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A stable systemic risk ranking in China's banking sector: Based on principal component analysis ☆

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HIGHLIGHTS

- We compare five popular systemic risk rankings for the Chinese banking sector.
- We find that PCA based on five popular methods provides a reliable risk ranking.
- PCA combined systemic risk ranking is mainly based on fundamentals for Chinese banking sector.
- Our results implicate that the PCA model provides a stable ranking for banking supervision.

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ABSTRACT

In this paper, we compare five popular systemic risk rankings, and apply principal component analysis (PCA) model to provide a stable systemic risk ranking for the Chinese banking sector. Our empirical results indicate that five methods suggest vastly different systemic risk rankings for the same bank, while the combined systemic risk measure based on PCA provides a reliable ranking. Furthermore, according to factor loadings of the first component, PCA combined ranking is mainly based on fundamentals instead of market price data. We clearly find that price-based rankings are not as practical a method as fundamentals-based ones. This PCA combined ranking directly shows systemic risk contributions of each bank for banking supervision purpose and reminds banks to prevent and cope with the financial crisis in advance.

1. Introduction

The International Monetary Fund (IMF, 2016) claims that continued and extensive Chinese financial reforms will support the growth and stability of China and the global economy.[1] China has attempted to or been an indispensable part of the world economy with many achievements in its monetary and financial system, especially with respect to the progress of reforming

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[1] The International Monetary Fund Annual Report, 2016, see at http://www.imf.org/external/pubs/ft/ar/2016/eng/sdr.htm.

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its banking system. According to the 2016 list of global systemically important banks (G-SIBs),[2] Chinese banks including Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB), Bank of China (BOC) and Agricultural Bank of China (ABC), are all in the top five banks by Tier 1 capital worldwide. Numerous literature pay specific attention to the banking sector as banks, which are the primary backstop providers of liquidity in the economy and issuers of federally guaranteed deposits to households, are critical to stability (see, e.g., [1–4]). With the rise of China, the stability of the Chinese banking sector is gradually becoming essential for global financial markets. Therefore, how to measure systemic risk properly in Chinese banking system is an inevitable issue not only for China, but also for global financial systems.

Ever since the outbreak of global financial crisis, many methods have been used to measure systemic risk of the institutions in financial sector, such as leverage ratio (short as LVG, [5,6]), SRISK [7,8], Value at Risk (short as VaR, [9,10]), ΔCoVaR [11,12], and capital assets pricing model beta times market capitalization (short as CAPM-$\beta\times$MV, [13,14]). However, these methods can hardly be used for supervision purpose because of their weak theoretical foundation and inherently volatile in rankings [15].

In this paper, we focus on providing a robust combined ranking by applying principal components analysis (PCA) to combine five prominent systemic risk rankings of financial institutions. Our work would also prefer to consider the absence of research in systemic risk during the post-crisis era. Following Nucera et al. [15], we apply five popular methods (LVG, VaR, SRISK, ΔCoVaR, and beta $\times$ size) to analyze the systemic risk rankings of China's banking sector, using the PCA method as the indicators, such as leverage ratio, provide fundamental information on the riskiness of individual banks (IOSCO, 2011). The indicators based on market data, such as VaR and ΔCoVaR, contribute market risk to the combination, and different measures contain rich information concerning systemic risk. Therefore, we combine these five popular systemic risk measurement rankings in our study by applying the PCA model, which contains sufficient information and generates a reliable systemic risk ranking. PCA is a standard tool in multivariate variable analysis to reduce the number of dimensions, while retaining the data's information. Using the PCA method, we can consider both the fundamental information and the price-based information simultaneously, analyze the systemic risk contribution of banks directly, and identify the top systemically risky banks, which is more reliable and convincing. Therefore, the method prompts banks to prevent and cope with the financial crisis beforehand, which is valuable for supervision purposes. In addition, important original variables that are the major contributors to the first few components can be identified through the PCA method.

We focus on three main empirical results in this paper. First, we apply five popular methods to analyze the systemic risk rankings of sixteen listed Chinese banks between September 2010 and October 2016 and it turns out that there are vastly different systemic risk rankings for the same bank. From the result of comparing stabilities of different rankings, we also notice that approaches of different basis deviate substantially when using a sample of Chinese banking market. Second, when we investigate rank volatility and state transition matrix of our five input methods and two combined rankings, it is not surprising to find a more concentrated diagonal line that reveals a stable ranking PCA model offers. Besides, the matrix also offer evidence that methods rely on market data are not practical as fundamental-based systemic risk measures. Third, we use principal component analysis to offer a reliable ranking to obtain a combined ranking that is less affected by model risk and estimation uncertainty for both regulators and market participants. The results of China's banking data are not the same as the previous study. Nucera et al. [15] focus on the mature market and study the systemic risk of banks in developed countries, while this paper examines the systemic risk in China. On the other hand, in comparison to Huang et al. [16], we employ five systemic risk measures and the PCA model to provide a comprehensive analysis of the Chinese banking system, rather than only employing the CoVaR, MES, systemic impact index (SII), and vulnerability index (VI).

Our paper makes several contributions to academic literature on systemic risk ranking of the Chinese banking system. First, we employ five methods to measure the systemic risk of the banking sector in China. As a unique part of the global economy, China plays an important role in global financial stability, particularly in its banking sector. In addition, as there is limited evidence on emerging markets, the samples from China are representative of the developing countries. We then compute standardized monthly rankings for different banks, and describe the time-series evolution and the cross-sectional of each ranking criterion. More importantly, we find that the price-based rankings (such as VaR and ΔCoVaR) are not practical methods in comparison to the fundamentals (such as LVG, SRISK, and CAPM-$\beta\times$MV) in China, as market data provides limited information on systemic risk.

Second, to the best of our knowledge, this is the first attempt to use principal components methodology to measure systemic risk ranking within banking system in China. We use principal component analysis (PCA) to obtain a reliable combined systemic risk ranking for supervision purpose in practice. More specifically, in this article, five popular systemic risk measurements (SRMs) are employed to obtain a standardized ranking (between 0 and 1) for each bank. We then apply PCA model to analyze five kinds of scaled rankings to obtain the CR1, which contains more than 60% information that the five SRMs provide. The CR1 is a linear combination of five systemic risk rankings. It can not only reduce the number of dimensions, but also retain as much information as possible. Our paper clearly finds that this combined ranking is mainly based on fundamentals instead of market price data, which cautions us to pay more attention to the operation of financial enterprises.

The remainder of the article is organized as follows. In Section 2, we introduce the related literature. Then, we focus on data and main methodology in Section 3. Section 4 discusses the empirical findings and conducts further analysis. We conclude in Section 5.

[2] The Financial Stability Board (FSB), in consultation with Basel Committee on Banking Supervision (BCBS) and national authorities, has identified the 2016 list of global systemically important banks (G-SIBs), using end-2015 data and the updated assessment methodology published by the BCBS in July 2013. See at http://www.fsb.org/wp-content/uploads/2016-list-of-global-systemically-important-banks-G-SIBs.pdf.

2. Literature review

During the financial crisis of 2007–2009, a bunch of literature focus on the systemic risk of markets in developed countries for the reason that these markets play an important role in global economy (see, e.g., [17,18]). Meanwhile, there are also several scholars concerned about the systemic risk in emerging markets [19,20]. Lin et al. [21] rely on a database of Taiwan financial institutions and indicate that leading systemic risk models are quite similar in identifying systemically important financial institutions (SIFIs). Engle et al. [6] analyze some financial issues that could contribute to the regional financial stability through focusing on Asian markets especially China and India. In view of the increasingly important role of the emerging markets, play in today's world, we find it necessary to investigate how to monitor systemic risk of developing countries, especially the Chinese market.[3] Papers focusing on them are not comprehensive or specific enough. However, there is a lack of evidence based on emerging market and sample from China is a representative of developing countries. Besides, the Financial Stability Board (FSB, 2016) has published a list of global systemically important banks (G-SIBs) and there are four banks belongs to China, indicating its influence on world economy. Therefore, our manuscript investigates the systemic risk within banking system in China.

In order to measure the systemic risk precisely and effectively, some famous systemic risk measurements have been put forward in recent years. Consequently, a strand of literature makes comparison between them (see, e.g., [27,28]). Among these, Danielsson et al. [5] empirically analyze the performance of leading risk measurement methods (VaR, SRISK, CoVaR) and find that they are incapable of providing either precise estimates of an individual bank's contribution to systemic risk or reliable rankings of banks by the amount of systemic risk they create. As we can see, there is no such an approach that can be selected as a useful tool for financial system for the reason that they are lack of theoretical basis and have natural noise.

Some scholars find interesting results about measurements of different basis when exploring systemic risk. Danielsson et al. [5] says when market-based measures lose their efficacy, less informationally intensive policies such as the leverage ratio is more practical. Danielsson et al. [29] note weak theoretical basis and model risks for the measurements of systemic risk. The International Organization of Securities Commissions (IOSCO, 2011) states that size and leverage are two key sources of systemic risk. Significant size is usually used to identify banks that are "too-big-to-fail" with a leverage ratio that allows them to have a disproportionate impact on the market when it comes to small financial institution. In addition, Pukthuanthong and Roll [30] suggest that the CAPM-β in nominal systemic risk can be easily influenced by characteristics of an emerging market. SRISK is proposed for spillovers effects among financial institutions. VaR and ΔCoVaR, which are estimated by dynamic conditional correlation (DCC) approach, can be influenced by market efficacy, since they are market-based measures. The literatures mentioned above mostly use a single indicator to research systemic risk. However, individual indicator only concentrates on a certain aspect of systemic risk. To overcome the challenges in front of us, principal component analysis has been employed in our paper and we have a strong faith that a scientific combination will improve the status quo vastly.

Our paper is closely related to two recent studies. Nucera et al. [15] typically apply principal component analysis to provide a less volatile and turnover ranking by using a sample of financial institutions in the European Union over the period 2002–2013. They find great difference between price-based rankings and fundamentals-based rankings for a prolonged time in the period before the financial crisis. Our work, on the other hand, shows adequate proof that difference between these two kinds of rankings come up during post-crisis era from 2010 to 2016. We also investigate whether this kind of methodology is widely applicable as well as reliable. Furthermore, Huang et al. [16] examine systemic risk in the Chinese banking industry by estimating the CoVaR, MES, the systemic impact index (SII) and the vulnerability index (VI) for 16 listed banks in China. Their results suggest that Chinese banks are at greater risk based on the CoVaR, the SII and the VI, but have the lowest MES. These measures are not comprehensive enough and none of them can provide a reliable ranking that of referable value, so we apply five popular systemic risk measurements and principal component analysis to complete the research in Chinese banking system.

3. Methodology and data

This section outlines the methodology and dataset we use in our work. First of all, in Section 3.1, our paper review five widely used ranking methods (leverage ratio, SRISK, VaR, ΔCoVaR, and CAPM-$\beta\times$MV) and explain the way we calculate them and the reason why we choose them. Section 3.2 provides a comprehensive combined ranking. We describe the sample in Section 3.3.

3.1. Ranking methodology

3.1.1. Leverage ratio (LVG)

We follow Engle et al. [6] and Brownlees and Engle [8] who define "the quasi leverage ratio" as leverage ratio

$$LVG_{it} = \frac{A_{it}}{W_{it}} = \frac{D_{it} + W_{it}}{W_{it}}, \tag{1}$$

[3] China's banking industry is one of the largest and most complex financial sectors among developing countries. Structural reforms of China's banking sector have attracted several scholars to take a new look at banks in China (see, e.g., [22,23]). The improvement in banking sector not only helps promote China's economic development, but also has a massive influence on the world economy, and it especially contributes to global systemic risk (see, e.g., [24–26]).

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where A_{it} is the value of quasi assets for institution i at time t, which equals the market value of equity plus the book value of debt, W_{it} is the market value of equity, and D_{it} is the book value of debt. Theoretically, leverage cycles associated with low expected asset returns [31] and default risk [32] reinforce the liquidity wedge cycle and cause contagion through portfolio and consumption effects [33]. Thus, LVG is considered as an indirect systemic risk measure in this paper. Danielsson et al. [5] also conclude that leverage ratio dominates a policy of systemic risk based on capital requirements after analyzing the performance of leading risk measurement methods.

3.1.2. SRISK

SRISK is defined as the capital shortfall a financial institution is expected to experience conditional on a systemic event, according to Brownlees and Engle [8].

$$\begin{aligned} SRISK_{it} &= E_t[CS_{it+h}|R_{mt+1:t+h} < C] \\ &= W_{it}[kLVG_{it} + (1-k)LRMES_{it} - 1], \\ LRMES_{it} &= -E_t[R_{it+1:t+h}|R_{mt+1:t+h} < C] \end{aligned} \tag{2}$$

where CS_{it} is capital shortfall of institution i on day t, $\{R_{mt+1:t+h} < C\}$ denotes the systemic event, which is a market decline below a threshold C over a time horizon h. Specifically, we set C to -10% and set h to a month. Besides, $R_{it+1:t+h}$ and $R_{mt+1:t+h}$ denote multiperiod arithmetic return from time t +1 to t +h for institution i and market, respectively. LVG_{it} is the leverage ratio we discuss above. k is the ratio for prudential capital and is set to 8%. $LRMES_{it}$ means Long Run Marginal Expected Shortfall, the expectation of the institution equity multiperiod arithmetic return of an institution conditional on the systemic event. SRISK is a function of an institution's size, leverage, and its expected equity loss given a market downturn and combines balance sheet data with market data.

3.1.3. Value at Risk (VaR)

The VaR is the maximum loss that a stock market will suffer over a defined time horizon at a given confidence level. The value at risk of institution i is defined as:

$$P(r_t^i \leq \mathrm{VaR}_{q,t}^i) = q, \tag{3}$$

where r^i is the return of institution i, VaR_q^i is the VaR of institution i at confidence level q in a given time horizon t. We set q to be 1% and t is set to be a month. In this paper, we consider VaR as an indirect measure to systemic risk because Adrian and Shin [34] believe it reflects the risk environment of the recent past and its high level will lead to the height of the credit crisis is suggestive of balance sheets that are under financial distress.

3.1.4. ΔCoVaR

Adrian and Brunnermeier [12] define $\mathrm{CoVaR}_{q,t}^{i|m}$ as the VaR of an institution i conditional on stock market m being in financial distress. In this paper, we follow Girardi and Ergün [11] to make a modification in the definition of CoVaR, which is the market m's distress is at most at its VaR, instead of being exactly at its VaR.

$$P(r_t^i \leq -\mathrm{CoVaR}_t^{i|m}(q_1, q_2)|r_t^m \leq -\mathrm{VaR}_t^m(q_2)) = q_1, \tag{4}$$

where q_1, q_2 are confidence levels of institution i and stock market m, respectively. They are both set to be 1%. This paper specifically focuses on systemic risk in banking sector thus m is considered to be the whole banking system and i is an indicator represents an institution. So ΔCoVaR can be calculated by

$$\Delta\mathrm{CoVaR}_{q,t}^{i|m}(q_1, q_2) = \mathrm{CoVaR}_{q,t}^{i|m}(q_1, q_2) - \mathrm{CoVaR}_{q,t}^{i|m}(q_1, s), \tag{5}$$

where s is the benchmark confidence level of i, which is the possibility of one standard deviation from the conditional mean. We then calculate the $\mathrm{CoVaR}_t^{i|m}(q_1, q_2)$ by the double integral as follow:

$$\int_{-\infty}^{-\mathrm{CoVaR}_t^{i|m}(q_1,q_2)} \int_{-\infty}^{-\mathrm{VaR}_t^m(q_2)} pdf_t(x, y)dxdy = q_1 q_2. \tag{6}$$

Our paper applies ADCC-EGARCH with skewed-t distribution to estimate ΔCoVaR, see Nelson [35], Engle [36], and Cappiello et al. [37].

3.1.5. Nominal systemic risk ($\beta \times$MV)

According to Nucera et al. [15], $\beta \times$MV combines an institution's beta estimate and market capitalization, which is the nominal risk of the institution's market capitalization to systemic shocks. The famous capital asset pricing model (CAPM), which can be simplify as

$$E[R_i] = R_f + \beta_{iM}(E[R_M] - R_f). \tag{7}$$

where $E[R_i]$ denotes the expectation return of institution i, R_f denotes risk-free interest rate, and the $E[R_M]-R_f$ is the market premium, which equals to the expectation return of the market minus risk-free interest rate. The β_{iM} in this equation is believed to be a method of measuring systemic risk. It represents the volatility of a security or a portfolio relative to the overall market and the degree of return on assets to market sensitivity. In this paper, CAPM-β is estimated by classic linear regression. Besides, we denote MV as market value of a financial institution, which is an important determinant of systemic importance in its own right ([38]; IOSCO, 2011).

3.1.6. Discussion

However, Danielsson et al. [29] points out there are weak theoretical basis and model risks in the systemic risk measurements (SRMs). Significant size is usually used to identify "too-big-to-fail" banks, and the leverage ratio allows small financial institutions to have a disproportionate impact on the market (IOSCO, 2011). SRISK is proposed for spillovers effects among financial institutions. VaR and ΔCoVaR can be influenced by market efficacy, since they are market-based measures. To summarize, each measurement can only concentrate on a certain aspect of systemic risk, yet they provide intuitive basis of principal component analysis.

3.2. Principal components analysis

With such weaknesses in the five systemic risk rankings, we combine these five popular systemic risk measurement rankings in our study by applying the PCA model, which can gather the main information on systemic risk and generate a reliable systemic risk ranking, using the following:

$$
\begin{aligned}
&X_{i,j,t} = 1 - \underset{N_{j,t}}{rank}(\mathrm{Y}_{i,j,t})/(\mathrm{N}_{j,t}+1),\\
&X_{i,t} = \Lambda_t f_{i,t} + \varepsilon_{i,t}, i = 1, \ldots, N, t = 1, \ldots, T.
\end{aligned}
\tag{8}
$$

where $Y_{i,j,t}$ is the ranking of institution i at time t using the jth method. T is the number of months, N denotes the number of financial institutions, and R and J denote the number of factors and systemic risk rankings, respectively.

All the data required are available and all parameters are obtained by our estimation within the model. In particular, we have

$$
\begin{aligned}
&\Lambda_t = U_t = [U_{i,t}, \ldots, U_{R,t}],\\
&\hat{f}_{i,t} = \hat{\Lambda}'_{i,t} X_{i,t},\\
&\hat{F} = (\hat{F}_{1,t}, \ldots, \hat{F}_{R,t}) = X_t \hat{\Lambda}_t,\\
&\hat{S}_t = \frac{1}{N}\sum_{i=1}^{N} X_{i,t}X'_{i,t} = \hat{\Lambda}_t \sum_t^f \hat{\Lambda}'_t + \sum_t^\varepsilon
\end{aligned}
\tag{9}
$$

where $\sum_t^f$ is the variance–covariance matrix of the common factors, $\sum_t^\varepsilon$ is the variance–covariance matrix of the error terms, and U_t collects the eigenvectors of $\hat{S}_t$ corresponding to its R largest eigenvalues $\hat{F}_t$ and with columns $\hat{F}_{r,t}$ for $r = 1, \ldots, R$.

PCA is a standard tool in multivariate variable analysis to reduce the number of dimensions, while retaining the data's information. Therefore, the main reason for using the PCA method in our manuscript is that PCA can provide complementary weights to the results of each method that measures the systemic risks in different aspects. Pukthuanthong and Roll [30] derive a new integration measure and suggest that the PCA model allows important eigenvalues accounting for different factors, which provides the most insightful information on systemic risk ranking. Allen et al. [39] define CATFIN to measure systemic risk, which suggests that PCA is suitable for gathering information on systemic risk. Unlike the other five measurements, the PCA cannot be compared with them as it already contains information of the other measurements. Therefore, the PCA can analyze the systemic risk contribution of banks and identify the top systemically risky banks, with a convincing ranking. Thus, it can directly provide systemic risk supervision, an obvious risk contribution of the banks, and prompt the banks to prevent and cope with financial crisis beforehand. In addition, important original variables that are the major contributors to the first few components can also be identified through the PCA method.

3.3. Data description

Consistent with Huang et al. [16], we consider 16 of the 24 Chinese listed banks from September 2010 to October 2016. We choose these 16 banks for two reasons. First, they have a long and stable record of earnings and are issued by large and well-established institutions that have impeccable financial credentials. Second, the eliminated banks are not listed over three years, yet it is hard to estimate parameters for lack of data. All five risk rankings are at a monthly frequency so our sample period comprises 74 months. The reason our sample period is not conclude global financial crisis is that our paper aims to investigate five systemic risk measurements in the post-crisis era to find out a stable method is not affected only by a crisis. We obtained our data from Bloomberg.

Table 1 reports the summary statistics of the Return, Leverage, and Size of 16 listed banks in China, including mean and standard deviation. We choose these three variables since they provide a general understanding of banks' condition. As we

Table 1
Data description. Summary statistics (mean and standard deviation) for the Return, Leverage, and Size of 16 listed banks in China.

Banks	Return (%)		Leverage		Size (billion ¥)	
	Mean	Std.	Mean	Std.	Mean	Std.
PAB	0.14	11.45	15.32	3.59	8.39	4.18
NBCB	0.91	9.94	16.21	3.06	3.36	1.15
SPDB	0.65	9.60	12.76	3.80	18.77	7.61
HXB	0.36	10.18	16.77	3.44	6.32	2.16
CMBC	1.15	9.75	19.25	3.34	19.36	5.87
CMB	0.73	8.87	14.35	1.60	25.86	6.70
BON	0.58	10.95	12.78	2.71	3.41	1.23
CIB	0.26	12.46	13.99	3.82	19.60	5.97
BOB	0.03	9.29	16.93	2.95	8.23	2.93
ABC	0.38	5.96	14.95	2.96	48.82	41.24
BCM	0.20	7.90	15.82	2.43	17.30	3.93
ICBC	0.24	5.20	16.50	2.92	110.52	12.13
CEB	0.49	8.51	12.88	2.15	9.35	5.98
CCB	0.45	7.95	17.02	3.93	4.60	0.68
BOC	0.22	6.41	12.82	2.83	64.29	13.25
CNCB	0.61	10.54	15.86	2.64	15.97	3.94

Note: The full name of the banks is provided in Appendix.

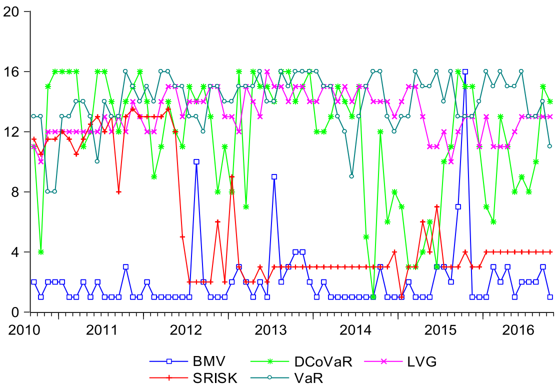

Fig. 1. Variation in five systemic risk ranks: Industrial and Commercial Bank of China (ICBC). The figure shows the time series plots of several rankings associated to ICBC over the sample period from 2010/09 to 2016/10, a total of 74 months. The raw input ranks on the vertical axis vary from $i = 1, 2, \ldots, 16$, where 1 denotes the most systemically risky bank in China. Here, LVG is short for Leverage ratio, BMV is short for $\beta \times$MV, and DCoVaR is short for ΔCoVaR.

can see, the average rates of return of all banks are positive and close to zero. In addition, the standard deviation of returns is 15% in all cases, and most banks are below 10%, which suggest low volatility in the returns in banking sector in China. We also notice that leverage in Chinese banking system is between 12 and 20, and the highest leverage ratio comes from China Construction Bank (CCB). Among 16 listed banks, Industrial and Commercial Bank of China (ICBC), Bank of China (BOC), and Agriculture Bank of China (ABC) are the biggest in size. The size standard deviations describe the change of banks' size during sample period. Since size is directly related to systemic risk, its change is significant to measure systemic risk and rankings.

4. Empirical results

4.1. Five popular systemic risk rankings

This section discusses the characters of five popular systemic risk rankings. We follow Nucera et al. [15] to carry out empirical tests in three steps. First, we give a general description showing that different rankings can give vastly different systemic risk ranks for the same institution. In addition, the cross-sectional correlation between different rankings indicate rankings based on different criteria function differently in Chinese banking system. Then, we investigate the volatility of these five input rankings by calculating standard deviation and it turns out that they are volatile in different sample periods to varying degrees. Finally, our paper provides evidence that fundamental-based systemic risk measures are more stable than price-based ones from state transition matrix.

Fig. 1 plots the systemic risk ranks of Industrial and Commercial Bank of China (ICBC) in time series using all five methodologies. ICBC is known as one of the top five banks in the world according to The Banker. It is also the biggest commercial bank in China so we choose ICBC to give a brief review the variation in five systemic risk ranks. This figure

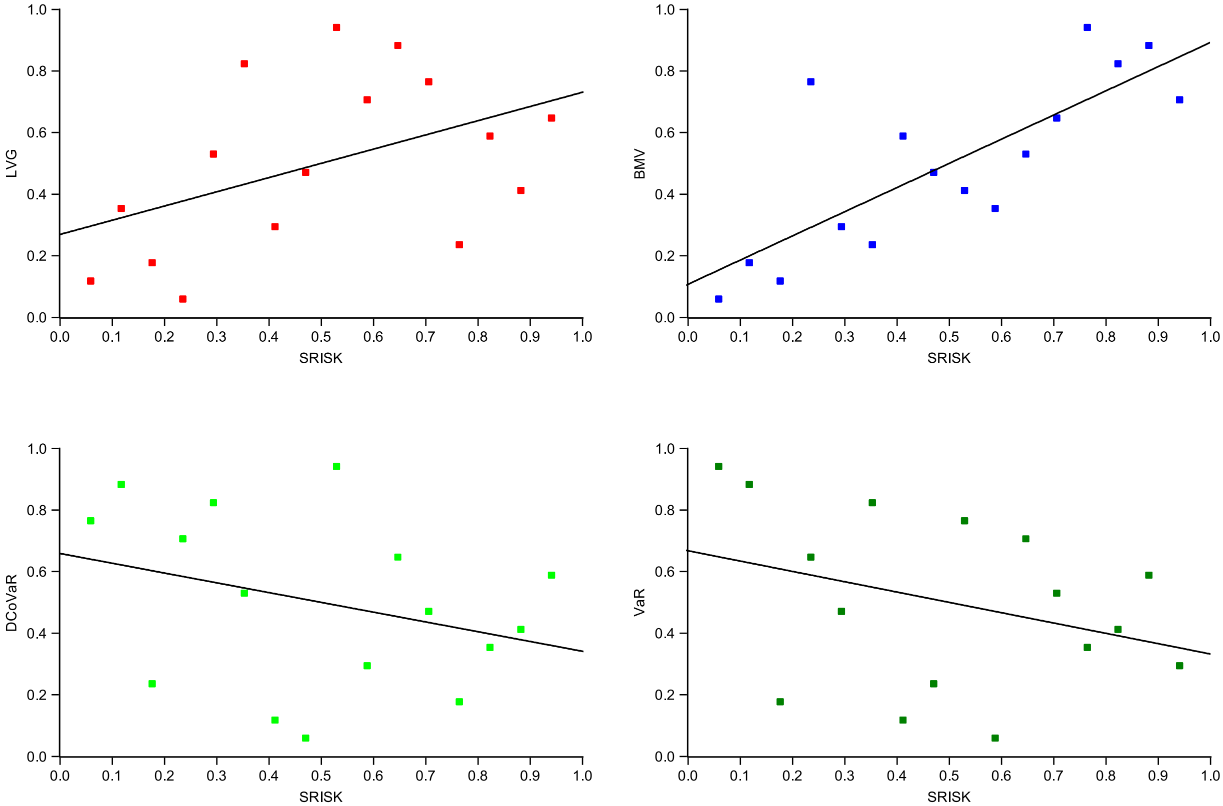

Fig. 2. SRISK ranking vs other systemic risk rankings. The figure shows the scatter plots of SRISK ranks versus other ranks in Oct 2016. Symbols refer to $i = 1, 2, \ldots, 16$ banks. Ranks (raw inputs on both vertical axis and horizontal axis) are calculated as we normalized in Section 3.2. SRISK is chosen as our benchmark because it combines balance sheet data with market data, thus this figure provides a clear relationship between fundamentals-based rankings and price-based ones.

can provide us several characters of ICBC and they are also applicable to all the banks in our sample. The first one is that, while we keep the time constant, these five popular approaches can give different ranks about the systemic importance for a specific bank. Take ICBC as an example. As we can see, ICBC is in the top three systemically important institutions according to $\beta\times$MV over 80% of our sample period. However, it is not as systemically important at the same time when systemic risk is measured in terms of LVG, or VaR. This may be a signal that in China the market value of ICBC drives its high rank in $\beta\times$MV, even though LVG or VaR on its own results in a less dominant systemic risk rank.

On the other hand, we see that none of these ranks is constant over time, yet they are volatile to varying degrees. $\beta\times$MV show three clear changes in the rankings during 2012, 2013, and 2015, meaning it is as a quite lower rank, whereas VaR appear very volatile during the Chinese Stock Market Boom period in 2014. Also, from the perspective of SRISK and ΔCoVaR in ICBC, they are never stable during the whole sample period. This is a clear evidence that they are not reliable enough as supervisory practice.

Fig. 2 shows a more specific picture where we present the cross-sectional scatter diagrams between SRISK and the other systemic risk rankings on a constant date, October 2016. We see a clear picture that the cross-sectional association between different rankings is not like in the slight. Not in line with Nucera et al. [15], we clearly find that the ranks correlation between SRISK and ΔCoVaR and VaR are negative. This remind us that these price-based rankings are not practical methods can be used in China. The result is consistent with principal component analysis in Section 4.2, which suggest the fundamentals-based rankings provide more information for the first component.

We also find, as expected, substantial correlation between SRISK and leverage as well as $\beta\times$MV. This situation can be explained as rankings which are based on different criteria function differently in Chinese banks. This scatter diagrams clearly indicate that it is symptomatic of the different rankings ordering the banks in the sample differently. This is a reference for the perfection of the global banking supervision system and for whoever intended to study systemic risk in Chinese market as well.

Table 2 reports cross-sectional linear correlations (Spearman) for seven different systemic risk rankings. We analysis this table to figure out if there exists consistency or close inner-connection between those rankings. Danielsson et al. [29] mentioned that different measures may accentuate different aspects of systemic importance or may be subject to substantial estimation uncertainty and model risk. The highest median correlation (0.79) is between SRISK and CR1. The cross-sectional

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Table 2
Correlation among systemic risk rankings. The table reports the time series medians of the cross-sectional linear (Spearman) correlations, as well as their time series inter-quartile ranges in brackets below. Fig. 2 is an example of cross-sectional correlation at a single point in time (Oct 2016). Average is an equal weighted average of all five rankings, CR1 is the first principal component.

	SRISK	$\beta\times$MV	LVG	VaR	ΔCoVaR	Average
$\beta\times$MV	0.69					
	[−0.43, 0.94]					
LVG	0.43	−0.09				
	[−0.46, 0.85]	[−0.72, 0.51]				
VaR	−0.31	−0.51	−0.02			
	[−0.80, 0.23]	[−0.90, 0.20]	[−0.41, 0.46]			
ΔCoVaR	−0.05	−0.25	0.19	0.21		
	[−0.68, 0.77]	[−0.75, 0.64]	[−0.31, 0.58]	[−0.64, 0.82]		
Average	0.73	0.29	0.66	0.24	0.46	
	[0.16, 0.95]	[−0.32, 0.77]	[0.19, 0.89]	[−0.45, 0.62]	[−0.64, 0.82]	
CR1	0.79	0.62	0.45	−0.28	0.50	0.51
	[−0.87, 0.99]	[−0.95, 0.97]	[−0.80, 0.90]	[−0.90, 0.95]	[−0.83, 0.88]	[−0.09, 0.91]

Table 3
Rank volatility. For each ranking, the table reports 100×the cross-sectional average of the time series standard deviations of the ranks. CR1 is the first principal component. We report results for the period Sep 2010–Oct 2016 (column two), and distinguish four different sub-samples (columns three to six). Row two and three show the beginning and end date of each sample period. Four Sub-sample periods are divided by the trend of shanghai composite index and we provide it in Appendix.

	2010–2016	Downtrend	Tranquil	Boom	Crash
Start	Sep 2010	Sep 2010	Jan 2013	Jun 2014	Jul 2015
End	Oct 2016	Dec 2012	May 2014	Jun 2015	Oct 2016
SRISK	16.71	13.94	11.81	7.08	6.79
$\beta\times$MV	10.38	8.59	7.42	5.37	13.55
LVG	16.73	11.38	10.94	15.33	10.63
ΔCoVaR	24.97	22.68	23.01	24.65	19.90
VaR	18.48	13.90	11.83	20.00	15.51
Average	9.27	6.70	6.55	6.69	7.76
CR1	9.11	6.24	5.88	6.43	7.23

correlation between ΔCoVaR and $\beta\times$MV (−0.25) shows these two different ranks are quite contradictory. The correlation ranges of CR1 against other rankings are almost cover from −1 to +1, and it is a great signal that the first component contains all the major information that other measurements have. As displayed in the table above, the cross-sectional correlations are in general at a large range and not in accordance over time, indicating rankings which are based on different criteria function differently in Chinese banking industry.

Table 3 presents 100 × the cross-sectional average of the time series standard deviations of our five input systemic risk rankings. The time series standard deviation is a representative of the ranking volatility and is computed over different periods, including a full-sample period and four sub-sample periods. The table lists volatilities of five kinds of approaches we have already given a detailed introduction in Section 3.1, and an "average" combined ranking that equals the unweighted average of the five.

For a full-sample period from September 2010 to October 2016, the $\beta\times$MV, SRISK, and LVG (not including Average) rankings tend to be the least volatile. The reason is the SRISK and the leverage ratio are based on the book value of assets. As for $\beta\times$MV, the increasing β as sharp falls in market value result in the relative position of $\beta\times$MV rather stable [15]. However, rankings that are based on market price data inputs are more volatile (Such as VaR and ΔCoVaR). It is worth mentioning that in the average of all rankings has the lowest instability than any other rankings. This inspires us to explore a better combined ranking that can be counted on for regulation purpose.

From another perspective, Table 3 also reports rank volatility results for our four different sub-samples in Chinese market. Our sub-sample periods are: a downtrend period (September 2010–December 2012), a period of tranquil in stock market (January 2013–May 2014), the stock market boom in China (June 2014–June 2015), and a severe crash period with its following days (July 2015–October 2016). We divide the full sample into four different sub-samples for three major reasons. First, China's economic growth is expected to target down to 7.5% in 2012, and this is the first time China has lowered its economic growth target since 2004. We set the first subsample in this period, since we believe this is a downtrend period. Second, the Shanghai-Hong Kong Stock Connect program accelerates the internationalization of capital markets. Since then, the market has shown a wave of leveraged push in the bull market, and the market capital flow has undergone a structural change. During 2014 to 2015, banks supported the stock market in China to rise by 5%. This is the second node in the timeline. Third, on June 15, 2015, the Shanghai Composite Index turned down after hitting a maximum of 5178.19. This led to the financial collapse in a domino effect. This is what we call a crash period.

In general, the rank volatility is higher during market boom and crash than that in the tranquil and downtrend periods. Furthermore, the unweighted average has less volatility than other ranking methods. This, again, proves that combining ranking is of highly possible to provide a reliable indicator.

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Table 4
State transition matrix. The table reports the state transition matrix of each ranking criteria. We divide bank rankings into three different states: Top (rank top 30%), Middle (rank between 30%–70%), and Bottom (rank the lowest 30%). Transition probabilities from one state to all the three states equal to 1.

	SRISK			**$\beta\times$MV**			**LVG**		
	Top	Middle	Bottom	Top	Middle	Bottom	Top	Middle	Bottom
Top	0.90	0.08	0.02	0.84	0.13	0.04	0.84	0.14	0.02
Middle	0.08	0.79	0.13	0.11	0.76	0.13	0.11	0.79	0.10
Bottom	0.00	0.12	0.88	0.02	0.14	0.84	0.01	0.10	0.89
	VaR			**ΔCoVaR**					
	Top	Middle	Bottom	Top	Middle	Bottom			
Top	0.73	0.23	0.04	0.59	0.30	0.11			
Middle	0.19	0.64	0.17	0.24	0.51	0.25			
Bottom	0.02	0.19	0.79	0.11	0.27	0.62			
	Average			**CR1**					
	Top	Middle	Bottom	Top	Middle	Bottom			
Top	0.74	0.23	0.03	0.86	0.12	0.02			
Middle	0.17	0.63	0.21	0.09	0.79	0.12			
Bottom	0.02	0.29	0.70	0.00	0.14	0.86			

Table 4 studies state transition matrix of seven rankings. Our paper makes improvement compared with Nucera et al. [15]. In this table, the Chinese banking system is divided into three parts according to available ranking criteria. The three states are Top (rank top 30%), Middle (rank between 30%–70%), and Bottom (rank the lowest 30%). We find an interesting feature. It is very clear that all fundamental-based rankings including LVG, $\beta\times$MV, and SRISK have concentrated state transition probability in diagonal line, while price-based rankings are more separated, especially ΔCoVaR. The higher the number in diagonal line are, the more stable is of that ranking. Also, among the five input rankings, SRISK is the most stable, followed by LVG, $\beta\times$MV, VaR, and ΔCoVaR. An unweighted combination better than VaR and ΔCoVaR, but not as good as SRISK, LVG, and $\beta\times$MV.

Most importantly, the CR1 also has concentrated state transition probability in diagonal line, which indicates persistent ranking in the Top over time. So it is reasonable to believe the principal component analysis is trustworthy. In fact, imposing banking supervision might care more about the turnover at the Top, which we can also say the Systemically Important Financial Institutions (SIFIs). The less turnover means a higher transition probability between top banks, as it shows in our state transition matrix. It is also a good evidence that our PCA combined ranking is reliable since it has already ruled out model risk and estimation uncertainty.

4.2. Principal components analysis in systemic risk rankings

In this part, our paper is going to discuss the application of principal components analysis in the systemic risk rankings. According to the distribution of five sum-normalized eigenvalues, the first eigenvalue explains approximately 50% of the information. Furthermore, more than 70% of the total variance can be explained by the first two eigenvalues. Even more important, we find that among five loadings of the first component, $\beta\times$MV and LVG are the highest, which means our PCA combined ranking in mainly based on fundamentals instead of market price data.

Fig. 3 presents the distribution of five ordered and sum-normalized eigenvalues which are based on principal components analysis model. From the first subgraph in Fig. 3, we can see that the first eigenvalue explains approximately 50% of the total variation. And as time goes by, there is a clear variation in how much of variance can be explained by the first principal component and it ranges from 30% to 70%. This is because that the information is not always concentrated at every stage of time. Furthermore, more than 70% of the total variance can be explained by the first two eigenvalues. In other words, the first and the second component are powerful enough to represent existing five ranking methods as an indicator we can count on.

Fig. 4 shows the time series of five different sum-normalized eigenvalues. This figure contains a few features. First and foremost, the information content carried by different components varies from time to time. When Chinese market suffers an unpredictable boom or crash, the first component will be a suitable indicator for supervisory purpose for the reason that its sum-normalized eigenvalue explains more of the total variation than usual. Second, there is a different trend between the first two eigenvalues. Specifically, the first component peaks at a value of 35% in the middle of 2012 when Chinese stock market was experiencing a Downtrend period. Meanwhile, the second eigenvalue shows completely different trend from the first eigenvalue. This may be caused by our five different input rankings whose various focuses on systemic risk. So it is unwise for us to only pay attention to one specific systemic risk measurement in case of changing and volatile market.

Panel A in Fig. 5 display the distribution of factor loadings for the first principal component. Our five systemic risk rankings do not share similar distributions of the loadings. There is no doubt that the time series dispersion of the loading on $\beta\times$MV and SRISK are the highest, while VaR and ΔCoVaR share similar distribution of factor loadings. That is, rankings measured by $\beta\times$MV and SRISK are most informative for the first principal component. It is reasonable to conclude that fundamentals-based rankings make more contributions to the first component.

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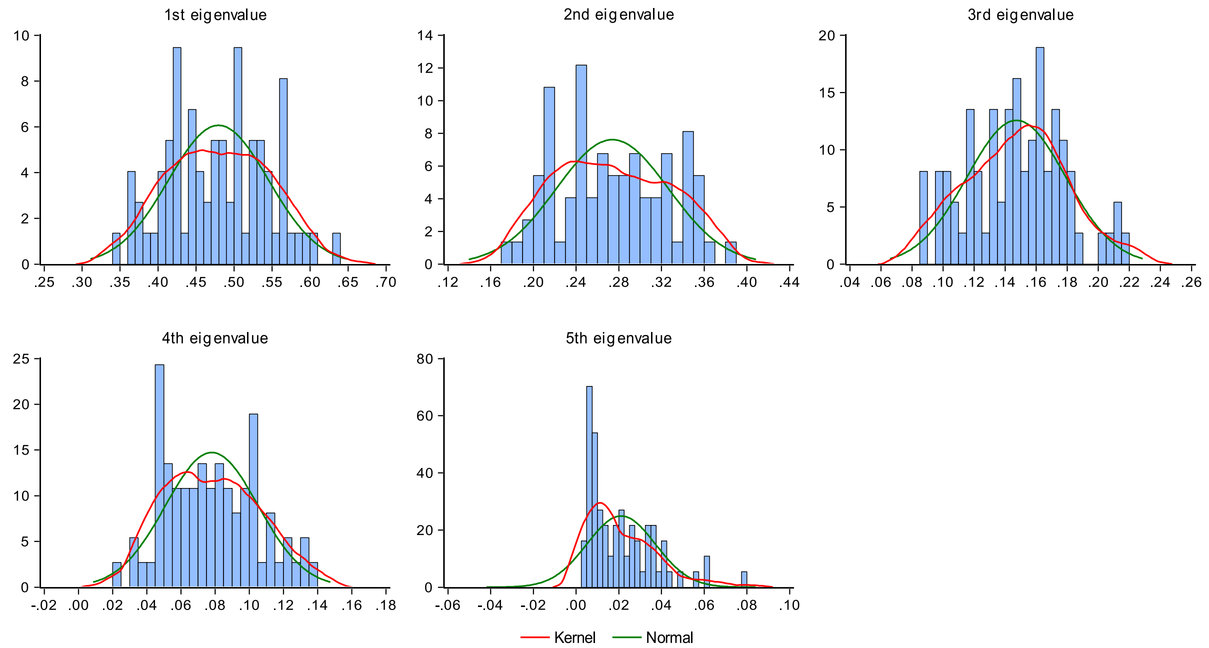


Fig. 3. Distribution of five ordered and sum-normalized eigenvalues. According to principal components model in Section 3.2, given five input rankings, there will be five eigenvalues. Each principal components analysis is performed over the cross-section of banks, with time t held fixed, $t = 1, 2, \ldots, 74$. The figure shows the distribution histograms of the five ordered and sum-normalized eigenvalues. The first subgraph shows evidence that the first eigenvalue can explain approximately 50% of the total variation over time.

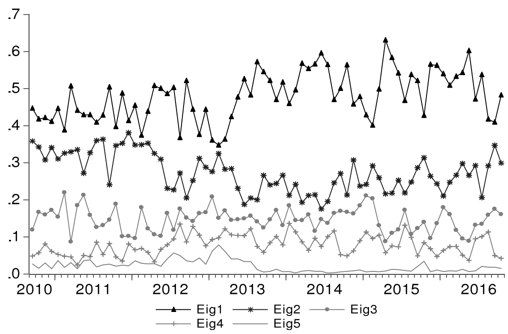


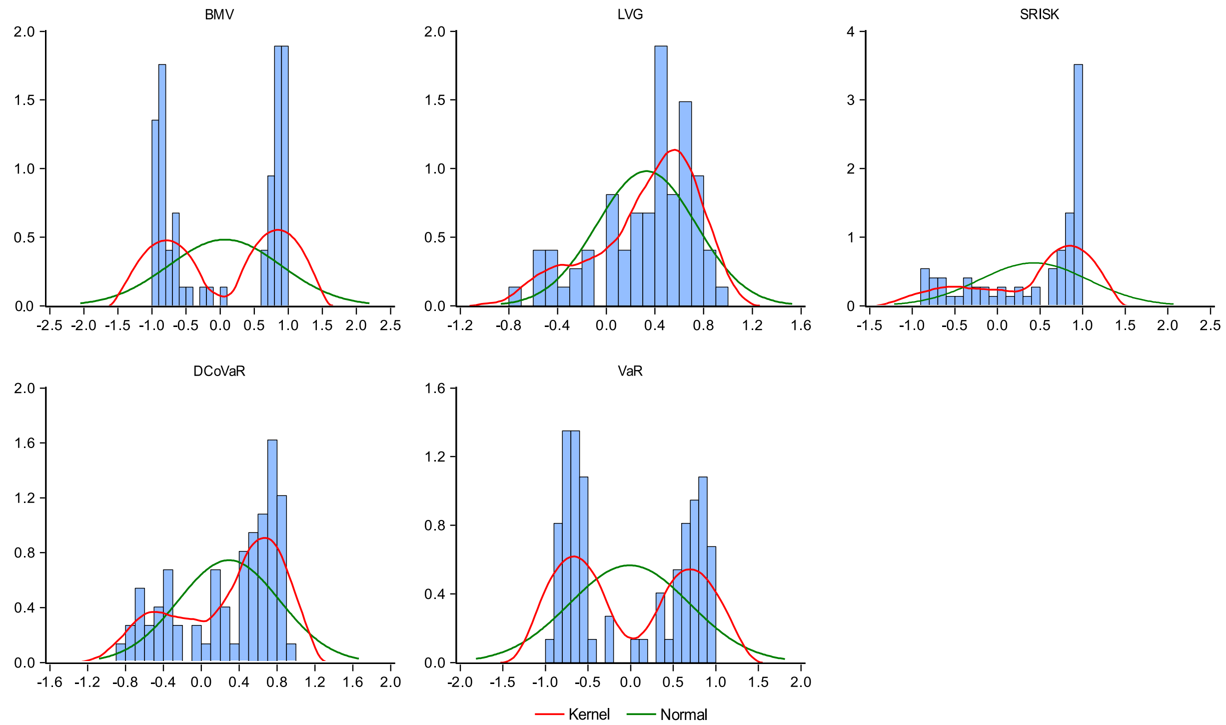
Fig. 4. Time series plot of ordered and sum-normalized eigenvalues. The figure shows the time series plots of five ordered and sum-normalized eigenvalues from the most important in terms of explained variance (top) to the least important (bottom). The sample is from September 2010 to October 2016. In this figure, Eig1 is short for the first sum-normalized eigenvalue and Eig2, Eig3, Eig4, and Eig5 are in like manner.

As a contrast, Panel B in Fig. 5 display the distribution of factor loadings for the second principal component. Here we can see that same with the first one, SRISK and $\beta\times$MV contributes more than other rankings to the composition of the second component. This strengthen our conclusion that fundamentals tell more than market data in Chinese banking system.

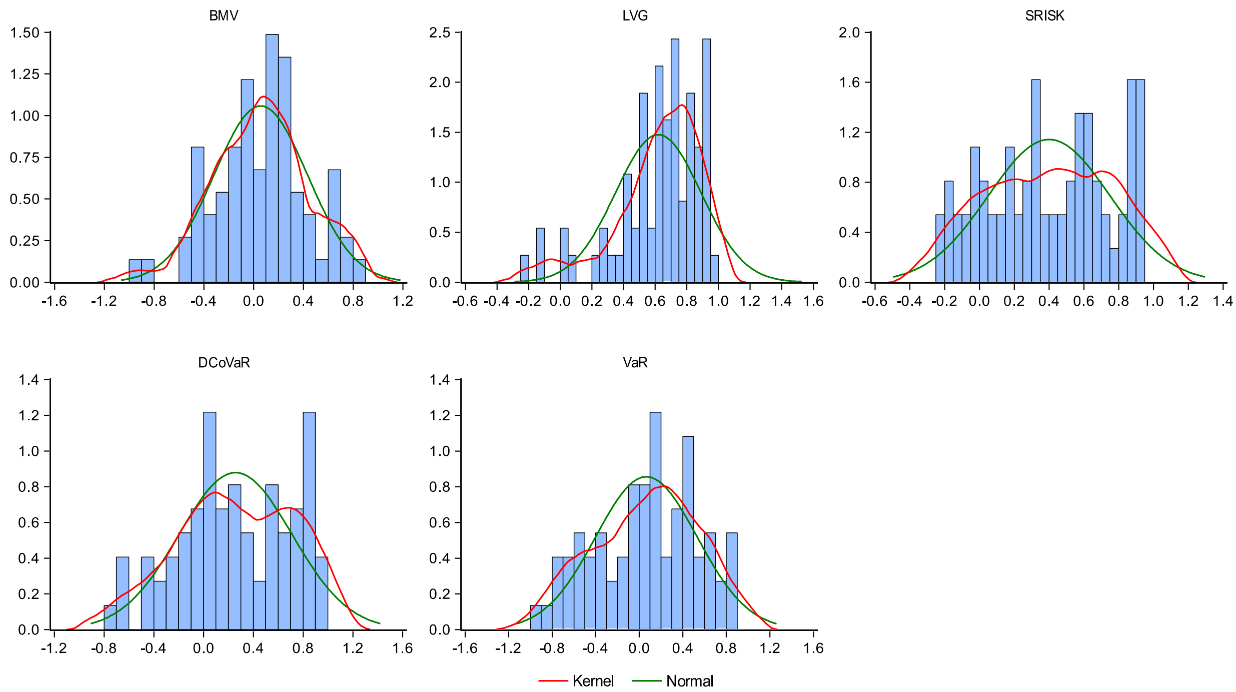
5. Conclusions

In this paper we investigate the systemic risk in Chinese banking industry during post-crisis era from 2010 to 2016 by employing five popular measurements (SRISK, Leverage, ΔCoVaR, VaR and CAPM-$\beta\times$MV). We also apply principal components analysis to combine the five systemic risk rankings in order to reduce estimation uncertainty and model risks, so we can provide a stable ranking for policy purposes and targeted banking supervision.

After calculating five kinds of standardized monthly rankings for 16 listed banks and discussing the time-series evolution and the cross-sectional of each criterion, our empirical results show plenty of evidence that all these methods are inherently volatile in rankings. Furthermore, according to the rank volatility and state transition matrix, price-based rankings (such as VaR and ΔCoVaR) are not practical methods that can be used in China. We attribute the high volatile of the measures to low



Panel A Loadings for factor1



Panel B Loadings for factor2

Fig. 5. Factor loadings for the first and second component. The distribution of loading parameters associated with the first component (top five panels) and second component (bottom five panels). For each figure, the rankings from top left to bottom right are: $\beta \times$MV, LVG, SRISK, ΔCoVaR, and VaR.

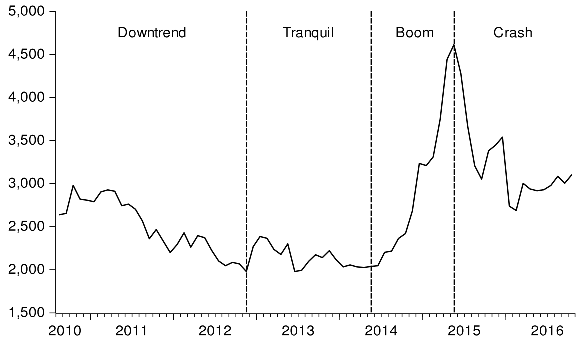


Fig. 6. Trend of shanghai composite index. This figure shows division criteria of four sub-samples. The solid line is the trend of Shanghai Composite Index, and dash lines provide four sub-sample periods. They are: a downtrend period (September 2010–December 2012), a period of tranquil in stock market (January 2013–May 2014), the stock market boom in China (June 2014–June 2015), and a severe crash period with its following days (July 2015–October 2016).

Table 5
Information (Stock code, Acronyms, and Full name) on 16 listed banks in China.

Code	Acronyms	Full name
000001	PAB	Ping An Bank
002142	NBCB	Bank of Ningbo
600000	SPDB	Shanghai Pudong Development Bank
600015	HXB	Hua Xia Bank
600016	CMBC	China Minsheng Bank Corp
600036	CMB	China Merchants Bank
601009	BON	Bank of Nanjing
601166	CIB	China Industrial Bank
601169	BOB	Bank of Beijing
601288	ABC	Agriculture Bank of China
601328	BCM	Bank of Communications
601398	ICBC	Industrial and Commercial Bank of China
601818	CEB	China Everbright Bank
601939	CCB	China Construction Bank
601988	BOC	Bank of China
601998	CNCB	China Citic Bank

estimating efficiency and measurement error of the individual indicator. Indicators that are at least partially based on book values (such as LVG and SRISK) are relatively better methods.

In addition, our combined ranking based on the PCA methodology provides a stable ranking in a unified framework, which is vitally valuable for supervision purposes. We clearly find that this PCA combined ranking is substantially less volatile over time than most rankings considered in isolation through the transition matrix. From the loadings of the first and second components, where SRISK and $\beta \times$MV contribute more, we conclude that fundamentals-based factors are the most important contributors to systemic risk in comparison to VaR and ΔCoVaR.

As for future research, the analysis could be extended to forthcoming approaches that be used to quantify systemic risk. It is also meaningful to compare different measures of systemic risk in as many countries as possible. This will make it possible to explain similarities and differences via panel models. On the other hand, the systemic risk accompanied by the financial innovation is also worth being studied, such as the great success of catering investors' preference in Hong Kong market [40].

Appendix

See Fig. 6 and Table 5.

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