Hindawi Publishing Corporation
Discrete Dynamics in Nature and Society
Volume 2016, Article ID 2967830, 5 pages
http://dx.doi.org/10.1155/2016/2967830

Research Article

Does Diversification Affect Banking Systemic Risk?

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Received 14 July 2016; Accepted 6 November 2016

Academic Editor: Ricardo López-Ruiz

This paper contributes to the understanding of the linear and nonlinear causal linkage from diversification to banking systemic risk. Employing data from China, within both linear and nonlinear causality frameworks, we find that diversification does not embody significant predictive power with respect to banking systemic risk.

1. Introduction

The 2007–2009 financial crisis has shed light on the significance of systemic risk and has made the concern about systemic risk increased by academics, regulatory bodies, and central banks. There is a growing literature on systemic risk. It mainly analyzes two aspects of systemic risk: the measure of systemic risk [1–3] and factors that may cause changes in the level of systemic risk, such as hedge funds [4], the opaque [5], financial system consolidation [6], and network structures [7–10].

It is well known that individual risk can be reduced through diversification [11]. However, the relationship between diversification and systemic risk is less commonly known [12]. And it is widely accepted that diversification at financial institutions benefits the stability of the financial system [13]. In fact, diversification has its costs. It enables institutions to become more similar to each other and hence systemic risk becomes more likely, which is the dark side of diversification [12, 13]. In the case of full diversification or full risk sharing, Shaffer [14] and Ibragimov et al. [15] find that diversification may benefit individual institutions but often increases systemic risk. Wagner (2010) shows that any degree of diversification increases systemic risk. Raffestin [16] also confirms the negative effect of diversification and goes more in depth by considering any level of diversification and any number of failures.

The above theoretical findings reveal the negative effect of diversification on systemic risk. Based on the linear and nonlinear causality tests, in this paper we aim to examine whether there is the causal relationship from diversification to banking systemic risk by using data from the Chinese banks. In fact, systemic risk is a complex phenomenon [17, 18]. In this paper, we focus on analyzing it from a technical-econometric point of view, which is useful to understand it from a different perspective. Similar to some studies [19–23], in this paper we measure banking systemic risk based on Contingent Claims Analysis. However, the purpose of this paper is different from theirs, and the novelties of this paper are as follows: the causal relationship from diversification to banking systemic risk is empirically tested; the causality tests are conducted within both linear and nonlinear frameworks; we conduct an empirical analysis for Chinese banking sector. After this introduction, Section 2 describes the methodology. Section 3 presents the data and empirical results, while Section 4 provides a conclusion.

2. Methodology

2.1. Diversification Measures. In this paper, the diversification indicator is calculated from the perspective of banks' profitability. There are different calculation methods for diversification of banks (e.g., [24–26]). We adopt the method proposed by Elsas et al. (2010). Moreover, we use the unweighted average diversification of banks (ADIV) and the weighted average diversification of banks (WADIV) to measure banking diversification, where the weight is the individual market-capital weight. Elsas et al. (2010) classify bank's non-interest-related activities into net commission revenue, net trading revenue, and all other net revenue and

illustrate the diversification indicator of bank i at time t as follows:

$$\mathrm{DIV}_{it} = 1 - \left[\left(\frac{\mathrm{INT}_{it}}{\mathrm{TOR}_{it}}\right)^2 + \left(\frac{\mathrm{COM}_{it}}{\mathrm{TOR}_{it}}\right)^2 + \left(\frac{\mathrm{TRAD}_{it}}{\mathrm{TOR}_{it}}\right)^2 + \left(\frac{\mathrm{OTH}_{it}}{\mathrm{TOR}_{it}}\right)^2\right], \tag{1}$$

where INT denotes gross interest revenue, COM net commission revenue, TRAD net trading revenue, and OTH all other net revenue, respectively. TOR indicates total operating revenue, which is equal to the sum of the absolute values of INT, COM, TRAD, and OTH.

2.2. Systemic Risk Measures. In this paper, we measure banking systemic risk based on Contingent Claims Analysis (CCA). It is a framework that combines market-based and balance sheet information to obtain financial risk indicators, such as Distance-to-Default (DD), probabilities of default, risk-neutral credit risk premia, and expected losses on senior debt [20]. The CCA approach has been adopted to investigate banking systemic risk based on aggregated DD series [19–23]. Therefore, we also use the unweighted average DD series (ADD) and weighted average DD series (WADD) to measure banking systemic risk, where the weight is the individual market-capital weight.

Similar to Singh et al. (2014), DD_{it}, the distance-to-default of bank i at time t, is calculated from the following equations:

$$\begin{aligned}
\mathrm{DD}_{it} &= \frac{A_{it} - D_{it}}{A_{it}\sigma_{it}},\\
E_{it} &= A_{it}N(d_1) - D_{it}e^{-rT}N(d_2),\\
\widehat{\sigma_{it}} &= \frac{A_{it}}{E_{it}}N(d_1)\sigma_{it},\\
d_1 &= \frac{\ln(A_{it}/D_{it}) + \left(r + \sigma_{it}^2/2\right)T}{\sigma_{it}\sqrt{T}},\\
d_2 &= d_1 - \sigma_{it}\sqrt{T},
\end{aligned} \tag{2}$$

where A is the value of bank assets, T the time horizon of debt, D the face value of the debt, σ the volatility of bank assets, r the risk-free rate, E the market value of bank equity capital, and $\widehat{\sigma}$ the volatility of bank equity capital, respectively.

2.3. Linear and Nonlinear Granger Causality Tests. Granger [27] defines causality between two variables in terms of predictability. The linear causal relationship between two variables can be tested within a VAR framework, where the null hypothesis of no causality is tested via the significant contribution that past values of one variable can offer in predicting current values of another [28]. Since the linear Granger causality test cannot capture nonlinear and higher order causal relationships [29], we further consider a nonlinear Granger causality test, which was developed by Baek and Brock [30] and modified by Hiemstra and Jones [31]. Under certain variance conditions, Diks and Panchenko [32] find that the Hiemstra-Jones (HJ) test could overreject the null hypothesis. To compensate this shortcoming, Diks and Panchenko (2006) propose a new test statistic (hereafter DP test). In this paper we adopt the DP test to check the nonlinear Granger causality.

Suppose $\{X_t\}$ and $\{Y_t\}$ are both strictly stationary time series, and $Z_t = Y_{t+1}$. In the null hypothesis that X does not Granger cause Y, Diks and Panchenko (2006) find that there is the following equation:

$$\begin{aligned}
q &\equiv E\left[f_{X,Y,Z}(X,Y,Z)\, f_Y(Y) - f_{X,Y}(X,Y)\, f_{Y,Z}(Y,Z)\right]\\
&= 0,
\end{aligned} \tag{3}$$

where $f_{\cdot}(\cdot)$ is the probability density function. Let $\widehat{f}_W(W_i)$ indicate the local density estimators of a d_W-variate random vector W at W_i by

$$\widehat{f}_W(W_i) = \frac{(2\varepsilon_n)^{-d_W}}{n-1}\sum_{j,j\neq i} I_{ij}^W, \tag{4}$$

where $I_{ij}^W = I(\|W_i - W_j\| < \varepsilon_n)$; $I(\cdot)$ is an indicator function and ε_n is the presetting bandwidth depending on the sample length n. Then, the new test statistic can be expressed as

$$\begin{aligned}
T_n(\varepsilon_n) = \frac{n-1}{n(n-2)}\sum_i \Big(&\widehat{f}_{X,Y,Z}(X_i,Y_i,Z_i)\,\widehat{f}_Y(Y_i)\\
&- \widehat{f}_{X,Y}(X_i,Y_i)\,\widehat{f}_{Y,Z}(Y_i,Z_i)\Big).
\end{aligned} \tag{5}$$

Diks and Panchenko (2006) demonstrate that $T_n(\varepsilon_n)$ converges to the standard normal distribution under certain conditions.

3. Data and Empirical Results

3.1. Data and Preliminary Analysis. Considering the difference of the listed times, in this paper we analyze 14 listed banks in China, where their stock codes are 600000.SH, 600015.SH, 600016.SH, 600036.SH, 601009.SH, 601166.SH, 601169.SH, 601328.SH, 601398.SH, 601939.SH, 601988.SH, 601998.SH, 000001.SZ, and 002142.SZ, respectively. Data employed in this paper stem from the Wind Database and the quarterly reports of banks, where the Wind Database is a leading integrated service provider of financial data in China. The time interval is from October 2007 to June 2014. In this paper, T is one year; D is total liabilities of banks; r is set as the one-year deposit interest rate during the trading period; $\widehat{\sigma}$ is calculated as the standard deviation of daily equity logarithmic returns multiplied by the square root of the number of trading days in a month. In addition, similar to Gropp and Moerman [33], Blundell-Wignall and Roulet [34], and Saldías (2013), the data from the quarterly reports of banks are interpolated to yield monthly observations by using a cubic spline. Through the calculation, the results of banking diversification and systemic risk are obtained and shown in Figures 1 and 2, respectively.

Table 1: Descriptive statistics, ADF, and PP tests.

	ADIV	WADIV	ADD	WADD
Mean	0.2033	0.2481	9.1082	12.1065
Max.	0.3387	0.3494	15.8531	21.7681
Min.	0.1712	0.1920	2.2956	2.7469
Std. Dev.	0.0261	0.0254	3.0371	4.4227
ADF-statistic	−3.9769 (0.0025)	−3.5122 (0.0105)	−4.9869 (0.0001)	−5.3665 (−0.0000)
PP-statistic	−5.7817 (0.0000)	−4.9423 (0.0001)	−5.1851 (0.0000)	−5.5970 (−0.0000)

Notes: the numbers in parentheses refer to the p values.

Table 2: Linear Granger causality tests.

Null hypothesis examined	VAR lag length	F-statistic	p value
ADIV does not Granger cause ADD	3	0.7397	0.5319
WADIV does not Granger cause WADD	5	0.4252	0.8295

Notes: the VAR lag lengths were selected based on the Schwartz Information Criterion (SIC).

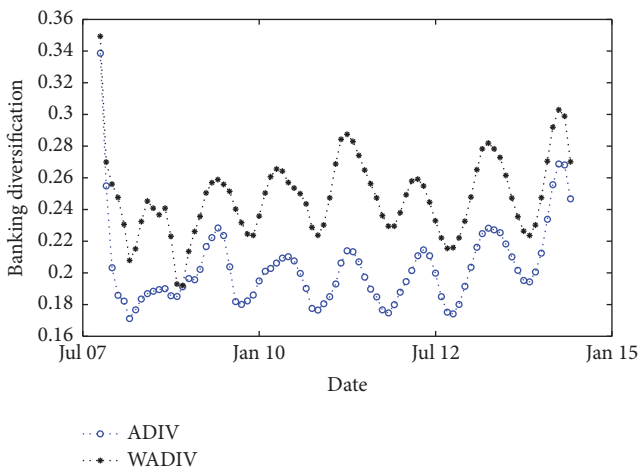

Figure 1: Banking diversification based on ADIV and WADIV.

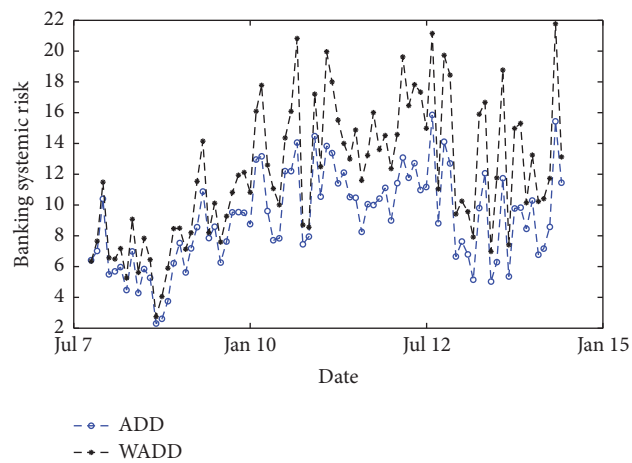

Figure 2: Banking systemic risk based on ADD and WADD.

3.2. Empirical Results. Before conducting the linear and nonlinear Granger causality tests, we apply Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test to analyze whether there are unit roots for all of the four variables, namely, ADIV, WADIV, ADD, and WADD. Table 1 illustrates the test results. In every case, we reject the null hypothesis of a unit root for the two tests. Obliviously, all of the variables are stationary and thus suitable for further statistical analysis with linear and nonlinear Granger causality tests.

We first investigate whether there is the linear causal relationship from diversification to banking systemic risk, by implementing the standard Granger causality test [27]. The results are reported in Table 2. They reveal that the null hypothesis of linear causality running from diversification to banking systemic risk is never rejected for both tests. Therefore, there is no linear causality running from diversification to banking systemic risk.

Before testing for nonlinear Granger causality, we conduct the Brock-Dechert-Scheinkman (BDS) test to investigate whether the residual series are characterized by nonlinearities, where the residual series are from VAR models. We estimate the VAR model with the endogenous variables ADIV, ADD, WADIV, and WADD, respectively, where the lag of the VAR model is set based on Schwartz Information Criterion. We use these residual series so that any linear predictive power has been removed. Table 3 displays the results of the BDS tests. We can see from it that nonlinearities are in diversification and systemic risk. Such result signifies that nonlinear Granger causality test is appropriate in our study.

Now we conduct the nonlinear causality test. Based on the standardized residuals of VAR models, we set the bandwidth as 1.5 and the embedding dimensions as 1 to 8, where the empirical results from the DP test are presented in Table 4. It can be seen from Table 4 that the null hypothesis of no nonlinear Granger causality from diversification to banking systemic risk is not rejected. Therefore, there is no nonlinear causality running from diversification to banking systemic risk.

4. Conclusion

Recently, the negative effect of diversification on systemic risk is analyzed in the some literature. This paper adopts both

Table 3: BDS tests for nonlinearity.

Dimension	ADIV	ADD	WADIV	WADD
2	−3.8423 (0.0001)	−0.6427 (0.5204)	−9.1869 (0.0000)	1.5600 (0.1187)
3	−0.4873 (0.6260)	−13.3144 (0.0000)	7.8086 (0.0000)	−15.3745 (0.0000)
4	9.3044 (0.0000)	−7.8907 (0.0000)	9.5483 (0.0000)	−9.0653 (0.0000)
5	13.2436 (0.0000)	−5.1281 (0.0000)	3.0661 (0.0022)	−5.9859 (0.0000)
6	9.5288 (0.0000)	−4.9559 (0.0007)	−1.4166 (0.0860)	−4.1693 (0.0000)

Notes: each column represents the test results of the VAR residuals for the corresponding variable as the dependent variable. The numbers represent the z-statistics and those in parentheses are the p values.

Table 4: Nonlinear Granger causality tests.

Embedding dimension	H_0: ADIV does not cause ADD DP statistic (p value)	H_0: WADIV does not cause WADD DP statistic (p value)
1	−1.2210 (0.8889)	−1.5430 (0.9386)
2	−0.9050 (0.8172)	−0.9670 (0.8332)
3	−1.0380 (0.8503)	−0.0640 (0.5254)
4	−1.2460 (0.8936)	−0.3470 (0.6357)
5	0.0450 (0.4820)	−0.3320 (0.6300)
6	−0.3640 (0.6422)	−0.2410 (0.5952)
7	−0.5360 (0.7041)	0.3320 (0.3700)
8	−0.0580 (0.5271)	1.0420 (0.1486)

Notes: the DP statistic is generated based on Diks and Panchenko (2006) methodology.

linear and nonlinear Granger causality tests to examine whether there is the causal relationship from diversification to banking systemic risk. Based on the banking data from China, our empirical findings reveal that there is no linear or nonlinear causal relationship from diversification to banking systemic risk. A possible reason is that banking systemic risk is largely derived from the cyclical fluctuations of the macroeconomy, while diversification mainly affects banking nonsystemic risk. Overall, our results show that diversification does not affect banking systemic risk in China.

Competing Interests

The author declares that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

This research is supported by NSFC (no. 71201023, no. 71371051, no. 71301078, and no. 71671037), Humanities and Social Science Planning Foundation of the Ministry of Education of China (no. 16YJA630026), Teaching and Research Program for Excellent Young Teachers of Southeast University (no. 2242015R30021), the Fundamental Research Funds for the Central Universities (no. 2242016K40118), and Social Science Fund Project of Jiangsu Province (no. 15GLC003).

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