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Do High-risk Investors Matter in Online P2P Lending Market? Evidence from China

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Abstract

The development of network technology has prompted the gradual rise of lending platforms, which not only meet the borrowing needs of the long-tail population, but also provide new investment methods for investors with idle funds. However, behind the rapid development of P2P online lending is accompanied by increasingly prominent risk issues. Using a Probit model and a dataset of 337,634 loan listings from a leading Chinese online Peer-to-Peer (P2P) lending platform (i.e., Renrendai platform), we investigate whether high-risk investors contribute to online P2P loan default risks and interest rates. Our empirical results show that, with 1% increase in the percentage of high-risk investors in a loan, the likelihood of loan default would increase by 0.79% and the loan's interest rate would increase by 4%. Our analysis suggests that the percentage of high-risk investors should be considered in online P2P lending risk management. To the best of our knowledge, this is the first paper to study the impact of fund providers' risk attitude on the online P2P lending market.

Keywords: P2P lending, high-risk investors, default risks, interest rates, China.

1. Introduction

Over the past decade, online peer-to-peer (P2P) lending has grown rapidly around the world, and China is no exception. For example, the Chinese P2P lending industry's transaction volume is about 6.07 trillion loan amounts by the end of 2018 (He et al., 2020).

However, the fast growth has been accompanied by some serious problems, such as loan defaults. He et al. (2020) found that that the Chinese P2P lending market has a default debt amount of 120 billion RMB in 2018. P2P lending mainly serves long-tail groups (which mainly includes low-income residents and small businesses, i.e., borrowers with low credit and very high risk) (Yum et al., 2012). Therefore, a key issue facing the P2P lending market is how to manage the risk of default in P2P lending. And few studies have examined the role of investors in determining loan default risk in P2P lending markets. Thus, it is imperative to examine the determinants of default risks of P2P loans.

The theory of information asymmetry refers to that in market economic activities, various types of people have different understanding of relevant information. This theory is at the core of creating default risk in the P2P lending market. And risk management refers to the management process of how to minimize the adverse or adverse effects of risks in a project or enterprise. As an important part of Internet finance, the risk management of P2P network lending platform is also the top priority of its management work. Risks are everywhere in the financial market. As an intermediary platform for small loans, P2P's main business is fundraising and investment activities, so its financial risk should be the top priority of the platform's financial management. Various emergencies, government policy changes or unforeseen changes in the external market and environment, coupled with certain unknown factors, such as the high-risk investors discussed in this article, may cause the platform to fall into financial difficulties. This puts the platform in crisis.

Previous literature on P2P loan default risks mainly focuses on borrowers’ characteristics and loan characteristics. Few studies have investigated the determinants of default risks of P2P loans from the perspective of lenders. Thus, our study fills the gap by studying whether high-risk investors contribute to online P2P loan default risks and interest rates. The study offers implications for P2P platform management and similar lending projects. Our finding suggests that high-risk investors would drive loans with higher default risk to be funded. Therefore, the managers and platforms should establish related mechanisms for high-risk investors so that the default risk can be better controlled.

We used a list of 337,634 loans on the Renren platform (a leading P2P lending platform in China) from 2013 to 2015. to examine how the ratio of high-risk investors affects loan default and interest rate. We define a high-risk investor whether her/his credit grade is HR. Our results show that, if the proportion of high-risk investors in a loan increases by 1%, the likelihood of loan default would rise by 0.79%. Furthermore, our analysis suggests that 1% increase in the proportion of high-risk investors in a loan, results in a 4% increase in the interest rate on the loan. This finding indicates that high-risk investors invest risky projects for higher returns. In our robustness checks, we change the definition of high-risk investors according to investors’ credit grades and measure the investors’ risk level by the percentage of high-risk investors’ bidding amount in a loan. The results are robust.

There are two contributions of this study. First, as mentioned before, our study contributes to research related to the default risk of P2P loans by investigating the impact of investor characteristics on the default risk of P2P loans. Moreover, this study also adds to the literature on determination of P2P loan interest rates. Most of previous studies have been focusing on how borrower characteristics, loan characteristics, and platform characteristics affect the P2P lending interest rates (e.g., Pope and Sydney, 2011; Michels, 2012; Gonzalez and Loureiro, 2014; Mohammadi and Shafi, 2018; Kgoroeadira et al., 2019; He et al., 2020). Few researches have considered the effect of investor characteristics on online P2P loan interest rates. Thus, our study contributes to this strand of literature.

The remainder of this study is shown below: Section 2 is a literature review. Section 3 provides a description of data, variables, and summary statistics. Section 4 set up the empirical models and Section 5 presents the estimation result. Section 6 concludes.

2. Literature Review

The development of network technology has prompted the gradual rise of P2P online lending, which not only meets the borrowing needs of the long-tail population, but also provides new investment methods for investors with idle funds, effectively contributing to inclusive finance. However, the rapid development of P2P online lending is accompanied by increasingly prominent risk issues, which has also attracted widespread attention from scholars at home and abroad.

Previous literature on P2P loan default risks more focus on borrowers' characteristics and loan characteristics. On the borrowers' level, factors that affect the risk of loan default include hard information such as gender, age, education, income, marriage, ethnicity (e.g., Herzenstein et al., 2008; Pope and Sydney, 2011; Lin et al., 2017; Li and Hu, 2019; Chen et al., 2020) and information such as social connections, the borrower's appearance, social status and credit ratings. (e.g., Duarte et al., 2012; Lin et al., 2013; Xu et al., 2015; Liu et al., 2015; Chen et al., 2016; Ding et al., 2019; Li and Hu, 2019; Wu and Zhang, 2020). On the loan level, loan characteristics that could predict the default risks include loan amount, terms, interest rates, loan type, loan descriptive texts, and so on (e.g., Barasinska and Schafer, 2014; Cinca et al., 2015; Dorfleitner et al., 2016; Jiang et al., 2018; Chen et al., 2018; Zhou and Wei, 2020). In addition, some other studies investigate how P2P platform characteristics affect loan default risks (e.g., Gong et al., 2020; Wang et al., 2020). For example, Gong et al. (2020) find that the loan default risks can be reduced if platforms' CEOs have banking experience. Of course, as a hub connecting borrowers and lenders, the P2P online lending platform is also very important. Therefore, some literatures have carried out research on the platform, discussing the factors affecting the platform's transaction volume, operational efficiency (e.g., Zheng et al., 2016; Luo et al., 2017), and platform risk prevention and control (e.g., Huang et al., 2016). Shao & Bo (2022) find that P2P platform behavior factors affect the P2P lending market. Finally, behind the rapid development of the online lending market, platform problems have repeatedly emerged. Therefore, some literatures have studied the supervision of P2P online lending platforms (e.g., Davis & Gelpern, 2010; Paul, 2013). Ding et al (2021) concluded that while encouraging the innovation of financial instruments, attention should also be paid to protecting the rights and interests of investors and preventing their risks.

However, few studies have addressed the importance of investors in determining loan default risks in P2P lending market. Exemptions are Herzenstein et al. (2011) and Zhang and Liu (2012). They mainly focus investors' behaviors such as herding. Deferent from previous studies, we investigate whether high-risk investors contribute to online P2P loan default risks and interest rates. In P2P lending market, individual investors choose which loan applications to bid. Consequently, investors' preference would affect which loans are funded and hence affect the probability of loan defaults. For example, high-risk investors may prefer to invest risky projects. As a result, risky projects are more likely to be succeed, but these projects have higher likelihood to default. And high-risk investors would require the borrowers to pay higher interest rate for these projects.

3. Data

Our main dataset is from Renrendai platform, one of the largest P2P lending platforms in China platforms. The dataset contains all loan application information on the platform from 2013 to 2015, with total loan listings of 500,563. It includes: (a) loan information, for instance the date, loan amount, loan interest rate, term, whether the loan application is funded, and whether the funded loan is overdue or bad-debt; (b) and borrowers' information, for instance gender, age, marriage status, education, income, house property, car property, and credit rating; (c) investors' information of the loan listings, such as investors' nickname, bidding amount, investors' credit grades, and investors' credit score.

We remove observations with missing values in key variables or with outliers. We also exclude observations with borrowers from Taiwan, Hong Kong, and Macau, because their institutions are different from mainland China. Moreover, following Butler et al. (2017), we remove observations of Institutional guaranteed loan applications and field certified loan applications due to the differences between these loan applications with unsecured loan requests. Consequently, our sample yields 337,634 loan applications in our analysis, covering 31 provinces in China.

In addition, we also obtain province-level economic characteristics (i.e., GDP per capita, marketization index, unemployment rate) from WIND database, which is a commonly used database in China.

Our main dependent variables are $Default$ and$Interest\ Rate$. $Default$ Indicates whether the loan is defaulted or not. It is measured by whether the loan is overdue and whether the loan is bad debt, respectively. $Interest\ Rate$ is the loan's annual interest rate.

The key independent variable in this study is HR_Ratio, i.e., the ratio of high-risk investors in a loan. For each loan listing, HR_Ratio is measured by the number of high-risk investors as a percentage of the total number of investors. An investor is high risk if her/his credit grade is HR. In our robustness check, we will test other measurements of HR_Ratio. The definitions of the variables used in this study are presented in Table 1.

Table 1: Definition of variables

Variables	Description
Success	Dummy variable indicating whether the loan application is funded.
Interest Rate (%)	Loan's annual interest rate.
Overdue	Dummy variable indicating whether the loan is overdue.
Bad debt	Dummy variable indicating whether the loan is bad debt.
HR_Ratio	Ratio of high-risk investors in a loan, measured by the number of high-risk investors as a percentage of the total number of investors..
lnAmount	The logarithm of the RMB amount of the loan application.
Term	The term of redemption of the loan request.
Gender	Dummy variable indicating whether the borrower is female.
Age	The borrower's age.
Married	The borrower's marriage status, denoted as 1 for married; and otherwise 0.
Education	The borrower's education level, denoted as 1 for high school or below, 2 for junior college, 3 for undergraduate, and 4 for graduate or above.
Income	The borrower's monthly income, denoted as 1 for 2,000-5,000 RMB, 2 for 5,000-10,000 RMB, 3 for 10,000-20,000 RMB, 4 for 20,000-50,000 RMB, and 5 for 50,0000 RMB and above.
House	Dummy variable indicating whether the borrower owns house property.
Car	Dummy variable indicating whether the borrower owns cars.
Credit	The borrowers' credit grade, denoted as 1 to 7 for HR, E, D, C, B, A, AA, respectively.
Market_index	Marketization index of each province each year.
lnGDP	The logarithm of the GDP per capita in the borrower's province.
Unemployment (%)	The unemployment rate in the borrower's province.

Summary statistics for each variable are reported in Table 2. From the table, we can find that about 24.98% of loan application get funded. The average loan interest rate is 12.93%. About 2.41% of the funded loan is overdue and 2.157% of the funded loan becomes bad debt. In terms of the ratio of high-risk investors, the mean of HR_Ratio is 0.1900, suggesting that about 19% of the investors has a credit grade of HR (high risk).

Table 2: Summary Statistics

Variable	Obs.	Mean	SD	Min	Max
Success	337,634	0.2498	0.4329	0	1
Interest Rate (%)	337,634	12.9301	2.2365	7	24
Overdue	84,326	0.0241	0.1535	0	1
Baddebt	84,326	0.02157	0.1453	0	1
HR_Ratio	316,477	0.1900	0.3862	0	1
lnAmount	337,634	10.5220	1.1093	8.01	13.12
Term	337,634	20.1768	10.7311	3	36
Gender	337,634	0.1664	0.3724	0	1
Age	337,634	32.2330	7.4825	17	70
Married	337,634	0.5490	0.4976	0	1
Education	337,634	1.8725	0.7699	1	4
Income	337,634	2.0838	1.1302	1	5
House	337,634	0.4454	0.4970	0	1
Car	337,634	0.1800	0.3842	0	1
Credit	337,634	2.1757	2.0989	1	7
Market_index	93	6.4286	2.1414	-0.30	10.11
lnGDP	93	10.7456	0.3966	10.05	11.59
Unemployment (%)	93	3.2808	0.6549	1.21	4.5

4. Model

It is worth to note that we can only observe whether the loan is defaulted for funded loans. Moreover, the interest rate of funded loans is the equilibrium interest rate under loan supply and demand dynamic. As a result, we only use the data on funded loans when we investigate the impacts of ratio of high-risk investors on loan default risk and interest rate. To avoid sample selection bias, we follow Michels (2012) and employ a two-step Heckman method. First, we estimate a Probit model because the dependent variable is $success$. With the estimation results, we calculate the Inverse-Mills ratio. Then, we add the Inverse-Mills ratio as a control variable to correct the sample selection bias. In our study, the dependent variable ($Default_{ijt}$) is a dummy variable. According to econometric theory, a Probit model is more suitable for our study. Thus, we employ Probit model to determine the impact of HR_Ratio on loan default risks, as shown below:

$$probit(Default_{ijt} = 1) = \alpha_0 + \beta HR\_Ratio_i + \gamma Z_{it} + \theta X_{jt} + \delta Mills + Province_j + Year_t + \varepsilon_{ijt} \quad (1)$$

Where i, j, t represent the loan listing, province, and year, respectively; and $Default_{ijt}$ is the dependent variable and is measured by whether the loan is past due and whether the loan is bad debt, respectively. HR_Ratio_i is the key independent variable, which measures the loan i's ratio of high-risk investors. $Z_{i,t}$ contains the loan-level and borrower-level control variables, including logarithm of loan amount, loan interest rate, loan term, borrower's gender, age, married, education, income level, house property, car property, and credit grade. Following Butler et al. (2017), we also control the province-level economic characteristics ($X_{j,t}$), including the marketization index, logarithm of the GDP per capita, and unemployment rate. $Mills$ is the inverse-mills ratio that corrects for sample selection bias. We also control the province fixed effects and year fixed effects in the model. $\varepsilon_{i,j,t}$ is the i.i.d. error term.

To examine the impact of ratio of high-risk investors on loan interest rate, we set up the following model:

$$Interest\ Rate_{ijt} = \alpha_0 + \beta HR\_Ratio_i + \gamma Z_{it} + \theta X_{jt} + \delta Mills + Province_j + Year_t + \varepsilon_{ijt} \quad (2)$$

Where the dependent variable is the interest rate of funded loan. Other variables are similar to those in equation (1). The difference is that $Z_{i,t}$ does not include loan interest rate.

5. Analysis and Results

5.1 Main Results

The estimation results for equations (1) and (2) are presented in Table 3. Columns (1) to (4) report the effect of HR_Ratio (i.e., the ratio of high-risk investors) on default risks of P2P lending. In columns (1) and (2), we measure default by whether the loan is overdue. Column (1) shows the baseline results without considering sample selection bias. It indicates that the percentage of high-risk investors in a loan has a significantly effect on loan defaults on P2P lending platforms at the 5% level. As shown in column (2), the Inverse-Mills ratio is significantly at 1% level, indicating that the Heckman two-step method could control the sample selection bias. The coefficient of HR_Ratio_i suggests that ratio of high-risk investors could increase loan defaults in P2P lending market. It suggests that as the proportion of high-risk investors in a loan increases by 1%, the probability of loan default would increase by 0.79%. In columns (3) and (4), we measure default by whether the loan is bad debt. The results show similar patterns as columns (1) and (2).

Columns (5) and (6) report the effect of ratio of high-risk investors on the loan interest rates. The results show that percentage of high-risk investors has a positive effect on loan interest rates of P2P lending. With 1% increase in percentage of high-risk investors in a loan, the loan's interest rate would increase by about 4%.

Moreover, the coefficients of other control variables are reasonable. In general, longer-term borrowing may mean tighter credit checks, while short-term borrowing may be less stringent, giving risk-lovers an opportunity to increase expectations and the likelihood of bad debts. As long-term borrowing is riskier, interest rates have also risen. Let's look at the impact of the investor's personal characteristics. Men are more "adventurous" than women, and they tend to have a higher risk appetite. Marital status does not seem to have a significant effect here. Age is closely related to income status, and generally speaking, they are almost positively correlated, except for the second-generation rich. Therefore, subject to the constraints of economic conditions, risk appetite just corresponds to it. When a lender applies for a loan, and the loan platform finds that it has assets such as a house and a car through a credit investigation, it will generally require a guarantee or increase the interest rate accordingly. Education and credit also appear to be causally linked, although this is not absolute, but borrowers with low education levels are far more likely to default on expectations than lenders with higher education levels. Because their legal literacy, investment awareness and knowledge are relatively lacking, and most of the people who lack credit often do not have a high degree of education. Provincial economic characteristics only seem to have a significant impact on interest rates because the population is mobile, but it is certain that in places with a higher level of economic level and marketization, interest rates will also be correspondingly higher than in other regions.

The following reasons for these results are intuitive. First, there is a high probability that high-risk investors are risk-preferred. They may prefer to invest risky loan applications which have higher default risks. Second, high-risk projects are usually associated with high returns. As a result, loans with more high-risk investors tend to have higher default risks and higher interest rates.

The Chinese 19th National Congress proposed that China should forestall and defuse major risks and carry out targeted poverty alleviation. On the one hand, P2P lending provides credits for long-tail groups and alleviate their financial constraints, which ultimately could increase their income and alleviate poverty. On the other hand, P2P lending has a high-risk exposure, which contradicts the government goal of forestalling and defusing major risks. Thus, both the financial regulations and platform managers should take measures to control the risk of P2P lending so that P2P lending can better provide credit for long-tail groups and serve for poverty alleviation programs. Our study finds that high-risk investors drive up online P2P loan default risks and interest rates. Thus, the financial authorities and platform managers should establish related mechanisms for high-risk investors so that the default risk can be better controlled.

Table 3: The Effects of Investors' Risk Level on Loan Defaults and Interest Rates

	Overdue		Bad Debt		Interest rate	
	(1)	(2)	(3)	(4)	(5)	(6)
HR_Ratio	0.2788**	0.3967***	0.2268*	0.3593**	0.0418***	0.0424***
	(0.1261)	(0.1522)	(0.1307)	(0.1594)	(0.0119)	(0.0123)
lnAmount	-0.1079**	-0.1405**	-0.0775*	-0.0910	-0.0189***	-0.0393***
	(0.0454)	(0.0578)	(0.0467)	(0.0593)	(0.0064)	(0.0049)
Interest rate	0.1790***	0.1635***	0.1713***	0.1618***		
	(0.0232)	(0.0244)	(0.0217)	(0.0234)		
Term	-0.0549***	-0.0609***	-0.0605***	-0.0667***	0.0799***	0.0815***
	(0.0029)	(0.0041)	(0.0031)	(0.0043)	(0.0004)	(0.0003)
Gender	-0.2142***	-0.2646***	-0.2503***	-0.2602***	-0.0048	-0.0007
	(0.0648)	(0.0798)	(0.0685)	(0.0834)	(0.0036)	(0.0042)
Age	0.0167***	0.0207***	0.0179***	0.0205***	-0.0005**	-0.0001
	(0.0035)	(0.0042)	(0.0036)	(0.0043)	(0.0002)	(0.0002)
Married	-0.0089	0.0262	-0.0405	-0.0494	-0.0068	-0.0017
	(0.0486)	(0.0579)	(0.0501)	(0.0596)	(0.0044)	(0.0043)
Education	-0.2450***	-0.2475***	-0.2592***	-0.2637***	-0.0137***	-0.0080***
	(0.0291)	(0.0348)	(0.0302)	(0.0362)	(0.0029)	(0.0027)
Income level	0.0858***	0.0721***	0.0878***	0.0729***	-0.0120***	-0.0041**
	(0.0219)	(0.0258)	(0.0226)	(0.0266)	(0.0020)	(0.0020)
House	-0.0784*	-0.0566	-0.0960*	-0.0955	0.0123**	0.0156***
	(0.0476)	(0.0573)	(0.0493)	(0.0596)	(0.0054)	(0.0046)
Car	0.2078***	0.2311***	0.2491***	0.2910***	0.0134***	0.0089**
	(0.0663)	(0.0780)	(0.0682)	(0.0801)	(0.0039)	(0.0043)
Credit	-0.7329***	-0.7586***	-0.7313***	-0.7635***	-0.2792***	-0.1539***
	(0.0270)	(0.0303)	(0.0283)	(0.0329)	(0.0039)	(0.0082)
Market_index	-0.0594	0.2650	-0.0423	0.3942	0.0568*	0.0539**
	(0.2521)	(0.4051)	(0.2646)	(0.4192)	(0.0307)	(0.0255)
lnGDP	-0.4135	0.5854	-0.0139	2.3484	0.7554***	0.7529***
	(1.7426)	(2.7122)	(1.8307)	(2.8545)	(0.1392)	(0.1324)
Unemployment	0.2591	0.1737	0.3545	0.2847	0.0355	0.0338

	(0.3178)	(0.6302)	(0.3329)	(0.6568)	(0.0375)	(0.2699)
Inverse Mills ratio		-9.6158^{***} (3.0763)		-9.2503^{***} (3.1423)		0.2817^{***} (0.0179)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	63,165	44,562	63,165	44,562	63,165	316,477

Note: Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In columns (1) and (2), we measure "default" by whether the loan listing is overdue. In columns (3) and (4), we measure "default" by whether the loan listing is bad debt. Columns (5) and (6) report the results of the model with dependent variable "Interest Rate". Columns (1), (3), and (5) report the results of baseline models without correcting sample selection bias, while columns (2), (4), and (6) use Heckman two-step method to correct sample selection bias.

5.2 Robustness Checks

In our main analysis, we measure the key independent variable "HR_Ratio" is the ratio of the number of high-risk investors to the number of investors for each loan. An investor is defined as high risk if her/his credit grade is HR. To examine whether the results are sensitive to the measure of this variable, we conduct two robustness checks in Table 4. First, we define an investor as high risk if her/his credit grade is HR or E or D. Then we construct the independent variable "HR_Ratio1" is the ratio of the adjusted number of high-risk investors to the number of investors for each loan. Second, we measure the percentage of high-risk investors' bidding amount "HR_Ratio2" by the total bidding amount of high-risk investors divided by the loan amount for each loan. As shown in Table 4, all results are robust to the main results shown in Table 3.

Table 4: Robustness Checks

	Overdue		**Bad Debt**		**Interest rate**	
	(1)	(2)	(3)	(4)	(5)	(6)
HR_Ratio1	0.6445** (0.3028)		0.6830** (0.3275)		0.0617** (0.0245)	
HR_Ratio2		0.2196* (0.1287)		0.2340* (0.1323)		0.0409*** (0.0110)
Inverse Mills Ratio	-9.5463*** (3.0898)	-9.6244*** (3.0779)	-9.1725*** (3.1561)	-9.2655*** (3.1450)	0.0644*** (0.0239)	0.2817*** (0.0179)
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	44,562	44,562	44,562	44,562	316,472	316,472

Note: Robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. All models include Inverse-Mills ratio to address sample selection problem. In columns (1) and (2), we measure "default" by whether the loan listing is overdue. In columns (3) and (4), we measure "default" by whether the loan listing is bad debt. Columns (5) and (6) report the results of the model with dependent variable "Interest Rate". In columns (1), (3), and (5), the key independent variable is "HR_Ratio1", measured by the ratio of the number of high-risk investors to the total number of investors. An investor is defined as high-risk if her/his credit grade is HR or E or D. In columns (2), (4), and (6), the key independent variable is "HR_Ratio2", measured by the total bidding number of high-risk investors divided by the loan amount. An investor is defined as high-risk if her/his credit grade is HR.

6. Conclusion

6.1 Main Conclusion

Using the data of 337,634 loan listings on Renrendai platform in China, this study investigates how high-risk investors affect P2P lending. Our results suggest that, as more high-risk investors involve in a loan, the loan is more likely to have a higher default risk and a higher interest rate. Our analysis provides implications for P2P lending platforms to manage default risks. Since high-risk investors are a driving force for risky loans to be funded, the platforms should pay attention to the percentage of high-risk investors in a loan when evaluating default risks. The platforms' managers can set an upper bound of percentage of high-risk investors for loans so that risky loans become less likely to be funded.

6.2 Contribution of the Study

This study has two contributions. First, our study contributes to the P2P loan default risk literature by investigating the impact of investor characteristics on P2P loan default risk. Additionally, this study adds to the literature on determining P2P lending rates. Few studies have considered the impact of investor characteristics on online P2P lending rates. Therefore, our study contributes to the literature in this field.

According to our analysis, high-risk investors are more likely to be risk-averse, and they may be more willing to invest in high-risk loan applications with a higher default risk. Second, high-risk projects are often accompanied by high returns. So here are some suggestions for P2P microfinance managers.

First, do due diligence and credit review. Be able to identify as high-risk investors as possible before borrowing so you can prepare ahead of time. For example, raising loan interest rates, strengthening restrictions on the use of funds by these high-risk investors, and strictly controlling the progress of fund recovery. At the same time, strengthen bad debt management. Second, standardize the internal management of the platform. Strengthen the internal financial management of the platform, improve the financial literacy of internal staff, and strengthen the concept of financial security. Reasonably improve the internal evaluation system of the platform, and establish a good internal control system and employee management system.

6.3 Limitations and Future Directions

Nevertheless, this paper still has certain limitations and many shortcomings. For example, when observing and analyzing data, we treat each loan as an observation. But in fact, the same person may borrow more than one single loan, and there is a problem of repeated borrowing. Therefore, we did not account for the repetition rate over time. This is also one of the areas that needs to be improved.

At present, the main factors affecting online lending are mainly studied from the perspective of online lending demand. At the same time, the P2P online lending platform as a hub connecting borrowers and lenders is also a research hotspot. However, few studies have examined the role of investors in determining loan default risks in P2P lending market. Therefore, in the future research direction, based on the perspective of investors, we can study how to supervise users more effectively, especially those with high risk tendencies.

Finally, few studies have considered the urgency of lenders and herding behavior of investors, etc, in determining P2P lending. Thus, future research can be devoted to these questions. The extensions will generate some useful and valuable findings.

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