE_t(D_{it} \mid R_{mt} < C) - (1-k)E_t(W_{it} \mid R_{mt} < C) \\ &= kD_{it} - (1-k)W_{it}(1 + MES_{it}) \\ &= W_{it}[kLVG_{it} - (1-k)MES_{it} - 1] \end{aligned} \tag{2.A.2}$$

where $R_{mt} < C$ is defined as a systemic event that the market return declines below a threshold C on day t; LVG_{it} denotes the leverage ratio (D+W)/W; MES is the marginal expected shortfall, defined in Section 2.3.2. There is an implicit assumption in the above equation that debt cannot be renegotiated in the case of a systemic event, implying that $E_t(D_{it} \mid R_{mt} < C) = D_{it}$.

Although $SRISK_{it}$ could be negative (that is, there is a capital surplus), Brownlees and Engle focus on the positive part. Then the above formulation is designed as follows:

$$SRISK_{it}^{+} = max(SRISK_{it}, 0). \tag{2.A.3}$$

And the total amount of systemic risk in the banking system is measured as

$$SRISK_t = \sum_{i=1}^{N} SRISK_{it}^{+}. \tag{2.A.4}$$

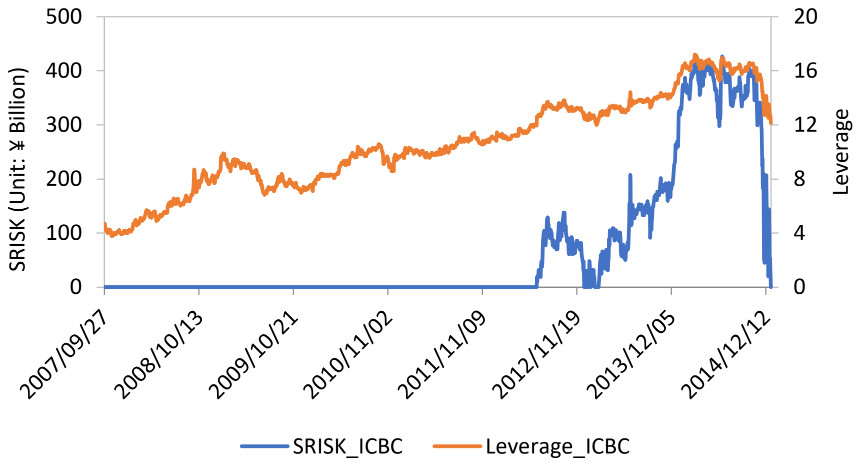
In contrast to Brownlees and Engle, we compute SRISK at a daily frequency rather than a monthly frequency, because we want to make it comparable with the other measures used in this study. In this setting, we can directly combine the results for MES in Section 2.4.2 and data on book value of debt and market value of equity to estimate banks' SRISK. In terms of the prudential capital fraction k, we set it to 8% following Brownlees and Engle.

2.A.2 Results for SRISK

For simplicity, we randomly choose one bank to illustrate the results of SRISK. Figure 2.A.1 shows the results of SRISK and leverage for ICBC. We find that SRISK of ICBC was zero before June 2012, but increased sharply after 2012. That is to say, the systemic risk of the ICBC was zero before June 2012, but increased sharply after 2012. In 2014, the capital shortfall of ICBC was as high as 40 billion Yuan. In addition, we find that only when the leverage is roughly larger than 12, SRISK is larger than zero, as shown in Figure 2.A.1.

Figure 2.A.2 shows the total systemic risk in the banking system (aggregate SRISK) and the average leverage of all banks. We can see that aggregate SRISK was nearly zero before June 2011 and the average leverage was smaller than 12. After 2011, aggregate SRISK rose sharply and its movement was associated with the average leverage.

The results might suggest that there is no systemic risk in the banking system when the leverage is small enough, such as the case of the Chinese banking system during 2007-2011. However, these results are counterintuitive. As everyone knows, we experienced a GFC in 2008, followed by the European debt



Note: SRISK is estimated according to Equation 2.A.3. Leverage is calculated as the ratio of the sum of book value of debt and market value of equity relative to market value of equity.

Figure 2.A.1. SRISK and leverage of ICBC

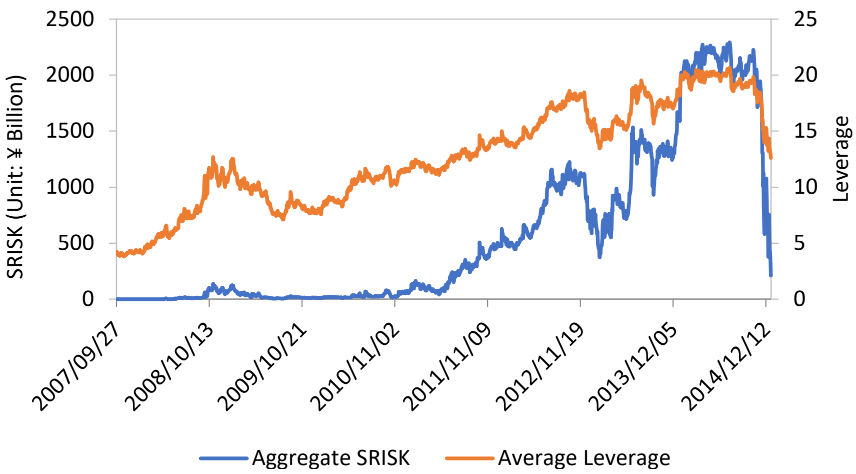


Figure 2.A.2. Aggregate SRISK and average leverage across banks

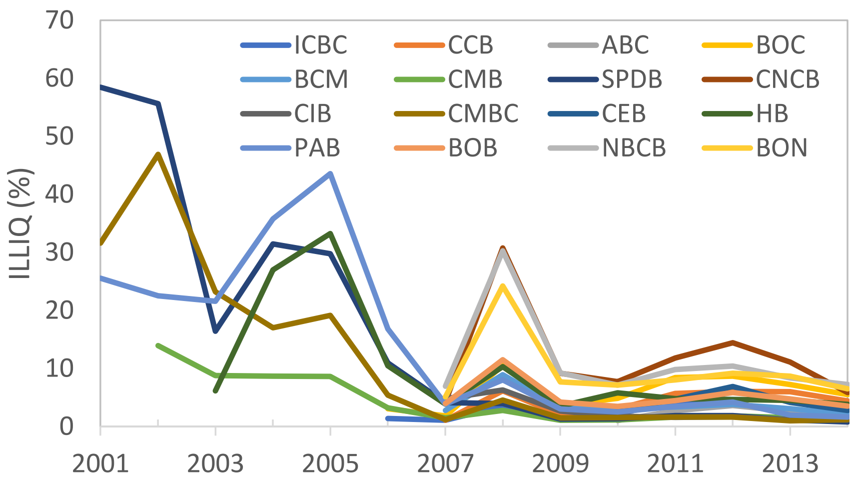
crisis in 2010. The Chinese banking system was affected by the deteriorating external environment. It doesn't make sense that systemic risk of Chinese banks were zero in that period. Hence, we think the SRISK measure might be not applicable to Chinese banks. One possible flaw of this measure is the method of estimating leverage. The leverage could be underestimated when it is calculated through market value of equity rather than book value of equity.

Appendix 2.B Market liquidity of bank stocks

This appendix examines the market liquidity of bank stocks based on the illiquidity measure of Amihud (2002). Following Amihud (2002), we define bank stock illiquidity as the average ratio of the daily absolute return to the trading volume on that day. For annual illiquidity, we take the average of daily illiquidity across total trading days in a given year:

$$ILLIQ_{iy} = \frac{10^9}{D_{iy}} \sum_{d=1}^{d=Diy} \frac{|R_{iyd}|}{VOLD_{iyd}}, \tag{2.B.5}$$

where $ILLIQ_{iy}$ indicates bank stock i's illiquidity in year y; D_{iy} is the number of days for which data are available for bank stock i in year y; R_{iyd} is bank stock i's daily return on day d of year y and $VOLD_{iyd}$ is the respective daily trading volume in Chinese Yuan. Thus, $ILLIQ$ gives the absolute (percentage) price change per 1 Billion Yuan of daily trading volume, reflecting the daily price impact of the order flow. A bank stock with lower $ILLIQ$ has higher liquidity and is expected to be priced more efficiently.



This figure displays annual illiquidity of bank stocks calculated according Equation 2.B.5. Some banks did not have information on ILLIQ before 2007 because they started to be publicly traded in 2007.

Figure 2.B.3. Illiquidity of bank stocks

Figure 2.B.3 shows the results of illiquidity for stocks of banks examined in this chapter. We can see that $ILLIQ$ tended to decrease for all banks before

2007 and remained relatively low in the post-GFC period. The simple average $ILLIQ$ across all banks was 3.3% in 2007, which means that, on average, a trading volume of 1 Billion Yuan resulted in an absolute change of 3.3% in price. The average $ILLIQ$ increased to 11.6% in 2008 which was probably due to the impact of the global financial crisis. After the crisis, the average $ILLIQ$ varied between 3.2% and 5.5%. The relatively low $ILLIQ$ for all bank stocks during our sample period 2007–2014 suggests that bank stocks have become more liquid. This finding is in line with studies showing that the Chinese stock market has become fairly efficient after the reform in 2005–2006 (e.g., see Beltratti et al., 2012; Chong et al., 2012; Beltratti et al., 2016; and Carpenter et al., 2015).