The Effects of the Stock Market on the Peer-to-peer (P2P) Lending market: An Empirical Study of a Chinese P2P Lending Platform

Master Thesis

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ABSTRACT

In the past decade, the online Peer-to-Peer (P2P) lending market has been rapidly expanding in China. I use the public dataset from Renrendai, a leading online P2P platform in China to study the effects of the stock market on the probability of funding and the default rate in the P2P market. By means of the empirical research, it is confirmed that in a bullish stock market, lenders become less concerned about the risk indicators of credit scores, interest rate spreads, and onsite verification. Moreover, the default rate has a significantly positive correlation with the stock market return on the origination day of the loan. However, for loans with high credit scores or low interest rate spreads, the default rates become less sensitive to the stock market return. These conclusions have practical value for lenders to control risks in the P2P lending market.
Key words: P2P lending market stock market probability of funding default rate

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1. INTRODUCTION

Online peer-to-peer (P2P) lending is a financing channel based on electronic platforms and electronic commerce credit. Borrowers and lenders can use Internet platforms to achieve transactions by themselves. This channel provides more opportunities for individual borrowers and small enterprises to acquire funds since it is difficult for them to access loans from banks. However, the default risk exists in this process, which refers to the possibility that borrowers would fail to repay the loans. At this time, lenders would suffer losses. It is therefore important for lenders to screen on the credit profile of the borrowers before lending.

However, under different stock market conditions, the P2P lenders would have different attitudes towards borrowers' risk profiles, causing different choices of loans. In this paper, the objective of my research is to explore the influences of the stock market return on the probability of funding and the default rate in the P2P market. The stock market return is measured at the time of origination of the loan. I use credit score, onsite verification and interest rate spread to represent loans' risk levels since they are three main indicators that lenders used to screen borrower's risk status. Credit score is provided by the platform based on static and dynamic evaluations of borrowers' credit characteristics. Onsite verification is a process of onsite auditing and investigation, which strengthens the risk management of the loan. Interest rate spread is calculated by subtracting risk-free rate (Shibor) from the loan rate, which eliminates the effect of overall market fluctuation. High credit score, onsite verification and low interest rate spread represent low risk level.

According to the result of the empirical study, it is confirmed that the lender's investment behaviors would be affected by different stock market status. The regression result shows that when the stock market outperforms, the probability of funding success would be less sensitive to credit score, interest rate spread and onsite verification. At this time, lenders tend to choose loans with low credit score, high spread or loans without onsite verification, which are associated with high default risks.

Also, the default rate of P2P lending is positively correlated to stock market return. For loans with the same interest rate spread or credit score, those loans which originated when the stock market is bullish have higher default rates than those that originated in the bearish stock market. Moreover, the credit score has a negative correlation to the default rate, and the interest rate spread is positively correlated with the default rate. All of the default records are loans without onsite verification. Consequently, in order to decrease the probability of default, lenders are supposed to choose loans with high credit scores and low spreads or loans with onsite verification. However, in reality, when the stock market is bullish, lenders' preferences are exactly contrary to this, leading to a high default rate later on.

Furthermore, for loans with high credit scores or low interest rate spreads, default rate becomes less sensitive to the stock market return. As a result, for a loan with a relatively good credit profile, the difference between their default risks in the bullish stock market and the bearish stock market is smaller than that for a loan with bad credit status. Thus, when the stock market is bullish, it is a better choice to invest in loans with high credit scores or low spreads to control default risk. Whereas, in a good stock market, lenders tend to be aggressive and are more likely to accept loans with low credit scores or high spreads, which is not appropriate to decrease the default rate.

The results of my research provide some instructions for lenders regarding how to screen borrowers' credit profiles to control default risk. When the stock market is bullish, lenders are supposed to remain prudential and choose loans with high credit scores, low interest rate spreads and onsite verification. In addition, apart from these three indicators, other soft information disclosed by borrowers should also be taken into consideration to make a comprehensive evaluation of borrowers' credit profiles when the stock market is bullish. Soft information refers to the loan description context, which cannot be quantified. Thus, a rounded assessment is necessary for lenders before investing in the P2P lending market.

Past researches mainly focus on the P2P market separately to explore the determinants of the probability of funding or the default rate in the P2P market. However, few studies explore the influence of stock market status on the P2P lending market. So my study is a supplement to this area. It contributes to a better understanding of the mechanics of the platform. Also, potential lenders can take advantage of my empirical result to control default risks more effectively.

This paper is organized as follows. In Part 2, I conduct a review of the literature on the P2P lending market and the stock market. The research background and hypotheses are presented in Part 3. I perform the empirical methods on the derived hypotheses in Part 4. In Part 5, I present the results of my research. Finally, the conclusion and relative suggestions are provided in Part 6.

2. LITERATURE REVIEWS

Peer-to-peer lending has become one of the most popular tools of funding in China. Wang et al. (2015) pointed out that P2P lending has been rapidly expanding in China since its inception in 2007. According to Deer et al. (2015), there were 1,575 P2P lending platforms in 2014 with an estimated volume of funded loans between USD 20 and 40 billion by the end of 2015. These numbers would make China the second largest P2P lending market in the world.

2.1 Determinants of funding success

A number of studies explore the factors that influence the funding success of P2P lending and the different ways in which lenders screen on borrowers' risk profile before investing.

Most studies focus on the importance of borrower's credit profile and their financial status. Iyer et al. (2009) reveal that, on Prosper.com, the credit score is a reliable proxy for creditworthiness and should play an important role in the decision making of lenders. Klafft (2008) analyses the determinants of success rate of a loan and finds that more than 57.4 % of the investees are considered to be "high risk" in prosper.com and that 5.5 % of those investees can obtain loans but also that up to 54 % of AA-ranked investees can obtain a loan. So he believes that borrowers with poor credit scores could neither get financing from banking system nor through the P2P market. Iyer et al. (2009) show that investors can distinguish among borrowers with different credit ratings and that borrowers' trustworthiness is primarily measured through some standard financial ratios, including loan-to-income ratio, the number of loan defaults or applications, etc. Herzenstein et al. (2008) find that lenders are relatively strongly affected by credit risk issues. Borrowers' financial strength and their effort when listing and publicizing the loan are more important than demographic attributes for funding success. Herzenstein et al. (2011) conclude that the debt-to-income ratio has a negative correlation with funding, while the credit grade has a positive correlation with funding. And they also find that there is no relationship between funding and home ownership or loan amount. Freedman and Jin (2008) show that funding success in the P2P market is a result of sufficient information disclosure about investees, such as their income. Sanjeev Kumar (2007) points out that investors consider historical failed funding number and the successful number as two indicators to screen borrowers' risk. On Chinese P2P platforms, investors also consider borrowers' risk in a similar way. Y. Yan, Z. Lv, B. Hu examine how to persuade investors to develop initial trust in P2P borrowers based on the elaboration likelihood model. The analysis results of over 70 Chinese P2P platforms show that the financial and credit status of P2P platforms are critical elements in building the trust of investors and impacting their decisions.

Some studies conclude that probability of funding would be influenced by the main character of loans. Song and Han (2013) believe that the willingness to make a P2P investment is influenced by both revenue (represented by the annual interest rate) and risk (represented by the loan amount and duration) because investors, as rational humans, prefer high liquidity and good profits. Meanwhile, Puro et al. (2010) confirm that lower loan amounts require fewer investors—thus increasing the likelihood of successful P2P financing—and that higher interest rates would satisfy those investors who were seeking higher revenues. Jenq et al. (2015) use the funding time to assess the attractiveness of a loan request and to analyze how it is influenced by the social distance, the competition between MFIs (Micro-financial Institutions), the entrepreneurial rhetoric of the description texts and the appearance of the borrowers, respectively. There are further indications that point to the fact that lenders do consider variables indicating higher credit risk. A high default rate of the MFI or an unrated MFI as well as long grace periods or long loan terms not only increase the repayment risk but also lead to reluctance among the lenders to fund such a loan.

Several studies confirm that disclosing the information properly is essential for borrowers to get fund. Larrimore et al. (2011) show that objective and specific description of loan has a positive effect on funding success. Chen et al. (2014) develop an integrated trust model for online P2P lending context and drew conclusions as following: first, In Chinese online P2P context, trust in borrower plays an essential role in influencing a lender's willingness to lend; second, it is more effective for borrowers to gain a lender's trust by providing high-quality information concerning their loan requests than by building up social capital when there is a lack of screening procedures for social network membership in the lending intermediary.

Other studies focus on the role of social connections of borrowers. Lin et al. (2013) and Freedman and Jin (2014) stress the importance of social relationships for funding success. They find that borrowers with better social ties are more likely to get their loans funded and to receive a lower interest rate. Lin et al. (2013) analyze the role of social connections of borrowers in evaluating credit risk and find that strong social networking relationship is an essential determinant of borrowing success.

2.2 Determinants of the default rate

Lending money in the P2P market is a risky activity because borrowers are likely to default. So it is important to explore the determination the default rate. There are some studies exploit this problem on different perspectives.

Godquin (2004) points out that loan size is positively correlated with credit default. The higher the loan size, the higher the probability of default as the difficulty in meeting repayment obligations in case of project failure increases as well as the gain of moral hazard behavior regarding non-repayment increases. Riza et al. (2015) use Cox Proportional Hazard regression technique to evaluate credit risk and measure loan performances. They find that credit grade, debt-to-income ratio, FICO score and revolving line utilization play an important role in loan defaults. Smith (2011) presents an investigation of FICO score changes over time for a sample of mortgage borrowers; the FICO score data is analyzed both as presented in an individual mortgage and grouped into categories referred to as grades; the results indicate credit scores provide information to investors and servicing agents in a fashion similar to credit ratings on commercial paper as to default potential.

Regarding the loan term, Hull (2015) confirms that borrowers' probability of default would increase over time. Serrano-Cinca et al. (2015) find that the current housing situation affects borrowers' probability of default. Home ownership (whether it is mortgaged or not) reflects lower chances of default compared to renting. However, home ownership may not become a reliable proxy for the loan default rate for different risk levels. They also conclude that the length of credit history has a negative correlation with borrowers' default. Moreover, default rate has no significant correlation with regular payment schedule. Field and Pande (2008) do not identify a relationship between high frequency of repayment and the probability of default in a field experiment in urban India. McIntosh (2008) finds no difference in repayment performance between borrowers paying weekly installments and borrowers paying fortnightly installments either. While, in a further field experiment in India, Field et al. (2013) note that the grace period has a positive correlation with the probability of default. Loans with a grace period of two months are more likely to default in the short- and long-run compared with classic loan contracts.

In the empirical study of Chinese P2P market, Y. Gao, J. Sun, Q. Zhou (2017) try to evaluate the effectiveness of the credit evaluation system using the data from a Chinese P2P lending platform called Renrendai, which shows that only the hard information reflecting borrowers credit ability can explain the default risk on the platform under the forward-looking credit evaluation mechanism, and it suggests that current ex-ante screening based on the information collected from the borrowers or repeated borrowings is inadequate to control the default risk in P2P lending markets and thus needs be improved. C. Jiang, Z. Wang, R. Wang, Y. Ding (2017) introduce a topic model to extract valuable features from the descriptive text concerning loans and construct four default prediction models using data from a major Chinese P2P lending platform. The result shows that these models can improve loan default prediction performance compared with existing methods based only on hard information.

2.3 The effect of the stock market on other financial markets

Researches on the impact of the stock market on other financial markets mainly focus on areas of bond markets, gold markets and macroeconomic variables. The stock market has a spillover effect on other markets, that is, when the stock market fluctuates, it will cause investors to change their investment behavior in other markets, thus transferring such fluctuations to other markets.

Wang Yintian and Wen Zhiwei (2010) find that the stock market has a one-way spillover effect on the bond market. The surge in stock prices will attract funds from the bond market into the stock market, and when the stock market plunges, panicked investors will sell stocks and buy government bonds with lower risk. Wen Yuechun et al. (2015) empirically analyze the volatility spillover effects of international stock markets on domestic stock markets and commodity markets. The spillover effects of the stock market on other markets are achieved through investor transactions. The rise in stock prices will reduce the trading activity of the private lending market.

According to the literature review, past researches mainly focus on P2P lending market separately. There are few studies exploring the influence of the stock market on the P2P market. So my study is a supplement to this area. This paper explores the effect of the stock market performance on lender's behavior and default rate. It contributes to a better understanding of the mechanics of the platform. Also, potential lenders can take advantage of my empirical result to control default risk more effectively.

3. BACKGROUND AND HYPOTHESIS

3.1 Background

3.1.1 Pricing Mechanism

In Chinese P2P markets, the contract interest rate is mainly a fixed interest rate set by borrowers in advance, which can be defined as a borrower pricing mechanism (BPM). As for Renrendai, the platform would set loan rate constraints for each borrower before they decide their interest rates. The upper limit of annual rate is 24% because loans with interest rates higher than 24% are considered to be usury. The lower limit depends on loans' credit rating and maturities. Borrowers have the right to set loan rate between these constraints.

The rates that set by borrowers also mainly depend on their credit rating and maturity. When the borrower submits all the application materials, the platform will give a credit rating according to its specific situation, from the lowest HR to the highest AA. Every credit rating has a corresponding interval of credit score, provided by the platform based on borrowers credit profile. Generally, the higher the credit score, the lower the interest rate. Interest is considered the compensation of investment risk. Besides credit rating, borrowers should also take consideration of different maturities. For example, if a borrower has a credit rating of HR, 6-month loan interest rate is different from that of a 12-month loan. In general, longer maturity leads to higher interest rate. Since the interest rate incorporates the information of borrowers' credit scores and maturities, it is a good proxy for lenders to recognize the risk levels of borrowers. The higher the interest rate, the higher the default risk.

In this paper, to eliminate the effect of the whole market fluctuation, I use the interest rate spread instead, which is calculated by subtracting loans' interest rate spreads by daily Shibor of the same maturity. Shibor is a daily reference rate based on the interest rates at which banks offer to lend unsecured funds to other banks in the Shanghai wholesale (or "interbank") money market. It is a representation of the risk-free rate of the financial market in China.

3.1.2 Credit Score

At present, Chinese P2P online lending platforms require the borrowers to provide relevant certification materials before evaluating credit rating. Renrendai is mostly based on the combination of static certification and dynamic evaluation. The static certification materials include necessary certification materials and optional certification materials. The necessary certification materials involve identity verification, personal credit report, labor contract or employment certification, bank account cash flow records, and business certification, etc. Optional certification materials include property certification, car certification, marriage certification, education certification, technical title certification, mobile real-name certification, micro-blog certification, residence certification. What's more, dynamic evaluation process investigates historical records of borrower's successful repayment, number of delinquency and serious delinquency which refers to the loans whose repayment is delayed for more than 30 days.

Through the comprehensive assessment of the borrower's risk profile, the platform will provide the borrower's credit score, and then the credit rating based on the score. Renrendai has seven credit ratings for borrowers, which are AA\A\B\C\D\E\HR. And the scores corresponding to each credit rating are: ≫210, 180-209, 150 -179, 130-149, 110-129, 100-109, 0-99.The higher the credit score, the better the borrowers' credit profile. What's more, as the platform can obtain the first-hand information of the borrower through the onsite verification, it will set the borrower's credit rating directly to level A as long as conducting onsite verification. According to the evaluation mechanism stated above, although certification materials are required by the platform, the credit rating system of Renrendai has no strict calculation formula and no standard regularity.

3.1.3 Onsite verification

On Renrendai platform, there are two types of loans. One is based on online verification, and the other is managed by onsite verification. For loans with online verification, borrowers should upload the certification materials through the Internet. The online loan review department conducts strict evaluation through the network and telephone. Due to the imperfect domestic credit system in China, the actual default rate is relatively high, which makes the risk of online lending difficult to control. As a result, Renrendai has developed onsite verification.

The onsite verification loan is a brand new product jointly launched by Renrendai and Youzhong Xinye Financial Information Service (Shanghai) Co., Ltd. Besides the original strict review, it has developed the onsite visits, audit investigations and post-loan services, which strengthen risk management and achieve the effect of double guarantee. After the onsite inspection, the borrower can get a credit rating of A and can enjoy relatively low interest and service fees.

3.1.4 Borrowing and lending process

Borrowers should register on the website to be Renrendai members and complete identity verification at first. Secondly, they need to choose the loan product to initiate an application. Thirdly, according to the requests, they are supposed to upload the necessary application materials. Fourthly, after the audit, borrowers can start to raise money. When fully funded, the loan is completed, and the money is released to borrowers immediately, after which borrowers only need to repay monthly. The amount they need to repay every month is equal installments of principal and interest. For lenders, they can choose different listed borrowings with different maturities and interests on the Renrendai website. For each target, they can decide the lending amount by themselves. If the loan is successfully repaid by the borrower, it is shown as “closed”. But if the borrower fails to repay, the loan is defaulted and shown as “bad debt”.

3.2 Hypothesis

The lenders’ attitudes towards borrowers’ credit profiles in the P2P market could be affected by the stock market returns. On Renrendai platform, three critical indicators enabling the lender to distinguish among different risk levels are credit score, onsite verification and interest rate spread (loan rate minus the Shibor of the same maturity). High credit score, onsite verification and low interest rate spread represent low credit risk for the borrowers. Consequently, my research is focused on these three proxies to analyze lenders’ different behavior in choosing loans under different stock market conditions.

The funding success of loans could be influenced by the stock market return. In a bullish stock market, lenders tend to be aggressive when choosing loans. At this time, lenders would show less consideration for risk indicators and would be more likely to choose loans with high risks, which would lead to high default rates in the future. I therefore propose the following hypotheses:

H1a: In the bullish stock market, the probability of funding would be less sensitive to credit scores than that of the bearish stock market.

H1b: In the bullish stock market, the probability of funding would be less sensitive to onsite verification than that of the bearish stock market.

H1c: In the bullish stock market, the probability of funding would be less sensitive to interest rate spreads than that of the bearish stock market.

In addition, among the loans fully funded by lenders, their default rates would have a positive correlation to the stock market returns on the origination day of the loans. However, this relationship would be influenced by the different credit profiles of borrowers. For a loan with a sound credit profile, default rate would be less affected by the stock market return. Even if the stock market is bullish, loans with high credit scores, low spreads and onsite verification would have good performances.

Consequently, in this case, the default rate would be less sensitive to the stock market return. I therefore propose three hypotheses as follows:

H2a: For a P2P loan with a high credit score, its default rate is less sensitive to the stock market return than that of a loan with a low credit score.

H2b: For a P2P loan with onsite verification, its default rate is less sensitive to the stock market return than that of a loan without onsite verification.

H2c: For a P2P loan with a low interest rate spread, its default rate is less sensitive to the stock market return than that of a loan with a high interest rate spread.

4. DATA AND EMPIRICAL METHODOLOGY

4.1 Data source

The data used in this study is obtained from Renrendai, one of the largest peer-to-peer lending platforms in China. I collect the data on P2P loans listed on Renrendai during 2015, which includes the loans that are successfully funded and failed to be fully funded. To analyze the effect of the stock market on the P2P market, I only collect the P2P loans on the stock transaction date. The data covers 301,207 loans, including 79,306 successfully funded loans and 221,901 failed loans. Among the loans that were fully funded, 77,516 borrowings were wholly repaid, and 1,791 loans defaulted.

To get the characteristics of the Chinese stock market in 2015, I collect data of the SSE composite index, which is a stock market index of all stocks that are traded at the Shanghai Stock Exchange. The daily return of the SSE composite index can represent the average daily return of Chinese stock market. In my study, I use the last one-week average return of SSE composite index at the time of the origination of the loan to represent the stock market status. Also, to calculate interest rate spread of each loan, I collect daily Shanghai Interbank Offered Rate (or Shibor) with maturities of one year in 2015. Shibor is a daily reference rate based on the interest rates at which banks offer to lend unsecured funds to other banks in the Shanghai wholesale (or "interbank") money market. It is a representation of the risk-free rate of the financial market in China. So I can get interest rate spread of each loan by subtracting Shibor from the loan rate, which eliminates the influence of the overall market fluctuation.

4.2 Key variables and summary statistics

To analyze the influence of the stock market on the P2P lending market, I collect three categories of data. The first category is the basic information related to loans, including borrowing amount, interest rate spread, loan term, onsite verification, the probability of funding and probability of default. The second category is the characteristic of borrowers, including credit score, income, gender, education, marriage, house, house loan, car, car loan, city, and provinces of borrowers. And the third category is the characteristic of the stock market, involving the last one-week average return of the SSE composite index at the time of the origination of the loan. The definition of each variable is shown in Table 1.

Table 1 Variables and definitions

Variable	**Name**	**Definition**
A. Loan Characteristics		
Probability of Funding	Fund	1 if the loan has been fully funded and 0 otherwise
Probability of Default	Default	1 if the loan has been defaulted and 0 otherwise
Loan Amount(in RMB)	Amount	Loan amount requested by the borrowers
Interest Rate Spread (in %)	Interest	The loan rate minus Shibor
Loan Term(in months)	Term	Loan term requested by the borrower
Onsite Verification	Onsite	1 if the loan has onsite verification and 0 otherwise
B. Borrower Characteristics		
Credit Score	Score	Credit score of the borrower
Borrower's monthly income(in RMB)	Income	Income level of borrowers, 0=less than 1,000, 1=1,001-2,000, 2=2,001-5,000, 3=5,001-10,000, 4=10,001-20,000, 5=20,001-50,000,6=more than 50,000
Gender	Gender	1 if male and 0 if female
Marriage	Marry	1 if borrower is married and 0 otherwise
Education	Education	1 if borrower has collage degree and 0 otherwise
House	House	1if borrower has house asset and 0 otherwise
House loan	House loan	1 if borrower has house loans and 0 otherwise
Car	Car	1if borrower has a car and 0 otherwise
Car loan	Car loan	1if borrower has car loans and 0 otherwise
City	City	City of the borrower
Province	Province	Province of the borrower
C. Stock Market Characteristics		
Average stock market return (in %)	Market return	Last one-week average daily return of SSE composite index

Table 2 provides the summary statistics of all listings posted by borrowers and Table 3 provides the summary statistics of fully funded listings. Panel A describes loan characteristics, panel B borrower characteristics, and panel C stock market characteristics. In Table 2, the data covers 301,207 borrowing requests listed by borrowers in 2015, part of which were not accepted by investors. In Table 3, the data covers 79,036 listings that were all successfully funded by lenders in 2015.

In Table 2, we can get that the mean of the probability of funding is 0.38, which indicates that 38% of borrowing requests were accepted by lenders. And a large number of requests were rejected. The average loan amount is 61,487.06 RMB. The average interest rate spread is 7.99%, ranging from 2.23% to 9.85%. The mean of dummy variable of onsite verification is 0.31, which indicates that 31% of new listings were conducted by onsite verification. And average credit score is 75.58.

In Table 3, among the listings that were fully funded, the mean of the probability of default is 0.023, which means that 2.3% of borrowings were not successfully repaid. The average loan amount is 59,106.37 RMB, which is smaller than that in Table 2 (61,487.06 RMB), implying that lenders preferred to choose borrowings of small size. Moreover, the average interest rate spread of fully funded borrowings was 7.61%, smaller than that of all listings in Table 2 (7.99%), indicating that listings accepted by lenders had relatively low interest rate spread. So lenders would care about risk indicator of spread and prefer loans with low risk. The average credit score of fully funded listings was 166.60, which is much higher than that in Table 2 (75.58), indicating that lenders preferred loans with high credit score which represents low credit risk.

By comparison, we can see that lenders take consideration of risk level when they choose borrowing requests. In general, they tend to fund loans with high credit scores or low interest rate spreads to control default risk. However, their investment decisions would be affected by stock market performances. Under different stock market conditions, lenders would have different preferences, which may not be appropriate, causing a higher default rate in a bullish stock market than that in a bearish one. So this paper mainly focuses on this phenomenon and exploits the reasons behind it.

4.3 Empirical Methodology

4.3.1 Funding success of loans

For the first hypothesis, when the stock market outperforms, lenders are not cautious enough about credit risk and tend to choose loans with high risks. In this part, I construct ordinary least square (OLS) regression models to justify these correlations. I use three indicators that investors mainly use to screen on the credit profile of borrowers, which are credit score, onsite verification and interest rate spread. I employ these three indicators separately in three equations. The models are as follows:

$$\Pr(\mathrm{Fund_i} = 1) = \alpha + \beta_1 \mathrm{market\ return_i} + \beta_2 \mathrm{score_i} + \beta_3 \mathrm{market\ return_i} \times \mathrm{score_i} + \sum_{i=1}^{n} \delta_i X_i + \varepsilon_i \quad (1)$$

$$\Pr(\mathrm{Fund_i} = 1) = \alpha + \beta_1 \mathrm{market\ return_i} + \beta_2 \mathrm{onsite_i} + \beta_3 \mathrm{market\ return_i} \times \mathrm{onsite_i} + \sum_{i=1}^{n} \delta_i X_i + \varepsilon_i \quad (2)$$

$$\Pr(\mathrm{Fund_i} = 1) = \alpha + \beta_1 \mathrm{market\ return_i} + \beta_2 \mathrm{spread_i} + \beta_3 \mathrm{market\ return_i} \times \mathrm{spread_i} + \sum_{i=1}^{n} \delta_i X_i + \varepsilon_i \quad (3)$$

For the equation (1), the dependent variable $\mathrm{Fund_i}$ is a binary variable equal to 1 if the loan is fully funded and 0 otherwise. $\mathrm{Market\ return_i}$ is represented by the last one-week average return of the SSE composite index (a stock market index of all stocks that are traded at the Shanghai Stock Exchange) on the day that loans originate. $\mathrm{Score_i}$ refers to each borrower's credit score provided by Renrendai platform. The interaction term of market return and score is to explore the effect of stock market return on the correlation between credit score and the probability of successful funding. Xi is a vector of the control variables, including the two categories: loan control variables and borrower control variables. Loan control variables include each loan's borrowing amount and maturity. Borrower control variables consist of the borrower's monthly income, gender, marriage, education, province, house asset, car asset, house loan, and car loan. The regression result of this equation is shown in Table 4.

In the equation (2), the dependent variable is the same as the equation (1). For the independent variables, I replace $\mathrm{score_i}$ with $\mathrm{onsite_i}$, which is a dummy variable of 1 if the loan has onsite verification and 0 otherwise. For the interaction term, I use a variable of $\mathrm{market\ return_i}$ multiplying by $\mathrm{onsite_i}$ to investigate the influence of the stock market on the correlation between onsite verification and funding success. Also, the vector of control variables Xi in this equation is the same as that in equation (1). The regression result of this equation is shown in Table 5.

For the equation (3), the variable of score_i is replaced by spread_i, which refers to each loan's interest rate spread (interest rate minus daily Shibor with the same maturity). Also, I construct the interaction term by multiplying the variable of market return_i by spread_i. Apart from this, the dependent variable and the control variables are all the same as that in equation (1). The regression result of this equation is shown in Table 6.

4.3.2 Default rates of loans

In this part, my research objective is to explore the relationship between the stock market returns on the origination days of the loans and default rates of the P2P lending. Also, I would figure out the effect of three indicators of the credit profile on the correlations between the stock market returns and the default rates. I employ OLS regression models as follows:

$$\Pr(\text{Default}_i = 1) = \alpha + \beta_1 \text{market return}_i + \beta_2 \text{score}_i + \beta_3 \text{market return}_i \times \text{score}_i + \textstyle\sum_{i=1}^{n} \delta_i X_i + \varepsilon_i \qquad (4)$$

$$\Pr(\text{Default}_i = 1) = \alpha + \beta_1 \text{market return}_i + \beta_2 \text{spread}_i + \beta_3 \text{market return}_i \times \text{spread}_i + \textstyle\sum_{i=1}^{n} \delta_i X_i + \varepsilon_i \qquad (5)$$

I do not construct the empirical model related to onsite verification since all of the default records are loans without onsite verification in my data sample. This indicates that onsite verification is a good indicator of default risk regardless of the stock market condition. The loans without onsite verification are more likely to default than those loans with onsite verification. However, from the regression result of the equation (2), we can see that lenders tend to invest more on loans without onsite verification when the stock market outperforms. So in terms of this indicator, lenders are not cautious enough to control risks when the stock market is good.

For the equation (4), the dependent variable is a dummy variable of Default_i, which is one if the borrower fails to repay the loan and 0 otherwise. The independent variables are the same as that in the equation (1). $\mathrm{Market\ return_i}$ refers to the average stock market return, which is the last one-week average return of the SSE index at the time of the origination of the loan. $\mathrm{Score_i}$ stands for each loan's credit score provided by Renrendai platform. The interaction term is the stock market return multiplied by credit score. By interpreting the interaction term, I can figure out the effect of credit scores on the relationship between the stock market return and the stock rate. Also, Xi is a vector of control variables, including two categories: loan control variables and borrower control variables. Loan control variables include each loan's borrowing amount and maturity. Borrower control variables consist of a borrower's monthly income, gender, marriage, education, house asset, car asset, house loan, car loan and province. In regression, I use clustered standard error by cities of borrowers. The regression result is shown in Table 7.

For the equation (5), the dependent variable is the same as that in the equation (4). For main explanatory variables, $\mathrm{score_i}$ is replaced by $\mathrm{spread_i}$, which is the interest rate spread of each loan. For the interaction term, I used continuous variables of $\mathrm{spread_i}$ multiplying by $\mathrm{market\ return_i}$. Through analyzing the coefficient of the interaction term, I can explore the effect of interest rate spreads on the relationship between the stock market return and the default rate. The regression result of this equation is shown in Table 8.

5. RESULTS

5.1 Funding success of loans

The regression result of the equation (1) is shown in Table 4. For specifications (1) and (2), the regression results without the interaction term are presented. The primary independent variables are the stock market return and the credit score. For the specifications (3) and (4), the interaction term is added in the regression model. Additionally, for specifications (1) and (3), control variables regarding the loan characteristics are used, including loan's amount and term. For specifications (2) and (4), both the loan control variables and borrower control variables are included. Borrower control variables involve characteristics of the borrower's monthly income, gender, marriage, etc.

As presented in the result, in the specifications (1) and (2), the coefficient of credit score is significantly positive, which indicates that lenders prefer to accept loans with high credit scores. According to the evaluation rules of the Renrendai platform, the higher the credit score, the lower the borrower's default risk. Thus, lenders have the awareness of controlling investment risk by screening on borrowers' credit score.

However, this correlation could be affected by the stock market status. In the specifications (3) and (4), the coefficient of interaction term is significantly negative, implying that the higher the stock market return, the weaker the effect of credit scores on funding success. Therefore, when the stock market is bullish, funding success becomes less sensitive to credit scores than that of a bearish market. From this result, we can explore the effect of the stock market on lenders' behaviors. When the stock market outperforms, lenders are less concerned about the credit score and are tend to accept loans with low credit scores which represent high default risks.

Table 5 reports the result of the equation (2). Specifications (1) and (2) represent regression results without interaction term, while specifications (3) and (4) include an interaction term in the model. Also, for the specifications (1) and (3), only control variables of loan characteristics are used. And the specifications (2) and (4) involve both loan control variables and borrower control variables. As shown in specifications (1) and (2), the positive coefficient of onsite verification indicates that lenders prefer loans with the onsite verification. For those loans, Renrendai platform would conduct strict investigations about the reality of borrowers' information by onsite visits, audit investigations. Also, the platform could provide some post-loan services to monitor the borrower's repayment. As a result, onsite verification is considered to be a guarantee that borrowers' information is real and they can get repaid at the end the maturity. In generally, lenders have the awareness to decrease the default risk by accepting loans with onsite verification.

However, in the specification (3) and (4), the coefficient of interaction term is significantly negative, indicating that when the stock market return is bullish, the loans with onsite verification have lower probabilities to be fully funded. This correlation implies that when stock market turns good, P2P lenders would be less prudential and be less concerned about the indicator of the onsite verification. At this time, the probability of funding success becomes less sensitive to onsite verification and lenders are more likely to invest in loans without onsite investigation, which leads to high default rate later on.

Table 6 shows the result of the equation (3). In specifications (1) and (2), the coefficient of spread is significantly negative, implying that the loans with high spreads are less likely to be fully funded. Based on the pricing mechanisms of the Renrendai platform, loan rates are set according to borrowers' credit scores. The lower the credit score, the higher the interest rate spread. Consequently, high interest rate spreads represent high credit risk. From this result, we can see that lenders would screen on borrowers' risk profile through interest rate spread and prefer loans with low spread and low risk.

Nevertheless, in specifications (1) and (2), the coefficient of the interaction term is significantly positive, indicating that the stock market return would weaken the negative effect of spread on the probability of funding. In the bullish stock market, the P2P lenders tend to be less sensitive about interest rate spreads and more likely to choose loans with high spreads which represent high credit risks.

5.2 Default rates of loans

Table 7 displays the regression result of the equation (4). Specifications (1) and (3) only include loan control variables and specification (2) and (4) involve both the loan control variables and borrower control variables. In specifications (1) and (2), the primary independent variables are stock market return and credit score. However, in the specification (3) and (4), the interaction term is included.

Firstly, in the specifications (1) and (2), the coefficient of market return is significantly positive, which means that the higher the stock market return, the higher the loan's default rate. For loans with the same credit scores, those loans which originated when the stock market is bullish have higher default rates than those that originated in the bearish stock market. Credit score only reflects the default risk based on the part of the hard information which can be accurately quantified and efficiently transmitted. This kind of information involves certification materials and records of the historical transaction disclosed by the borrowers. Furthermore, there is soft information which also reflects the default rate. Soft information refers to the information that is hard to quantify, such as description of loan purpose, spelling errors, text length and positive emotion evoking keywords in the loan description context. When the stock market is bullish, P2P lenders tend to be less cautious when choosing loans. As a result, they would put less effort into screen borrowers' risk profile comprehensively and neglected the soft information disclosed by borrowers. Consequently, without prudential evaluation, the loans chosen by lenders would have higher default risks at this time, even with regard to the loans with the same credit score.

Secondly, the coefficient of the credit score is significantly negative, implying that the higher the credit score, the lower the default rate. Credit score is assessed based on the static certification and dynamic evaluation of borrowers' credit profiles. Static certification materials include identity verification, personal credit reports, employment certification, property certification and so on. Dynamic evaluation process investigates historical payment records of borrowers on Renrendai platform. Through comprehensive assessments, borrowers who have better credit profiles can obtain higher credit scores and have lower default rates.

Thirdly, in the specifications (3) and (4), the coefficient of the interaction term is significantly negative, which indicates that the credit score would mitigate the positive effect of the stock market return on the default rate. For a loan with a high credit score, its default rate is less sensitive to market return than a loan with a low credit score. When stock market is bullish, even if lenders would not be cautious enough to evaluate all of the hard information and the soft information disclosed by borrowers, for loans with high credit score, they would still have good performances, and the difference between their default risks in the bullish stock market and the bearish stock market is smaller than that for a loan with bad credit status. Therefore, when the stock market outperforms, it is a wise choice for lenders to accept loans with high credit scores to control the default risk. However, according to the regression result of the equation (1), the behavior of lenders is exactly contrary to this, which causes a high probability of default in a bullish stock market.

Table 8 displays the regression result of the equation (5). Specifications (1) and (2) present the result without the interaction term. The coefficients of market return are all significantly positive, implying that for loans with the same interest rate spread when the stock market return is higher, its probability of default is higher. Interest rate of the loan is set based on credit score and maturity of the loan. So it reflects loan characteristics and borrowers' hard information including certification materials and records of the historical transaction. Apart from this information, there is also other important soft information that reflects the borrowers' risk profile, such as debt description context. When the stock market outperforms, lenders tend to be less prudential and are more likely to neglect this information. So without a comprehensive evaluation of borrowers' risk level, loans that are chosen by lenders are riskier in a bullish stock market.

Moreover, the coefficient of spread is significantly positive, suggesting that the higher the interest rate spread, the higher the probability of default. Interest is considered the compensation of credit risk. Loans with low credit score have relatively high interest rate. Thus, a high spread is associated with a high credit risk.

Additionally, in the specifications (3) and (4), the coefficient of the interaction term is significantly positive, indicating that the higher the spread, the more positive effect of the stock market on default rate. For a loan with high interest rate spread, its probability of default is more sensitive to stock market status than that for a loan with low spread. So when the stock market outperforms, it is better to fund a loan with a low interest rate spread, which involves a lower risk. However, according to the regression result of the equation (3), lenders tend to choose loans with high spreads in a bullish stock market, which would lead to a high probability of default.

5.3 Robustness test

In the above analysis, I suppose that the P2P lender's behavior would be affected by the last one-week average stock market return, which covers a short period. However, lenders maybe form their views of stock market status based on a longer period of market performance and then make their investment decisions. Therefore, for robustness test, I use the last one-month average return of SSE index at the time of the origination of the loan to represent the average return of the stock market.

5.3.1 Funding success of loans

The regression models are the same as that in part 4. The objective is to explore the effect of the stock market on lenders' behavior to accept loans with different risk levels. The indicators I use to represent risk levels are credit score, onsite verification and interest rate spread. What's more, I use a more extended period of the average stock market return, which is the last one-month average return of the SSE index, to represent the stock market return. The objective is to explore that based on the one-month historical performance of the stock market if P2P lenders would behave the same as what I have observed in Part 4. The OLS regression result is shown in Table 9-Table 11.

The signs of the central coefficients shown in Table 9 are the same as those in Table 4. Both results are based on the same empirical model:

$$\Pr(\mathrm{Fund}_i = 1) = \alpha + \beta_1 \mathrm{market\ return}_i + \beta_2 \mathrm{score}_i + \beta_3 \mathrm{market\ return}_i \times \mathrm{score}_i + \sum_{i=1}^{n} \delta_i X_i + \varepsilon_i$$

In specifications (1) and (2), the coefficient of score is significantly positive, which means that loans with higher credit scores have higher probabilities of funding success. In specifications (3) and (4), the coefficients of the interaction terms are significantly negative, implying that when stock market outperforms, the positive effect of credit score on the probability of funding would become weaker. So in this case, lenders would care less about credit score when choosing loans and are more likely to accept loans with low credit scores and relatively high risks.

From Table 10, the signs of the main coefficients are the same as those in Table 5. Both of them are based on the same model:

$$\Pr(\mathrm{Fund}_i = 1) = \alpha + \beta_1 \mathrm{market\ return}_i + \beta_2 \mathrm{onsite}_i + \beta_3 \mathrm{market\ return}_i \times \mathrm{onsite}_i + \sum_{i=1}^{n} \delta_i X_i + \varepsilon_i$$

When lenders make investment decisions given the one-month performance of the stock market, their behaviors would be the same as what I have explored above. In columns (1) and (2), the coefficients of the onsite verification are significantly positive, indicating that loans with onsite verifications are more likely to be fully funded. While, in columns (3) and (4), the coefficients of the interaction terms are significantly negative, implying that the stock market weakens the effect of onsite verification on the probability of funding. When the stock market is bullish, lenders are less sensitive to the indicator of onsite verification and would invest more in loans without onsite verification.

The signs of coefficients shown in Table 11 are the same as those in Table 6. Both results are based on the following equation:

$$\Pr(\mathrm{Fund_i} = 1) = \alpha + \beta_1 \mathrm{market\ return_i} + \beta_2 \mathrm{spread_i} + \beta_3 \mathrm{market\ return_i} \times \mathrm{spread_i} + \textstyle\sum_{i=1}^{n} \delta_i X_i + \varepsilon_i$$

If P2P lenders make evaluations about stock market based on last one-month average return of the SSE index, they will make similar investment decisions as that if they base on the last one-week average stock market return. The coefficient of the interest rate spread is significantly negative, implying that the lower the spread, the higher the probability of successful funding. Moreover, the sign of the coefficient of interaction term is positive, which indicates that the stock market weakens the negative effect of spread on funding success. When stock market outperforms, lenders would be less sensitive to interest rate spread and are more likely to choose loans with the higher spreads, which leads to higher default rates.

5.3.2 Default rates of loans

In order to explore the effect of credit score on the relationship between stock market return and default rate, I employ the same equation as that in part 4. The equation is as follows:

$$\Pr(\mathrm{Default_i} = 1) = \alpha + \beta_1 \mathrm{market\ return_i} + \beta_2 \mathrm{score_i} + \beta_3 \mathrm{market\ return_i} \times \mathrm{score_i} + \textstyle\sum_{i=1}^{n} \delta_i X_i + \varepsilon_i$$

Here, I use the last one-month average return of the SSE index on the day of the origination of the loan to represent average stock market return. The regression result is shown in Table 12.

From Table 12, in the specifications (1) and (2), the coefficient of stock market return is significantly positive, suggesting that the higher the market return, the higher the default rate. In a bullish stock market, the probability of default in the P2P lending market would be higher than that in a bearish market. Also, credit score is negatively correlated with default rate, indicating that high credit score represents a low default risk. Furthermore, in columns (3) and (4), the coefficients of interaction term are both significantly negative, which implies that for a loan with high credit score, its default rate would be less sensitive to the market return. Thus, when the stock market outperforms during the last one month, it is a wise choice for lenders to invest in loans with high credit scores to decrease default risks.

To analyze the effect of the interest rate spread on the relationship between stock market return and default rate, I employ the same equation as following:

$$\Pr(\mathrm{Default}_i = 1) = \alpha + \beta_1 \mathrm{market\ return}_i + \beta_2 \mathrm{spread}_i + \beta_3 \mathrm{market\ return}_i \times \mathrm{spread}_i + \sum_{i=1}^{n} \delta_i X_i + \varepsilon_i$$

Also, the stock market return is represented by the last one-month average return of the SSE index on the origination day of each loan. The result is shown in Table 13. We can see that the coefficients of the primary independent variables are all significant and the signs are the same as those in Part 4. The coefficient of the market return is positive, indicating that the higher the market return, the higher the default rate. The negative coefficient of interest rate spread implies that the higher the spread, the higher the default rate. High spread reflects the high risk of the borrower. Moreover, the coefficient of interaction term is significantly positive, which means that the spread would strengthen the positive effect of stock market return on default rate. For a loan with high spread, its default rate becomes more sensitive to the stock market status. So in a bullish stock market, in order to control default risk effectively, lenders are supposed to fund loans with relatively low interest rate spread.

In summary, no matter based on the last one-week or one-month average stock market returns at the times of the origination of the loans, the regression results remain consistent and robust.

6. CONCLUSION

The P2P lending platform connects people who need loans with people who are willing to lend their money. Through this channel, some individual borrowers or small enterprise that cannot get funded in banks could raise money easily. However, the problem of information asymmetry exists on the P2P platform. Lenders need to evaluate the risk level of different borrowers based on some indicators provided by the platform, i.e. credit score, onsite verification, interest rate, etc. However, another problem is that the behaviors of lenders would be affected by stock market status. Also, the default rate could be influenced by the stock market. So this paper explores the effects of the stock market on the P2P lending and provides some suggestions for lenders.

To begin with, the stock market has effects on lenders' behaviors when choosing loans among all of the loan requests listed by borrowers on the platform. The result confirms that lenders would be less concerned about credit score, onsite verification and interest rate spread when the stock market outperforms. In a bullish stock market, lenders are less likely to accept loans with high credit score, low interest rate spread or loans with onsite verification than that of a bearish market.

Moreover, among the loans fully funded by lenders, the probability of default has a positive correlation with the stock market return, and this relationship would be affected by borrowers' credit score and interest rate spread. According to the empirical result, the higher the stock market return, the higher the default rate. However, credit score would weaken the positive effect of stock market return on default rate. So when the stock market outperforms, it is appropriate to fund loans with high credit scores to decrease default risk. Additionally, interest rate spread would strengthen the positive effect of stock market return on default rate. For a loan with a low spread, its default rate is less sensitive to stock market return than that for a loan with a high spread. So lenders are supposed to accept loans with low interest rate spread when stock market outperforms. As for onsite verification, all of the default records in my sample are loans without onsite verification. So it is a wise choice to invest in loans with onsite verification to control default risk. While, lenders' funding behaviors are just contrary to what they are supposed to do, causing a high default rate in the bullish stock market.

Based on the analysis above, I would give some suggestions to P2P lenders. Firstly, when the stock market is bullish, they should remain prudential. Loans with high credit score, low interest rate spread and onsite verification are wise choices for lenders since these loans' default risk is relatively lower compared to other borrowings. Moreover, it is not enough to just focus on these risk indicators because when the stock market is good, the default rate of loans with the same credit score or spread would be higher than that in a bearish stock market. Credit score and spread only reflect a part of hard information (i.e. borrowing term, certifications and historical borrowing records disclosed by borrowers, but there is also other information that is essential to determine risks, such as debt-to-income ratio, loan purpose, the length of credit history and loan description. Thus, lenders are supposed to explore all of this information on the platform and make a comprehensive evaluation of borrower's risk profile.

REFERENCES

B. C. Smith, 2011, Stability in consumer credit scores: Level and direction of fico score drift as a precursor to mortgage default and prepayment, *Journal of Housing Economics* 20 (4) (2011) 285–298.

Carlos Serrano-Cinca, Bego˜na Guti´errez-Nieto, and Luz L ́opez-Palacios, 2015, Determinants of Default in P2P Lending, *PLOS ONE*, 10(10):1–22, oct 2015. ISSN 1932-6203.

C. Jiang, Z. Wang, R. Wang, Y. Ding, 2017, Loan default prediction by combining soft information extracted from descriptive text in online peer-to-peer lending, *Analytical Models for Financial Modeling and Risk Management* 266:511-529.

D. Chen, F. Lai, Z. Lin, 2014, A trust model for online peer-to-peer lending: a lenders perspective, *Information Technology and Management* 15 (4) 239–254.

Freedman, S. and Jin, G, 2014 The signaling value of online social networks: lessons from peer-to-peer lending. *NBER Working Paper* No. 19820.

Field, E., & Pande, R, 2008, Repayment frequency and default in microfinance: Evidence from India, *Journal of the European Economic Association*, 6, 501–509.

Field, E., Pande, R., Papp, J., & Rigol, N, 2013, Does the classic microfinance model discourage entrepreneurship among the poor? Experimental evidence from India, *American Economic Review*, 103, 2196–2226.

Godquin, M, 2004, Microfinance repayment performance in Bangladesh: How to improve the allocation of loans by MFIs. *World Development*, 32, 1909–1926.

Hull, J. 2015. *Risk management and financial institutions* (4th ed.). Hoboken/New Jersey: John Wiley & Sons.

Iyer R, Khwaja AI, Luttmer EFP, et al, 2009, Screening in new credit markets: can individual lenders infer borrower creditworthiness in peer-to-peer lending? (In: AFA 2011 Denver meetings paper)

Jiazhuo Wang, Hongwei Xu, and Jun Ma, 2015, *Financing the Underfinanced*, Springer Berlin Heidelberg.

Jenq, C., Pan, J., & Theseira, W, 2015, Beauty, weight, and skin color in charitable giving, *Journal of Economic Behavior & Organization*, 119, 234 – 253.

Klafft M, 2008, Peer to peer lending: auctioning microcredits over the internet. (In: Agarwal A, Khurana R (eds) Proceedings of the international conference on information systems, technology and management).

Luke Deer, Jackson Mi, and Yu Yuxin, 2015, The rise of peer-to-peer lending in China:An overview and survey case study, The Association of Chartered Certified Accountants Report.

Larrimore, L., Jiang, L., Larrimore, J.et al, 2011, Peer to peer lending: the relationship between language features, trustworthiness, and persuasion success, *Journal of Applied Communication Research,* 39, 19–37.

Lin, M., Prabhala, N. and Viswanathan, S, 2013, Judging borrowers by the company they keep: friendship networks and information asymmetry in online peer-topeer lending, *Management Science,* 59, 17–35.

M. Herzenstein, R. Andrews, U. Dholakia, et al, 2008, The democratization of personal consumer loans? Determinants of success in online peer-to-peer lending communities, Working Paper.

Michal Herzenstein, Utpal M. Dholakia, and Rick L. Andrews, 2011, Strategic Herding Behavior in Peer-to-Peer Loan Auctions, *Journal of Interactive Marketing*, 25(1):27–36.

Puro L, Teich JE, Wallenius H et al, 2010, Borrower decision aid for people-to-people lending, *Decis Support Syst* 49(1):52–60.

Riza Emekter, Yanbin Tu, Benjamas Jirasakuldech, and Min Lu, 2015, Evaluating credit risk and loan performance in online Peer-to-Peer (P2P) lending, *Applied Economics*, 47(1):54–70, 2015.

R.A. Eisenbeis, 1977, Pitfalls in the application of discriminant analysis in business, finance, and economics, *The Journal of Finance* 32 (3) (1977) 875–900.

Riza Emekter, Yanbin Tu, Benjamas Jirasakuldech & Min Lu, 2015, Evaluating credit risk and loan performance in online Peer-to-Peer (P2P) lending, *Applied Economics,* 2015, 47:1, 54-70.

Sanjeev Kumar, 2007, Bank of One: Empirical Analysis of Peer-to-Peer Financial Market Places, (AMCIS Proceedings).

Song W, Han L, 2013, Influence factor analysis of lending willingness in p2p online lending, *J Southwest Univ Natl* (Nat Sci Ed) 39(5):795–799

Y. Yan, Z. Lv, B. Hu, 2011, Building investor trust in the p2p lending platform with a focus on chinese p2p lending platforms, *Electronic Commerce Research* 1–22.

Y. Gao, Y. Gao, J. Sun, J. Sun, Q. Zhou, Q. Zhou, 2017, Forward looking vs. backward looking: An empirical study on the effectiveness of credit evaluation system in china's online p2p lending market, *China Finance Review International* 7 (2) (2017) 228–248.

Yuejin Zhang, Haifeng Li, Mo Hai, Jiaxuan Li, Aihua Li, 2017, Determinants of loan funded successful in online P2P Lending, *Procedia Computer Science* 122 (2017) 896–901.

APPENDIX

Table 2 Summary Statistics of all listings

The table displays the summary statistics of all borrowing requests listed on Renrendai platform during 2015. Panel A describes loan characteristics, Panel B borrower characteristics, Panel C stock market characteristics. All variables are defined in detail in Table 1.

Variable	Obs	Mean	Std.Dev	Min	Max
A. Loan Characteristics					
Probability of funding	301,207	0.38	0.48	0	1
Loan Amount (in RMB)	301,207	61,487.06	70,325.55	0	500,000
Interest Rate spread (in %)	301,207	7.99	1.09	2.23	9.85
Onsite Verification	301,207	0.31	0.46	0	1
Loan Term(in months)	301,207	21.34	10.26	3	48
B. Borrower Characteristics					
Credit Score	301,207	75.58	79.07	0	231
Borrower's monthly income(in RMB)	301,207	3.08	1.15	0	6
Marriage	301,207	0.58	0.49	0	1
Education	301,207	0.68	0.47	0	1
House	301,207	0.46	0.50	0	1
House loan	301,207	0.24	0.42	0	1
Car	301,207	0.25	0.43	0	1
Car loan	301,207	0.06	0.25	0	1
C. Stock Market Characteristics					
Average stock market return (in %)	244	0.001	0.01	-0.04	0.02

Table 3 Summary Statistics of fully funded listings

The table displays the summary statistics of all listings that were fully funded by lenders on Renrendai platform during 2015. Panel A describes loan characteristics, Panel B borrower characteristics, Panel C stock market characteristics. All variables are defined in detail in Table 1.

Variable	Obs	Mean	Std.Dev	Min	Max
A. Loan Characteristics					
Probability of default	79,306	0.02	0.15	0	1
Loan Amount (in RMB)	79,306	59,106.37	33,977.43	3,000	500,000
Interest Rate spread (in %)	79,306	7.61	0.95	3.05	9.85
Onsite Verification	79,306	0.13	0.33	0	1
Loan Term(in months)	79,306	26.21	9.63	3	48
B. Borrower Characteristics					
Credit Score	79,306	166.60	41.04	0	231
Borrower's monthly income(in RMB)	79,306	3.37	1.23	0	6
Gender	79,306	0.73	0.44	0	1
Marriage	79,306	0.71	0.45	0	1
Education	79,306	0.75	0.43	0	1
House	79,306	0.55	0.50	0	1
House loan	79,306	0.36	0.48	0	1
Car	79,306	0.29	0.45	0	1
Car loan	79,306	0.08	0.45	0	1
C. Stock Market Characteristics					
Average stock market return (in %)	244	0.001	0.01	-0.04	0.02

Table 4 The effect of the stock market return on the correlation between credit score and funding success

The table reports the estimates of:

$$\alpha \quad \beta \qquad\qquad\qquad \beta \qquad\qquad \beta \qquad\qquad\qquad\qquad\qquad \delta \qquad \varepsilon$$

For this equation, the dependent variable Fund_i is a binary variable equal to 1 if the loan is fully funded and 0 otherwise. $\mathrm{Market\ return}_i$ is represented by last one-week average return of the SSE composite index (a stock market index of all stocks that are traded at the Shanghai Stock Exchange) on the days that the loans originate. e refers to each borrower's credit score provided by Renrendai platform. Xi is a vector of control variables, including two categories: the loan control variables and the borrower control variables. The loan control variables include each loan's borrowing amount and maturity. The borrower control variables consist of borrower's monthly income, gender, marriage, education, house asset, car asset, house loan, car loan and province. In specifications (1)-(2), the regression results without the interaction term are presented. The main independent variables are the stock market return and credit score. In specifications (3)-(4), the interaction term is added in the model. For specifications (1) and (3), the control variables regarding loan characteristics are used. For specifications (2) and (4), both the loan control variables and the borrower control variables are included. In the regression, I use clustered standard error identified by the cities of borrowers. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels respectively.

	Fund			
	（1）	（2）	(3)	(4)
Market return(1w)	0.27***	0.26***	0.30***	0.297***
	(9.12)	(8.83)	(7.54)	(7.51)
score	0.0059***	0.0058***	0.0059***	0.0058***
	(505.60)	(354.56)	(505.65)	(354.57)
market return×score			-0.0004***	-0.0005***
			(-3.30)	(-5.62)
loan controls	Y	Y	Y	Y
borrower controls	N	Y	N	Y
	89.48%	89.53%	89.48%	89.53%
N	301,207	301,207	301,207	301,207

Table 5 The effect of the stock market return on the correlation between onsite verification and funding success

The table reports the estimates of:

$$\alpha \quad \beta \qquad \beta \qquad \beta \qquad \delta \quad \varepsilon$$

For this equation, the dependent variable is a binary variable equal to 1 if the loan is fully funded and 0 otherwise. M is represented by the last one-week average return of the SSE composite index on the origination days of loans. is a dummy variable of 1 if the loan has onsite verification and 0 otherwise. Xi is a vector of control variables, including two categories: the loan control variables and the borrower control variables. All of them are identical with that in Table 4. In specifications (1)-(2), the regression results without interaction term are presented. The main independent variables are stock market return and the dummy variable of onsite verification. In specifications (3)-(4), the interaction term is added in the model. For specifications (1) and (3), control variables regarding loan characteristics are used. For specifications (2) and (4), both loan control variables and borrower control variables are included. In the regression, I use clustered standard error by cities of borrowers. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels respectively.

	Fund			
	(1)	(2)	(3)	(4)
Market return(1w)	0.27***	0.22***	0.34***	0.30***
	(3.52)	(3.24)	(3.08)	(3.06)
onsite	0.88***	0.83***	0.88***	0.83***
	(65.48)	(54.06)	(65.48)	(54.05)
market return×onsite			-0.22*	-0.25***
			(-1.85)	(-2.09)
loan controls	Y	Y	Y	Y
borrower controls	N	Y	N	Y
	72.62%	75.33%	72.62%	75.33%
N	301,207	301,207	301,207	301,207

Table 6 The effect of the stock market return on the correlation between spread and funding success

The table displays the estimates of:

$$\Pr(\mathrm{Fund_i} = 1) = \alpha + \beta_1 \mathrm{market\ return_i} + \beta_2 \mathrm{spread_i} + \beta_3 \mathrm{market\ return_i} \times \mathrm{spread_i} + \sum_{i=1}^{n} \delta_i X_i + \varepsilon_i$$

For this equation, the dependent variable $\mathrm{Fund_i}$ is a binary variable equal to 1 if the loan is fully funded and 0 otherwise. $\mathrm{Market\ return_i}$ is represented by the last one-week average return of the SSE composite index on the days that loans originate. $\mathrm{Spread_i}$ refers to each loan's interest rate spread (interest rate minus daily Shibor with the same maturity). Xi is a vector of control variables, including two categories: the loan control variables and the borrower control variables. All of them are identical with that in Table 4. In specifications (1)-(2), the regression results without interaction term are presented. The main independent variables are stock market return and interest rate spread. In specifications (3)-(4), the interaction term is added in the model. For specifications (1) and (3), control variables regarding loan characteristics are used. For specifications (2) and (4), both loan control variables and borrower control variables are included. As for standard errors, they are clustered by cities of borrowers. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels respectively.

	Fund			
	(1)	(2)	(3)	(4)
Market return(1w)	5.19***	4.54***	17.19***	15.21***
	(39.79)	(38.66)	(25.33)	(24.04)
spread	-0.26***	-0.23***	-0.26***	-0.23***
	(-77.21)	(-63.38)	(-77.79)	(-63.80)
market return×spread			1.44***	1.28***
			(18.81)	(18.19)
loan controls	Y	Y	Y	Y
borrower controls	N	Y	N	Y
R^2	58.09%	62.44%	58.20%	62.52%
N	301,207	301,207	301,207	301,207

Table 7 The effect of the credit score on the correlation between the stock market return and default rate

The table reports the estimates of:

$$\alpha \quad \beta \qquad\qquad \beta \qquad \beta \qquad\qquad\qquad \delta \quad \varepsilon$$

For this equation, the dependent variable is a dummy variable of , which is one if borrowers fail to repay the loan and 0 otherwise. M is represented by the last one-week average return of SSE composite index on the days that loans originate. refers to each borrower's credit score provided by Renrendai platform. Xi is a vector of control variables, including two categories: loan control variables and borrower control variables. All of them are identical with that in Table 4. In specifications (1)-(2), the regression results without interaction term are presented. The main independent variables are the stock market return and credit score. In specifications (3)-(4), the interaction term is included in the model. For specifications (1) and (3), control variables regarding loan characteristics are used. For specifications (2) and (4), both loan control variables and borrower control variables are included. As for standard errors, they are clustered by cities of borrowers. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels respectively.

	Default			
	(1)	(2)	(3)	(4)
Market return(1w）	0.13***	0.165***	0.24***	0.28***
	(2.91)	(3.91)	(3.38)	(4.45)
score	-0.004***	-0.003***	-0.003***	-0.003***
	(-52.87)	(-54.55)	(-52.43)	(-54.17)
market return×score			-0.002***	-0.003***
			(-5.62)	(-4.76)
loan controls	Y	Y	Y	Y
borrower controls	N	Y	N	Y
	55.96%	57.48%	55.96%	57.48%
N	79,306	79,306	79,306	79,306

Table 8 The effect of the spread on correlation between the stock market return and default rate

The table reports the estimates of:

$$\alpha \quad \beta \qquad\qquad \beta \qquad\qquad \beta \qquad\qquad\qquad \delta \quad \varepsilon$$

For this equation, the dependent variable is a dummy variable of , which is one if borrowers fail to repay the loan and 0 otherwise. is represented by the last one-week average return of the SSE composite index on the days that loans originate. refers to each loan's interest rate spread (interest rate minus daily Shibor with the same maturity). Xi is a vector of control variables, including two categories: the loan control variables and the borrower control variables. All of them are identical with that in Table 4. In specifications (1)-(2), the regression results without interaction term are presented. The main independent variables are stock market return and interest rate spread. In specifications (3)-(4), the interaction term is included in the model. For specifications (1) and (3), control variables regarding loan characteristics are used. For specifications (2) and (4), both loan control variables and borrower control variables are included. As for standard errors, they are clustered by cities of borrowers. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels respectively.

	Default			
	(1)	(2)	(3)	(4)
Market return(1w）	0.95***	0.92***	1.56**	1.65***
	(11.63)	(11.41)	(2.43)	(2.57)
spread	0.046***	0.046***	0.046***	0.046***
	(16.65)	(16.32)	(16.60)	(16.27)
market return×spread			0.076***	0.092***
			(5.91)	(6.10)
loan controls	Y	Y	Y	Y
borrower controls	N	Y	N	Y
	8.14%	9.13%	8.14%	9.14%
N	79,306	79,306	79,306	79,306

Table 9 The effect of the stock market return on the correlation between credit score and funding success

The table reports the estimates of:

$$\Pr(\mathrm{Fund}_i = 1) = \alpha + \beta_1 \mathrm{market\ return}_i + \beta_2 \mathrm{score}_i + \beta_3 \mathrm{market\ return}_i \times \mathrm{score}_i + \sum_{i=1}^{n} \delta_i X_i + \varepsilon_i$$

For this equation, the dependent variable Fund_i is a binary variable equal to 1 if the loan is fully funded and 0 otherwise. $\mathrm{Market\ return}_i$ represents the last one-month average return of the SSE composite index (a stock market index of all stocks that are traded at the Shanghai Stock Exchange) on the days that loans originate. Score_i refers to each borrower's credit score provided by Renrendai platform. Xi is a vector of control variables, including two categories: loan control variables and borrower control variables. All of them are identical with that in Table 4. In specifications (1)-(2), the regression results without interaction term are presented. The main independent variables are stock market return and credit score. In specifications (3)-(4), the interaction term is added in the model. For specifications (1) and (3), control variables regarding loan characteristics are used. For specifications (2) and (4), both loan control variables and borrower control variables are included. As for standard errors, they are clustered by cities of borrowers. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels respectively.

	Fund			
	(1)	(2)	(3)	(4)
Market return(1m)	1.24***	1.20***	1.11***	1.10***
	(15.80)	(15.87)	(13.34)	(13.30)
score	0.006***	0.006***	0.006***	0.006***
	(509.65)	(357.92)	(486.80)	(347.66)
market return×score			-0.002***	-0.001***
			(-3.65)	(-3.37)
loan controls	Y	Y	Y	Y
borrower controls	N	Y	N	Y
R^2	89.50%	89.54%	89.50%	89.53%
N	301,207	301,207	301,207	301,207

Table 10 The effect of the stock market return on the correlation between onsite verification and funding success

The table reports the estimates of:

$$\Pr(\text{Fund}_i = 1) = \alpha + \beta_1 \text{market return}_i + \beta_2 \text{onsite}_i + \beta_3 \text{market return}_i \times \text{onsite}_i + \sum_{i=1}^{n} \delta_i X_i + \varepsilon_i$$

For this equation, the dependent variable Fund_i is a binary variable equal to 1 if the loan is fully funded and 0 otherwise. Market return_i represents last one-month average return of the SSE composite index on the origination days of loans. Onsite_i is a dummy variable of 1 if the loan has onsite verification and 0 otherwise. Xi is a vector of control variables, including two categories: the loan control variables and the borrower control variables. All of them are identical with that in Table 4. In specifications (1)-(2), the regression results without interaction term are presented. The main independent variables are the stock market return and the dummy variable of onsite verification. In specifications (3)-(4), the interaction term is added in the model. For specifications (1) and (3), control variables regarding loan characteristics are used. For specifications (2) and (4), both loan control variables and borrower control variables are included. As for standard errors, they are clustered by cities of borrowers. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels respectively.

	Fund			
	(1)	(2)	(3)	(4)
Market return(1m)	1.18***	1.09***	1.57***	1.44***
	(5.27)	(5.35)	(4.95)	(5.39)
onsite	0.88***	0.84***	0.88***	0.84***
	(66.06)	(54.46)	(66.74)	(54.65)
market return×onsite			-1.32***	-1.18***
			(-3.73)	(-3.84)
loan controls	Y	Y	Y	Y
borrower controls	N	Y	N	Y
R^2	72.64%	75.35%	72.64%	75.35%
N	301,207	301,207	301,207	301,207

Table 11 The effect of the stock market return on the correlation between interest rate spread and funding success

The table reports the estimates of:

$$\Pr(Fund \quad \alpha \quad \beta \quad \beta \quad \beta \quad \delta \quad \varepsilon$$

For this equation, the dependent variable is a binary variable equal to 1 if the loan is fully funded and 0 otherwise. M represents the last one-month average return of the SSE composite index on the origination days of loans. refers to each loan's interest rate spread (interest rate minus daily Shibor with the same maturity). Xi is a vector of control variables, including two categories: loan control variables and borrower control variables. All of them are identical with that in Table 4. In specifications (1)-(2), the regression results without interaction term are presented. The main independent variables are stock market return and interest rate spread. In specifications (3)-(4), the interaction term is added in the model. For specifications (1) and (3), control variables regarding loan characteristics are used. For specifications (2) and (4), both loan control variables and borrower control variables are included. As for standard errors, they are clustered by cities of borrowers. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels respectively.

	Fund			
	(1)	(2)	(3)	(4)
Market return(1m)	21.07***	18.64***	43.10***	39.18***
	(61.73)	(58.29)	(23.32)	(23.51)
spread	-0.29***	-0.26***	-0.30***	-0.26***
	(-87.15)	(-72.59)	(-89.39)	(-73.88)
market return×spread			2.71***	2.53***
			(12.34)	(12.97)
loan controls	Y	Y	Y	Y
borrower controls	N	Y	N	Y
	61.80%	65.29%	61.90%	65.37%
N	301,207	301,207	301,207	301,207

Table 12 The effect of the credit score on the correlation between the stock market return and default rate

The table reports the estimates of:

$$\alpha \quad \beta \quad \beta \quad \beta \quad \delta \quad \varepsilon$$

For this equation, the dependent variable is a dummy variable of , which is 1 if borrowers fail to repay the loan and 0 otherwise. is represented by the last one-month average return of the SSE composite index on the days that loans originate. refers to each borrower's credit score provided by Renrendai platform. Xi is a vector of control variables, including two categories: loan control variables and borrower control variables. All of them are identical with that in Table 4. In specifications (1)-(2), the regression results without interaction term are presented. The main independent variables are the stock market return and credit score. In specifications (3)-(4), the interaction term is included in the model. For specifications (1) and (3), control variables regarding to loan characteristics are used. For specifications (2) and (4), both loan control variables and borrower control variables are included. As for standard errors, they are clustered by cities of borrowers. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels respectively.

	Default			
	(1)	(2)	(3)	(4)
Market return（1m）	3.80***	3.80***	0.07***	0.03***
	(17.04)	(16.51)	(4.05)	(6.02)
score	-0.05***	-0.05***	-0.003***	-0.003***
	(-18.34)	(-17.94)	(-49.44)	(-51.23)
market return×score			-0.006*	-0.006*
			(-1.74)	(-1.72)
loan controls	Y	Y	Y	Y
borrower controls	N	Y	N	Y
	55.95%	57.51%	56.06%	57.58%
N	79,306	79,306	79,306	79,306

Table 13 The effect of the spread on the correlation between the stock market return and default rate

The table reports the estimates of:

$$\alpha \quad \beta \qquad \beta \qquad \beta \qquad \delta \quad \varepsilon$$

For this equation, the dependent variable is a dummy variable of , which is one if borrowers fail to repay the loan and 0 otherwise. M is represented by the last one-month average return of the SSE composite index on the days that loans originate. refers to each loan's interest rate spread (interest rate minus daily Shibor with the same maturity). Xi is a vector of the control variables, including two categories: loan control variables and borrower control variables. All of them are identical with that in Table 4. In specifications (1)-(2), the regression results without the interaction term are presented. The main independent variables are stock market return and interest rate spread. In specifications (3)-(4), the interaction term is included in the model. For specifications (1) and (3), control variables regarding loan characteristics are used. For specifications (2) and (4), both loan control variables and borrower control variables are included. As for standard errors, they are clustered by cities of borrowers. The symbols *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels respectively.

	Default			
	(1)	(2)	(3)	(4)
Market return（1m）	3.80***	3.80***	2.10*	2.30**
	(17.04)	(16.51)	(1.83)	(1.99)
spread	0.05***	0.05***	0.05***	0.05***
	(18.34)	(17.94)	(18.31)	(17.88)
market return×spread			0.22***	0.19***
			(3.40)	(3.24)
loan controls	Y	Y	Y	Y
borrower controls	N	Y	N	Y
	9.32%	10.33%	9.33%	10.33%
N	79,306	79,306	79,306	79,306