The Risk Contagion Mechanism between P2P Industry and Banking Industry in China - based on the DCC-BEKK-MVGARCH model

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Abstract

Encouraged constantly by government policy, Internet finance achieved a full-speed development in China. Since 2016, however, a large number of P2P platforms have gone bankrupt. The risks and crises arising from P2P platforms are being transmitted to the commercial banks as there are various capital trusteeship relations between P2P industry and banking industry. DCC-BEKK-MVGARCH model is adopted to verify the risk contagion mechanism. We use the daily income of each platform from July 1, 2013 to July 1, 2017 to make the P2P platform development index, and match them with the Shanghai Stock Exchange Index to explore the risk linkage between Internet finance and banking industry and the direction of risk spill over effects. The results show that there exists a risk linkage between P2P industry and banking industry, and the direction is from P2P platforms to banks. Among them, the P2P platforms in the listing system are more contagious, followed by the P2P platforms of the private sector, the P2P platforms of the state-owned system and the P2P platforms of the VC system respectively.

Keywords: P2P Industry, the risk contagion mechanism, DCC-BEKK-MVGARCH model, risk spill over

Introduction

Encouraged constantly by government policy, Internet finance achieved a full-speed development in China. There were more than 5,000 P2P platforms by the end of 2015. Since 2016, however, a number of P2P platforms have gone bankrupt. Currently, about 3,058 P2P platforms have difficulties in withdrawing cash and have closed down, including Fan Ya, Zhong Jin, E-Zu Bao and Kuai Lu, whose scales reached hundreds of millions of dollars. What is even worse is that more than 90% of P2P platforms are expected to fail in the next five years. It can be said that there is a crisis in P2P industry in China.

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Since its birth, P2P industry has been closely linked to the banking industry and formed three fund channels with commercial banks, namely, No Trusteeship Channel, Third-Party Payment Trusteeship Channel and Bank Trusteeship Channel.

In No Trusteeship Channel, borrowers and lenders in P2P platforms register accounts respectively. Lenders transfer funds in banking account into P2P platforms, which put the money into the borrower accounts through the third-party payment and match the loan information. Borrowers then put the money back into their bank accounts, completing the lending process.

In Third-Party Payment Trusteeship Channel, borrowers and lenders in P2P platforms register accounts respectively and open virtual accounts in third-party payment platforms. After matching the loan information, the third-party payment platforms adjust the virtual account balance and send the data to the banks' reserve account. P2P platforms increase or decrease the funds of borrowers and lenders accordingly to complete the lending process.

In Bank Trusteeship Channel, borrowers and lenders register accounts respectively in P2P platforms and open special bank fund deposit sub-accounts, which are linked to P2P platform accounts. P2P platforms transfer funds into corresponding sub-accounts and match lending information. The banks are responsible for the handling and transferring funds while P2P platforms are responsible for adjusting the borrowers' and lenders' funds to complete the lending process.

Through the three channels, it can be seen that there are various capital trusteeship relationships between P2P industry and banking industry. Users transfer funds from their bank accounts to P2P platform accounts. After matching the information, the platforms can transfer the money directly, or deposit it in the bank account opened by themselves, or transfer it to the bank fund deposit account, or transfer the precipitation funds to the third-party payment. Although the account names are different, from the ordinary bank deposit accounts, to the reserve fund accounts, through to the special funding deposit sub-accounts, the essence is the same, transferring funds from the P2P platforms to the banks. Along with other funds, these funds enter the capital operation process of commercial banks. In the process of fund transmission, risk contagion occurs from P2P platforms to the balance sheet system of commercial banks, carrying the crisis wave of P2P industry into the banking industry at the same time.

Originating from epidemiology, the term “contagion” in risk contagion has been an academic term in financial research in the past 20 years. Depending on the route of risk transmission or the extent of infection, researchers define risk contagion from different perspectives, but most researchers believe that the nature of risk transmission is risk spill over. For example, Masson (1999), Forbes and Rigobon (2002) refer to the risk contagion caused by the economic fundamentals like trade links, financial flows and financial links as "risk spill over effect". Forbes (2012) uses the intensity of impact to define risk contagion, and believes that the extreme negative impact of a financial market on another market can result in risk spillovers and contagion.

The early research on risk contagion focuses on the banking industry. Allen and Gale (2000) believed that when a bank suffered from a banking crisis, other banks also suffered losses due to holding the equity of the bank, which formed the spill over effect of losses and caused the risk contagion. Nier, Yang, Yorulmazer, and Alentorn (2007) found that the relation between the risk contagion and the size of inter-bank loans were non-linear. When interbank lending increases upward from a lower scale, risk spillovers are low. However when the size of the interbank loan exceeds a threshold, risk spillovers emerge and risk starts to contagion rapidly. Brunnermeier and Yogo (2009) believed that systemically important institutions would have negative spillover effects on other institutions. When some large financial institutions are insolvent, they will impact other financial institutions and the whole financial market and aggravate the instability of domestic or global financial order by affecting their counterparties and transmitting market panic.

Many researchers in China also explore the risk spillover between banks (Gong, 2012; Zhou, Zhou and Huang, 2012). However, with the rapid development of P2P industry, there are more and more researches on the risk spillover effect between P2P platforms and commercial banks, mainly following the research pattern from the micro spill over to the macro. It includes the spillover analysis of P2P platforms business to traditional bank business (transaction participants) and the spillover analysis of P2P market interest rate pricing to traditional commercial bank market interest rate pricing (transaction price).

Financial markets are interconnected. Judging from the spill over effect of transaction participants, the risk of P2P industry is not only reflected in the P2P lending markets, but also spreading to traditional financial institutions through such channels as guarantee, payment, settlement and interest rate liberalization, thus forming the risk spill over of P2P industry (Yang and Wu, 2015). The high efficiency, frictionless, low threshold of P2P lending will accelerate the risk contagion in different markets (Ruan and He, 2016), and form the risk spill over effect on traditional commercial banks directly and indirectly (Wei and Zhang, 2015). Direct risk spill over includes trusteeship cooperation and direct business transactions while indirect risk spillovers include securities model promoting systematic risk, high yield increasing market volatility, credit risk due to lack of supervision and liquidity risk caused by weak monetary policy effect.

Judging from the spill over effect of transaction price, the pricing level and volatility characteristics of P2P market determine the spill over effect of P2P markets on traditional financial markets. During the rapid development of P2P platforms, the interest rate of the P2P industry is counter-cyclical, and there is spill over effect between the interest rate and Shanghai Interbank Offered Rate (Chen and Ye, 2016). Based on the unitary and multiple GARCH model, He and Peng (2016) analyzed the price transmission relationship between P2P interest rate, Shanghai Interbank Offered Rate and National Debt Rate, and found that the P2P interest rate has risk accumulation effect, and has one-way spill over effect on Shanghai Interbank Offered Rate and National Debt Rate. When the interest rate of P2P market is far higher than the return rate of bank financial products, and when more financing parties default, market fluctuations will spill over to commercial banks through price linkage, causing the collapse of banking system (Zheng, 2015).

As an innovative financial industry in emerging markets, P2P industry has showed geometric growth for a long time, presenting non-linear impact on the balance sheet of commercial banks. In addition, different P2P platforms with different backgrounds and strengths have different cost/benefit functions, and the rate of return is significantly different. However, at present, there are few studies on the quantitative characteristics of the impact of P2P industry on the asset and liability of commercial banks and the heterogeneity of risk spill over capacity of different platforms.

Therefore, we use the DCC-BEKK-MVGARCH model to verify how P2P platforms can spread their risk to commercial banks through their capital trusteeship and business transaction. Specifically, we divide the current Chinese 1585 P2P platforms into Private, Listed, State-Owned and Venture-Capital according to the platform background. We collect the daily income of each type of P2P platforms from July 1, 2013 to July 1, 2017, make the *P2P Platform Development Index*, and match with *Shanghai Stock Exchange Banks Index* to explore the risk linkage between P2P industry and banking industry, and the direction of risk spill over effect.

Our paper contributes to a large and growing literature on financial risk spill over effect in at least two ways. Unlike most prior papers that examine the specific impact of P2P industry on the banking industry, we analyzed how P2P platforms can spread the crisis of P2P industry to the banking industry through three fund related channels: No Trusteeship Channel, Third-Party Payment Trusteeship Channel and Bank Trusteeship Channel. Besides, we used the DCC-BEKK-MVGARCH model to study the heterogeneity and quantitative characteristics of risk spill over capability of P2P platforms from different backgrounds.

The rest of this paper is arranged as follows: Part 2 introduces research methods, Part 3 is data description, Part 4 is empirical results and discussion, and Part 5 is conclusion.

Model Setting

For the test of financial risk contagion, the complex network models and GARCH models are widely used in current research. The complex network models can depict the interaction and association within the financial system directly and vividly by regarding financial institutions as the nodes of the network and the asset-liability relationship between financial institutions as the chain of the network (Gai and Kapadia, 2010; Glasserman and Young, 2015; Lux, 2015). Meanwhile, many researchers use the extended models of GARCH model such as EGARCH, VAR-GARCH-BEKK, GJR-GARCH and DCC-GARCH to study the financial risk spillover effect (Schröde and Schüler, 2003; Bekiros, 2014).

Since the GARCH cluster models can capture the time-varying fluctuating correlation degree between the rates of return sequences, it can solve the computational complexity of conditional variance and covariance matrix that change with time, making the correlation estimation between multiple variables simpler. Besides, it can help us to get the time-varying correlation coefficient between different variables, suitable for the study of P2P platforms. Therefore, DCC-BEKK-MVGARCH model is used here to describe the risk linkage between P2P industry and the banking industry, and to verify the direction of risk contagion.

MVGARCH model has two main problems in estimating conditional covariance matrix. First, as the number of asset types increases, the dimensions of the covariance matrix increase rapidly. In addition, the MVGARCH model can hardly meet the requirements of semi positive-definite matrix. However, Constant Conditional Correlation model (CCC) and Dynamic Conditional Correlation model (DCC) greatly improve the efficiency of model estimation by using correlation coefficient and conditional variance for parameter estimation, instead of direct estimation of conditional covariance. The BEKK model is only applicable to relatively low dimensions. The CCC model assumes that conditional correlation coefficient is constant, which reduces the number of estimated parameters. Nevertheless, the assumption of constancy is too restrictive, so we use the DCC model to guarantee the time-varying conditional correlation coefficient and multidimensional data.

The general form of DCC-MVGARCH model is as follows[1]:

$$y_t = \mu + \varphi y_{t-1} + \varepsilon_t, \quad \varepsilon_t | \Psi_{t-1} \sim N(0, H_t) \qquad (1)$$

$$H_t = D_t R_t D_t \qquad (2)$$

$$Qt = \left(1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n\right)\bar{Q} + \sum_{m=1}^{M} \alpha_m \left(\varepsilon_{t-m} \varepsilon'_{t-m}\right) + \sum_{n=1}^{N} \beta_n Q_{t-n} \qquad (3)$$

$$Q_t^* = \mathrm{diag}\left(\sqrt{q_{11,t}}, \sqrt{q_{22,t}}, \dots, \sqrt{q_{kk,t}}\right) \qquad (4)$$

$$R_t = (Q_t^*)^{-1} Q_t (Q_t^*)^{-1} \qquad (5)$$

Yield vector $y_t = (y_{1t,} y_{2t}, \dots y_{kt})$. $\mu, \varphi, \varepsilon$ are the mean value, the coefficient of lagged variable and disturbing term of y_t. ε_t follows that the mean is zero. The covariance matrix is the normal distribution of H_t.

$$D_t = \mathrm{diag}\left(\sqrt{h_{i,t}}\right) \qquad (6)$$

$h_{i,t}$ is the variance of the GARCH model. Each asset yield is subject to the following single variable $\mathrm{GARCH}(p, q)$ process:

[1] Engle R. Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroscedasticity models [J]. Journal of Business & Economic Statistics, 2002, 20(3): 339-350.

$$h_{i,t} = \omega_i + \sum_{p=1}^{P} \alpha_{i,p}\, e_{i,t-p}^2 + \sum_{q=1}^{q} \beta_{i,q}\, h_{i,t-q}^2 \qquad (7)$$

We use the univariate GARCH model to estimate the conditional variance and residual sequence of the rate of return to eliminate the correlation of the sequence and volatility clustering. Then we use the standardized residual sequence obtained in the previous step to estimate the parameters of the DCC model.

The maximum likelihood estimation for the first stage is shown in the following formula:

$$QL_1(\phi|r_t) = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + \log(|I_k|) + 2\log(|Dt|) + r_t' D_t^{-1} I_k D_t^{-1} r_t) \quad (8)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + 2\log(|Dt|) + r_t' D_t^{-2} r_t) \qquad (9)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}\left(k\log(2\pi) + \sum_{n=1}^{k}(\log(h_{it}) + \frac{r_{it}^2}{h_{it}})\right) \qquad (10)$$

$$= -\frac{1}{2}\sum_{n=1}^{k}\left(T\log(2\pi) + \sum_{t=1}^{T}(\log(h_{it}) + \frac{r_{it}^2}{h_{it}})\right) \qquad (11)$$

The parameter maximum likelihood function in the second stage can be expressed as:

$$QL_2\left(\psi\middle|\hat{\phi}, r_t\right) = -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + \log(|R_t|) + 2\log(|Dt|) + r_t' D_t^{-1} I_k D_t^{-1} r_t) \quad (12)$$

$$= -\frac{1}{2}\sum_{t=1}^{T}(k\log(2\pi) + \log(|R_t|) + 2\log(|Dt|) + \epsilon_t' R_t^{-1} \epsilon_t) \qquad (13)$$

Since the second stage is based on $\hat{\phi}$, only $\log(|R_t|) + \epsilon_t' R_t^{-1} \epsilon_t$ affects the final parameters, we just need to maximize the maximum likelihood function below to obtain the parameter results of DCC model.

$$QL_2\left(\psi\middle|\hat{\phi}, r_t\right) = -\frac{1}{2}\sum_{t=1}^{T}(\log(|R_t|) + \epsilon_t' R_t^{-1} \epsilon_t) \qquad (14)$$

After the two-stage maximum likelihood estimation, we obtain the dynamic correlation coefficient, the estimated value of R_t, and the coefficient matrix form between R_t variables is:

$$R_t = \begin{bmatrix} 1 & \cdots & \rho_{i1,t} \\ \vdots & \ddots & \vdots \\ \rho_{1j,t} & \cdots & 1 \end{bmatrix} \qquad (15)$$

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ρ_{it} is the corresponding correlation coefficient.

The object of this paper belongs to the binary DCC-GARCH model. In the model estimation results, the form of R_t is as follows:

$$R_t = \begin{bmatrix} \rho_{is,t} & 1 \\ 1 & \rho_{is,t} \end{bmatrix} \quad (16)$$

$\rho_{is,t}$ is the coefficient of correlation between i and s at time t, and, as time goes on, the value of $\rho_{i,s}$ is different.

The setting form of BEKK variance equation is as follows:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \quad (17)$$

We take the binary model as an example to explain the parameters, where H_t is the symmetric matrix of 2×2, and C is the upper triangular matrix, which can guarantee the positive definiteness of the conditional variance covariance matrix H_t. A is coefficient matrix of 2×2, representing the ARCH coefficient. B is coefficient matrix of 2×2, representing the GARCH coefficient. The specific equation is as follows:

$$\begin{cases} h_{11,t} = C_{11}{}^2 + a_{11}{}^2\varepsilon_{1,t-1}{}^2 + 2a_{11}a_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}{}^2\varepsilon_{2,t-1}{}^2 + b_{11}{}^2h_{11,t-1} \\ \quad +2b_{11}b_{21}h_{12,t-1} + b_{21}{}^2h_{22,t-1} \\ h_{12,t} = C_{11}C_{21} + a_{11}a_{12}\varepsilon_{1,t-1}{}^2 + (a_{21}a_{12} + a_{11}a_{22})\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{21}a_{22}\varepsilon_{2,t-1}{}^2 \\ \quad +b_{11}b_{21}h_{11,t-1} + (b_{21}b_{12} + b_{11}b_{22})h_{12,t-1} + b_{21}b_{22}h_{22,t-1} \\ h_{11,t} = C_{11}{}^2 + C_{22}{}^2 + a_{12}{}^2\varepsilon_{1,t-1}{}^2 + 2a_{12}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + a_{22}{}^2\varepsilon_{2,t-1}{}^2 + b_{12}{}^2h_{11,t-1} \\ \quad +2b_{12}b_{22}h_{12,t-1} + b_{22}{}^2h_{22,t-1} \end{cases} \quad (18)$$

The parameter matrices in the above equation are:

$$C = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{21} \end{pmatrix}, A = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}, B = \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix} \quad (19)$$

$CoVaR_q^{j|i}$ is defined as the VaR of institution j when one type of P2P Platform i is at $X^i = VaR_q^i$. VaR refers to the maximum loss faced by a financial asset or portfolio at a confidence level of $1 - \alpha$:

$$\Pr(X \le VaR_q) = q \quad (20)$$

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$$\mathrm{VaR_q} = -\mathrm{F}^{-1}(1-\mathrm{q}) \qquad (21)$$

F(*) is the cumulative distribution function of the rate of return of the financial asset or portfolio.

The CoVaR of one type of P2P Platform i represents the degree of risk to the entire banking system s when this type of P2P Platform is hit by a bad shock.

$$\Pr(\mathrm{X^j} \le \mathrm{CoVaR_q^{j|i}} | \mathrm{X^i} = \mathrm{VaR_q^i} = \mathrm{q} \qquad (22)$$

We regard institution j as the whole banking system s, so comes

$$\Pr(\mathrm{X^s} \le \mathrm{CoVaR_q^{s|i}} | \mathrm{X^i} = \mathrm{VaR_q^i} = \mathrm{q} \qquad (23)$$

q is the confidence interval, which is 0.05 in this paper. The difference between the CoVaR of platform type i and the VaR of the whole banking system is denoted as $\Delta\mathrm{CoVaR}$： .

$$\mathrm{CoVaR_{q,t}^{s|i}} = \phi^{-1}(\mathrm{q})\sigma_{\mathrm{s,t}}\sqrt{1-\rho_{\mathrm{is,t}}^2} + \phi^{-1}(\mathrm{q})\rho_{\mathrm{is,t}}\sigma_{\mathrm{s,t}} \qquad (24)$$

Systemic risk contribution of platform type i is $\Delta\mathrm{CoVaR_{q,t}^{s|i}} = \phi^{-1}(\mathrm{q})\ \rho_{\mathrm{is,t}}\sigma_{\mathrm{s,t}}$

Data

Our main purpose is to study whether there is risk linkage between P2P industry and the banking industry. If there is a risk linkage, what is the direction of risk overflow based on the model estimation results. Therefore, explanatory variables and interpreted variables are profitability indicators. We select the *Shanghai Stock Exchange Banks Index* (SSE Banks Index) as the bank earnings level data[2]. The index components of the SSE Banks Index is nearly all the large commercial banks in China, whose total assets and net profits account for about 92% of the total assets and profits of Chinese Banking Industry, which can represent the overall banking level.

$\mathrm{Index\ of\ reporting\ period} =$
$\mathrm{The\ adjusted\ market\ value\ of\ constituent\ stocks\ during\ the\ reporting\ perio}$
$\mathrm{base\ period} \times 1000$
(25)

[2] Patro, Qi和Sun（2010）put forward that the stock return correlation of large financial institutions is robust and forward-looking for banking risk prediction and can be used as an effective measure of banking risk.

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The Shanghai bank stock index is based on December 31, 2007, taking the adjusted market value of all sample stocks after the close of the day as the base period, taking 1000 as the basis point. The formula for calculating the index is as above. Among them,

$$\text{Adjusted Market Value} = \sum(\text{Stock Price} \times \text{Adjusted Share Capital Number} \times \text{Weighting Upper Bound Factor}) \quad (26)$$

Adjusted share capital adopts the grading gear method to adjust share capital of component stock. According to international practice and the opinions of the expert committee, the classification method of SSE Banks Index is shown in the following table[3].

Table 1 Circulation Ratio and Weighting Ratio

Circulation Ratio（%）	≤10	(10,20]	(20,30]	(30,40]	(40,50]	(50,60]	(60,70]	(70,80]	>80
Weighting Ratio（%）	Circulation Ratio	20	30	40	50	60	70	80	100

The weight upper limit factor is between 0 and 1 in order to make the weight of sample stock no more than 15%.

There are not many P2P platforms in China in the list, as all of them are small-sized at present. Therefore, the daily income of each type of P2P platform should be collected from individual P2P platform. The calculation method of *P2P platform Development Index* (P2P Index) is similar to the SSE Banks Index. 1,585 P2P platforms in China are used here as samples, which are divided into Private, Listed, State-Owned and Venture-Capital platforms according to the platform background. The index of every type of P2P platforms is calculated.

The data required by this research is mainly from the WIND database and the Home of P2P Lending. Some of the data come from the People's Bank of China and the China Banking Regulatory Commission. The time range is from July 1, 2013 to July 1, 2017. During this period,

[3] For example, if the percentage of outstanding shares of a stock (outstanding share capital/total share capital) is 7% and less than 10%, the circulating share capital is used as the weight. If a stock is 35% in circulation and falls within the range (30,40], the corresponding weighting is 40%, then 40% of the total equity is considered as weight

P2P industry experienced a series of stages, from the initial start to a rapid rise and then to a stable development[4].

Considering that the capital market can digest the information more fully and the analysis results are more representative in a longer period, we have done the following processing on the original data. Of the opening price, closing price, highest price and lowest price of the index, we select the closing price data, and take logarithm of the daily closing price, and obtain logarithmic rate of return after the first order difference (the same for the P2P Index). To reduce the error, the daily rate of return is multiplied by 100, which is calculated as follows:

$$r_{i,t} = 100 \times \ln \frac{p_{i,t}}{p_{i,t-1}} \qquad (27)$$

$p_{i,t}$ and $p_{i,t-1}$ is the closing price on day t and day $t-1$. $r_{i,t}$ is the return on the asset on the day t. Statistical analysis of data was carried out in Excel. DCC, BEKK, CoVaR parameter estimation software was UCSD-GARCH toolkit of MATLAB.

Results and Discussion

Data Inspection

Descriptive statistical results of SSE Banks Index and P2P Index are as follows:

Table 2 Descriptive Statistics Results

	mean	median	Max	Min	SD	skewness	kurtosis	JB statistics
SSE Banks Index	0.05	-0.02	7.79	-9.36	1.61	-0.22	9.76	1896.52
Private P2P Index	0.08	0.15	6.20	-9.82	2.00	-0.69	5.73	461.36
Listed P2P Index	0.10	0.92	9.60	-10.56	3.21	-0.05	5.42	251.85
State-Owned P2P Index	0.16	0.00	9.56	-10.55	4.09	0.00	3.81	26.85
Venture-Capital P2P Index	0.05	0.00	9.62	-13.56	2.98	-0.25	6.39	504.41

[4] Before 2013, P2P industry did not enter full speed development. After 2017, the government began to regulate them, and the development speed of P2P industry slowed down

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The mean, median and standard deviation of P2P industry are higher than that of banking industry. Therefore, P2P industry is a typical high-risk and high-yield market. This feature accords with the status quo of disorderly development and barbarous growth of P2P industry. From the results of kurtosis and skewness, the skewness is not 0, and the skewness is all higher than 3, which is in line with the characteristics of financial investment products “sharp peak and heavy tail”. The statistical results of Jarque Bera presented significant non-normal distribution characteristics.

The premise of using GARCH model is that the selected sample sequence must be a stable time sequence and there is ARCH effect. Therefore, we need to carry out the ADF test and ARCH test for the above data respectively. The ARCH effect applies LM test method. The results are as follows:

Table 3 Stability and ARCH Effect Test Results

	ADF test	ARCH test
SSE Banks Index	-34.509	5.287
	(0.000)	(0.000)
Private P2P Index	-30.357	9.401
	(0.000)	(0.000)
Listed P2P Index	-30.490	8.925
	(0.000)	(0.000)
State-Owned P2P Index	-28.028	5.194
	(0.000)	(0.000)
Venture-Capital P2P Index	-30.725	10.295
	(0.000)	(0.000)

Note: the values in brackets are p-values at the level of 1% significance

In the ADF test, the time series of the five sets of data all reject the null hypothesis at the level of 1%, indicating that the five sets of data were all stable. From the results of ARCH test, it can be seen that at the significance level of 1%, the LM statistics of the time series of five sets of data are all larger than the critical value, rejecting the original hypothesis, and the time series data have a significant ARCH effect.

Vol. 3, No. 01; 2019

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The following are GARCH model estimation results and residual error test, specifically the ARCH coefficient, GARCH coefficient, and the ARCH test for residual error. The test results are shown in Table 4:

Table 4 GARCH Model Estimation Results and Residual Error Test

	ARCH coefficient α	GARCH coefficient β	$\alpha+\beta$	ARCH Test
SSE Banks Index	0.0853	0.9125	0.9978	0.2573
Private P2P Index	0.1028	0.8862	0.9890	0.7118
Listed P2P Index	0.0641	0.9312	0.9953	0.3961
State-Owned P2P Index	0.0740	0.9152	0.9892	0.8112
Venture-Capital P2P Index	0.1610	0.8370	0.9980	0.6007

The estimated results of all parameters are significant at the level of 1%, and the sum of the ARCH coefficient, the GARCH coefficient is close to 1, indicating that the conditional variance of the five groups of index is subject to persistent external shocks.

Then we tested the residual error of $\mathrm{GARCH}(1,1)$ model of five indexes, and found that the ARCH effect mentioned above no longer existed in the residual sequence data, so the next step of model estimation is to be carried out.

DCC-GARCH estimation results

After the data test, the co-mobility analysis of P2P industry and banking industry was conducted, that is, the DCC-GARCH model was used to estimate whether there is any risk spill over effect between them, and to measure the effect degree. The DCC-GARCH model process also adopts the $\mathrm{GARCH}(1,1)$ model. As both banks and P2P platforms have data missing, when estimating the model, the two indexes should be measured first to reduce the massive loss of data caused by low data coincidence. The measurement results are shown in Table 5:

Table 5 DCC-GARCH model Estimation Results

	α	β	$\alpha+\beta$
Banks and Private P2P Platforms	0.0309	0.9333	0.9642

	(0.000)	(0.015)	
Banks and Listed P2P Platforms	0.0320 (0.000)	0.9521 (0.000)	0.9841
Banks and State-Owned P2P Platforms	0.0120 (0.000)	0.9846 (0.000)	0.9966
Banks and Venture-Capital P2P Platforms	0.0275 (0.000)	0.9319 (0.000)	0.9594
Note: standard error in brackets			

It can be seen from the estimation results that, the result of $\alpha+\beta$ is close to 1, indicating that the correlation between P2P industry and the banking industry has a long memory and the correlation impact lasts a long time. According to the analysis above, the impact of the money contagion of P2P industry on the banking industry is long lasting. According to Table 5, we can describe the dynamic correlation coefficient and risk contribution between P2P platforms and banks. The first is the risk correlation coefficient between P2P platforms and banks, and the second is the risk contribution of P2P industry in the two figures.

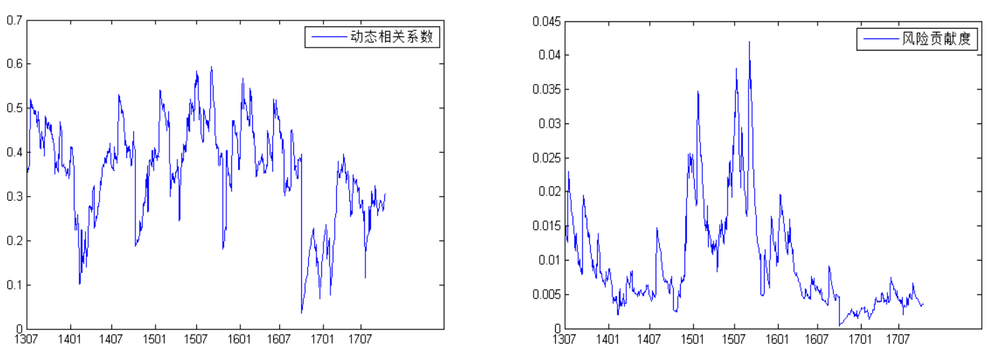

Figure 4 Risk Correlation between Banks and Private P2P Platforms and Risk Contribution of Private P2P Platforms

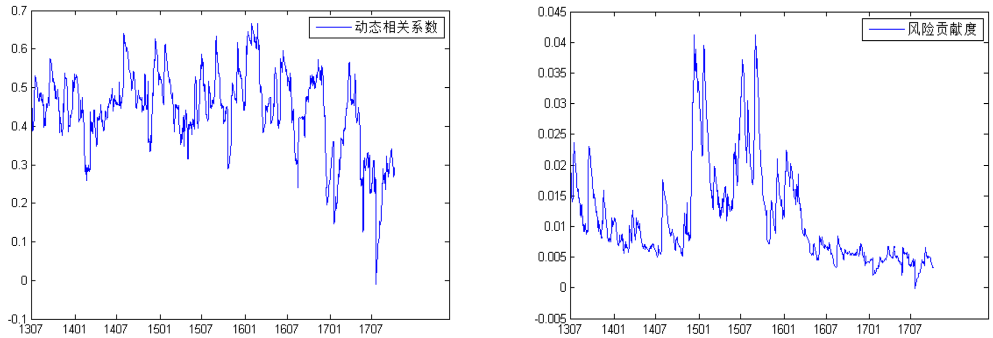

Figure 5 Risk Correlation between Banks and Listed P2P Platforms and Risk Contribution of Listed P2P Platforms

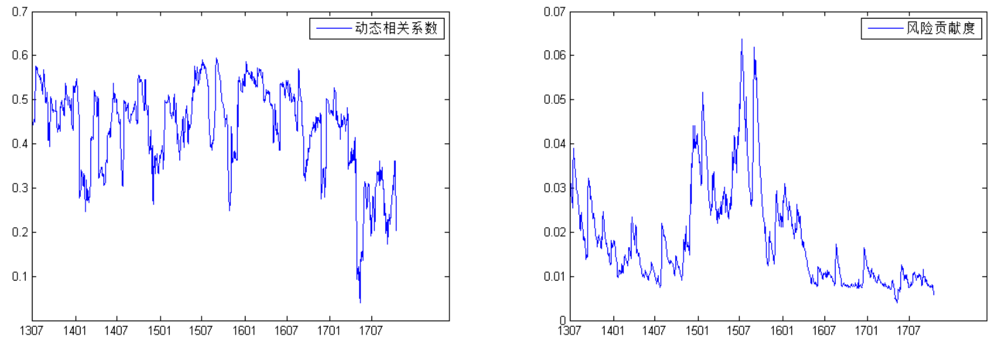

Figure 6 Risk Correlation between Banks and State-Owned P2P Platforms and Risk Contribution of State-Owned P2P Platforms

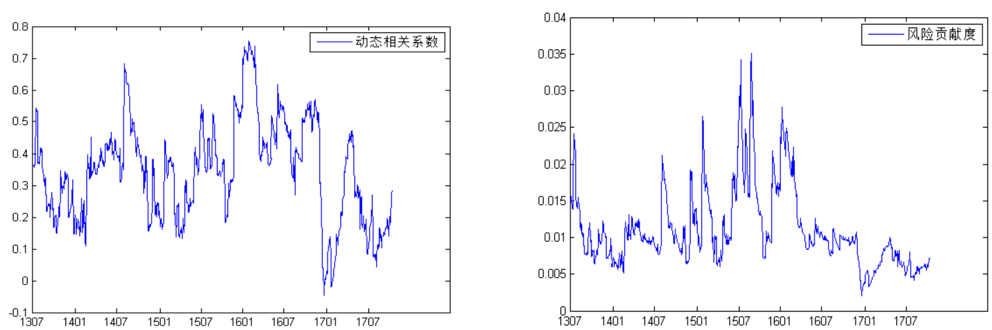

Figure 7 Risk Correlation between Banks and Venture-Capital P2P Platforms and Risk Contribution of Venture-Capital P2P Platforms

1307 in Figures 4 to 7 represents July 2013 while 1401 represents January 2014. The rest can be inferred in a similar manner. As can be seen from the correlation coefficient, which is stable,

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around 0.5, there is a significant risk correlation between P2P industry and the banking industry. Therefore, it is preliminarily proved that there exists the risk contagion channel mentioned above. Among them, listed P2P platforms and Banks are more contagious, with private P2P platforms secondary, and State-owned P2P platforms and venture-capital P2P platforms less contagious. However, the risk contribution rate is different. The highest risk contribution lies in the State-Owned P2P platforms, with the value reaching 0.06. The Listed P2P platforms come next, about 0.04. The contribution rate of Venture-Capital P2P platforms is relatively lower, about 0.035.

We take the Listed P2P platforms as an example. In 2013, the risk correlation between P2P platforms and banks was around 0.5. After half a year, it declined briefly, but soon rose to 0.6. Between 2014 and 2015, the correlation coefficient fluctuated between 0.5 and 0.6. In the middle of 2015, the correlation gradually decreased, but there were many fluctuations. The correlation between the two has been at a low point recently and is expected to rebound in the future.

The risk contribution fluctuation is similar to that of the risk correlation. At the beginning, the contribution slowly decreased to 0.005 at the bottom, but in the middle of 2014, there was a sudden explosion, with the highest value exceeding 0.04. After a month, the risk contribution declined, then quickly recovered above 0.04. After that, there was a significant decline. From the tail situation, it can be seen that there is room for the risk contribution to rise in the future.

As far as the background is concerned, Listed P2P platforms have the closest relationship with bank capital, since they are based on listed companies in China. The precipitation and trusteeship of funds are inseparable from banks, so the Listed P2P platforms have the strongest risk linkage with banks, with the risk contribution rate relatively high. P2P platforms have strong linkage with commercial banks due to the lack of supervision of the P2P industry, which started a disorderly growth trend since 2013. At the very beginning, the banking industry did not regard P2P industry as a risk point due to advanced development itself, and they even joined hands with P2P platforms to create an innovative model of cooperation to adhere to the financial innovation, which sowed the seeds of the risk capital contagion.

BEKK Estimation Results

Table 6 Volatility Spill over Effects of Private P2P Platforms and Banks

BEKK Estimation in private P2P platform			
B		A	
0.97	0.017	0.24	-0.05
（16.79）	（0.756）	（9.059）	（-0.98）
-0.04	0.93	0.075	0.419

Vol. 3, No. 01; 2019

ISSN: 2456-7760

(-1.908)	(13.06)	(5.58)	(13.94)
Log Likelihood Ratio L=-4326.85			
Test the hypothesis of spillover effect			
There is no spillover effect：H_0		L=-4319.35	
$\beta_{21}=0$，$\alpha_{21}=0$		LR=29.34（0.057）	
$\beta_{12}=0$，$\alpha_{12}=0$		Wald=6.176（<0.019）	
There is no spillover from A to B：H_0		L=-4318.44	
$\beta_{12}=0$，$\alpha_{12}=0$		LR=1.424（0.491）	
		Wald=2.26（0.32）	
There is no spillover from B to A：H_0		L=-4320.19	
$\beta_{21}=0$，$\alpha_{21}=0$		LR=19.48（0.038）	
		Wald=13.77（<0.01）	
Note: t-values in parentheses			

Table 7 Volatility Spill over Effects of Listed P2P Platforms and Banks

BEKK Estimation in listed P2P platform			
B		A	
0.94	0.02	0.356	0.018
(109.6)	(0.27)	(10.31)	(0.13)
0.008	0.976	-0.045	0.199
(1.79)	(187.16)	(-1.69)	(8.313)
Log Likelihood Ratio L=-4160.56			
Test the hypothesis of spillover effect			

There is no spillover effect：H_0	L=-4167.90
$\beta_{21}=0$，$\alpha_{21}=0$	LR=12.07（0.01）
$\beta_{12}=0$，$\alpha_{12}=0$	Wald=24.32（<0.01）
There is no spillover from A to B：H_0	L=-4167.78
$\beta_{12}=0$，$\alpha_{12}=0$	LR=0.554（0.73）
	Wald=1.53（0.47）
There is no spillover from B to A：H_0	L=-4165.68
$\beta_{21}=0$，$\alpha_{21}=0$	LR=15.03（<0.01）
	Wald=23.96（<0.01）
Note: t-values in parentheses	

Table 8 Volatility Spill over Effects of State-owned P2P Platforms and Banks

BEKK Estimation in state-owned P2P platform			
B		A	
0.97	0.092	0.199	-0.039
（73.79）	（0.25）	（6.67）	（-0.46）
-0.114	0.85	0.02	0.163
（-25.71）	（62.75）	（2.629）	（5.035）
Log Likelihood Ratio L=-4287.12			
Test the hypothesis of spillover effect			
There is no spillover effect：H_0		L=-4280.37	
$\beta_{21}=0$，$\alpha_{21}=0$		LR=6.83（0.13）	
$\beta_{12}=0$，$\alpha_{12}=0$		Wald=12.53（<0.01）	

There is no spillover from A to B：H_0	L=-4275.49
$\beta_{12}=0$，$\alpha_{12}=0$	LR=0.98（0.67）
	Wald=1.609（0.45）
There is no spillover from B to A：H_0	L=-4295.33
$\beta_{21}=0$，$\alpha_{21}=0$	LR=6.7（0.031）
	Wald=13.57（<0.01）
Note: t-values in parentheses	

Table 9 Volatility Spill over Effects of Venture-capital P2P Platforms and Banks

BEKK Estimation in venture-capital P2P platform			
B		A	
0.968	0.093	0.028	-0.028
（65.12）	（0.25）	（8.39）	（-0.56）
-0.22	0.74	0.037	0.194
（-2.98）	（43.83）	（2.96）	（9.21）
Log Likelihood Ratio L=-4200.49			
Test the hypothesis of spillover effect			
There is no spillover effect：H_0		L=-4210.49	
$\beta_{21}=0$，$\alpha_{21}=0$		LR=6.99（0.17）	
$\beta_{12}=0$，$\alpha_{12}=0$		Wald=15.44（<0.01）	
There is no spillover from A to B：H_0		L=-4212.53	
$\beta_{12}=0$，$\alpha_{12}=0$		LR=0.142（0.93）	
		Wald=0.188（0.91）	

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There is no spillover from B to A ：H_0	L=-4215.44
$\beta_{21}=0$，$\alpha_{21}=0$	LR=33.15（<0.01）
	Wald=93.61（<0.01）
Note: t-values in parentheses	

The tables above contain BEKK results of four types of P2P platforms. The first part is the results of the BEKK model maximum likelihood estimation without limiting the parameters. Angle elements in the matrix A and B are significant, indicating that the fluctuation of P2P platforms and banks is significantly affected by the previous fluctuation degree. From the analysis of single market results, the volatility has clustering property, and the parameter estimation result meets the condition of covariance stationarity required by the BEKK model. In addition, the sum of the eigenvalues is close to 1, indicating that volatility is highly persistent.

The second part is the hypothesis test of the spillover effect. The original hypothesis is that "non-diagonal elements of parametric matrices A and B are all 0", that is, none of them has spill-over effects: H_0：$\beta_{21}=0$，$\alpha_{21}=0$，$\beta_{12}=0$，$\alpha_{12}=0$.The LR value of diagonal GARCH model is significantly reduced compared to the BEKK estimation results without restriction conditions, so the original hypothesis can be rejected at the significance level of 1%. Similarly WALD tests indicate that not all four elements are 0. This test proves again the estimation results of the DCC-GARCH model above, that is, there is risk linkage between P2P industry and the banking industry. However, this linkage cannot determine the risk direction, so we need to conduct the next step of separate hypothesis testing, namely the infectious direction verification of risk linkage.

First, we make the hypothesis that "P2P platform does not have overflow effect on Banks" and "Banks do not have overflow effect on P2P platforms", that is, there is no overflow effect from A to B: H_0：$\beta_{12}=0$，$\alpha_{12}=0$ and there is no overflow effect from B to A: H_0：$\beta_{21}=0$，$\alpha_{21}=0$. For the first hypothesis, the L value of the model is not significantly reduced, but the p-value of LR test and WALD test are greater than 1%, so the original hypothesis cannot be rejected. For the second hypothesis, the p-value tested by LR and WALD was less than 1%, so the original hypothesis was rejected. In addition, the lower trig elements of matrices A and B are close to 0, and t-values are not significant. However, the upper triangular element is more significant, especially, β_{12} is not 0 at the 99% confidence level. Based on the two hypotheses and relevant analysis, we can see that the risk co-mobility between P2P industry and banking industry is mainly from P2P platforms to Banks.

Conclusion

This paper takes the P2P platforms in Internet finance as subjects to explore how the P2P platforms can transmit its own risks to commercial banks through its fund deposit and business transactions with the banking industry, that is, to explore the risk contact infection mechanism caused by capital transactions. We use the DCC-BEKK-MVGARCH model to verify the infection mechanism. Specifically, the model divides the current domestic 1585 P2P platforms into private, listing, state-owned, and venture capital platforms according to the platform background. This paper uses the daily income of each platform from July 1, 2013 to July 1, 2017 to make the P2P platform development index, and matches them with the Shanghai Stock Exchange Index to explore the risk linkage between Internet finance and banking industry and the direction of risk spill over effects. Research findings show that there is indeed a risk linkage between the P2P platforms and the banking industry, that is, the fund-contagion mechanism, and the direction is from the P2P platform to the banking industry. Among them, the P2P platforms in the listing system are more contagious, followed by the P2P platforms of the private sector, the P2P platforms of the state-owned system and the P2P platforms of the VC system respectively.

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