Hindawi
Complexity
Volume 2019, Article ID 1635793, 8 pages
https://doi.org/10.1155/2019/1635793

Research Article

Dynamic Cross-Correlations between Participants' Attentions to P2P Lending and Offline Loan in the Private Lending Market

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Received 19 August 2019; Revised 15 October 2019; Accepted 15 November 2019; Published 12 December 2019

Guest Editor: Shu-Heng Chen

In this paper, we examine the dynamic cross-correlations between participants' attentions to the P2P lending and offline loan (lending) with the method of multifractal detrended cross-correlation analysis (MF-DCCA). The empirical result mainly shows that (1) the power-law cross-correlation exists between participants' attentions to the P2P lending and offline loan and is persistent, (2) the cross-correlation is more stable in the short term, and (3) the relation subjected to a small fluctuation is more cross-correlated than that under larger ones. Furthermore, we carry out the robustness test to verify the result. The Granger causality test indicates that participants' attentions to P2P lending and offline loan Granger cause each other in the short term.

1. Introduction

The formal credit market, the subject of which includes banks, mainly provides loans for enterprises and institutions and seldom provides funds for either small and medium enterprises (SMEs) or individuals [1, 2]. Therefore, it is difficult for SMEs and individuals to raise funds [3, 4]. Luckily, the informal credit market serves SMEs and individuals, mitigating this problem effectively [5–7]. Schreiner [5] describes multiple ways for microfinance to acquire the virtues of informal finance, such as using collateral that is easy to repossess. Barslund and Tarp [6] and Khoi et al. [7] find that informal finance has effectively alleviated the problem of Vietnamese farmers' borrowing. The informal credit market, in which present cash is exchanged for promises of cash in the future through contracts or agreements conducted without reference or recourse to the legal system, primarily comprises private lending, and savings group [8–10]. In China, lending is the dominant part of informal finance [11]. The offline loan (lending) has a smaller business radius and a stronger social network and is more conducive to obtaining "soft" information on borrowers by reducing the geographical distance between borrowers and lenders and strengthening the social network [12, 13]. Before 2007, the offline loan is the main body of the informal credit market. With the development of Internet finance, the P2P (peer-to-peer) lending platform has received more attention [14]. So far, online lending and offline loan constitute the private lending system, forming the major constituent of the informal finance network.

While offline loan has existed for quite a long time, the first online lending platform in China came into being in 2007. From then on, the P2P lending platform has been growing rapidly, with the number of platforms soaring to more than 6000 and the quantity of participants reaching as high as 10 million at the peak (https://shuju.wdzj.com/industry-list.html). However, after the government implemented regulatory measures aiming to standardize market behavior and guard against financial risks, a pyramid of P2P lending platforms that did not meet the requirements of provisions were squeezed out of market (http://wdzjosscdn.oss-cn-hangzhou.aliyuncs.com/pdf/2018年中国网络借贷 行业年报.pdf). At present, there are only about 600 platforms, and the quantity of participants has been reduced to 4 million (https://shuju.wdzj.com/industry-list.html). It is intuitive to come up with the anticipation that offline loan would rise to fill the vacancy of vanishing P2P lending, and consequently investors would be more likely to turn to offline loan to attend their need, but further consideration and reflection render the speculation to criticism. For platforms, policy orientation is sure to cast enormous influence on their subsistence and operation, but for participants, a common influence factor of more importance is price of money, which is determined by the base interest rate and market support demand. The credit side and the debtor agree on the lending rate and then conclude a transaction. From this point of view, the lending rate partly affects participants in selecting the way of lending. While P2P lending and offline lending organizations share the overall same fluctuation trend in the loan interest rate [13], participants' attentions to offline loan and P2P lending show difference to a more sophisticated and complex extent: when investors are eager to obtain funds from offline loan institutions, they either withdraw their appeal from P2P lending platforms to lower capital cost or do not mind borrowing in two different ways to catch market opportunity, and vice versa. In this paper, we employ Baidu Search Index on P2P lending and offline loan as proxies of participants' attentions to P2P lending and offline loan, respectively. Baidu Search Index can represent participants' attentions. (Baidu Search Index is a data sharing platform based on Baidu's massive behavior data of Internet users. Here, you can study keyword search trends and insight into the interests and needs of netizens and monitor public opinion trends (http://zhishu.baidu.com/Helper/?tpl=duty). There exist other factors that influence the selection between P2P lending and offline loan, such as qualification review, i.e., the level of difficulty to grant a loan, yet they are not the focus of this paper. As discussed above, the nexus between participants' attention to P2P lending and that to offline loan is complex and dynamic. And, it is meaningful to explore the correlation of participants' attentions in the whole private lending market in China. Recent research on the private lending market system mainly includes (1) the related research on the P2P lending market, such as borrowing success rate and default rate [14–18], investor behavior [19–22], and credit evaluation and market mechanism [23–28]; (2) the relationship between the informal credit market and the formal credit market [6, 29–32]; and (3) the research on offline loan [33–35]. Therefore, this paper expands the research scope of the existing literature by investigating the extent of interdependence across time to clarify whether participants' attentions to P2P lending and offline loan are segmented or becoming more integrated.

The Pearson, Spearman, and Kendall correlations are conventional methods extensively used in investigating the relationship between two variables. The Pearson coefficient measures linear correlation, yet its application relies on the precondition that the time series are stationary and obey the normal distribution. Different from the Pearson correlation, Spearman and Kendall correlations are nonparametric tests of rank correlation. Each of them does not depend on any assumptions on the distribution and assesses the significance of the relation by comparing rankings of the variables. While multifractality is ubiquitously observed in socioeconomic systems [36], the aforementioned traditional correlation methodologies are not tested and verified by existing documents to examine multifractality. Therefore, both detrended cross-correlation analysis (DCCA) advanced by Podobnik and Stanley [37] and multifractal detrended cross-correlation analysis (MF-DCCA) proposed by Zhou [38] are selected to study the cross-correlations between participants' attentions to P2P lending and offline loan. After implementing numerical experiments with mathematical models, researchers have confirmed the characteristics of the DCCA coefficient and justified its advantage over the Pearson coefficient [36, 39–44]. Kristoufek [40] confirms that, for the nonstationary series, the DCCA coefficient measures correlation accurately despite various levels of nonstationarity and dominates the Pearson coefficient. Compared with the Pearson correlation coefficients, the DCCA coefficients are scale-dependent and more robust to the amplitude ratio between slow and fast components and contaminated noises [45].

The remainder of this paper is organized as follows: Section 2 describes the data used in this paper and their statistical characteristics. Section 3 describes the procedure of the methodology of MF-DCCA. Section 4 reports the relevant empirical results of MF-DCCA, and Section 5 concludes this paper.

2. Data Description

We obtain daily search volume data of P2P lending and offline loan from Baidu Search Index. Like Google Trends [46], Baidu Search Index has been used as a proxy of attention [47, 48]. In this paper, we choose the keywords "P2P lending" and "offline loan" to achieve searching volumes. The P2P lending search volume reflects participants' attention. The higher the index, the more the attention P2P lending arouses. The offline loan search volume has a similar meaning. P2P lending and offline loan constitute the private lending network system. So the search volumes can represent participants' attention to the approach of borrowing or lending in the private lending network. The whole sample period extends from January 1, 2011, to July 3, 2019.

In order to explore cross-correlations between participants' attention to P2P lending and that to offline loan, we define two variables as follows:

$$\begin{aligned} \mathrm{P2P}_t &= \ln\left(\mathrm{P2P}_t\right),\\ \mathrm{loan}_t &= \ln\left(\mathrm{loan}_t\right), \end{aligned} \tag{1}$$

where $\mathrm{P2P}_t$ is the Baidu index of P2P lending and loan_t is the Baidu index of offline loan in time t, respectively.

Table 1 shows the statistical properties of P2P lending and offline loan searching indices, including mean, median, stand deviation, kurtosis, max value, min value, skewness, and Jarque–Bera test values. As we can see in Table 1, the mean, median, min, and max values of the P2P lending searching index are larger than those of the offline loan searching index, indicating keen interest for P2P lending. It is reasonable to speculate that P2P lending raises far more attention than does offline loan because of its Internet foundation. Both the KPSS test and augmented Dickey–Fuller test reject the null hypothesis that a unit root exists at

Table 1: Statistics of searching indices.

Var.	Obs.	Mean	Median	Std.	Max	Min	Ske.	Kur.	Jar.
P2P	3106	9436.146	7496.5	5102.071	63190	1868	1.841	9.923	7957.118***
Loan	3106	1404.857	1279	549.201	10784	218	2.939	38.905	171316.870***

***indicates statistical significance at the 1% level. Ske. is skewness; Kur. is Kurtosis; Jar. is Jarque–Bera; Std. is standard deviation.

the 1% significance level and justify the appropriateness of the Jarque–Bera test. The Jarque–Bera test values of two variables are all significant, and the null hypothesis of following a normal distribution is rejected.

3. Empirical Methodology

We employ the method of MF-DCCA introduced by Zhou [38] to analyze the cross-correlation between participants' attention to P2P lending and that to offline loan. Consider two equal time series $\{x_i\}$ and $\{y_i\}$, where $i = 1, 2, \ldots, N$. The detailed steps of the methodology can be described as follows:

Step 1: construct two profiles by the two time series as

$$X_i = \sum_{k=1}^{i} (x_k - \overline{x}),$$
$$Y_i = \sum_{k=1}^{i} (y_k - \overline{y}), \quad (2)$$
$$i = 1, 2, \ldots, N,$$

where $\overline{x} = 1/N\sum_{k=1}^{N} x_k$ and $\overline{y} = 1/N\sum_{k=1}^{N} y_k$.

Step 2: the two profiles are divided into $N_s = [N/s]$ nonoverlapping segments of equal length s. If the length N cannot be divisible by scale s, a short part segment at the end of each profile will be left. In order to extract all the information involved in the profiles, the same division procedure is repeated from the other end of the profile and we obtain $2N_s$ segments of each profile consequently. According to the research of Zhang et al. [43], which employs Internet-based data as is the case in this paper, we set the scale s as $10 < s < N/4$, and the step is 1 in this paper.

Step 3: the detrended covariance is calculated by

$$F^2(s, v) = \frac{1}{s}\sum_{j=1}^{s}\left[X_{(v-1)s+j} - \widetilde{X}_{(v-1)s+j}\right]\left[Y_{(v-1)s+j} - \widetilde{Y}_{(v-1)s+j}\right],$$
$$\text{for } v = 1, 2, \ldots, N_s, \quad (3)$$

$$F^2(s, v) = \frac{1}{s}\sum_{j=1}^{s}\left[X_{N-(v-N_s)s+j} - \widetilde{X}_{N-(v-N_s)s+j}\right]\left[Y_{N-(v-N_s)s+j} - \widetilde{Y}_{N-(v-N_s)s+j}\right], \quad (4)$$

for $v = N_s + 1, N_s + 2, \ldots, 2N_s$, where $\widetilde{X}$ and $\widetilde{Y}$ are local trends estimated in each segment through the OLS method.

Step 4: average all detrended segments to get the q th-order fluctuation function as

$$F_q(s) = \left\{\frac{1}{2N_s}\sum_{v=1}^{2N_s} F^2(s, v)^{q/2}\right\}^{1/q}. \quad (5)$$

When $q = 0$, the equation is defined as

$$F_0(s) = \exp\left\{\frac{1}{4N_s}\sum_{v=1}^{2N_s} \ln\left[F^2(s, v)\right]\right\}. \quad (6)$$

Step 5: observe the log-log plots of $F_q(s)$ versus s and analyze the scaling behavior of the fluctuation function. If the two series are long-range cross-correlated, there exists a following power-law relation between them:

$$F_q(s) \propto s^{H_{xy}(q)}. \quad (7)$$

The slope of the log-log plots of $F_q(s)$ versus s can be estimated with the method of OLS and denoted as $H_{xy}(q)$, which is an indicator of the cross-correlation of the two time series. If $H_{xy}(q) < 0.5$, the cross-correlation between them is antipersistent (negative); if $H_{xy}(q) > 0.5$, the cross-correlation between them is persistent (positive); when $H_{xy}(q) = 0.5$, no cross-correlation exists between the two time series. In particular, when $q = 2$, the scaling exponent $H_{xy}(q)$ turns into the generalized Hurst exponents.

4. Empirical Results

4.1. Cross-Correlation Test. In order to have a macroscopic and qualitative view of the correlation participants' attention in the private lending market to P2P lending and that to offline loan, we first carry out a cross-correlation test advanced by Podobnik and Stanley [37], which is defined as

$$Q_{cc}(m) = N^2\sum_{i=1}^{m}\frac{X_i^2}{N-i}, \quad (8)$$

where X_i^2 is the cross-correlation function defined as

$$X_i^2 = \frac{\sum_{k=i+1}^{N} x_k y_{k-i}}{\sqrt{\sum_{k=1}^{N} x_k^2 \sum_{k=1}^{N} y_k^2}}, \quad (9)$$

where $\{x_i\}$ and $\{y_i\}$ are the two time series that have the same length N.

The test statistic $Q_{cc}(m)$ is approximately chi square distributed with m degrees of freedom. The null hypothesis of this cross-correlation test is that none of the first m cross-correlation coefficient is different from zero. Thereby, if the value of the test statistic $Q_{cc}(m)$ exceeds the critical value of $\chi^2(m)$, a significant cross-correlation between the two time series exists.

Figure 1 shows the results of the test statistic $Q_{cc}(m)$ between P2P lending and offline loan. The degrees of freedom vary from 1 to 1000, and the black line denotes the critical value of $\chi^2(m)$ at the 5% significant level. The $Q_{cc}(m)$ statistics are always larger than the critical value, and thus, the null hypothesis of no cross-correlations can be rejected. There are long-range cross-correlations in series of participants' attentions to P2P lending and offline loan.

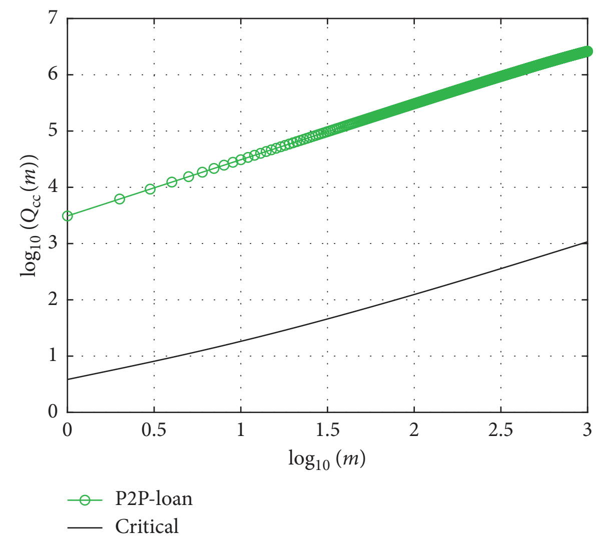

Figure 1: Cross-correlation test ($Q_{cc}(m)$).

4.2. Multifractal Detrended Cross-Correlation Analysis. Now that the test statistic $Q_{cc}(m)$ provides qualitative evidence that the long-range cross-correlation between attention to P2P lending and that to offline loan is existent, we then conduct the quantitative method, MF-DCCA, to analyze the cross-correlations of attentions. In this paper, the order q is set from −10 to 10, and the step is 1. If $q < 0$, the paired time series means a small fluctuation; if not, it symbolizes a large fluctuation. Figure 2 depicts the log-log plots of $F_{xyq}(s)$ versus s for P2P lending and offline loan, and the order q of lines increases from the bottom to the top. As we can see, all lines fit the log-log line of $F_{xyq}(s)$ versus s, proving that the power-law cross-correlation between the pair exists.

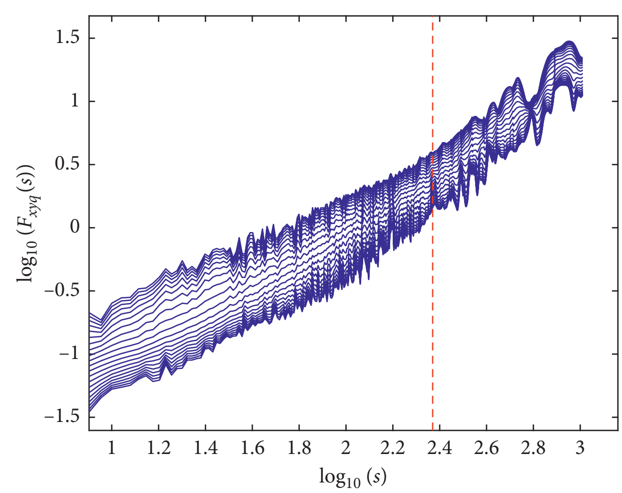

Figure 2: Log-log plots of $F_{xyq}(s)$ versus s for P2P-loan.

Figure 3 shows the scaling exponents of cross-correlation for P2P lending-offline loan with the varying order of q. The values of $H_{xy}(q)$ for P2P-loan are both above 0.5, indicating that the cross-correlation between attention to P2P lending and that to offline loan is persistent. As q increases, $H_{xy}(q)$ for P2P-loan has a mainly downward trend, demonstrating that the relation during a small fluctuation is more cross-correlated than that during the large one.

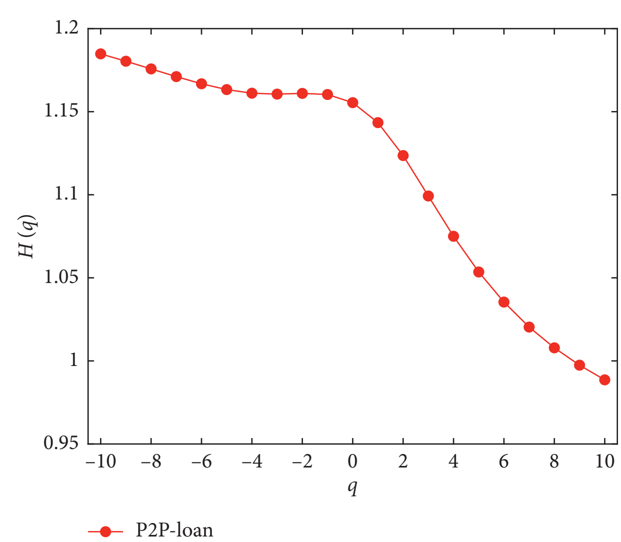

Figure 3: MF-DCCA scaling exponents for P2P-loan.

Podobnik et al. [49] suggest that a turning point S^* referred to as the "crossover" can indicate the fundamental change in the linear trend of the curves. In this paper, we can find $S^* = 2.37$ (about 234 days) in Figure 2. As is vividly pictured in Figure 4, the scaling exponents for P2P-loan in the long term $(S > S^*)$ are larger than those in the short term $(S < S^*)$, implying that the cross-correlations in the short term are less persistent. As q increases, P2P-loan scale exponents in both long and short terms incline to reduce in general, and we can infer that relations subjected to small fluctuations are more cross-correlated than those under larger ones. ΔH_q is introduced to explore the degree of multifractality by Yuan et al. [50], and the larger the ΔH_q, the higher the degree of multifractality.

$$\Delta H_q = \max\left(H_q\right) - \min\left(H_q\right). \tag{10}$$

ΔH_q of P2P-loan in the short term reported in Table 2 is smaller than that in the long term. From ΔH_q, we can conclude that the cross-correlation of attention to P2P lending and that to offline loan is more stable in the short term.

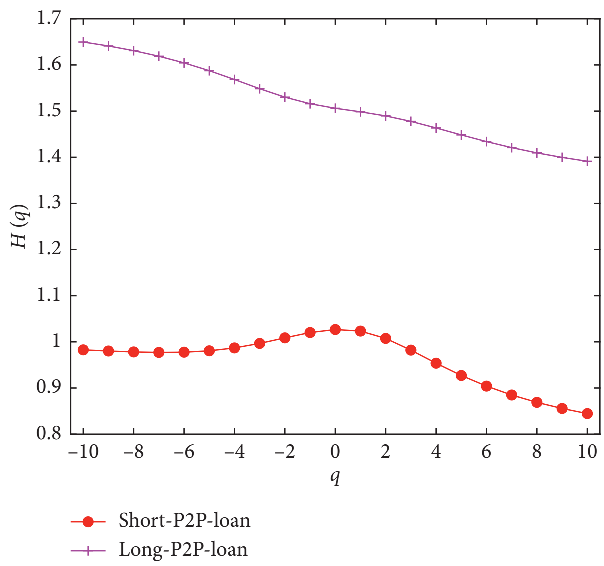

Figure 4: Short and long scaling exponents for P2P lending-offline loan.

Table 2: Cross-correlation scaling exponents $H_{xy}(q)$ for P2P-loan with q varying from −10 to 10.

q	P2P-loan $S^* = 234$	
	$S < S^*$	$S > S^*$
−10	0.9827	1.6497
−9	0.9802	1.6411
−8	0.9782	1.6310
−7	0.9771	1.6189
−6	0.9776	1.6045
−5	0.9806	1.5875
−4	0.9868	1.5684
−3	0.9966	1.5485
−2	1.0087	1.5302
−1	1.0202	1.5159
0	1.0267	1.5061
1	1.0233	1.4984
2	1.0074	1.4895
3	0.9821	1.4777
4	0.9537	1.4634
5	0.9271	1.4484
6	0.9041	1.4339
7	0.8848	1.4208
8	0.8689	1.4094
9	0.8556	1.3996
10	0.8445	1.3913
ΔH_q	0.1821	0.2584

S^* is a turning point at which the linear tendency of the curve changes fundamentally. When $S < S^*$, the scale exponent denotes short-term-related behavior. And when $S > S^*$, the scale exponent reflects long-term-related behavior. q indicates the order of fluctuation function described in equation (5). ΔH_q denotes the degree of multifractality.

4.3. Quantile Regression. The above nonlinear pattern motivates a further examination of the relationship between search volumes of P2P lending and offline loan. We apply a quantile regression to examine whether such a relationship exhibits a systematic change. Quantile regression is first proposed by Koenker and Bassett [51] and, more recently, is employed to study stock return autocorrelations [52], research the effect of investor sentiment on stock returns [53], and examine the relationship between the magnitude of the herding effect and the number of investors [54]. In this paper, the quantiles including 5%, 10%, 25%, 50%, 75%, and 90% are chosen to conduct the quantile regression analysis. The regression model is

$$\text{loan}_{(\tau)t} = \alpha_{(\tau)} + \beta_{(\tau)}\text{P2P}_{(\tau)t}, \tag{11}$$

in which τ represents the quantile and $\alpha_{(\tau)}$ and $\beta_{(\tau)}$ denote the coefficient of regression terms. From Table 3, we see that the estimated coefficients for cross-correlation remain statistically significant across different quantiles, indicating the robustness of cross-correlations between attentions to P2P lending and offline loan.

4.4. Granger Causality Test. Before performing the Granger causality test, we tested the stationary property of the time series in the regression model by carrying out the augmented Dickey–Fuller test and KPSS test. And the null hypothesis that a unit root exists is rejected. The pairwise Granger causality test employed in this paper follows the following equation:

$$\begin{aligned} \text{P2P}_t &= \sum_{i=1}^{m} \alpha_i \text{loan}_{t-i} + \sum_{j=1}^{m} \beta_j \text{P2P}_{t-j} + \mu_{1t}, \\ \text{loan}_t &= \sum_{i=1}^{n} \lambda_i \text{loan}_{t-i} + \sum_{j=1}^{n} \delta_j \text{P2P}_{t-j} + \mu_{2t}, \end{aligned} \tag{12}$$

in which m and n signify "model order," i.e., the quantity of lagged observations contained in the multivariate regression model. And the result of the pairwise Granger causality test is depicted in Figure 5. A low p value (<0.1) rejects the hypothesis of no causality and indicates a significant causal relation. When lag < 32, the attention to P2P lending always Granger causes that to offline loan at the 10% significance level; when lag = $[2, 3, 4, 6, 7, 8, 9, 10]$, the attentions to P2P lending and offline loan Granger cause each other at the 10% significance level.

However, there might exist a large number of neutral participants in the credit market that have no preference for either of the two types of lending and search both P2P lending and offline loan on Baidu to get informed before making decisions. In this case, the empirical result that participants' attentions to P2P lending and offline loan Granger cause each other in the short run can even be reduced to unreliable. To ruling out this possibility, we construct two new series, i.e., loan_P2P$_t$ and P2P_loan$_t$, both of which are derived from the following equation:

$$\begin{aligned} \text{loan\_P2P}_t &= \max\left(\text{loan}'_t - \text{P2P}'_t, 0\right), \\ \text{P2P\_loan}_t &= \max\left(\text{P2P}'_t - \text{loan}'_t, 0\right), \end{aligned} \tag{13}$$

in which loan'_t and $\text{P2P}'_t$ are obtained from normalizing loan_t and P2P_t to the scale of 0 to 100, respectively.

Table 3: Estimation results of quantile regression.

Quantile	$\alpha_{(\tau)}$	$\beta_{(\tau)}$
0.05	426.9315 (0.0000)***	0.0369 (0.0000)***
0.10	488.3254 (0.0000)***	0.0426 (0.0000)***
0.25	739.9957 (0.0000)***	0.0386 (0.0000)***
0.50	933.3032 (0.0000)***	0.0402 (0.0000)***
0.75	1055.0440 (0.0000)***	0.0654 (0.0000)***
0.90	1550.3950 (0.0000)***	0.0550 (0.0000)***

The regression model is $\text{loan}_{(\tau)t} = \alpha_{(\tau)} + \beta_{(\tau)}\text{P2P}_{(\tau)t}$, in which $\text{P2P}_{(\tau)t}$ is the Baidu index of P2P lending, $\text{loan}_{(\tau)t}$ is the Baidu index of offline loan in time t, τ represents the quantile, and $\alpha_{(\tau)}$ and $\beta_{(\tau)}$ denote the coefficient of regression terms. p values and t statistics are in parentheses $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

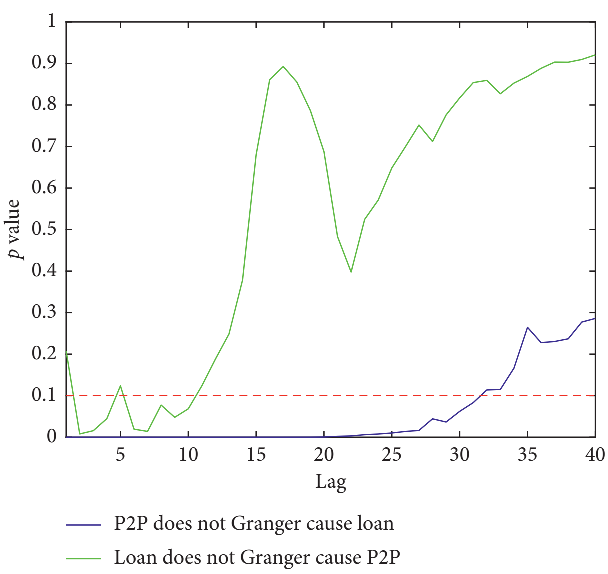

Figure 5: Granger causality test. The dashed line represents the significance level of 10%.

loan_P2P_t (P2P_loan_t) is supposed to capture the participants' attention to offline loan (P2P-lending) with neutral participants' searching behavior for P2P lending (offline loan) excluded. Then, we employ the Granger causality test with the two new series. As Figure 6 depicts, the consequent robustness result is consistent with the empirical result in the short term: when lag < 6, the attentions to P2P lending and offline loan Granger cause each other at the 10% significance level.

5. Conclusions

In this paper, we focus on the private lending network system which consists of P2P lending and offline loan and investigate the cross-correlations of participants' attention between two types of lending. In particular, we conduct the cross-correlation test with multifractal

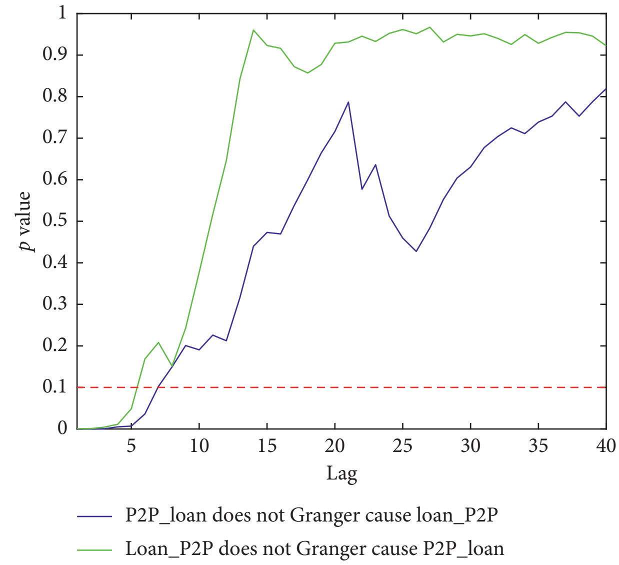

Figure 6: Granger causality test with the new series. The dashed line represents the significance level of 10%.

detrended cross-correlation analysis (MF-DCCA). Based on the search volumes of P2P lending and offline loan from Baidu Search Index, the empirical results show that (1) there are long-range cross-correlations in series of attentions to P2P lending and offline loan, (2) the cross-correlation exponents $H_{xy}(q)$ of attentions to P2P lending and offline loan are both above 0.5, denoting persistent correlation between attentions to P2P lending and offline loan in the private lending, and (3) as order q increases, $H_{xy}(q)$ for P2P lending and offline loan has a mainly downward trend, and the small fluctuation is more cross-correlated than the large one. Furthermore, quantile regression and Granger causality test consolidate the conclusion. The Granger causality test further indicates that participants' attentions to P2P lending and offline loan Granger cause each other during a period less than two weeks, while in a relatively longer time span, i.e., a month, the attention to P2P lending always Granger causes that to offline loan.

Admittedly, the above results cannot completely reveal the relationship between attentions to the two types of lending. To further explore the attentions to P2P lending and offline loan in the credit market, factors such as the interest rate, qualification examination, and mutual transformation between offline loan and P2P lending remain to be investigated in the future.

Data Availability

The data of participants' preferences for P2P lending and offline loan used to support the findings of this study are currently under embargo, while the research findings are commercialized. Requests for data, 12 months after publication of this article, will be considered by the corresponding author. Our data are derived from Baidu Search Index, and we have complied with terms of use stated on the website http://index.baidu.com.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This research was supported by the National Natural Science Foundation of China (71532009 and 71661137001).

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