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Abstract

We examine systemic risk in the Chinese banking system by estimating the conditional value at risk (CoVaR), the marginal expected shortfall (MES), the systemic impact index (SII) and the vulnerability index (VI) for 16 listed banks in China. Although these measures show different patterns, our results suggest that systemic risk in the Chinese banking system decreased after the financial crisis, but started rising in 2014. Compared to the banking systems of Korea and the US, we find that Chinese banks are at greater risk according to the CoVaR, the SII and the VI approaches, but have the lowest MES.

JEL-Code: G210, G280, G140.

Keywords: systemic risk, Chinese banking system, CoVaR, capital shortfall.

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1. Introduction

This paper analyzes systemic risk in the Chinese banking system. China has achieved remarkable progress in reforming its banking system. There are 117 Chinese banks in the 2015 Top 1000 of banks;[1] three of them (the Bank of China, the Industrial and Commercial Bank of China, and the Agricultural Bank of China)[2] are rated as global systemically important banks. 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 global financial crisis; overcapacity in some sectors is becoming increasingly serious; the stock market recently has faced severe blows; and there seems to be a bubble in the real estate market, whose financing mainly depends on banking loans. No doubt, these challenges seriously 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). This was illustrated at the start of 2014 with the default (or near-default) of several trusts exposed to the coalmining sector.[5] Banks are not immune to the risks of the shadow-banking sector, as many of them distribute wealth management products or refinance trust companies.

A banking crisis in China would create enormous problems, not only in China but also in other countries given the size of the Chinese economy and its position within the global economy. It therefore seems wise to nip the risk in the bud but the first step would be to analyze systemic risk objectively and accurately. According to official reports, the ratio of non-performing loans is only about 1% for the vast majority of banks, suggesting that the banking system is stable. However, China's official figures are often of questionable reliability, as argued by Krugman (2011). Therefore, our research resorts to market data, providing a less politicized and more objective analysis of the soundness of the Chinese banking system.

We investigate systemic risk with the help of several measures. More specifically, we apply the conditional value at risk (CoVaR) measure of Adrian and Brunnermeier (2011), the marginal expected shortfall (MES) measure of Acharya et al. (2010), the systemic impact index (SII) and the vulnerability index (VI) of Zhou (2010) to 16 listed banks in China for the 2007-2014 period. The former two are widely used to monitor financial institutions by central bankers and bank

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

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

3 See http://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.

regulators and have a high impact in the academia (Benoit et al., 2013). The latter two, which based on different method of estimation (namely, Extreme Value Theory), can be used to make a cautious comparison with the former two. These measures, calculated using daily equity returns, are used to capture each bank's contribution to systemic risk.

Our paper 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, Garcia-Herrero et al. (2006), Fu and Heffernan (2009), Jia (2009), Lin and Zhang (2009), and Dong et al. (2014) focus on the reform and/or performance of the Chinese banking system; Berger et al. (2009), Ariff and Luc (2008), and Asmild and Matthews (2012) investigate the efficiency of China's banks; Bailey et al. (2012) and Fenech et al. (2014) investigate the quality of bank loans and some other characteristic 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. To the best of our knowledge, this is the first study that constructs multiple measures of systemic risk for Chinese banks. Our paper not only examines systemic risk in the Chinese banking system from different perspectives, but also compares systemic risk of Chinese banks to that of banks in some other countries.

We find that the four measures of systemic risk diverge, as they capture different aspects of systemic risk in the banking system. However, the time series results for the CoVaR and MES measures suggest that systemic risk in the Chinese banking system decreased after the global financial crisis but started rising in 2014. We relate the results for systemic bank risk in China to the banking system of Korea and the US, and find that Chinese banks have the highest CoVaR and the lowest MES among the three countries, suggesting that the Chinese banking system is systemically riskier but that is seems better capable of avoiding losses from banking system distress. Besides, Chinese banks are also systemically riskier than US banks according to the SII and the VI approaches.

The rest of this paper is organized as follows. Section 2 reviews the Chinese banking system. Section 3 introduces the systemic risk measures and describes the data. Section 4 provides the results. Section 5 concludes our study.

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 on 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 successively 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.[6]

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 institution, one postal savings bank, and 92 foreign banks' branches or non-bank financial institutions, according to the classifications and statistics of the China Banking Regulatory Commission (CBRC) and the People's Bank of China (PBC).[7] According to the Chinese Financial Stability Report (2009-2014), the banking system accounted for more than 90% of total asset of financial institutions 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 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).

[Insert Figures 1 and 2 here]

Although the Chinese banking system has become more diversified, it is still dominated by a few big 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 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 4).

[Insert Figures 3 and 4 here]

3. Method and data

Several measures of systemic risk have been developed since the global financial crisis (Bisias et al. (2012) provide a detailed overview of 31 quantitative measures of systemic risk). These measures mainly rely on market data, as they are believed to effectively reflect information about

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

[7] 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.

publicly traded firms.[8] In this paper the conditional value at risk (CoVaR) measure, the marginal expected shortfall (MES), the systemic impact index (SII) and the vulnerability index (VI) are applied to the Chinese banking system.

We choose these four measures of systemic risk because they are widely used in recent years, having a high influence upon the academia and regulatory institutions. Besides, they capture systemic risk from different angles. The CoVaR and SII measures aim to detect the spillover effects from a bank's distress to the banking system whereas the MES and VI measures are designed to evaluate a bank's fragility by calculating the expected loss or the probability of distress of the bank when the banking system is confronted with distress. 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 there is no one single measure being able to capture all aspects of systemic risk.

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 (2011), henceforth AB. 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:

$$\mathrm{P}\left(r^i \leq VaR_q^i\right) = q, \tag{1}$$

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:

$$\mathrm{P}\left(r_t^s \leq CoVaR_q^{s|i} \middle| r_t^i = VaR_{q,t}^i\right) = q, \tag{2}$$

where $CoVaR_{q,t}^{s|i}$ 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

$$\Delta CoVaR_q^{s|i} = CoVaR_q^{s|r^i=VaR_q^i} - CoVaR_q^{s|r^i=Median^i}. \tag{3}$$

where $\Delta CoVaR_q^{s|i}$ is the contribution of institution *i* to the systemic risk of the system. AB use the median return of institution *i* as a proxy of a normal state of institution *i.*

Girardi and Tolga Ergun (2013) modify AB'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) is replaced by:

[8] We focus on measures relying on stock returns because there is no CDS market in China so far. Recent research suggests that the Chinese stock market has become fairly efficient after the reform in 2005-2006 (Wang et al., 2010; Patel et al., 2012; Chong et al., 2012).

$$\mathrm{P}\left(r^s \leq CoVaR_q^{s|i} \middle| r_t^i \leq VaR_{q,t}^i\right) = q. \tag{4}$$

This specification has three advantages over AB's CoVaR. First, it allows us 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 Tolga Ergun's (2013) CoVaR, it allows the linkage to be changing over time while this is assumed to be constant in AB.

Therefore, we adopt the version of Girardi and Tolga Ergun (2013) and calculate the CoVaR metric following their three-step procedure. Firstly, we calculate VaR of each bank *i* based on a GARCH model and secondly, using the DCC model we estimate the bivariate density of each bank and the system.[9] After these two steps, we can calculate CoVaR at the distressed state (q=0.05)[10] 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 integral equations (5) and (6).

$$\int_{-\infty}^{CoVaR_{q,t}^{s|i}} \int_{-\infty}^{VaR_{q,t}^i} pdf_t(x,y)dydx = q^2, \tag{5}$$

$$\int_{-\infty}^{CoVaR_{q,t}^{s|i}} \int_{\mu_t^i - \sigma_t^i}^{\mu_t^i + \sigma_t^i} pdf_t(x,y)dydx = p_t^i q, \tag{6}$$

where $p_t^i = P(\mu_t^i - \sigma_t^i \leq r_t^i \leq \mu_t^i + \sigma_t^i)$.

Finally, the ΔCoVaR will be the percentage difference between the CoVaR at the distressed state and at the benchmark state, as defined in Equation (7).

$$\Delta CoVaR_{q,t}^{s|i} = 100 \times (CoVaR_{q,t}^{s|i} - CoVaR_{q,t}^{s|b^i})/CoVaR_{q,t}^{s|b^i}. \tag{7}$$

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

3.2 MES: definition and estimation

Acharya et al. (2010) 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 (1), the expected shortfall (ES), which is the expected loss conditional on something bad happening, can be defined as follows:

$$ES_\alpha = E[R | R \leq VaR_\alpha]. \tag{8}$$

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:

[9] The dynamic conditional correlation (DCC) model has been introduced by Engle (2002). We adopt this model to obtain the time-varying correlations between returns of the system and the institution.

[10] 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 for two reasons: 1) since banking crises have not occurred in China, there are too few observations in the tail distributions of banks' return at quantile 0.01; 2) papers used to compare our findings for the Chinese banking system with those of other countries also use the 0.05 quantile.

$$ES_\alpha = \sum_i y_i E[r_i | R \leq VaR_\alpha], \quad (9)$$

and

$$MES_\alpha^i = \frac{\partial ES_\alpha}{\partial y_i} = \mathrm{E}[r_i | R \leq VaR_\alpha]. \quad (10)$$

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. (2010), 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:

$$MES_i = \frac{1}{number\ of\ the\ 5\%\ worst\ days} \sum_{\{t: system\ is\ in\ its\ 5\%\ tail\}} R_{i,t}. \quad (11)$$

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. (2010) 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 (2012) 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:

$$MES_{t-1}^{i|s} = \sigma_{i,t}\rho_{is,t}E_{t-1}\left(\epsilon_{s,t} | \epsilon_{s,t} \leq VaR_{s,t}/\sigma_{s,t}\right) + \sigma_{i,t}\sqrt{1-\rho_{is,t}^2}E_{t-1}(\varepsilon_{i,t} | \epsilon_{s,t} \leq VaR_{s,t}/\sigma_{s,t}), \quad (12)$$

where E() is the tail expectation of the standardized innovations distribution, ρ_{is} 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 (2012), we resort to a nonparametric kernel estimation approach to compute the tail expectations. Let

$$K_h(\mathrm{t}) = \int_{-\infty}^{t/h} k(u)du, \quad (13)$$

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

$$\hat{E}_h\left(\epsilon_{s,t} | \epsilon_{s,t} \leq k\right) = \frac{\sum_{i=1}^n \epsilon_{s,t} K_h(\epsilon_{s,t} - k)}{n\hat{p}_h}, \quad (14)$$

and

$$\hat{E}_h\left(\varepsilon_{i,t} | \epsilon_{s,t} \leq k\right) = \frac{\sum_{i=1}^n \varepsilon_{s,t} K_h(\epsilon_{s,t} - k)}{n\hat{p}_h}, \quad (15)$$

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.

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 methods of estimation. 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 Equations (16) and (17), respectively:

$$SII_i(p) = E\left(\sum_{j=1}^{d} 1_{X_j > VaR_j(p)} | X_i > VaR_i(p)\right) , \tag{16}$$

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

$$VI_i(p) = P\big(X_i > VaR_i(p) | \{\exists j \neq i,\ \ s.t.\ X_j > VaR_j(p)\}\big). \tag{17}$$

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

$$SII_i = \lim_{p\to 0} SII_i(p) = \sum_{j=1}^{d}(2 - L_{i,j}(1,1)), \tag{18}$$

and

$$VI_i = \lim_{p\to 0} VI_i(p) = \frac{L_{i\neq 1}(1,1,\cdots,1) + 1 - L(1,1,\cdots,1)}{L_{i\neq 1}(1,1,\cdots,1)}. \tag{19}$$

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 equations (18) and (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. Following Zhou (2010), a counting measure[11] is applied to estimate the $L(1,1,\cdots,1)$, so that we have

$$\hat{L}(1,1,\cdots,1) = \frac{1}{k}\sum_{s=1}^{n} 1_{\exists 1\le i\le d,}\ s.t.\ X_{is} > X_{i,n-k}. \tag{20}$$

In Equation (20), a critical issue is the choice of the value of *k*. Zhou (2010) suggests to calculate the estimator of $L(1,1,\ldots 1)$ 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

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

when a particular bank becomes distressed. The VI mirrors a bank's capacity to cope with shocks from other banks' failures by calculating the probability of failure of a particular bank.

3.4 Sample and data summary

This paper investigates the systemic risk of Chinese banks employing different measures using time series data of 14 commercial banks' equity price during September 25, 2007 - December 31, 2014. This paper focuses on 16 banks listed in China's stock exchange and two of them are listed only since 2010 (the Agricultural Bank of China and the China Everbright Bank). The chosen period depends on data availability and our goal that we attempt to use a long time period to observe the dynamics of banks' systemic risk pre- and post the global financial crisis. We also compute the systemic risk of the other two banks during September 1, 2010 to December 31, 2014. Although there are only 16 banks to be investigated in this paper, they reflect the situation of the whole 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 China Banking Regulatory Commission. Their combined assets account for more than 79% of all commercial banks.

The data for equity prices of banks is obtained from TDX[12], as are the data of the banking sector index (BSI). The summary statistics for the banks and the BSI are listed in Table 1. As Table 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.

[Insert Table 1 here]

4. Results and analysis

This section first presents the results for the four measures of systemic risk. Then we compare pairwise correlations. Finally, we compare our systemic bank risk estimations with those for a few other countries to get a better understanding of the degree of systemic risk in the Chinese banking system.

4.1 Results for ΔCoVaR

Table 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), indicating strong links between each bank and the banking system, which implies that distress in one bank will easily propagate to the rest of the banking system. 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.

[12] 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.

[Insert Table 2 here]

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 a 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 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 Chinese banking system has undergone substantial change since the global financial crisis.

[Insert Table 3 here]

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 for different periods. The last row of Table 3 shows the results. The correlation between the ranking based on average ΔCoVaR and that based on asset size drops from 0.57 in the 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 of years, indicating that the link between bank size and ΔCoVaR is not very strong. This result reminds us that a small bank can 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 state-owned 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 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 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 highest in 2008 for all three groups and tends to decrease slowly in the following four years. 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 the means of different groups' ΔCoVaR and find that these differences 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 are significantly bigger than those of the National-8 and City-3. This suggests that systemic risk of banks may be changing over time.

[Insert Table 4 here]

4.2 Results for MES

Table 5 shows the dynamic conditional correlations (DCC) between each bank and the banking system, the value at risk (VaR) at 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. The equity returns of NBCB will drop on average by 1.02% when the banking system's return is below its VaR (5%). It should be noticed that large banks, such as ICBC and ABC, have a relatively small MES, which means that their marginal contribution to systemic risk is relatively low. In addition, we find that there is not a high cross-sectional correlation between MES and DCC (correlation coefficient is 0.106), or between VaR and DCC (correlation coefficient is -0.109). However, the correlation coefficient of MES and the absolute value of VaR is as high as 0.877. This suggests that banks with high VaR will suffer from banking system distress.

[Insert Table 5 here]

To observe the change in the banks' ranking based on MES, Table 6 shows their rankings during different periods. We also present in the last row of Table 6 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 the systemic risk of the banking system.

[Insert Table 6 here]

Table 7 presents the results for the three groups of banks according to the classification of 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 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-test shows 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.

[Insert Table 7 here]

4.3 Results for SII

We employ the SII approach to 14 listed banks[13] in China across the full sample period. Table 8 reports the outcomes. To understand these results, 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 the smallest banks, but are medium-sized banks. SPDB and CNCB, which rank in 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 and is not significant (shown in the last row of Table 8).

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, which are all higher than 0.8 (see Table 2).

[Insert Table 8 here]

4.4 Results for VI

We apply the VI approach to 14 listed banks in China across the full sample period. Table 9 presents the rankings as well as the Spearman rank correlation between the VI and bank size. To understand the result, 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 9, suggesting that large banks are not the most systemically important banks.

[Insert Table 9 here]

4.5 Comparing the results for the four systemic bank risk measures

There is no criterion derived from theoretical or empirical research for comparing our measures for systemic risk. In addition, we cannot compare the outcomes directly because the measures have different economic meanings, capturing different aspects of systemic risk. One possible solution is comparing the rankings of the banks considered based on different measures. Therefore, we rank the banks according to our measures within the full sample period (see Table 10), and compute the pairwise correlations among the rankings (see Table 11). The comparison focuses on 14 banks[14] for the full sample period (from 09-25-2007 to 12-31-2014) as the SII measure and the VI measure cannot be calculated on an annual basis due to the limited observations in the paper.

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[13] 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.

[14] 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 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, respectively. 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 least at the 0.05 level, but all of them only have very weak relations with the ranking based on the MES measure (see Table 11).

[Insert Table 10 and Table 11 here]

For further understanding the results of ΔCoVaR and MES, we compare them over time.[15] Figure 5 shows the average for ΔCoVaR and MES. In general, these are roughly aligned, indicating that systemic risks in the Chinese banking system tended to increase before the global financial crisis and reached a peak in October 2008. After the global financial crisis, systemic risk was at a relatively low level. However, systemic risk began to rise in 2014, arriving at a relatively high level at the end of 2014.

[Insert Figure 5 here]

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

4.6 Comparison with other countries

Finally, we compare our results for China with those for the US and Korea where applicable. For ΔCoVaR we use the results in Girardi and Tolga Ergun (2013) for the US and in Yun and Moon (2014) for Korea. The results shown in Table 12 for China and Korea are calculated for the same period, 2008-2013, while those for the US are calculated for 2000-2008. We find that, on average, Chinese banks have the highest ΔCoVaR among the three countries. The mean ΔCoVaR of China is nearly twice as high as that of Korea, and more than 1.3 times that of the US, which means that systemic risk of Chinese banks is much higher. The similarities and the differences of our measures of systemic risk are also country-varying. For instance, we find that rankings based on the ΔCoVaR and the MES measures have no significant correlation for Chinese banks while Yun and Moon (2014) find they are highly correlated for Korean banks.

[Insert Table 12 here]

Table 13 shows the results for the MES measure for China, Korea and the US. The mean

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

MES of China is the smallest among the three countries, followed by Korea's. So the marginal systemic risk contribution of Chinese banks is lower than that of Korean and US banks. This result contrasts with the findings for ΔCoVaR.

[Insert Table 13 here]

To compare results for SII and VI measures for Chinese banks with banks in other countries, we can only rely on the study by Zhou (2010) for the US (see Table 14). For comparison purposes, the results of SII are scaled by the total numbers of banks in the sample for the corresponding countries. We find that Chinese banks are riskier than US banks according to the SII and VI measures. The average scaled SII of China's banks is 64%, which means that a banking crisis will on average result in 64% of the banks being distressed. This is nearly twice as much as in the US. The average VI of Chinese banks is 35%, which means that the probability of a bank being distressed is 35% when there is at least one other bank in distress. This is more than four times the average for US banks. Besides, we find that there is little variation of SII among China's banks compared with US banks. The same holds true for the VI measure. This may be attributed to the more similar business models of China's banks than those of US banks.

[Insert Table 14 here]

5. Conclusions

In this paper we review the development of Chinese banking system since the1990s and study its systemic risks since the recent global financial crisis by employing CoVaR, MES, SII and VI measures to Chinese listed 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 which is also used to estimate the original CoVaR measure in Adrian and Brunnermeier (2011). 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.

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 are significant. We also find that these similarities and differences are time-varying. Despite of the difference of ΔCoVaR and MES they both suggest that systemic risk in the Chinese banking system tended to increase during the global financial crisis and was relatively low after the crisis. However, the systemic risk began to rise in 2014, reaching a relatively high level at the end of 2014.

Finally, we compare our results of ΔCoVaR and MES with those for banks in Korea and the US. It shows that Chinese banks have the highest ΔCoVaR and the lowest MES among the three countries, probably implying that Chinese banks are systemic riskier but they are more capable to avoid losses from banking system's distress. We also compare our results for SII and VI with those for banks in the US, finding that SII and VI of Chinese banks are much higher. An important policy implication is that financial regulators should acknowledge the different meaning of (changes in) ΔCoVaR, MES, SII and VI, and they should not simply rely on one single measure.

As for future research, we advocate a thorough and systematic comparison of different measures of systemic risk in as many countries as possible and meaningful. This would also make it possible to explain similarities and differences via panel models.

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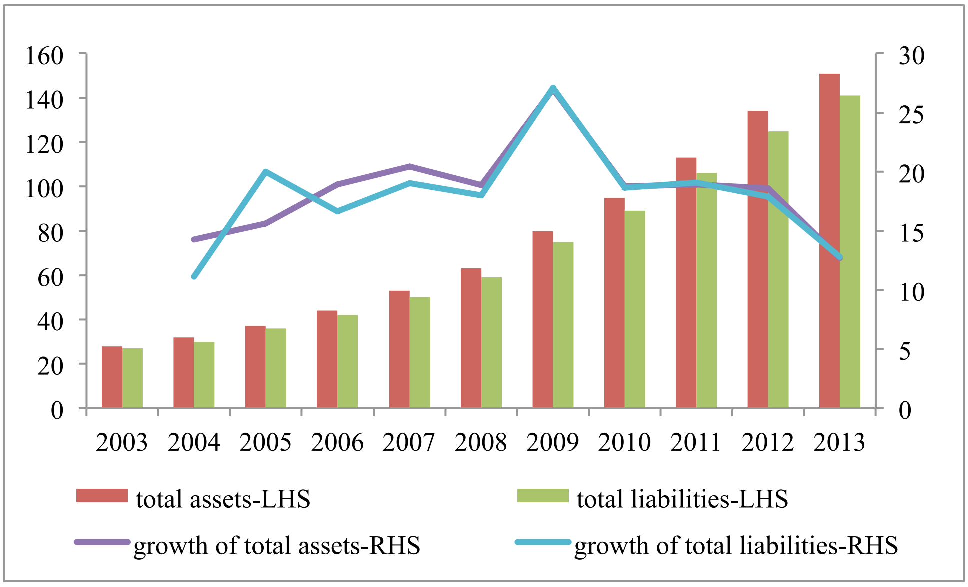
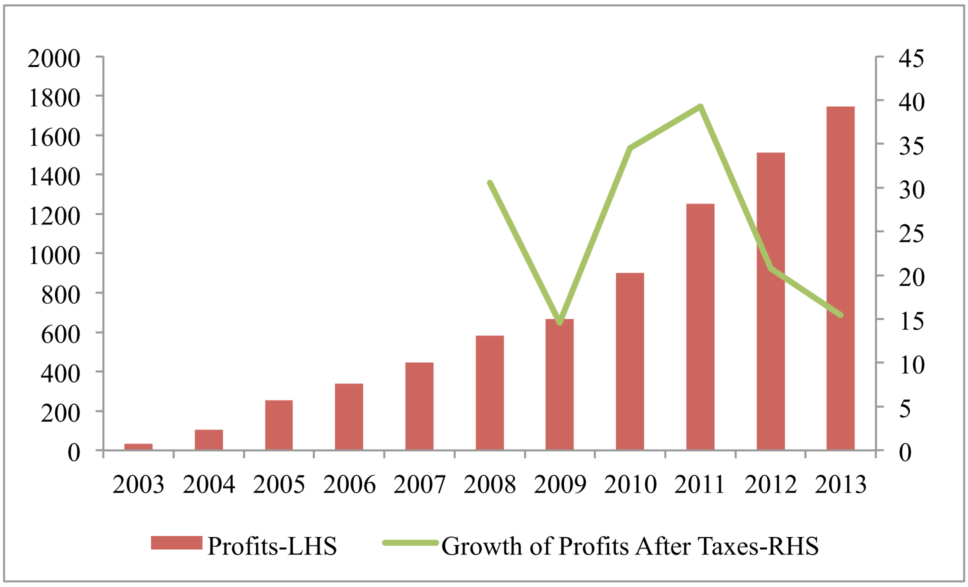
Figures

Figure 1. Assets and liabilities of the Chinese banking system



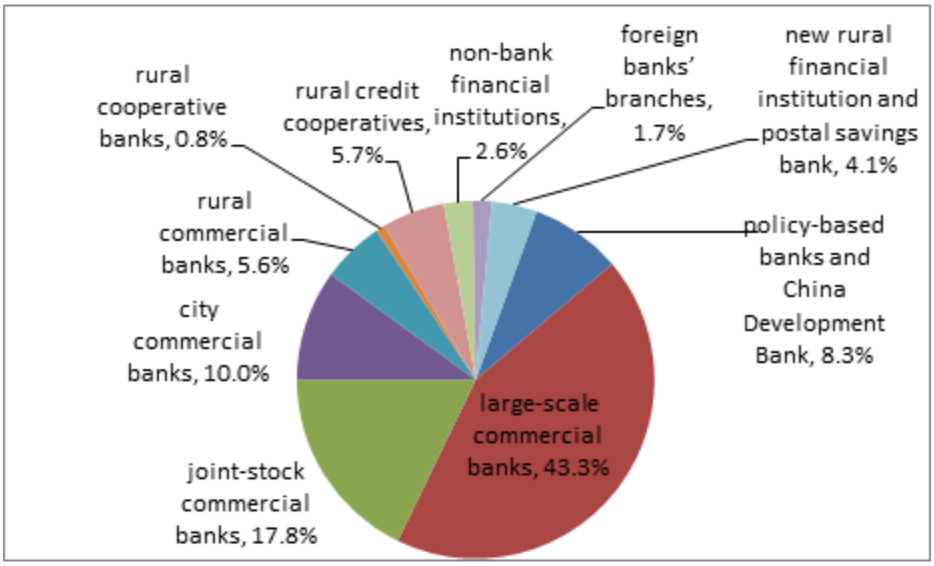
Note: The unit of the assets and liabilities is trillion Yuan. The unit of the growth rate is percent. Source: China Banking Regulatory Commission Annual Report 2013; and authors' calculation.

Figure 2. Profits of the Chinese banking system



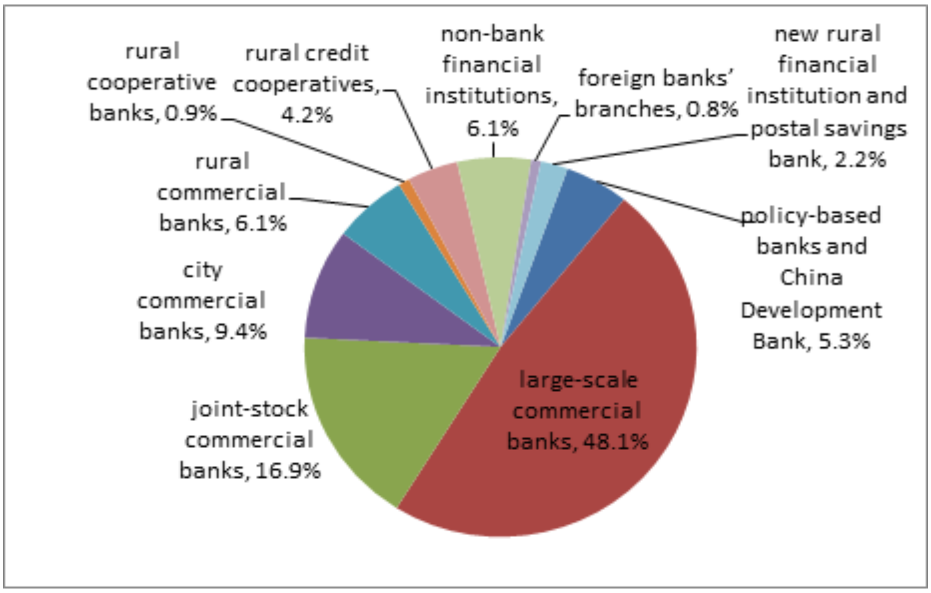
Note: The unit of the profits is million Yuan. The unit of the growth rate is percent. Profits before taxes are shown for 2003- 2006 and after taxes for 2007- 2013 due to a change in statistical standard. Source: China Banking Regulatory Commission Annual Report 2013; and authors' calculation.

Figure 3. Distribution of Banking Assets in 2013



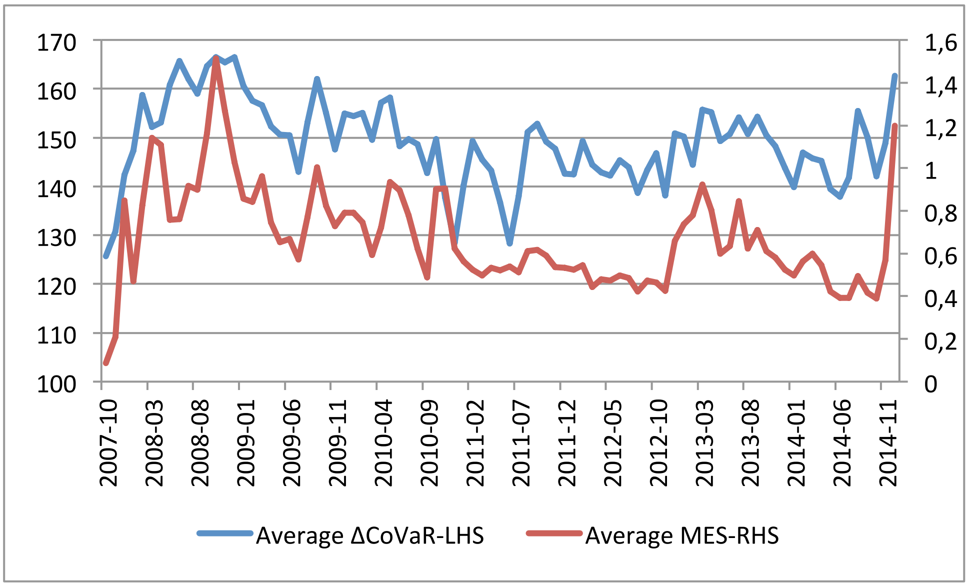
Source: China Banking Regulatory Commission Annual Report 2013; and authors' calculation.

Figure 4. Distribution of Banking Profits after Taxes in 2013



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

Figure 5. Average ΔCoVaR and average MES



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

Tables

Table 1. Descriptive statistics of the daily log-returns of 16 Chinese banks 9/25/2007-12/31/2014

Banks	Mean	Std. Dev.	Max.	Min.	Skew.	Kurtosis	Observations
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

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.

Table 2. Descriptive statistics of ΔCoVaR, DCC and VaR (5%)

Banks	Mean (%)	Std. Dev.	Max.	Min.	Skew.	Kurt.	DCC Ave.	VaR (5%) Ave.
ICBC	156.59	11.68	193.71	88.14	-0.91	6.57	0.88	-0.0305
CCB	147.53	18.18	191.67	68.66	-0.70	3.73	0.86	-0.0321
ABC	138.32	18.34	187.67	78.45	0.06	3.28	0.83	-0.0212
BOC	148.90	11.07	194.94	106.35	-0.39	4.32	0.86	-0.0282
BCM	157.32	7.07	198.30	64.00	-1.99	30.17	0.89	-0.0350
CMB	164.87	15.75	194.98	112.67	-0.51	3.03	0.90	-0.0355
SPDB	166.85	13.40	196.86	120.18	-0.50	3.01	0.91	-0.0464
CNCB	139.28	18.45	176.34	75.21	-0.50	3.41	0.83	-0.0389
CIB	160.42	10.43	184.55	120.35	-0.55	4.09	0.89	-0.0441
CMBC	152.59	20.32	194.97	78.01	-0.41	3.00	0.87	-0.0417
CEB	136.41	20.22	203.72	24.44	-1.30	7.49	0.82	-0.0283
HB	142.95	17.41	182.63	50.25	-1.65	8.27	0.84	-0.0458
PAB	136.51	26.54	193.72	17.54	-1.28	5.44	0.81	-0.0442
BOB	143.95	13.94	166.67	52.86	-3.39	17.75	0.85	-0.0393
NBCB	132.36	13.69	161.54	69.57	-1.49	6.75	0.81	-0.0430
BON	143.83	15.92	183.03	66.85	-1.56	7.26	0.85	-0.0371

Notes: see Table 1 for abbreviations for the banks. 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.

Table 3. Ranking of banks based on yearly average ΔCoVaR of each bank

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

Notes: see Table 1 for abbreviations for the banks. 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 banks' sizes and systemic importance.

Table 4. Yearly average ΔCoVaR of different banks groups (%)

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

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.

Table 5. Descriptive statistics of MES, DCC and VaR (5%)

Banks	Mean (%)	Std. (%)	Max (%)	Min (%)	Skewness	Kurtosis	DCC Ave.	VaR (5%) Ave.
ICBC	0.56%	0.34%	2.84%	0.20%	1.94	8.80	0.88	-0.0305
CCB	0.63%	0.38%	2.95%	0.23%	1.90	7.82	0.86	-0.0321
ABC	0.32%	0.11%	1.14%	0.15%	3.30	17.42	0.83	-0.0212
BOC	0.56%	0.31%	2.20%	0.20%	1.58	5.70	0.86	-0.0282
BCM	0.60%	0.28%	2.10%	0.26%	1.50	5.89	0.89	-0.0350
CMB	0.72%	0.31%	1.86%	0.32%	1.31	4.55	0.9	-0.0355
SPDB	0.83%	0.46%	2.78%	0.29%	1.63	5.64	0.91	-0.0464
CNCB	0.68%	0.23%	1.84%	0.35%	1.38	5.39	0.83	-0.0389
CIB	0.85%	0.33%	2.07%	0.39%	1.11	4.08	0.89	-0.0441
CMBC	0.84%	0.40%	2.56%	0.31%	1.27	4.74	0.87	-0.0417
CEB	0.35%	0.16%	1.23%	0.18%	2.23	8.69	0.82	-0.0283
HB	0.92%	0.39%	2.40%	0.40%	1.51	4.97	0.84	-0.0458
PAB	0.71%	0.31%	1.76%	0.09%	0.88	3.25	0.81	-0.0442
BOB	0.92%	0.38%	2.66%	0.43%	1.48	5.54	0.85	-0.0393
NBCB	1.02%	0.38%	2.65%	0.46%	1.23	4.48	0.81	-0.0430
BON	0.76%	0.27%	1.77%	0.33%	1.08	4.12	0.85	-0.0371

Notes: see Table 1 for abbreviations for the banks. 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.

Table 6. Ranking of banks based on yearly average of MES

Banks	2007- 10	2011-14	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**

Notes: see Table 1 for abbreviations for the banks. 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. **. Correlation is significant at the 0.01 level. The last row shows the Spearman correlation between banks' sizes and systemic importance.

Table 7. Yearly average MES of different banks groups

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%	0.90%	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%

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.

Table 8. Results for SII

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

Notes: SII is the systemic importance index, defined as the number of expected banks failures given a particular bank fails. See Table 1 for abbreviations for the banks. 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 banks' sizes and systemic importance.

Table 9. Results for VI

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

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 1 for abbreviations for the banks. 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 banks' sizes and systemic importance.

Table 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 11. Pearson correlations among rankings of systemically important banks

	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

Notes: **. Correlation is significant at the 0.01 level. *. Correlation is significant at the 0.05 level.

Table 12. Systemic risk in different countries: ΔCoVaR

Results	ΔCoVaR Mean (%)	ΔCoVaR Std. (%)	ΔCoVaR Max (%)	ΔCoVaR Min (%)
Results in this paper	148.4	11.1	168.1	131.6
Results in Yun and Moon (2014)	79.9	21.4	106.8	33.4
Results in Girardi and Tolga Ergun (2013)	110.3	17.4	141.3	68.2

Notes: Results in Yun and Moon (2014) and in this paper reported here are the mean ΔCoVaR of ten banks in Korea during 2008-2013. Results in this paper reported here are the mean ΔCoVaR of 16 banks in China during 2008-2013. Results in Girardi and Tolga Ergun (2013) are the mean ΔCoVaR of 28 depositories in US from 6/26/2000 to 2/29/2008.

Table 13. Systemic risk in different countries: MES

Results	MES Mean (%)	MES Std. (%)	MES Max (%)	MES Min (%)
Results in this paper for China	0.72	0.21	1.06	0.32
Results in Yun and Moon (2014) for Korea	2.84	0.9	3.8	0.7
Results in Brownlees and Engle (2012) for US	6	5	14	2

Notes: Results in Yun and Moon (2014) are the mean MES of ten banks in Korea during 2008-2013. Results in this paper reported here are the mean MES of 16 banks in China during 2008-2013. Results in Brownlees and Engle (2012) are the mean MES of 29 depositories in US during 2008-2010, the results are approximate values because the authors don't provide statistics in their paper but a figure of the time-varying MES.

Table 14. Systemic risk in different countries: SII and VI

Results	SII/ Numbers of banks				VI			
	Mean (%)	Std. (%)	Max (%)	Min (%)	Mean (%)	Std. (%)	Max (%)	Min (%)
Results in this paper	64	2.2	67.7	61.2	35	0.9	36.3	33.2
Results in Zhou (2010)	36	5.8	44.4	23.3	9	1.2	10.3	6.6

Notes: Results in Zhou (2010) are estimated for 28 banks in US from 1987 to 2009. Results in this paper are estimated for 14 banks in China from 2007 to 2014. For comparison, the results of SII are scaled by the numbers of banks in the sample for the corresponding countries.