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Article

Non-Traditional Systemic Risk Contagion within the Chinese Banking Industry

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Abstract: Systemic risk contagion is a key issue in the banking sector in maintaining financial system stability. This study is among the first few to use three different distance-to-risk measures to empirically assess the domestic interbank linkages and systemic contagion risk of the Chinese banking industry, by using bivariate dynamic conditional correlation GARCH model on data collected from eight prominent Chinese banks for the period 2006–2018. The results show a relatively high correlation among almost all the banks, suggesting an interconnectedness among the banks. We found evidence that the banking system is exposed to significant domestic contagion risks arising from systemic defaults. Given that Chinese markets deliver weak signals of forthcoming stress in banking sectors, new policy intervention is crucial to resolve the hidden stress in the system. The results have important policy implications and will provide scholars and policymakers further insight into the risk contagion originating from interbank networks.

Keywords: contagion; DCC-GARCH model; distance to capital; distance to default; distance to insolvency; Chinese banks

1. Introduction

Since its path-breaking initiatives of reforms launched over four decades ago, China's economic development has been miraculous. According to the World Bank, China's GDP grew from USD 149.5 billion in 1978 to USD 14.3 trillion by 2019, with real GDP growth averaging nearly 10% a year despite the recent slowdown. The GDP value of China accounts for 11.8% of the world economy. Since 2010, China has surpassed Japan to become the world's second-largest economy by nominal GDP, and overtaken the United States as the world's largest economy in terms of purchasing power parity (PPP) since 2014. Equally remarkable has been the incredible expansion of China's banking system, accounting for 11.7% of the top 1000 banks worldwide [1]. The Chinese banking system is critical to the functioning of the Chinese economy and plays a pivotal role in monitoring the practices of state-owned enterprises to ensure that these enterprises comply with sound commercial principles. Hence, maintaining the stability and soundness of the banking system hinges on the regular and timely assessment and measurement of bank risk. Its importance is also highlighted by the global financial crisis in 2008 and subsequent policy measures to reform global banking regulations in response to the perceived lessons of this crisis [2]. In its 13th five-year plan (2016–2020), China has shifted its focus away from unfettered growth rates towards initiatives to improve the quality of China's economic growth, particularly in the financial sector [3]. In 2019, the economic growth of China was projected to be 6.2% due to a strong and stable traditional financial sector that could only be multiplied by the new 'One Belt One Road' initiative [4,5]. This tremendous current and future growth in the Chinese financial and banking sector requires a better understanding of their banking sector's systemic risk from a local and global standpoint [6,7] given the systemic risk spillover between China and other countries [8], especially that the growing Chinese economy cannot be sustained with fragile and backward banking infrastructure.

Recent authors in the field have heavily supported this view through their scholarly works [9,10], pointing out that the contagion risk of the Chinese banking sector can adversely affect the rest of the world [11]. They have used traditional methodologies including COVAR [12], Marginal expected shortfall [13], and Granger causality networks [14], where they mostly looked into tail risk network [15], conventional GARCH contagion [16], or network hypothesis [17]. Given the nature of these models, they all investigate the Chinese financial sector from a conventional point of view and provide consistent results throughout. These characteristics of the conventional results have been well documented as they failed to predict the last Global Financial Crisis (GFC) and thus financial macroprudential authorities including International Monetary Fund (IMF) and Organization for Economic Co-operation and Development (OECD) have been using different distance to risk (DR)-based models to better understand the spillover effect within the post-GFC banking sector [18,19]. However, there have been no studies that have incorporated these distances to risk measures into Chinese banks to investigate the spillover effects.

In this paper, we intend to fill this gap by using three different distance-to-risk measures (Distance to default (DD), Distance to insolvency (DI), and Distance to capital (DC)) to empirically assess the domestic interbank linkages and systemic contagion in China, following the footsteps of [8,20]. We believe these measurements complement each other and can validate each other's findings as used by other authors in the field similarly. Next, we employ the bivariate DCC-GARCH model to investigate the systemic risk spillovers between the eight prominent Chinese banks (see Table 1), including Agricultural Bank of China (ABC), Bank of China (BOC), China Construction Bank (CCB), China Merchants Bank (CMB), China Minsheng Banking Corp, Ltd. (CMS), Hua Xia Bank Co, Ltd. (HUX), Industrial and Commercial Bank of China (ICC), and Shanghai Pudong Development Bank (SPB). We have chosen these eight largest banks based on their size and share market capitalization within China per following the footsteps of previous authors. These banks control more than half of the reported net assets in China and a significant portion of assets in the world banking sector with remarkably healthy risk indicators (Beta, Sharp, and Stock Reports Risk Score). The results show relatively high quasi-correlations among almost all the banks (except ABC), suggesting a marked interconnectedness among these banks. Our sample period covers the daily data from 2006 to 2018 which includes waves of financial turmoil in the global market including the Global Financial Crisis (GFC). As the DD, DI, and DC are simulated using yearly interpolation, these fluctuations can be observed every year as per following the previous authors in our field. We do not focus on the individual event impact as we are focused on the overall spillover from bank to bank. We find evidence that the internal banking system is exposed to extreme contagion risks from the domestic interbank defaults. Given that Chinese markets deliver weak signals of forthcoming stress in banking sectors, new policy intervention is crucial to resolve the hidden stress in the system. The results have important policy implications and will provide scholars and policymakers further insight into the risk contagion originating from interbank networks.

The rest of the paper is organized as follows. Section 2 presents the data and sample used in this study, followed by the model specifications in Section 3. Section 4 discusses and analyzes the results of the dynamic conditional correlation generalized autoregressive conditional heteroscedasticity (DCC-GARCH) model incorporated to measure the contagion among the Chinese banks. Section 5 concludes by providing recommendations.

Table 1. Key financial information for sample Chinese banks.

S. No.	Banks	Short Name	Net Asset Value—Actual	Beta Up 5-Yr Mthly	Sharpe Ratio 5-Yr Mthly	Stock Reports + Risk Score by Data Stream
1.	Agricultural Bank of China Ltd.	ABC	249,551,048,992.73	0.87	0.04	10
2.	Bank of China Ltd.	BOC	257,092,174,275.84	0.86	0.02	10
3.	China Construction Bank Corp.	CCB	296,094,971,900.93	1.02	0.12	10
4.	China Merchants Bank Co, Ltd.	CMB	80,063,183,940.38	0.99	0.30	9
5.	China Minsheng Banking Corp, Ltd.	CMS	64,218,282,053.19	1.18	−0.01	10
6.	Hua Xia Bank Co, Ltd.	HUX	32,312,167,973.69	1.22	0.03	10
7.	Industrial and Commercial Bank of China Ltd.	ICC	348,003,591,516.90	0.62	0.08	10
8.	Shanghai Pudong Development Bank Co, Ltd.	SGP	69,625,080,048.90	0.89	0.10	10

Note: This table provides basic financial and identifying information for the sample banks.

2. Data and Sample

2.1. Distance to Default

The DD measure is a market-based measurement approach of default risk derived from the Merton [21] model. Following the model, a larger DD value that results in a lower default risk thus is a better indicator for the financial institutions. The Merton model has been modified and summarized in subsequent empirical research to condense a wider range of financial activities. It measures both liquidity risk and solvency risk at an entity level [22]. This has been an important advantage of this model above others. Thus, we have seen regulators having a keen interest in implementing the outcome from the model [23]. However, as the model uses significant theoretical simulations to generate the risk measures, the model can sometimes over depend on the interpretation of the theory rather than reality. Based on the Merton [24] model, the daily DD at time *t* can be calculated as follows:

$$\text{DD}_t = \frac{\log\left(\frac{A_t}{L_t}\right) + \left(r_f - 0.5\sigma_A^2\right)(T-t)}{\sigma_A \cdot \sqrt{T-t}} \tag{1}$$

where the values of A_t and L_t are the asset and liability values at time *t*, respectively, with risk-free rate noted as R_f. The equation also uses volatility of asset value σ_A. We followed [25] to compute asset, liability, risk-free rate, and asset volatility. Previous researchers in the contagion research field have also preferred this procedure [18,19]. This procedure gives us a sample of 3130 daily observations for our period. We can calculate the daily return of these values using Equation (2) following the footsteps of the previous researchers in our field studying the contagion effect inside the Chinese financial sector [26,27], thus effectively ensuring the data normality and stationarity as discussed later. In this paper, we refer to the DD return values as DD values.

$$\Delta DD_t = \frac{DD_t - DD_{t-1}}{|DD_{t-1}|} \tag{2}$$

The descriptive statistics of these values are given in Table 2 with a mean of approximately between −0.01 and 0.1. It can be seen, the DD value for all the sample banks shows significant similarity in the descriptive statistics including the stationarity test for time series analysis using Dickey-Fuller *p*-value. We can deduce that the sample is acceptable for time series analysis. A timeline of these DD return values is shown in Figure 1. In Figure 1, we can observe significant fluctuations at the beginning of 2008 for most banks

except ABC and SGP. Throughout the data, SGP has shown significant stability compared to others.

Table 2. Descriptive statistics for DD return values.

	ABC	BOC	CCB	CMB	CMS	HUX	ICC	SGP
Mean	−0.01	−0.01	−0.01	0.01	0.01	0.01	−0.01	0.01
Standard Error	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Dickey-Fuller *p*-Value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Standard Deviation	0.02	0.02	0.03	0.03	0.03	0.03	0.02	0.17
Sample Variance	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.03
Kurtosis	29.53	9.64	22.30	6.52	8.38	21.50	9.55	730.30
Skewness	−0.89	−0.46	0.94	0.25	0.63	−0.17	−0.44	−2.85
Minimum	−0.21	−0.16	−0.17	−0.15	−0.15	−0.37	−0.16	−5.34
Maximum	0.14	0.13	0.32	0.19	0.27	0.33	0.12	5.35
Count	3129.00	3129.00	3129.00	3129.00	3129.00	3129.00	3129.00	3129.00

Note: This table provides basic descriptive statistics for the sample banks' daily DD.
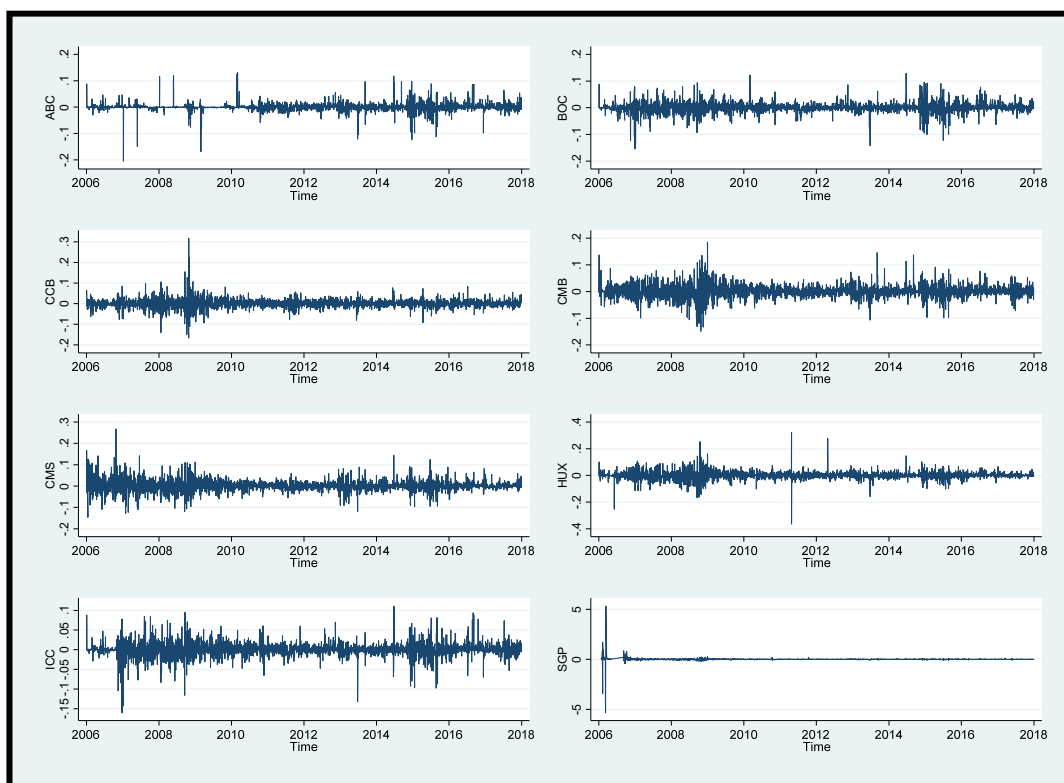

Figure 1. Distance to default for the sample Chinese banks in the period 2006–2018. Source: This figure visualizes the daily distance to default statistics for our sample banks for 2006–2018. Authors' calculation.

2.2. Distance to Insolvency

Volatility is a variable that is extensively used for measuring default risk. According to the Merton [24] model, an entity will be in default if the asset value falls below a default threshold level. Consequently, the proximity of an entity to the default threshold level is a function of the anticipated difference between values of assets and volatility as well as debt commitments. Higher expected volatility for a given capital structure and asset value suggests a greater probability regarding the failure of future asset values to meet debt commitments [28]. The extended version of Merton's model incorporates decisions on

investments, while not considering long-term borrowing. In contrast, the Leland model [29] comprises long-term strategic bankruptcy and debt financing. From here based on the structural models of credit risk proposed by [24,29,30] proposed a robust and intuitive approach for obtaining the financial soundness of individual entities by using data on equity volatility, termed distance to insolvency (DI). DI is defined as the ratio of a measure of the percent difference between the asset value of an entity and liabilities at time *t* (known as leverage) to annualized percent standard deviation of innovations concerning the asset value of an entity at time *t* (known as asset volatility). According to [30], DI recapitulates the distortions to incentives of equity owners that reasonably occur when the entity gets financially distressed. As the DI computation requires only equity volatility data, it can be computed for a wide-range set of cross-sectional and temporal data compared to other measuring approaches. DI as a measure still inherits the limitations of DD but as an extension, it supersedes DD's contribution in risk management. Similarly, a larger DI value results in a lower default risk and is thus a better indicator for financial institutions. The DI at time *t* can be defined as:

$$DI = \frac{\left(\frac{A_t - L_t}{A_t}\right)}{\sigma_A} \tag{3}$$

where A_t and L_t are the asset and liability at time *t*, respectively, and σ_A is the asset volatility. Although in a default scenario, the L_t of an entity will be over the current value of A_t, $A_t \geq L_t$ is true for perfect conditions. Thus, firm leverage can be defined as the percentage difference between A_t and L_t. Following the procedure of the previous section, we can calculate the daily return on these values using Equation (4). In this paper, we refer to the DI return values as DI values. These DI values are shown in Table 3, followed by Figure 2 with the timeline of the sample DIs. This procedure gives us a sample of 3129 daily observations with properties similar to DD, including stationarity. Figure 2 illustrates that DIs are significantly less volatile than DDs. This phenomenon was most likely caused by ongoing balance sheet stress rising from poor asset quality and increased provisions required by the regulators [31,32]. Mismatches in maturity have resulted in the disclosure of interest rate risk and liquidity.

$$\Delta DI_t = \frac{DI_t - DI_{t-1}}{|DI_{t-1}|} \tag{4}$$

Table 3. Descriptive statistics for DI return values.

	ABC	BOC	CCB	CMB	CMS	HUX	ICC	SGP
Mean	−0.01	−0.01	−0.01	0.01	0.01	−0.01	−0.01	0.01
Standard Error	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Dickey-Fuller *p*-Value	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01
Standard Deviation	0.04	0.11	0.03	0.04	0.07	0.10	0.04	0.13
Sample Variance	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.02
Kurtosis	21.40	129.12	39.52	19.67	208.47	251.10	10.89	408.52
Skewness	−0.46	−0.71	1.61	0.26	−1.96	−7.15	−0.40	3.33
Minimum	−0.40	−1.66	−0.29	−0.49	−1.79	−2.73	−0.32	−2.95
Maximum	0.32	2.02	0.50	0.41	1.41	1.39	0.27	3.58
Count	3129.00	3129.00	3129.00	3129.00	3129.00	3129.00	3129.00	3129.00

Note: This table provides basic descriptive statistics for the sample banks' daily DI.
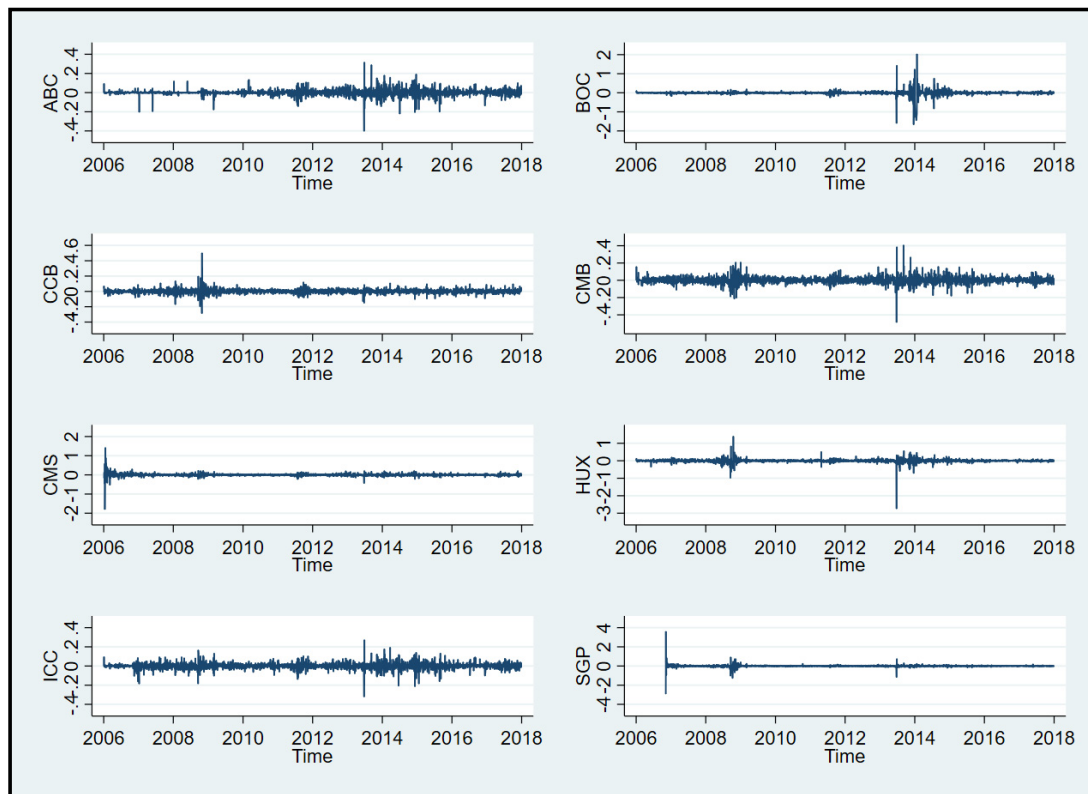
Figure 2. Distance to insolvency for the sample Chinese banks in the period 2006–2018. Source: This figure visualizes the daily distance to insolvency statistics for our sample banks for 2006–2018. Authors' calculations.

2.3. Distance to Capital

The DD has acceptance among the market-based measures due to its predictive ability to segregate rating downgrades for banks [33,34]. However, the DD concept acts as an absolute default risk measuring approach when applied to banks, which has some limitations [19]. First, the risk inherent in a bank's leverage varies substantially compared to a non-financial entity, as the former is more leveraged for an assigned level of credit risk. Second, the DD measure considers the total equity capital of a bank as a buffer, though bank regulators typically take necessary actions before losing its total equity capital [35,36]. For instance, it is recommended by the BASEL Committee on Banking Supervision (BASEL) that banks should possess excess capital over a regulatory minimum because of risk factors [37]. The distance-to-capital (DC) measure is an alternative to the DD measure originated from the structural model of corporate debt proposed by [24,38]. The DC measure considers a level of default point (i.e., a dissimilar distance measure of risk). It considers capital thresholds (as outlined by the Prompt Corrective Action [PCA] framework) that permit early intervention by bank regulators [39] rather than considering the face value of a bank's liabilities (L) as the pertinent barrier. Similar to DD, it also uses theory to simulate the risk prediction, and a larger DC value results in a lower risk. It can be stated as Equation (5) below, following [19] where CAR = capital adequacy ratio at a given time t. Previous researchers in our field have also followed the same procedure [40]:

$$DC_t = \frac{ln\left(\frac{A_t}{\frac{1}{1-CAR_t}L}\right) + (\mu - 0.5\sigma_A^2)T}{\sigma_A\sqrt{T}} \quad (5)$$

and then,

$$\Delta DC_t = \frac{DC_t - DC_{t-1}}{|DC_{t-1}|} \quad (6)$$

Following the procedure of the previous sections, we can calculate the daily return on these values using Equation (6). In this paper, we refer to the DC return values as DC values. These DC values are shown in Table 4 and presented in Figure 3. This procedure gives us a sample of 3129 daily observations with properties similar to DD including stationarity where we can observe the same mean, standard error, and Dickey-Fuller *p*-value of most of the cases. Figure 3 illustrates that DCs are significantly less volatile than DDs and DIs. Most of the curves in this figure are picked at the same time as DC is risk-adjusted using BASEL requirements; such change in the value is similar to all the sample banks as per regulatory shocks.

Table 4. Descriptive statistics for DC return values.

	ABC	BOC	CCB	CMB	CMS	HUX	ICC	SGP
Mean	−0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Standard Error	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Dickey-Fuller *p*-Value	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	−0.01	0.01
Standard Deviation	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Sample Variance	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Kurtosis	367.97	351.15	247.76	253.10	218.59	257.42	392.18	199.94
Skewness	−6.59	−7.68	−2.00	−6.55	−5.65	−6.64	−7.40	−3.86
Minimum	−0.82	−0.82	−0.59	−0.69	−0.58	−0.74	−0.88	−0.63
Maximum	0.57	0.54	0.53	0.44	0.44	0.42	0.54	0.50
Count	3129.00	3129.00	3129.00	3129.00	3129.00	3129.00	3129.00	3129.00

Note: This table provides basic descriptive statistics for the sample banks' daily DC.
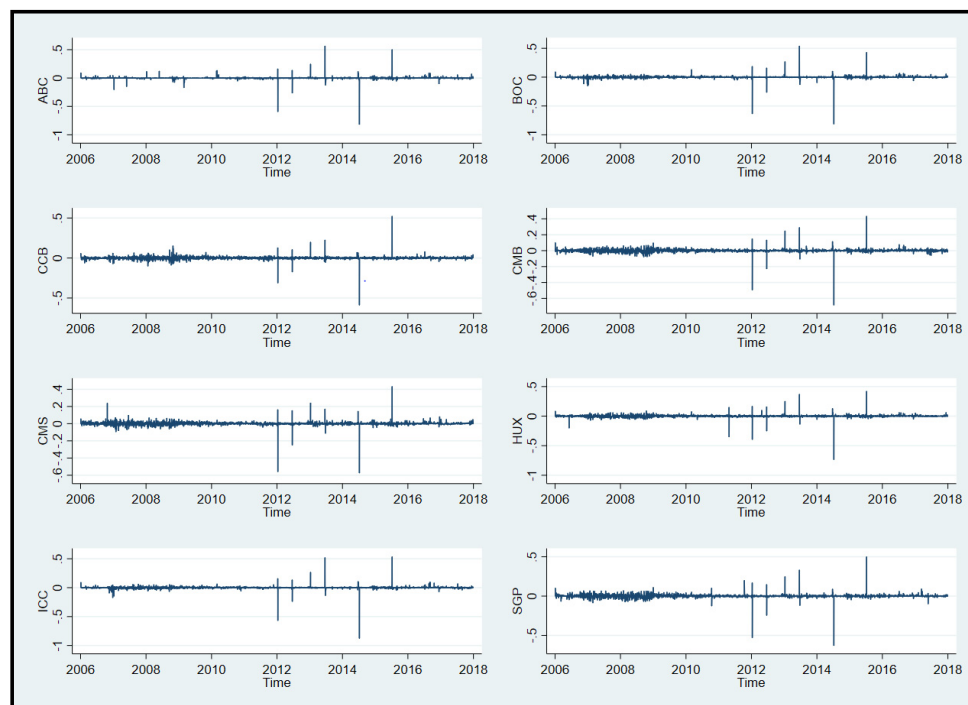

Figure 3. Distance to capital for the sample Chinese banks in the period 2006–2018. Source: This figure visualizes the daily distance to capital statistics for our sample banks for 2006–2018. Authors' calculations.

3. Methodology

Model Specifications

We employ the DCC-GARCH model, proposed by [41,42], to examine the contagion risks among Chinese banks. The model calculates the correlation coefficients of the standardized residuals and continually regulates the correlation for time-varying volatility, and allows simultaneous modeling of the variances and conditional correlations of several series. Despite the limits of DCC, such as no regularity conditions and asymptotic properties of consistency with asymptotic normality [43–45], it remains a popular representation of dynamic conditional correlations because of its dynamic structure of the correlation [46] and its inherent ability to handle a large set of computational data [47]. Furthermore, DCC-GARCH can provide a superior measurement for the correlation that accounts for heteroskedasticity straightforwardly. The bivariate DCC-GARCH model is derived as follows:

$$\varepsilon_{i,t} = z_{i,t}\sqrt{h_{i,t}} \tag{7}$$

$$h_{i,t} = \omega_{i0} + \sum \alpha_{ij}\epsilon_{j,t-1} + \sum \beta_{ij}h_{j,t-1}, \ for \ i,j = 1,2 \tag{8}$$

$$R_{i,t} = \mu_i + \lambda_i R_{t-1} + \sum_{j=1}^{n} \rho_i R_{i,t-j} + e_{i,t} \tag{9}$$

where $z_{i,t}$ = standardized residual, $R_{i,t}$ = mean, and $h_{i,j}$ = conditional variance. The conditional variance-covariance matrix can be specified as:

$$H_t = D_t \ P_t \ D_t \tag{10}$$

where H_t = 2 × 2 conditional covariance matrix, P_t = conditional correlation matrix, and D_t = diagonal matrix with time-varying standard deviations.

$$D_t = diag\left(\sqrt{h_{11}}, \sqrt{h_{22}}\right) \tag{11}$$

and

$$P_t = diag\left(Q_t^{-1/2}\right) Q_t diag\left((Q_t^{-1/2})\right) \tag{12}$$

where Q_t = 2 × 2 symmetric positive definite matrix and $Q_t = (q_t{}^{ij})$ and is defined as in Equation (13).

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 z_{t-1}z'_{t-1} + \theta_2 Q_{t-1} \tag{13}$$

where $\overline{Q}$ = 2 × 2 matrix of the unconditional correlation of standardized residual. θ_1 and θ_2 = non-negative scalars and it is presumed that $\theta_1 + \theta_2 < 1$. The correlation estimates are derived using Equation (14).

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t}q_{j,j,t}}} \tag{14}$$

where $\rho_{i,j,t}$ = dynamic conditional correlation between assets. The diagonal bivariate GARCH model considers that $\rho_{i,j,t} = 0$ for all i and j. In contrast, the constant conditional correlation assumes $P_{ij} = \rho_{ij}$ and $P_t = P$.

4. Results

4.1. Distance-to-Default Contagion

Table 5 reports the estimation results based on the bivariate DCC-GARCH (1,1) model for the period 2006–2018 using the DD data. Panel A of Table 5 reports the coefficients of the mean equation, followed by the variance equation in Panel B and the correlation equation in Panel C. The correlation results show that all the estimates are positive and significant mostly at the one percent level. In addition, the DCC results for the variance equation are quite significant for each pair in our sample. Overall, all the coefficients are significant and positive even at the one percent level, except the HUX pairs. The strongest correlation

exists between ABC and BOC (0.92), whereas HUX and ABC are the least correlated pair. Overall, the DCC results in Table 5 for DD show highly significant and positive correlations between the Chinese banks.

Table 5. Estimation results of distance to default from the bivariate DCC-GARCH model.

	ABC	BOC	CCB	CMB	CMS	HUX	ICC	SGP
Panel A: Mean Equation								
ABC								
BOC	−0.01							
CCB	0.01	0.01 *						
CMB	0.01 *	0.01 **	0.01 ***					
CMS	0.01 **	0.01 **	0.01***	0.01 ***				
HUX	0.01	0.01 **	0.01 **	0.01 ***	0.01*			
ICC	−0.01 ***	0.01 **	0.01 ***	0.01 ***	0.01 ***	0.01 ***		
SGP	0.01	0.01	0.01 ***	0.01 *	0.01	0.01 **	0.01 **	
Panel B: Variance Equation								
ABC								
BOC	0.01 ***							
CCB	0.01 **	0.01 *						
CMB	0.01 *	0.01	0.01					
CMS	0.01 ***	0.01 ***	0.01 **	0.01 *				
HUX	0.01 **	0.01 **	0.01 **	0.01 **	0.01 **			
ICC	0.01 ***	0.01 ***	0.01 **	0.01 **	0.01 ***	0.01 ***		
SGP	0.01 **	0.01 ***	0.01 **	0.01 ***	0.01 ***	0.01 ***	0.01 ***	
Panel C: Correlation Equation								
ABC								
BOC	0.73 ***							
CCB	0.26 ***	0.36 ***						
CMB	0.39 ***	0.63 ***	0.42 ***					
CMS	0.42 ***	0.66 ***	0.37 ***	0.73 ***				
HUX	0.21	0.49 **	0.33 ***	0.56 ***	0.67 ***			
ICC	0.59 ***	0.82 ***	0.38 ***	0.63 ***	0.63 ***	0.47 ***		
SGP	0.31 *	0.60 ***	0.38 ***	0.70 ***	0.70 ***	0.57 ***	0.58 ***	

Note: The table reports the μ_i of mean Equation (9), ω_{i0} of variable Equation (8), and $\rho_{i,j,t}$ from time-varying DCC correlation from Equation (14) from the regression. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

To visualize the results reported in Table 5, the DD correlation patterns (pair-wise) over the considered study period for eight Chinese banks are presented in Figure 4. As apparent in Figure 4, regardless of the fluctuations, the results follow a straight-line pattern around 0.5 and similar for all pairs. This proves that the correlation between Chinese banks is significantly stable compared to the rest of the world. We can also clearly observe that the larger banks are more stable than their smaller counterparts in the pair-wise comparison. For example, BOC and CCB are more stable in correlations than ABC and SGP. Based on these, it is safe to infer that DCC correlations and systematic risk contagion are extremely high in Chinese banks regardless of the period.
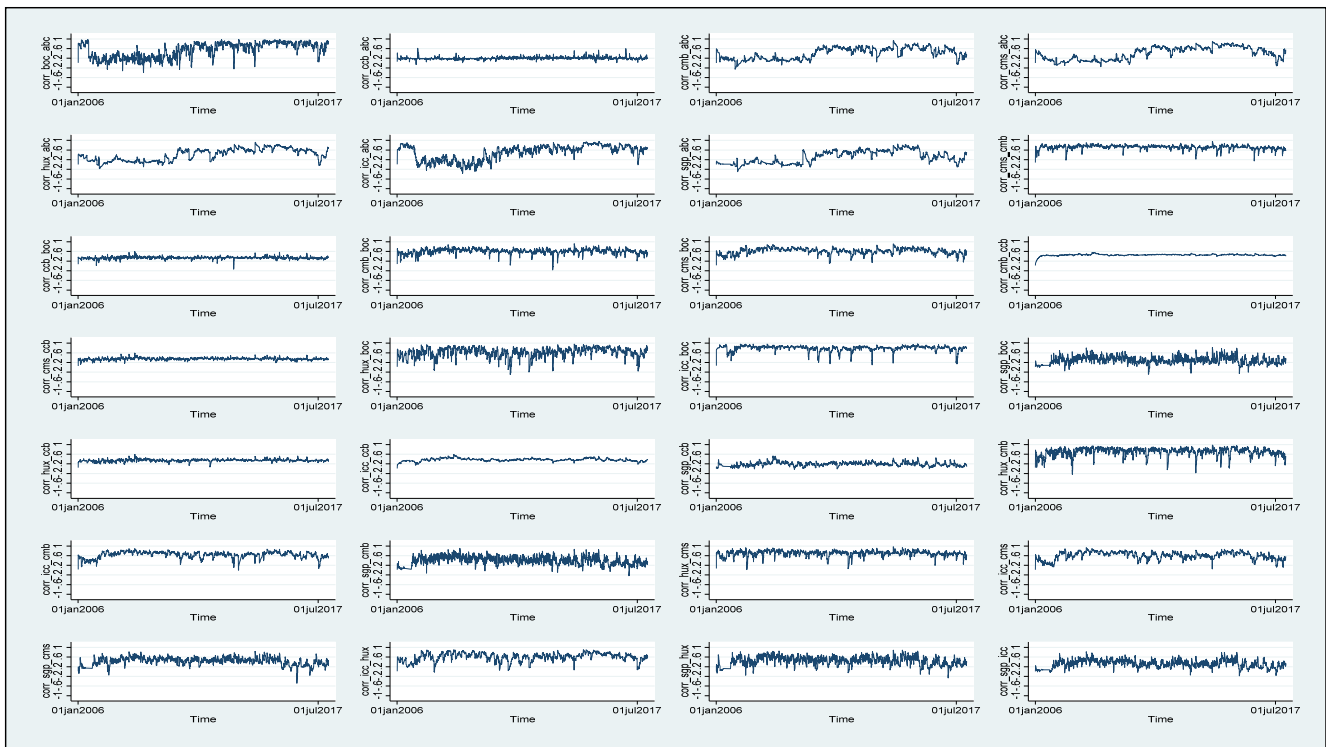
Figure 4. Pair-wise distance-to-default sample correlations. Sources: This figure visualizes the daily $\rho_{i,j,t}$ from time-varying DCC correlation from Equation (14) from the regression model for all the sample banks. Authors' calculations.

4.2. Distance-to-Insolvency Contagion

Table 6 reports the estimation results of the DI using the bivariate DCC-GARCH (1,1) model. As can be seen in Panel A of Table 6, the intercept terms in the mean and variance equation are moderately significant for half of the banks. However, the parameter estimates for the correlation equation in Panel C are very high, positive, and significant, even at the one percent level. CMS–CCB stands out as the most correlated pair in the sample, with a value of 0.79, whereas the weakest correlation in the sample is 0.3 between CCB–ABC. Similar to the results for DD in Table 5, the DCC results for DI further confirm that Chinese banks are highly prone to systematic risk contagion among themselves.

The DI correlation patterns (pair-wise) over the considered study period for the eight Chinese banks are presented in Figure 5. Plots here depict a pattern very similar to that for DD in Figure 4. Most of the plots are stable for the entire time as expected. However, the number of extreme fluctuations from the mean result increases compared to the DD. Overall, our results for DI confirm the presence of contagion risk among Chinese banks, suggesting that there is a high vulnerability of the Chinese banking system to spillover effects of risk among each other. The size of the banks' effects holds a similar finding from the DD.

Table 6. Estimation results of distance to insolvency from the bivariate DCC-GARCH model.

	ABC	BOC	CCB	CMB	CMS	HUX	ICC	SGP
Panel A: Mean Equation								
ABC								
BOC	−0.01							
CCB	0.01	0.01 *						
CMB	0.01 *	0.01	0.01 *					
CMS	0.01	−0.01	0.01 *	0.01				
HUX	0.01 *	0.01	0.01	0.01 **	0.01 **			
ICC	0.01	0.01	0.01 *	0.01 **	0.01 **	0.01 ***		
SGP	0.01	0.01*	0.01 ***	0.01	0.01	0.01	0.01	
Panel B: Variance Equation								
ABC								
BOC	0.01 ***							
CCB	0.01 ***	0.01 ***						
CMB	0.01	0.01	0.01 *					
CMS	0.01 ***	0.01 **	0.01 **	0.01 ***				
HUX	0.01 **	0.01 **	0.01	0.01 **	0.01 **			
ICC	0.01 **	0.01 *	0.01 **	0.01	0.01	0.01		
SGP	0.01 **	0.01 **	0.01 *	0.01 *	0.01 ***	0.01 **	0.01 **	
Panel C: Correlation Equation								
ABC								
BOC	0.52 ***							
CCB	0.30 ***	0.39 ***						
CMB	0.37 ***	0.65 ***	0.40 ***					
CMS	0.42 **	0.67 ***	0.48 ***	0.79 ***				
HUX	0.44 ***	0.58 ***	0.33 ***	0.66 ***	0.73 ***			
ICC	0.61 ***	0.81 ***	0.46 ***	0.73 ***	0.73 ***	0.63 ***		
SGP	0.40 **	0.65 ***	0.42 ***	0.77 ***	0.77 ***	0.69 ***	0.70 ***	

Note: The table reports the μ_i of mean Equation (9), ω_{i0} of variable Equation (8), and $\rho_{i,j,t}$ from time-varying DCC correlation from Equation (14) from the regression model. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

4.3. Distance-to-Capital Contagion

The results of the DCC-GARCH (1,1) model for DC are tabulated in Table 7. As can be seen in Panel A and B of Table 7, the coefficients show significant similarity to the DI results. In addition, the results of the correlation equation for DC are consistent with the previous findings on DD and DI. All the coefficients are positive and significant for all the banks' pairs at the one percent level. Compared to the results for DD and DI, the results for DC are even stronger where all the correlations are above 0.5. The BOC–ICC pair reports the highest correlation (0.87) in our sample on DC.
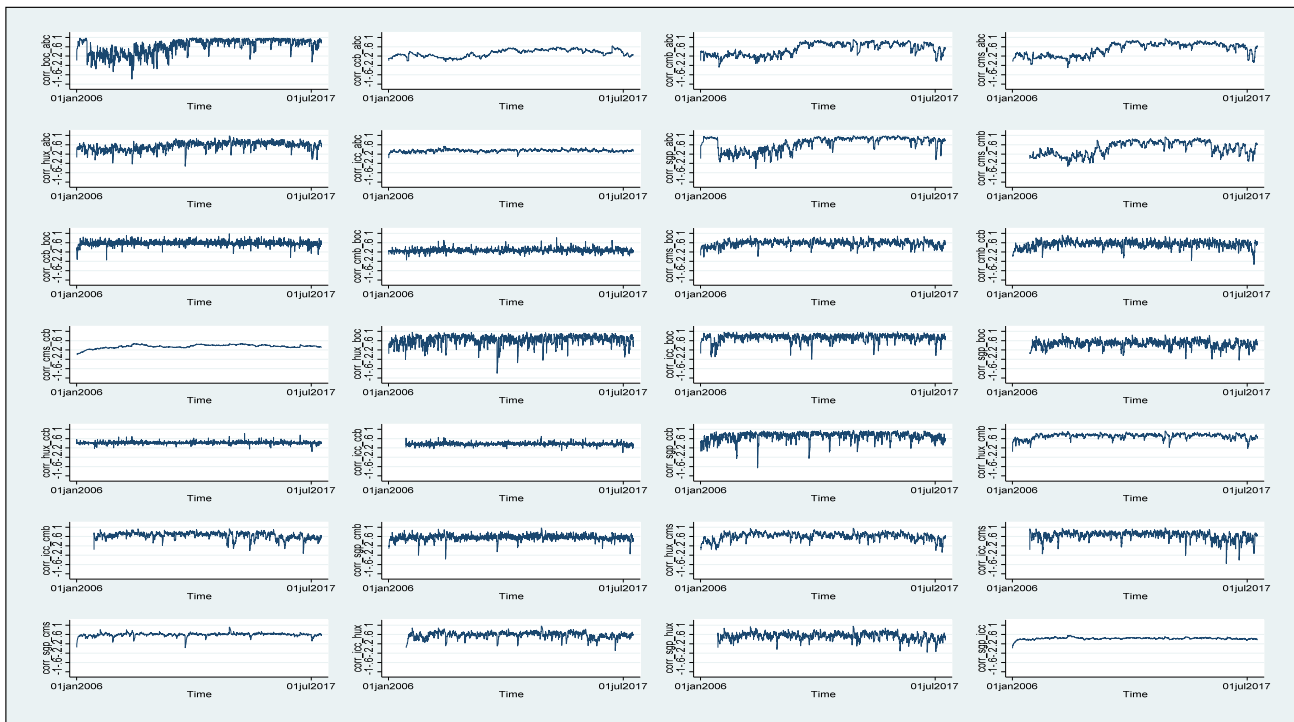
Figure 5. Pair-wise distance-to-insolvency sample correlations. Sources: This figure visualizes the daily $\rho_{i,j,t}$ from time-varying DCC correlation from Equation (14) from the regression model for all the sample banks. Authors' calculations.

Table 7. Estimation results of distance to capital from the bivariate DCC-GARCH model.

	ABC	BOC	CCB	CMB	CMS	HUX	ICC	SGP
Panel A: Mean Equation								
ABC								
BOC	−0.01							
CCB	−0.01	0.01 *						
CMB	0.01	0.01	0.01 ***					
CMS	0.01	0.01	0.01 ***	0.01 **				
HUX	−0.01	0.01	0.01 *	0.01 *	0.01 **			
ICC	−0.01 **	0.01 *	0.01 *	0.01 **	−0.01	0.01 **		
SGP	−0.01	0.01	0.01	0.01 ***	0.01 *	0.01	0.01	
Panel B: Variance Equation								
ABC								
BOC	0.01							
CCB	0.01	0.01 *						
CMB	0.01	0.01 **	0.01					
CMS	0.01	0.01	0.01	0.01				
HUX	0.01	0.01 ***	0.01 *	0.01 **	0.01 *			
ICC	0.01	0.01 ***	0.01 ***	0.01 ***	0.01	0.01 ***		
SGP	0.01	0.01	0.01	0.01 ***	0.01	0.01	0.01	

Table 7. *Cont.*

	ABC	BOC	CCB	CMB	CMS	HUX	ICC	SGP
Panel A: Mean Equation								
Panel C: Correlation Equation								
ABC								
BOC	0.84 ***							
CCB	0.58 ***	0.63 ***						
CMB	0.72 ***	0.79 ***	0.65 ***					
CMS	0.66 ***	0.76 ***	0.62 ***	0.80 ***				
HUX	0.73 ***	0.81 ***	0.66 ***	0.83 ***	0.79 ***			
ICC	0.82 ***	0.87 ***	0.64 ***	0.80 ***	0.77 ***	0.79 ***		
SGP	0.65 ***	0.78 ***	0.68 ***	0.83 ***	0.82 ***	0.83 ***	0.74 ***	

Note: The table reports the μ_i of mean Equation (9), ω_{i0} of variable Equation (8), and $\rho_{i,j,t}$ from time-varying DCC correlation from Equation (14) from the regression model. *, **, and *** indicate significance at the 10, 5, and 1 percent levels, respectively.

The patterns of pair-wise DC correlations for the sample Chinese banks over the considered period 2006–2018 are depicted in Figure 6. For all the plots involving ABC, correlations are comparatively high and stable. Although there are some rare spikes closer to 0 for some of the plots during the early years, most of the time they are stable above or around 0.5, indicating their low sensitivity to contagion risk. Overall, the plots in Figure 6 validate the high exposure of Chinese banks to the spillover effect of the systematic risk in support of DD and DI.
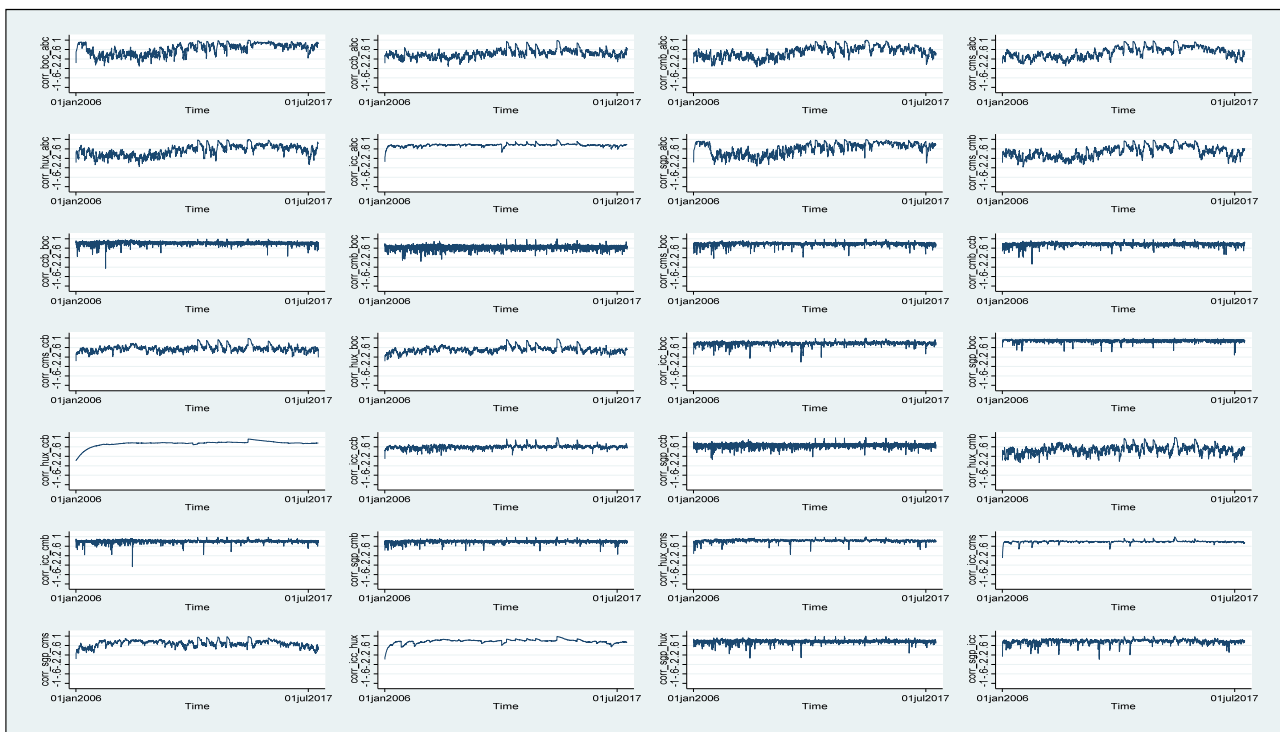

Figure 6. Pair-wise distance-to-capital sample correlations. Sources: This figure visualizes the daily $\rho_{i,j,t}$ from time-varying DCC correlation from Equation (14) from the regression model for all the sample banks. Authors' calculations.

5. Conclusions

This paper presents a comprehensive analysis of the systemic risk contagion of Chinese banks. The DD, DI, and DC results indicate the achievement of the soundness of banks while showing a continuous deterioration for all banks post-2008 and recovery only after 2010. The results attained from the bivariate DCC-GARCH (1,1) model suggest that the correlation parameters are statistically significant at the one percent level for all risk measures. The patterns of pair-wise correlations for distance measures show relatively high and stable correlations among most of the banks during the period.

Overall, the results imply that there is remarkable interconnectedness among the banking sectors in China, which is largely consistent with the existing studies [11,15,48]. Although these Chinese banks have remained largely isolated from the global financial crisis, risks exist from within its banking system due to a high level of non-performing assets, extended credit dispersed to non-banking financial companies, muted corporate demand for credit, and corporate governance issues. Further, there is evidence that some banks were susceptible to the global financial crisis, as a trough is observed for DD, DI, and DC during the period post-2008 to 2010.

The world economy and financial sectors have experienced significant changes during the current global pandemic [49,50]. A strong and resilient banking system is the foundation for sustainable economic growth, as banks are the hubs for credit intermediation and a well-acknowledged connection for service activities [51]. The results presented in this study suggest that the banking system is exposed to significant domestic contagion risks arising from systemic defaults supported by other authors in the field [52]. This is because the Chinese markets provide weak signals of forthcoming stress in banking systems. Thus, new policy interventions are needed to overcome the hidden stress in the system. From the viewpoint of structure and activities, the Chinese banking system has changed over the past decade. Therefore, it is recommended that the regulatory oversight of interbank exposures and interbank market structures be prioritized.

As a policy implication, regulators can clearly distinguish that the Chinese banking industry is more connected than the peer banking communities. However, a shock in one bank will transmit quickly and severely to other banks. Given these parameters, regulators need to monitor all banks closely rather than on one or two underperforming ones. Furthermore, they can also control the capital and investment flow between banks to mitigate spillover risk within the banking system.

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