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Research on investors' preference for the borrowers' occupational identity: Evidence from P2P lending platform in China

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A R T I C L E I N F O

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A B S T R A C T

This paper explores the intricate issue of credit discrimination based on occupational identity within China's rapidly growing P2P lending sector. Leveraging the rich transactional data from the RENRENDAI lending platform, the study carefully examines how a borrower's occupational identity (OI) subtly influences investor preferences and thoroughly investigates the underlying currents of credit discrimination that may exist on such platforms. A logit model serves as the core analytical tool to empirically uncover and quantify investors' nuanced inclinations toward various occupational identities (OIs). The findings reveal a distinct pattern: investors show a clear tendency to favor borrowers whose occupational identity (OI) aligns with that of a wage-earner. This form of occupational-based credit discrimination, when viewed through the lens of investor rationality, can be understood as a calculated risk assessment, whereas the discriminatory treatment of network merchants often leans toward irrationality. The origins of such credit discrimination, it is found, lie not solely in social status prejudice but rather in investors' informed understanding and interpretation of the inherent economic characteristics and stability profiles associated with different borrowers' occupational identities. The irrational discriminatory behavior directed at network merchants is primarily attributed to cognitive biases that cloud investors' judgment. Furthermore, the study observes that occupational identity (OI) emerges as a strong predictor of credit risk, suggesting that the methodologies proposed here hold significant potential for practical application in real-world P2P lending platforms, potentially enhancing both efficiency and fairness. The primary contribution of this study lies in bridging a critical gap in existing literature by offering novel insights into the complex relationship between occupational identity and credit allocation within digital lending ecosystems.

Introduction

With the continuous development of internet and information technologies has facilitated the emergence of online peer-to-peer (P2P) lending as an innovative business model (Greiner and Wang, 2010). Functioning as intermediaries, P2P lending platforms connect investors and borrowers by providing credit services (Boase and Ling, 2013). In contrast to traditional financial institutions, these platforms offer information services to investors characterized by lower entry barriers, enhanced convenience, and reduced operational costs (Zhao et al., 2017; Guo and Zhou, 2016). These distinct advantages attract significant participation from both investors and borrowers, thereby accelerating the development of China's internet finance industry.

While peer-to-peer (P2P) online lending got its start later in China, it has grown remarkably. According to data from WDZJ (http://www.wdzj.com), by 2017, there were a cumulative total of 6,486 online lending platforms. These platforms collectively handled a transaction volume of 2.805 trillion RMB. Additionally, the number of borrowers and lenders on P2P online lending platforms reached 4.4 million and 4.7 million, respectively. To compare with the Renrendai platform, we chose Lending Club (http://lendingclub.com), which is a prominent and the largest P2P lending platform in the United States. As illustrated in Figure 1, this comparison clearly shows that China's P2P industry is developing at a faster pace than Lending Club's. (Lending Club was selected for data access purposes, as detailed data from other platforms was not available.)

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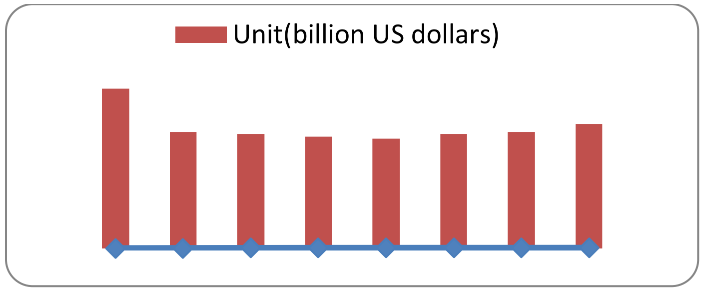

Figure1. Growth Trends of the Chinese P2P Industry and Lending Clubs

Peer-to-peer (P2P) platforms facilitate the direct connection between borrowers and lenders, streamlining the loan process and reducing costs for both parties (Song et al., 2018). This financing model circumvents traditional credit intermediaries, such as commercial banks, and has gained traction as a means to address financial exclusion. According to Beck et al. (2007), approximately 40-80% of individuals in China are unable to obtain loans from conventional banks. In 2014, small businesses in the country secured only 30.4% of the total loan amount, highlighting the disparity in access to capital within the banking system. In response to these challenges, P2P platforms have emerged as a viable alternative for low-income individuals and small businesses that are often excluded from traditional banking services, thereby enhancing their access to financing.

As a result, P2P platforms offer significant benefits for these underserved groups while also contributing to the rapid economic development of China. Therefore, we have chosen P2P platforms as the focus of our research topic due to their impact on both financial inclusion and economic growth in China. However, beneath the surface phenomenon of the rapid development of P2P lending platform, there exist numerous issues with P2P lending platforms. These include borrower defaults, platform evasion, and platform closures. Data from WDZJ (website: http://www.wdzj.com) in 2014 showed that 275 P2P platforms had experienced borrower defaults, platform closures, and shutdowns. In 2016, the number of problematic platforms increased from 1,884 to 3,412, causing significant losses to investors. This prompted us to conduct an in-depth exploration of the credit risk issues facing Chinese P2P platforms.

The rapid growth of peer-to-peer (P2P) online lending has garnered significant attention within the academic community, although the scope of previous literature research remains relatively limited. A key area of focus is the factors influencing a borrower's likelihood of successfully obtaining a loan. Previous scholars' research has examined various factors, including hard and soft information related to borrowers (Duarte et al., 2012; Chen et al., 2014; Herzenstein et al., 2011; Pope and Sydnor, 2011; Emekter et al., 2015; Barasinska and Schäfer, 2014; Ravina, 2018 Dorfleitner et al., 2016). Another crucial aspect to consider is the behavior of investors in P2P lending activities, with representative studies shedding light on this behavior (Paravisini et al., 2016) and the conformity effect (Zhang and Liu, 2012). To the best of our knowledge, there is a limited body of research specifically examining investors' preferences regarding borrowers' professional identities on P2P platforms. That said, the existing literature on evaluating investors' preferences for P2P platforms is quite extensive and offers valuable insights that we can draw upon. Some studies have focused on investors' preferences for P2P lending loans, including racial discrimination (Ravina, 2012), gender discrimination (Blanchflower et al., 2002; Storey, 2004; Alsina et al., 2013; Barasinska and Schäfer, 2014; Duarte et al., 2015; Bert et al., 2011;Armendariz and Morduch, 2010; Aggarwal et al., 2015), age discrimination (Pope and Sydnor, 2011), appearance-based lookism (Loureiro and Gonzalez, 2015;Gonzalez and Loureiro, 2014), discrimination in Social Relations (Everett, 2015; Berger and Gleisner, 2009), marital discrimination (Herzenstein et al., 2008), and regional discrimination (Lin et al., 2013), among others. These studies aim to better understand investors' preferences on P2P platforms.

While previous researches on assessing borrowers' credit risk using these factors can provide valuable insights, It is significant to acknowledge that peer-to-peer (P2P) platforms in China carry inherent credit risk, stemming from the nascent nature of the industry and an imperfect regulatory framework. Many P2P platforms operate without authoritative regulations, often prioritizing gaining a first-mover advantage in the peer-to-peer (P2P) internet lending market over effectively managing their own risks. According to WDZJ (http://www.wdzj.com), as a result of inadequate risk management and overextension, more than 2000 P2P platforms were on the brink of bankruptcy in the first half of 2018. This highlights a tendency among most P2P platforms to prioritize market expansion over risk management, ultimately leading to increased risks associated with P2P online lending.

In this article, our aim is to examine investors' preferences for borrowers' professional identity and determine whether these preferences are justified. We are utilizing a dataset from the Renrendai platform, which was collected in 2017 in China. The novelty and value of this study are centered on two key areas: (1) this paper marks the first systematic exploration of the professional identity of borrowers on P2P platforms. Acknowledging that investors exhibit diverse preferences across different professional identities, we classify borrowers' professional identities into three distinct categories: wage-earners, micro-enterprise owners, and network merchants. (2) Additionally, this research aims to examine the rationality of investors in the current online lending market and to provide a theoretical foundation for the stable, sustainable, and healthy development of this sector.

This paper is structured as follows: Section 1 provides a literature review. Section 2 interprets the operational mechanism of the P2P platform. Section 3 presents detailed information on the logit model and data. Section 4 demonstrates the empirical test results and robustness checks. The final section includes the article's conclusion and suggestions for future research.

Mechanism of Online Lending Platform Operations

Figure 2 illustrates the process of P2P online lending. Peer-to-peer (P2P) platforms create a direct and engaging space for borrowers and investors to connect and communicate. To initiate the process, borrowers provide personal details—including age, gender, marital status, education level, identity documentation, and income—as well as their loan requests, which specify the desired amount, interest rate, repayment term, and intended repayment date, to P2P platforms for a review of authenticity. Once the borrowers' information is verified, the platforms publish the borrowers' financing needs and certifications on their websites. Investors can then select trustworthy and creditworthy borrowers based on the disclosed information and proceed to lend money to them. If borrowers fail to raise sufficient funds within a specified timeframe, their loan request will be canceled - referred to as a "loan failure". Conversely, if they attract enough investors and secure adequate funding within the stipulated time frame it is considered a "loan success". Subsequently investors await regular payments from the borrowers according to schedule. Some platforms even compensate for defaulted payments with risk provisions which are viewed as a form of guarantee behavior. To mitigate investment risks each borrower typically has multiple investors. Furthermore, the platforms require detailed borrower information in order to reduce information asymmetry (Jensen and Meckling, 1976).

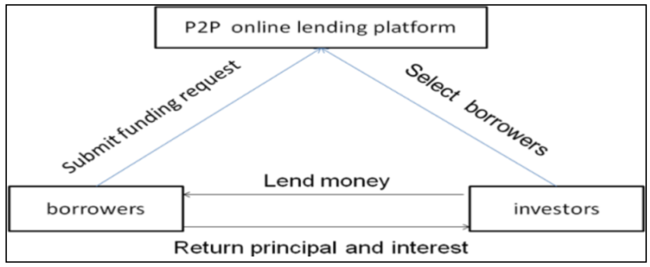

Figure 2. Peer-to-Peer (P2P) Process Flow Chart

Empirical Methodology

First, we will examine whether there are notable differences in loan success rates among borrowers with distinct occupational identities (OIs). If such significant differences are found, this would suggest that borrowers' occupational identity (OI) plays a role in influencing investors' preferences. In this paper, we will use a logit model to estimate the impact of occupational identity on investors' preferences. The empirical model is as follows:

$$\Pr(Success_i = 1) = \alpha_0 + \alpha_1 Identity_i + \alpha_2 X_i + \varepsilon_i \tag{1}$$

The dependent variable, $Success_i$, is a binary variable defined as 1 if the borrower's loan request is successfully granted and 0 otherwise. The primary explanatory variable of interest is $Identity_i$, which denotes occupational identities (OI). Specifically, Identity1 represents wage-earners (OI1), Identity2 represents private business owners (OI2), and Identity3 represents network merchants (OI3). Xi is a vector of control variables. α0, α1, and α2 represent the coefficient vector, while ε denotes the random disturbance term. If there is discrimination in the P2P online lending market based on occupational identity (OI) credit, it is important to further investigate whether it is rational for investors to lend money to borrowers based on their professional identities (OIs). This article examines different occupational identities (OIs) and their impact on repayment behavior. A low default rate coupled with a high borrowing success rate among borrowers would indicate rational investment preferences, whereas a high default rate alongside a high borrowing success rate would suggest irrational decision-making. In this study, we utilize the logit model to assess the influence of occupational identities (OIs) on borrower default. The empirical equation is as follows

$$\Pr(Defualt_i = 1) = \beta_0 + \beta_1 Identity_i + \beta_2 X_i + \varepsilon_i \tag{2}$$

The dependent variable, $Default_i$, is a binary indicator that takes the value 1 when the borrower defaults and 0 otherwise. X_i represents a vector of control variables, β denotes the coefficient vector, and ε is the random disturbance term.

Data Sources and Variable Descriptions

This empirical research focuses on the Renrendai platform, one of China's largest P2P lending platforms. Launched in May 2010, by December 2017 it had attracted over 3.2 million members and facilitated transaction value exceeding 46 billion CNY. To thoroughly examine whether investors' investment preferences and behaviors are rational, the study collected all loan requests posted on Renrendai from January to December 2017. To ensure accuracy, initial data was processed to eliminate irrational trade-offs stemming from early investors' inexperience and limitations, as well as the influence of investor sentiment driven by online public opinions prevalent in the online loan industry in 2016. Additionally, loan orders with missing information or associated with individuals younger than 20 or older than 55 were excluded. This careful processing resulted in a valid sample size of 75,763, which includes 56,720 failed loans, 19,043 successful loans, and an additional 567 successful loans that ultimately failed to be repaid as promised.

Explained Variables

This paper selects $Success_i$ and $Default_i$ as the dependent variables. The success of a loan is measured by the extent to which investors approve of the borrowers' trustworthiness, while default reflects the true repayment performance and the borrower's creditworthiness. Through comparative analysis at these two levels, we aim to explore whether investors exhibit a preference for behavioral decision-making and whether this preference is rational. The status of successful loans is indicated as repaying, platform repaid, overdue, and paid off. $Success_i$ is defined as 1 for borrowers with a successful loan and 0 for borrowers with a failed loan. The status of default loans is indicated as 'overdue' and 'platform repaid'. $Default_i$ equals 0 if the borrower's repayment is overdue or platform repaid, and 1 if the borrower repays on time.

Explanatory Variables

In this paper, the borrower's professional identity is considered an explanatory variable. The Renrendai Platform itself employs objective authenticity and scientific risk control technologies and methods to effectively process big data. It can scientifically and objectively assess the authenticity and credit risk of a borrower's personal information based on loan order data. The platform verifies the authenticity of information provided by borrowers, such as age and occupation, and then categorizes them into three groups according to its risk control model: wage-earners (OI1), private business owners (OI2), and network merchants (OI3). According to the study's statistics, OI2 constitutes a relatively large share of the total sample at 38.29%, while OI1 represents 28.12% and OI3 represents 33.59%. This indicates that the majority of borrowers on P2P online lending platforms fall under category OI2. Furthermore, in terms of loan success rates, OI1 outperforms both OI2 and OI3; conversely, OI1 exhibits lower default rates compared to both categories. This suggests that investors may have distinct preferences for various professional identities; however, further regression analysis is required to validate this inference.

Control Variables

To mitigate the influence of extraneous factors on regression results, this paper exercises control over various variables. These variables include borrowing information and borrowers' personal details. Borrowing information encompasses loan amount, interest rate, and repayment period. Personal details encompass age, gender, education level, marital status, income level, length of employment, homeownership status, mortgage status, car ownership status, car loan status, and credit rating grade.

The definitions of each variable are as follows: Amount refers to the loan amount specified in the loan application, a tangible figure representing the initial sum of money the borrower seeks to borrow, often written in bold on the application form. The interest rate represents the annual interest rate of the loan as stated in the loan application, a percentage indicating the cost of borrowing, calculated and printed with meticulous care to reflect the lender's risk assessment. The loan term denotes the loan term requested by the borrower, measured in months, a timeline specified in the contract that dictates the repayment rhythm, ranging from a few short months to a decade or more. Age indicates the borrower's age in years, a number that reflects life experience, maturity, and potential stability, neatly noted in the demographic section. Gender is a dummy variable taking a value of 1 if the borrower is male and 0 otherwise, a simple binary code for categorization, a silent note in the data tapestry. Marriage is a dummy variable taking a value of 1 if the borrower is married and 0 otherwise, a marker of partnership and shared responsibility, adding a layer of complexity to the borrower's financial profile. Education represents the borrower's education level, with 1 = middle/high school, 2 = 3-year college, 3 = 4-year college, and 4 = graduate school, a numerical scale reflecting foundational learning through advanced academic achievement, embodying years of dedication and intellectual growth. Income indicates the borrower's monthly income level, categorized as 1 = Less than 1000, 2 = 1001 - 2000, 3 = 2001 - 5000, 4 = 5001 - 10000, 5 = 10001 - 20000, 6 = 20001 - 50000, and 7 = more than 50000, a spectrum of financial capacity that illustrates the borrower's earning power and daily sustenance. House is a dummy variable taking a value of 1 if the borrower owns a house and 0 otherwise, a symbol of stability and rootedness, a tangible asset anchoring the borrower's financial world. House loan is a dummy variable taking a value of 1 if the borrower has a mortgage and 0 otherwise, a long-term debt tied to housing, shaping financial freedom. Car is a dummy variable taking a value of 1 if the borrower owns a car and 0 otherwise, a tool of mobility and independence, a common companion in modern life. Car loan is a dummy variable taking a value of 1 if the borrower has a car loan and 0 otherwise, a temporary financial obligation for a vehicle that bridges distances and connects lives. Work certification loan is a dummy variable taking a value of 1 if the borrower has a work certification loan and 0 otherwise, a specialized debt tied to professional development, bridging to new opportunities and skill enhancement. Credit grade represents the borrower's credit grade at the time the listing was created, a numerical score encapsulating financial trustworthiness, ranging from 1 (high risk) to 7 (AA), reflecting past borrowing behavior and repayment history, serving as a seal of approval or cautionary flag in lenders' eyes.

Based on the statistical analysis of all variables in this research, the results indicate that 8.2% of loan listings are successfully funded, and the average loan default rate is 26.5%. Among borrowers, 73.5% are classified as PI1s, 15.5% as PI2s, and a minimum of 5.5% fall under the PI3 category. The average loan amount is approximately RMB 6,800, with an average interest rate of 12.21% and an average loan term of 16.63%. Borrower credit grades indicate that the majority (96%) are rated as high risk (HR). Additionally, 14.3% of all borrowers have mortgages, and 6.3% have car loans. Table 2 further reveals that men are more active than women in the P2P lending market, accounting for 86.3% of all borrowers. Of these, 48.6% are married, with an average age of 31. Furthermore, 71.1% of borrowers fall within an income range of RMB 2,001–10,000, and 62.6% have a college education or higher. This level of education is substantially higher than the national average, as reported by data from the sixth population census, which indicates that only 8.93% of Chinese people (excluding those from Hong Kong, Macao, and Taiwan) have attained a college education or higher. Additionally, 45.3% of borrowers own houses, 19.5% own cars, and their average working time is 2.5 years. In summary, the majority of borrowers on the P2P online lending platform are young, well-educated individuals with moderate incomes and some work experience.

Empirical Methodology

Whether Investors Have Preferences for Loan Orders with Different OIs

In this subsection, the paper explore model (1) by investigating the relationship between $Success_i$ and the various OIs. The estimation results are presented in Table 1. In Table 1, columns (1), (3), and (5) present the results of a benchmark regression model that incorporates OI1, OI2, and OI3 as the primary explanatory variables, with no control variables included. Columns (2), (3), and (4) summarize the results of the explanatory variables and control variables. The main variable has been utilized in previous literature to explain the probability of funding success. In line with existing research, loan requests characterized by lower interest rates, smaller loan amounts, and shorter repayment periods are more likely to be approved for funding (Liu et al., 2015; Dorfleitner et al., 2016; Mild et al., 2015;Iyer et al., 2016). The study reveals that column (1) shows a positive and significant coefficient (0.485) for wage earners. This suggests that individuals who earn a wage are more likely to have their loan requests approved. Columns (3) and (5) indicate that the coefficients are negatively significant, suggesting that OI2 and OI3 are associated with a lower probability of a loan request being granted. Column (2) presents a positive and statistically significant coefficient of 0.852 for OI1, indicating that OI1s are more likely to secure successful loans. Typically, wage earners exhibit higher creditworthiness and lower default rates on the platform, which creates a positive impression among investors. The primary reason is that OI1s' income levels are stable, and regular wages are sufficient to meet repayment obligations, resulting in relatively lower credit risk and characteristics typical of high-quality credit customers. OI1 also exhibits a higher loan success rate compared to OI2 and OI3.

In Table 1, column (3) shows a coefficient of -0.518 without adding control variables, and column (4) shows a coefficient of -0.875 with added control variables. This suggests that OI2 may have a negative impact on the success rate of loans. The primary reason is that OI2 typically needs to borrow funds during production and operations to expand sales, which can lead to income instability and uncertainty in cash flow turnover. Consequently, OI2 have unstable income, lower repayment capacity, and higher credit risk. This creates the impression among investors of uncertain expected income, weak repayment capacity, and high corresponding credit default risk for OI2. As a result, P2P investors tend to be less favorable toward the identity of OI2. In Table 1, column (5) presents a coefficient of -0.162 in the model without control variables, and column (6) shows a coefficient of -0.419 after incorporating control variables. This indicates that OI3 faces difficulties in obtaining loans. OI3 typically has a broader business scope than OI2 and often incorporates part-time OI1 individuals with stable income and cash flow. Thus, OI3 are associated with relatively lower credit risk. However, empirical results indicate that investors do not favor OI2. This may be because, in investors' credit decision-making, network merchants are perceived similarly to OI2, as small and medium-sized entrepreneurs. Borrowers with such identities are likely to exhibit characteristics of higher operational risk, uncertain expected income, weak repayment ability, and a higher probability of credit default. Hence, investors do not favor network merchants. Regression analysis reveals significant differences in the success rate of P2P online lending loans among borrowers with different occupational identities (OIs), indicating that investors exhibit preferences for borrowers from various OIs.

Are Investors' Preferences Rational?

The empirical evidence presented in the previous section confirms that OI can effectively predict investors' preferences. This subsection explores the rationality behind these preferences. Table 2 shows the regression results for Model 2, along with the estimated relationship between OI and default loans. By comparing the columns, we observe that including control variables helps to increase the R-squared value, thereby enhancing the model's ability to explain the data. In column (1), the coefficient is -0.089 and is statistically significant in the negative direction. Column (2) displays a coefficient of -0.038, which is also significantly negative.

Table 1 The impact of OI on the successful loan (Success)

Variable	Success					
	(1)	(2)	(3)	(4)	(5)	(6)
OI_1	0.485***	0.852***				
	(0.0191)	(0.0342)				
OI_2			– 0.518***	– 0.875***		
			(0.0254)	(0.0601)		
OI_3					– 0.162***	– 0.419***
					(0.0331)	(0.0368)
LnAmount		-0.460***		-0.613***		-0.645***
		(0.0108)		(0.0105)		(0.0105)
Rate		0.223***		0.415***		0.320***
		(0.0311)		(0.0285)		(0.0286)
Time		-0.038***		-0.042***		-0.0362***
		(0.0041)		(0.0041)		(0.0039)
Credit		1.125***		1.155***		1.136***
		(0.0416)		(0.0411)		(0.0501)
Age		0.0135***		0.0163***		0.0120***
		(0.0018)		(0.0019)		(0.0018)
Gender		-0.175***		-0.140***		-0.151***
		(0.0240)		(0.0251)		(0.0278)
Marry		0.098***		0.112***		0.092***
		(0.0200)		(0.0201)		(0.0221)
Education		0.196***		0.227***		0.263***
		(0.0122)		(0.0131)		(0.0125)
worktime		0.162***		0.185***		0.192***
		(0.0110)		(0.0106)		(0.0108)
Income		0.223***		0.195***		0.112***
		(0.0119)		(0.0118)		(0.0119)
House		-0.0255		-0.0156		-0.0290
		(0.0119)		(0.0215)		(0.0228)
House_l		0.0621***		0.0588**		0.077**
		(0.0253)		(0.0306)		(0.0286)
Car		-0.043		-0.041		-0.0845***
		(0.0301)		(0.0265)		(0.0271)
Car_l		0.153***		0.178***		0.133**
		(0.0612)		(0.0522)		(0.0520)
-cons	-1.795***	-3.654***	-1.401***	-2.857***	-1.450***	-2.510***
	(0.0210)	(0.3125)	(0.0755)	(0.359)	(0.0075)	(0.413)
N	75761	75761	75761	75761	75761	75761
Pseudo R2	0.0169	0.4382	0.0181	0.4451	0.0001	0.4225

Note: *p< 0.1, **p< 0.05, ***p< 0.001; in parentheses are the Z statistical value

Table 2 The impact of OI on the defaulted loan (Default)

Variable	Default					
	(1)	(2)	(3)	(4)	(5)	(6)
PI_1	-0.089*** (0.0691)	-0.038*** (0.120)				
PI_2			0.131 (0.0954)	0.275** (0.1410)		
PI_3					– 0.329*** (0.1102)	– 0.195*** (0.1300)
LnAmount		0.021 (0.0592)		0.004 (0.0558)		0.020 (0.0972)
Rate		0.201*** (0.0985)		0.211** (0.0978)		0.202** (0.0972)
Time		0.073*** (0.0250)		0.073*** (0.0142)		0.075*** (0.0128)
Grate		-0.075*** (0.0755)		-0.076*** (0.0779)		-0.079*** (0.0788)
Age		0.029*** (0.0063)		0.0272*** (0.0056)		0.028*** (0.0057)
Gender		0.095 (0.922)		0.098 (0.0886)		0.098 (0.0893)
Marry		-0.136*** (0.0715)		-0.129* (0.0703)		-0.130* (0.0711)
Educantion		-0.0355*** (0.0372)		-0.322*** (0.0410)		-0.348*** (0.0398)
Worktime		0.009 (0.0329)		0.014 (0.0344)		0.008 (0.0335)
Income		0.028 (0.0762)		0.004 (0.0396)		0.042 (0.0365)
House		0.209*** (0.0717)		0.227*** (0.0758)		0.223*** (0.0745)
House_1		-0.409*** (0.0885)		-0.416*** (0.0893)		-0.416*** (0.0891)
Car		-0.201** (0.0856)		-0.210** (0.0861)		-0.190** (0.0828)
Car_1		-0.316* (0.1510)		-0.286* (0.1500)		-0.271* (0.1475)
_cons	-0.554*** (0.0710)	-4.015*** (1.175)	-0.586*** (0.0281)	-3.823*** (1.1926)	-0.578*** (0.0269)	-4.058*** (1.166)
N	576	576	576	576	576	576
Pseudo R^2	0.0003	0.2596	0.0003	0.2607	0.0041	0.2580

Note: *p< 0.1, **p< 0.05, ***p< 0.001; in parentheses are the Z statistical values

The analysis indicates that OI1 exhibits a higher probability of repayment and lower default loan rates. This conclusion is derived from comparing columns (1) and (2) in Table 1. OI1 demonstrates a higher success rate, attributed to its lower default loans. The stable income of OI1 ensures that monthly income can effectively meet current repayment needs, resulting in a small credit risk. Consequently, OI1 is favored by investors and can be considered rational biased behavior.

Column (3) presents the benchmark regression model, which does not include additional control variables, and the coefficient on OI2 is 0.131. Column (4) shows a coefficient of 0.275, which is statistically significant, indicating that OI2 is more likely to default on the loan. By comparing the loan success rates in Tables 1 and 2 with the default rates, it is found that the lower loan success rate for OI2 is due to its higher default rate, leading it to be subject to investor rational bias. This rational bias stems from the perception that PI2 have higher investment risk, unstable income, and monthly income that cannot effectively meet current repayment needs. In columns (5) and (6), the regression results indicate that the explanatory variables of OI3 have coefficients of -0.329 and -0.195, both of which are statistically significant in a negative direction. This suggests that OI3 individuals have a lower probability of defaulting on their loans, likely due to their status as mostly part-time workers with stable incomes, enabling them to effectively meet repayment demands. However, Table 1 shows that OI3 individuals also have a lower success rate for obtaining loans. Therefore, it may be irrational for investors to choose OI3 individuals as potential loan recipients.

Robustness Checks: A Probit Model Approach

This subsection utilizes a Probit Model approach to perform robustness checks and assess the validity of the regression results presented in the preceding two subsections. To reduce potential errors that may stem from selective measurement methods, $Success_i$ and $Default_i$ are re-estimated using the Probit Model. The regression results from these two models are presented in Table 3 and Table 4. In Table 3, the coefficient for OI1 is positively significant, whereas the coefficients for OI2 and PI3 are negatively significant. In Table 4, we observe that the coefficient for OI1 is negatively significant, while the coefficients for OI2 and PI3 are positively significant. These findings further support and confirm our initial results.

Table 3 The impact of OI on the successful loan (Success)

Variable	Success					
	(1)	(2)	(3)	(4)	(5)	(6)
OI_1	0.356*** (0.0233）	0.749*** (0.0426）				
OI_2			− 0.418*** (0.0326）	−0.795*** (0.0592）		
OI_3					− 0.201*** (0.0223）	− 0.522*** (0.0356）
LnAmount		-0.418*** (0.0213)		-0.702*** (0.0114)		-0.719*** (0.0138)
Rate		0.125*** (0.0263)		0.322*** (0.0253)		0.226*** (0.0198)
Time		-0.040*** (0.0034)		-0.046*** (0.0032)		-0.041*** (0.0041)
Grate		1.012*** (0.0326)		1.227*** (0.0354)		1.039*** (0.0492)
Age		0.021*** (0.0020)		0.018*** (0.0021)		0.014*** (0.0017)
Gender		-0.224*** (0.0228)		-0.136*** (0.0323)		-0.165*** (0.0269)
Marry		0.103*** (0.0117)		0.109*** (0.0115)		0.095*** (0.0215)
Education		0.185*** (0.0133)		0.236*** (0.0135)		0.274*** (0.0130)
Worktime		0.159*** (0.0109)		0.191*** (0.0137)		0.192*** (0.0124)
Income		0.235*** (0.0221)		0.205*** (0.0213)		0.146*** (0.0211)
House		-0.036 (0.0136)		-0.018 (0.0227)		-0.030 (0.0234)
House_l		0.052*** (0.0261)		0.062** (0.0314)		0.079** (0.0297)
Car		-0.051 (0.0312)		-0.039 (0.0271)		-0.088*** (0.0286)
Car_l		0.167*** (0.0622)		0.185*** (0.0535)		0.143** (0.0549)
_cons	-1.802*** (0.0222)	-3.743*** (0.3336)	-1.463*** (0.0663)	-2.913*** (0.3621)	-1.501*** (0.0080)	-2.536*** (0.4422)
N	75761	75761	75761	75761	75761	75761
Pseudo R^2	0.0152	0.4475	0.0176	0.4526	0.0003	0.4426

Note: *p< 0.1, **p< 0.05, ***p< 0.001; in parentheses are the Z statistical values.

Table 4 The impact of OI on the default loan (Default)

variable	Default					
	(1)	(2)	(3)	(4)	(5)	(6)
OI_1	-0.326***	-0.773***				
	(0.0203)	(0.0411)				
OI_2			0.520***	0.885***		
			(0.0320)	(0.0752)		
OI_3					0.155***	0.420***
					(0.0221)	(0.0521)
LnAmount		0.018		0.006		0.017
		(0.0613)		(0.0574)		(0.0988)
Rate		0.196***		0.223**		0.215**
		(0.0997)		(0.0983)		(0.0961)
Time		0.069***		0.065***		0.080***
		(0.0231)		(0.0155)		(0.0139)
Grate		-0.081***		-0.083***		-0.080***
		(0.0688)		(0.0697)		(0.0645)
Age		0.031***		0.030***		0.029***
		(0.0055)		(0.0042)		(0.0047)
Gender		0.086		0.087		0.086
		(0.0889)		(0.0863)		(0.0871)
Marry		-0.145***		-0.131*		-0.141*
		(0.0693)		(0.0698)		(0.0654)
Education		-0.042***		-0.411***		-0.366***
		(0.0377)		(0.0409)		(0.0406)
Worktime		0.011		0.016		0.007
		(0.0336)		(0.0358)		(0.0321)
Income		0.033		0.008		0.056
		(0.0773)		(0.0411)		(0.0389)
House		0.213***		0.230***		0.245***
		(0.0699)		(0.0746)		(0.0732)
House_l		-0.415***		-0.422***		-0.430***
		(0.0799)		(0.0864)		(0.0885)
Car		-0.196**		-0.208**		-0.194**
		(0.0821)		(0.0855)		(0.0808)
Car_l		-0.311*		-0.288*		-0.265*
		(0.1421)		(0.1550)		(0.1520)
_cons	-0.441***	-4.011***	-0.487***	-3.635***	-0.458***	-4.103***
	(0.0821)	(1.125)	(0.0303)	(1.2010)	(0.0271)	(1.1741)
N	576	576	576	576	576	576
Pseudo R^2	0.0005	0.4651	0.0005	0.3376	0.0058	0.3571

Note: *p< 0.1, **p< 0.05, ***p< 0.001; in parentheses are the Z statistical value

Conclusion

The intricate signal transmission that courses through the veins of the P2P lending market has compelled us to delve deeply into the pivotal role of professional identity in bridging the chasm of information that often separates borrowers and investors. Specifically, by harnessing the rich tapestry of actual transaction data from Renrendai, one of China's largest and most bustling P2P lending platforms, and meticulously applying the logit model, we have been able to dissect and assess the profound impact of professional identity on the nuanced landscape of investment preferences. The main conclusions of this study unfurl as follows: (1) Amidst the turbulent seas of P2P investing, where many investors navigate with limited risk identification capabilities and often face the specter of potential losses, key information emerges as a lighthouse, guiding through the fog of uncertainty for effective risk assessment. Thus, it can be profoundly inferred that professional identity stands as a towering beacon of significance within the dynamic context of P2P lending, illuminating paths where others might falter. (2) Our investigative journey into the influence of professional identity on the fates of successful and default loans unveils a compelling narrative: a positive association between OI1 and successful loans, and a negative correlation with default loans. This suggests that investors, like skilled navigators, tend to favor OI1, steering their investments towards shores of rationality and prudence. Furthermore, investors engage in a meticulous dance of consideration when evaluating borrowing information tied to OI2 and OI3. Their risk perception, honed by experience and expertise, aligns seamlessly with the true credit levels of borrowers, painting a vivid picture of investment bias rooted in rational behavior, a testament to the power of informed decision-making. (3) We also embarked on a journey to categorize the OI based on their distinct professional backgrounds, recognizing that professional identity acts as a master key in distinguishing the subtle nuances of credit risk. The robustness check, a rigorous gatekeeper of our findings, indicates that professional identity was the primary architect influencing risk assessment, indirectly casting a spotlight on the inherent advantages of OI within the vibrant ecosystem of P2P platforms. While this article presents a pioneering, systematic study on the OI of P2P platforms, it is crucial to interpret the findings through the lens of its limitations. The transaction data were carefully collected from Renrendai, a single thread in the vast fabric of P2P lending. Caution must be exercised when weaving these conclusions into a broader tapestry applicable to other P2P platforms, for each operates within diverse settings for financing loans, which may cast unique shadows and light on OI dynamics in the market. As future research directions in this ever-evolving field, further studies can focus on predicting the tempests of crises or the undercurrents of credit risk within a P2P platform, directly addressing the current public concerns that ripple through the industry. Looking ahead, we anticipate that the horizon of P2P platforms will brim with more valuable and thought-provoking topics, each worthy of dedicated scholarly exploration.

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