Internet Financial Risks and Investors' Risk Awareness ——Evidence from Transaction Data of Online Lending Platforms

Dongsheng Deng, Zhao Chen*

For the first time, this paper uses the operation data of 575 online P2P lending platforms to test whether investors have a strong risk awareness of online lending products. It is found that investors' behavior shows a certain risk awareness, both for the individual risk of specific platforms and for the overall market risk of the industry. On the one hand, raising interest rates and shortening the term does attract more investment, but for potentially problematic platforms, the effect of attracting investment is significantly worse, with excessive interest rates on the platforms even causing investors to invest less. On the other hand, when there are more online lending platforms in the market, investors will behave more cautiously.

Keywords: online P2P lending, problematic platforms, market risk, risk awareness

1. Introduction

Internet finance refers to a new business model in which traditional financial institutions and Internet enterprises rely on Internet technology and tools to provide financial communication, payment, investment and information intermediary services. Internet payment and online peer-to-peer lending (P2P lending) are the two most concerned forms of Internet finance. However, the supervision of P2P lending in China has just started, which provides us with a rare research opportunity to examine the possible risks of Internet finance and investors' risk awareness of this emerging financial industry under the background of lack of supervision.

With the convenient procedures of P2P lending, all the processes of authentication, bookkeeping, liquidation and delivery are completed through the Internet, and the threshold of P2P lending is much lower than that of traditional banks. Therefore, this new financial model has developed rapidly since it was introduced into China. Since the establishment of PPDAI, the first P2P lending platform, in Shanghai in August 2007, the number of operating platforms has reached 800 by the end of 2013. Figure 1 shows the evolution of the number of P2P platforms in operation.

* Dongsheng Deng (email: ddswhu@outlook.com), Doctoral candidate at China Center for Economic Studies, Fudan University, China; Zhao Chen, Professor at China Center for Economic Studies, Fudan University, China.

But there are concerns and doubts about this new, unregulated industry. Following the successive problems of many online lending platforms, on December 28, 2015, the government issued *The Interim Measures for the Management of Business Activities of Internet Lending Information Intermediaries (Draft for Opinions)*, which was officially issued in August 2016, thus opening the prelude to the supervision of the P2P online lending. As can be seen from Figure 1, the number of online lending platforms did decline in 2016 due to government regulation, and the number of platforms fell below 2000 for the first time in the fourth quarter of 2017. However, according to wdzj.com, the total transaction size of P2P lending is growing steadily, only declining slightly in the fourth quarter of 2017.

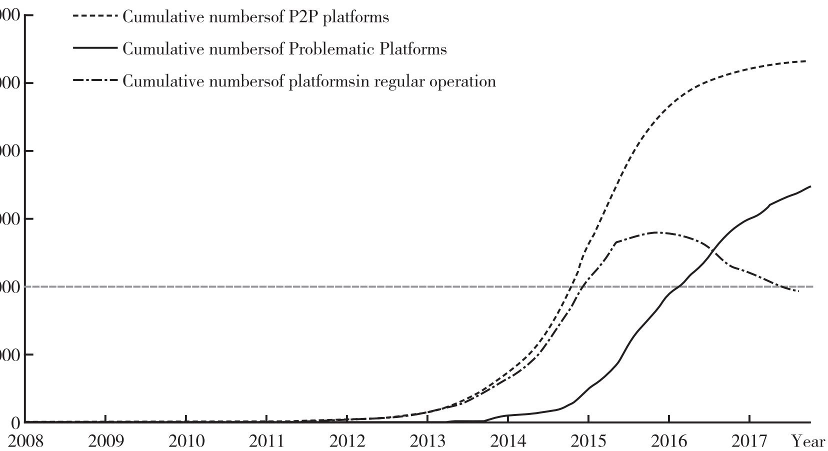

Figure 1. Monthly Cumulative Numbers of P2P Platforms, Problematic Platforms and Platforms in Regular Operation

Source: data.01caijing.com.

Concerns about P2P lending can be summarized as the following three points. First, the interest rate of the online lending platforms is higher, and the central bank has repeatedly said that the annual compound interest rate is not protected by law if it exceeds the bank interest rate by four times. [1] Second, P2P platforms have the right to allocate intermediate funds account, and the lack of regulation may lead to the risk of misappropriating funds and owners running away with investors' money. Third, investors blindly pursue Internet finance as a new thing, lacking the necessary risk awareness.

However, up to now, the research on investors' cognition and recognition of risk in P2P online lending market is still relatively preliminary. Current research on P2P mainly involves: (1) The impact of characteristics of the borrower or subject

[1] The fixed interest rate of the bank (one-year) is about 1.5%–2.25%, while the comprehensive annual interest rate of the P2P industry is 23.43% in 2012, 24.93% in 2013, 17.52% in 2014 and 12.05% in 2015 (bank rate data source: *The Latest Deposit Rate of 42 banks in Early 2017* by Rong360; P2P interest rate data source: *National P2P Online Lending Industry Express 2015* by P2P001).

matter on the outcomes od lending; (2) Influencing factors of investors' investment decisions; (3) The determinants of the return on investment of P2P platforms and the characteristics of interest rate; (4) Risks and regulatory countermeasures of P2P platforms. However, none of the above studies provides a direct test of investors' risk awareness on the online lending platform. The research most relevant to this paper is identification of lending risk by Liao *et al.* (2014), which found that the interest rate level of online lending products can indeed reflect the level of future default risk of products. In contrast, this paper takes a different perspective by examining investors' risk awareness in the following two aspects. Firstly, this paper will directly measure the operational risk of the platform according to the characteristics of online lending products. Secondly, we also examine investors' perception of the individual risk of the platform and the overall risk of the online lending market.

Based on the micro-operational data of 575 P2P online lending platforms, this paper investigates whether the investors' investment behavior shows that they have an understanding of the operational risk of the online lending platforms and the overall market risk of the online lending industry. As far as we know, it is the first time in China to use such micro-data to distinguish the individual risk of online lending platform from the overall risk of online lending industry, and to examine the investors' risk awareness. The main findings of this paper are: (1) Platforms with high interest rate and short term will also have greater operational risk; (2) Investors have some understanding of the risks of the online lending platform they invest in. Specifically, investors are more cautious about potentially risky platforms when attracted by high interest rates on platform products. In particular, investors will reduce their investment if the higher risks are reflected in the operation of the platform; (3) Investors also have an understanding of the market risk of the online lending platform as a whole. Investors will also be more cautious as there are more problematic platforms in the market. This paper provides us with a rare empirical basis for judging whether investors can have a certain risk awareness in the absence of supervision.

2. Data and Descriptive Statistics

The data used in this paper includes two data sets. The first data set is the operation data of the platforms. We get the unbalanced panel data of 575 P2P online lending platforms from the 47th week of 2014 to the 32nd week of 2016 on wdzj.com.[1] The core data period is from the 32nd week in 2015 to the 32nd week in 2016. Due to the volatility of daily data, the main part of the paper is to analyze weekly data. The

[1] wdzj.com is the largest, most authoritative and most influential industry web portal in China's P2P industry, bringing together more P2P platform operating data. As far as we know, data from this website is the only available source of domestic P2P platform operating data, with the widest coverage.

second data set is platform-level information (6142 platforms), mainly from wdzj.com, and information from p2peye.com is used for proofreading.

After comparing the data used in this paper with the data of the online lending industry, we find that although the number of platforms in regular operation in the sample is about 500, accounting for less than one-sixth of the total number of industries, these platforms in the sample are usually large in scale and stable in operation, so the overall market share is higher. Generally speaking, in this sample, platform turnover accounts for 65%-70% of the industry, and net capital inflow accounts for 50–90% of the industry. The average duration of products of the sample platforms is 1–2 months longer than that of the whole industry, and the average interest rate is 1%–2% lower. This is because the online lending platforms with higher risk and smaller scale are usually not in our sample. While this also means that the conclusions of this paper are not appropriate for too much extended inference, this finding is undoubtedly meaningful if we can find that investors are still risk-conscious about such relatively safe online lending platforms. In addition, in view of the availability of data samples, we believe that the samples in this paper are currently available data, which can best represent most of the platforms in regular operation.

Table 1 shows the main variables of the above database and their explanations. Since the products purchased by investors in a week may have different durations and interest rates, the "average term" in the table refers to the weighted average value of the duration of all investment products in a week according to their principal amount, while the "average interest rate" refers to the weighted average value of the interest rates of all investment products in a week according to the principal amount. The variable of "net inflow of funds" is also provided directly by the platform, and its value is equivalent to the total investment within one week minus the amount reimbursed by the platform to investors (in principal). Therefore, by subtracting the net inflow of funds from the total investment, we can get the principal that the platform actually repays to the investor within a week, which we call "real repayment of principal". The above variables are calculated on the basis of the amount of weekly occurrence, and we include them in the upper part of Table 1, while the variables in the lower half are the concept of stock. We distinguish problematic platforms from normal platforms[1] according to whether the platforms are involved in problems such as broken capital flow, running away (website closure, high-level management running away), shutdown, financial crime investigation, etc. This standard is unified in the two largest online lending portals in China, wdzj.com and p2peye.com, but the online lending platforms included in the two websites are slightly different. This paper takes wdzj.com as the criterion. In order to measure the overall investment risk of the online lending market, we also calculated the indicator of

[1] Of course, the normal platforms here are the platforms that have not yet had a problem until April 1, 2018, so the coefficient we get from comparing the performance difference between normal platforms and problematic platforms should be a lower bound.

“market risk”, i.e., the number of all problematic platforms before a specific time point divided by the total number of platforms (number of platforms in regular operation + number of problem platforms). This indicator reflects the overall risk of the online lending market that investors can perceive.

Table 1. Core Variables and Meanings

Variable	Name	Variable description
Number of investors	*investors*	Number of people investing in the platform in a week
Per capita investment	*investment_pe*	Per capita investment in one week (10000 yuan)
Total investment*	*investment*	By multiplying “number of investors” and “per capita investment” (10000 yuan)
Average interest rate	*interest*	Weighted average interest rate of investment products on the platform in a week (%)
Average term	*term*	Weighted average term of investment products on the platform in a week (month)
Net inflow of funds	*net_flow*	Total investment-repayment to investors during the week (according to principal, 10000 yuan)
Real repayment of principal*	*repayment*	Total investment–net inflow of funds during the week (according to principal, 10000 yuan)
Problematic platforms	D_i	Platforms having the problems such as failing to repay, absconding, shutdown, financial crime investigations are defined as problematic platforms, and platforms free of the problems are regarded as normal platforms (variable 0~1, with 1 representing the problematic platform)
Occurrence of problematic platforms*	*mkt_risk*	Cumulative number of problematic platforms before a specific time point / total number of platforms

Note: The variables with the label* are calculated by other raw data provided by the platforms.

On the basis of 27285 raw data, we deleted 2 samples with negative number of investments to be received and number of borrowers to be repaid, 5 samples with no investment in one week, 13 samples with an interest rate less than 1, and kept the 27266 valid samples. Descriptive statistics are not included here due to limited length of the paper.

3. Hypotheses and Empirical Testing

This paper aims to examine the identification of individual platform risk and overall market risk by investors in the online lending market. Therefore, we first measure the above two kinds of risks, and then test the risk awareness of investors.

3.1. Measurement of Platform Risk and Market Risk

The most direct indicator of platform risk is to see if a platform becomes a problem platform afterwards. If a platform ends up being a problematic platform, it is a potentially problematic platform during its regular operations, and we believe the platform has greater risks. Another way to measure platform risk is to find indicators that can reflect the operational risk of individual platforms. To this end, we need to examine the characteristics of problematic platforms.

Table 2 compares normal platforms with problematic platforms based on several core variables. It shows that the proportion of problematic platforms is small, and their investment products usually have higher average interest rates, shorter average duration, and smaller scale, and the difference is significant.

Table 2. Comparison between Normal Platforms and Problematic Platforms

	Average interest rate	Average term	Real payment of principal	Total investment	Number of platforms
Normal platforms	12.87 (3.41)	4.62 (5.06)	201335.60 (668882.40)	329836.30 (1123316.00)	412
Problematic platforms	16.49 (5.14)	3.20 (2.25)	35208.54 (71224.09)	43352.37 (85431.05)	163
Difference	3.61***	–1.42***	–166127.10***	–286484.00***	249

Notes: The standard deviation in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, similarly hereinafter.

There are two main reasons for the problem of an online lending platform. First, the platform is flawed in the early stage of its establishment, and even the platform was set up to pool money. The owners may use high interest rates to attract more investors, and then run with money after raising enough funds. Second, due to the pressure of market competition, in order to attract investors or cope with the pressures of cash withdrawal, platforms issue products with high interest rates and short term, resulting in greater repayment pressure in the later period, and even become problematic platforms. Both of these risks may be manifested by high interest rates and short term. Interest rates affect repayment pressures, so it is natural that interest rates will affect whether the platform will be in trouble. In addition, in order to solve the differential borrowing needs of borrowers and the standardized product needs of investors, many platforms will involve term mismatch, which will affect the cash flow of the platforms, so the term itself will also affect the probability of platform problems, and the term will also affect whether the platforms will get into trouble through interest rates. To this end, we set the following empirical regression (Probit model) to further test whether interest rates and term can be used as a measure of platform risk:

$$\begin{aligned} D_i &= \alpha + \beta interest_i + \gamma term_i + X_i + \epsilon_i \\ D_i &= \alpha + \beta high\_interest_i + \gamma short\_term_i + X_i + \epsilon_i \end{aligned} \tag{1}$$

where D_i indicates whether the platform i has become a problematic platform as of April 1, 2018 (the problematic platform has a value of 1, otherwise the value is zero), *interest* and *term* are categorical variables of the average interest rate and average term of the platform during the data observation period, wherein the interest rate value is 1–5, and the higher the value, the higher the interest rate, the term value is 1–7, and the higher the value, the longer the duration. *high_interest* and *short_term* are dumb variables, defined as below: if the average interest rate of the platform during a week of data observation is higher than 16%, the high interest rate is defined as 1, otherwise 0; the same goes for the term, if the average term of the platform in a certain week during the data observation period is shorter than 3 months, then the short term is defined as 1, otherwise 0. These two variables measure whether the platform has had high-risk product characteristics (high interest rates, short term) throughout the operation. are other characteristic variables for the platform, including registered capital and paid-in capital. They are categorical variables with the value of 1–6, and the higher the value, the larger the registered capital / paid-in capital. We use this regression to examine if platforms that issue high-interest, short-term investment products over the entire sample period are more likely to be problematic in the future.

Table 3 gives the regression result of the regression equation (1), and the explanatory variable is whether the platform is the problem platform (problem platform=1, normal platform=0).

Table 3. High Interest Rate, Short Term and Probit Regression of Problematic Platforms

	(1)	(2)	(3)	(4)	(5)	(6)
Registered capital	-0.146^{**} (0.059)		-0.257^{***} (0.055)		-0.136^{**} (0.061)	
Paid-in capital		−0.002 (0.0450)		-0.126^{***} (0.0396)		0.012 (0.047)
Interest rate	0.193^{***} (0.055)	0.202^{***} (0.055)			0.168^{***} (0.057)	0.174^{***} (0.057)
Term	-0.399^{***} (0.055)	-0.428^{***} (0.057)			-0.401^{***} (0.057)	-0.435^{***} (0.060)
High interest rate			0.462^{***} (0.142)	0.459^{***} (0.142)	0.247 (0.162)	0.294^{*} (0.163)
Short term			0.582^{**} (0.264)	0.584^{**} (0.261)	0.563^{*} (0.311)	0.562^{*} (0.310)
Constant term	−0.202 (0.303)	-0.786^{***} (0.218)	-0.761^{**} (0.349)	-1.495^{***} (0.283)	-0.843^{**} (0.423)	-1.436^{***} (0.363)
Sample	575	575	575	575	575	575

As can be seen from Table 3, the higher the registered capital/paid-in capital of the platform, the more likely the platform may be a normal platform, which is also easy to understand, because some of the problematic platforms are intended for short-term fund-raising in the early stage of the establishment, and then they are ready to run away, and will not provide more paid-in capital. Moreover, the more powerful in terms of capital the platform is, the less likely it is to have operational problems caused by term mismatch. And the two indicators of interest rate and term, which are our core concerns, can be used to measure the future risks of the platform. [1] As can be seen, the higher the interest rate, the more likely the platform with a shorter term is to be a problematic platform, and this result is very robust. Looking at high interest rates and short-term products alone, platforms that have issued products with very high interest rates and very short term are more likely to be problematic platforms.

However, when we measure individual risk on a particular platform directly with platform interest rates or terms, we are subject to fluctuations in interest rates or maturities caused by market factors. It would therefore be more reasonable to exclude such interference with the average interest rate of the industry or the average term of the industry. The difference between the platform interest rate and the industry interest rate, and that between the platform term and the industry term, may be two important factors reflecting the platform risk (we conduct regression with the survival panel analysis, which is omitted in this paper due to the relatively cumbersome process). In order to measure the difference between platform characteristics and the overall level of the industry, we calculate the difference between the platform interest rate (term) and the industry interest rate (term) over time, and use this variable to measure the individual risk of a particular platform. We considere the situations of the past week and the past month respectively. The average interest rate and the average term of the industry in this paper are represented by the monthly average. The formula for calculating interest rate difference (*interest_diff*) is as follows (similar calculation for the term):

$$interest\_diff_{it}(T) = \frac{1}{T}\sum_{\tau=1}^{T}(interest_{i,t-\tau} - interest\_ind_{m(t-\tau)}) \tag{2}$$

where i represents the platform, t the week, $m(t\text{-}\tau)$ the month corresponding to the week $t\text{-}\tau$, *interest* the average interest rate for the platform (weekly data), *interest_ind* the average interest rate for the online lending industry (monthly data). T represents the lag order (week), the value of T in this paper is 1 or 4 (as a robustness test). When the

[1] Another way to measure platform risk is to examine the impact of various factors on risk over time through survival analysis. Since the indicators used to measure risk in the following sections also vary over time, we have not reported survival analysis so as to save space.

value of T is 1, Formula (2) calculates the difference between the platform interest rate and the industry rate in the past week. When the value of T is 4, Formula (2) calculates the difference between the platform interest rate and the industry rate in the past month. Term differences are calculated in a similar way to Formula (2), except that the interest rate is replaced with the term.

In order to measure the overall risk of the online lending market, we define and use the indicator of occurrence rate of problematic platforms, which refers to the proportion of the number of problematic platforms that accumulate before a specific time point to the total number of platforms. This indicator can better measure the overall market risk that investors can perceive in the online lending market. In fact, investors can learn about the occurrence of problematic platforms through wdzj.com and p2peye.com.

3.2. Testing Investors' Risk Awareness

In the P2P online lending industry, a question which is very important but still lacks relevant evidence is: Do investors have risk awareness? This can be further decomposed into the following two sub-questions: First, can investors' investment behavior respond to the risks of specific platforms they invest in? Second, can investors' investment behavior respond to the overall risk of the online lending market? If investors have risk awareness, we propose the following hypotheses to be tested for the first sub-problem:

Hypothesis 1: (a) It is more difficult for potentially problematic platforms to attract more investment by raising product interest rates: (b) When platform risk increases, the effect of products with high interest rates or short terms to attract investment will diminish.

Hypothesis 1 (a) measures the individual risk of the platform with the potentially problematic platforms, and hypothesis 1 (b) measures the individual risk of the platform with the difference of interest rate and term. To further test whether investors can identify the industry risks in the online lending market, we propose the following hypothesis:

Hypothesis 2: When the overall risk of the online lending market increases, the effect products with high interest rates or short terms to attract investment will be reduced.

Next, to verify Hypothesis 1 (a), we conduct regressions of the following regression models according to the types of platforms.

$$investment_{it} = \alpha + \beta interest_{it} + \gamma term_{it} + \mu_i + \nu_t + \epsilon_{it} \tag{3}$$

where i represents the platform, t the time (week), *investment* the total investment, *interest* the average interest rate, *term* the average term, μ_i the platform fixed effect, v_t the weekly fixed effect. Regression results are shown in Table 4. Since we have many unobservable factors, the platform's own characteristics may determine the interest rate or term characteristics of the products it issues, and we need to control the unobserved factors and invariant features as much as possible through time-fixed effect and platform fixed effect to minimize the estimation error. It can be seen from column (1) that, on average, raising interest rates or shortening the term can indeed enable the platform to attract more investment. Interestingly, as shown in columns (2) and (3), the financing effect of raising product interest rates or shortening the maturity of normal platforms is far greater than that of problematic platforms. By raising the interest rate by one percentage point, the normal platform can get an additional 2.01 million yuan of total investment, while the problematic platform can only attract an additional 0.4479 million yuan of total investment. This is completely consistent with our hypothesis, indicating that investors are aware of the potential risks of the platform before the problems become exposed. For the problematic platform, the effect of shortening the term is not significant. This may reflect investors' risk awareness, or it may be because the term of the problematic platform is already very short, and it is not effective to further shorten the term to attract investment.

Table 4. Platform Interest Rate (Term) and Platform Financing

Explained variable: total investment or $\log_{10}$(total investment) (week)						
	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Normal platforms	Problematic platforms	Full sample	Normal platforms	Problematic platforms
Average interest rate	132.896*** (33.985)	200.134*** (58.808)	44.793*** (4.730)	0.008*** (0.002)	0.007*** (0.002)	0.005*** (0.002)
Average term	–297.799*** (27.553)	–367.461*** (35.529)	–7.512 (6.582)	0.001 (0.001)	–0.0001 (0.001)	0.009*** (0.002)
Constant term	2,010.981 (1955.597)	2,582.378 (7367.542)	–182.762 (218.700)	2.721*** (0.067)	2.391*** (0.211)	2.464*** (0.079)
Number of samples	27266	20239	7027	27266	20239	7027
R^2	0.013	0.016	0.031	0.057	0.088	0.055
Number of platforms	575	412	163	575	412	163
Platform fixed effect	YES	YES	YES	YES	YES	YES
Weekly fixed effect	YES	YES	YES	YES	YES	YES

Since the scale of different platforms is different, the scope of business involved varies greatly (which will affect the structure of product interest rate and term). Although we control the fixed effect of platforms, we use the logarithm of investment as the explained variables in columns (4)~(6) in order to facilitate the comparison of coefficients. The comparison of columns (5) and (6) shows that, as the most direct way to attract investment, raising interest rates does draw more investment (percentage) for normal platforms. In addition, it should be noted that for the problematic platforms, column (3) indicates that shortening terms cannot absorb investment, but column (6) shows that if the problematic platforms shorten the term, the effect of absorbing investment is even negative. All this evidence suggests that investors are actually able to identify the risks of potentially problematic platforms through interest rates and terms.

In addition to the information on whether the platform became a problematic platform during the sample period, as previous Probit regressions show, features in platform operations can also be used to measure the risk of the platform. So, next we want to test Hypothesis 1 (b), i.e. can investors identify the changes in the platform's own risk?

To validate Hypothesis 1 (b), we use the differences in interest rates and terms between the platform and the industry for the measurement of platform risk—added as an interaction term to Formula (3) to get:

$$\begin{aligned} investment_{it} = {} & \alpha + \beta interest_{it} + \beta' interest_{it} \times interest\_diff_{it}(T) \\ & + \gamma term_{it} + \gamma' term_{it} \times interest\_diff_{it}(T) + \mu_i + \upsilon_t + \epsilon_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} investment_{it} = {} & \alpha + \beta interest_{it} + \beta' interest_{it} \times term\_diff_{it}(T) \\ & + \gamma term_{it} + \gamma' term_{it} \times term\_diff_{it}(T) + \mu_i + \upsilon_t + \epsilon_{it} \end{aligned} \tag{5}$$

where the interest rate difference or term difference between the platform and the industry is calculated according to Formula (2). When the interest rate difference between the platform and the industry increases, i.e. the risk of the platform increases, we expect that the effect of raising interest rate on attracting investment will be weakened. That is, in Formula (4), the symbols of β, the coefficients β in front of the interest rate and β', the coefficients of the interaction term should be opposite. Correspondingly, the effect of shortening the term on attracting investment will also be reduced, that is, the symbols of γ and γ' are also opposite. Similarly, when the time difference between platform and industry is used as a measure of platform risk, when the term of platform product is shorter than the average term of industry product, the value of $term\_diff_{it}(T)$ will be smaller, the platform risk will increase, and the effect of raising interest rate or shortening the term on attracting investment will also be weakened, so we expect the symbols of β *and* β', the coefficient of the interaction term, as well as the symbols of γ and γ' in Formula (5) are the same. The regression results are shown in Table 5.

Table 5. Platform Risk and Platform Financing

Explained variables	(1)	(2)	(3)	(4)
Total investment (week)	T=1		T=4	
Interest rate	46.043 (51.160)	204.419*** (36.954)	76.726 (51.076)	235.899*** (37.011)
Term	–306.645*** (28.639)	–12.666 (35.371)	–297.696*** (28.172)	18.171 (34.051)
Interest rate × interest rate difference	–8.552*** (2.247)		–10.959*** (2.641)	
Term × interest rate difference	99.101*** (6.550)		112.945*** (6.869)	
Interest rate × term difference		33.423*** (3.053)		42.336*** (3.762)
Term × term difference		–47.433*** (1.953)		–61.871*** (2.194)
Constant term	3726.802* (2058.117)	2032.475 (1976.625)	3446.041* (2036.982)	1994.235 (1949.865)
Number of samples	26353	26353	26675	26675
R^2	0.021	0.035	0.023	0.042
Number of platforms	575	575	575	575
Platform fixed effect	YES	YES	YES	YES
Weekly fixed effect	YES	YES	YES	YES

Column (1) and column (2) use the difference between the platform interest rate (or term) of the past week and the industry rate (or term) to measure the operational risk of the platform. As shown in column (1), the appeal of platform products' high interest rate of and short term to investors' funds will decline as operational risk increases (higher interest rate differences). In column (2), operational risk is measured by smaller term differences, and the results remain in line with our expectations. If we measure the operational risk of the platform using the characteristics of the platform over the past month, the regression results remain robust, as shown in column (3) and (4).

To test Hypothesis 2, that is, the investors' response to the overall market risk, we set the following regression equation:

$$\begin{aligned} investment_{it} &= \alpha + \beta interest_{it} + \beta' interest_{it} \times mkt\_riks_{m(t)} \\ &\quad + \gamma term_{it} + \gamma' term_{it} \times mkt\_risk_{m(t)} + \mu_i + \upsilon_t + \epsilon_{it} \end{aligned} \tag{6}$$

where the measure of market risk (*mkt_risk*) is the proportion of the cumulative number of problematic platforms before the month $m(t)$ in the total number of platforms (we also use the ratio of the number of new problematic platforms to that of the normally operating platforms in the t-period as a measure of market risk for robustness testing, we also consider the effect of lagging first order, the results are not much different). We expect the interaction coefficient to be the opposite of the corresponding one-time item coefficient symbol. Regression results are shown in Table 6.

Table 6. Market Risk and Platform Financing

	(1) All the platforms	(2) Normal platforms	(3) Problematic platforms	(4) Problematic platforms (limited to 3 months before)
Average interest rate	748.946*** (94.365)	1178.741*** (152.751)	63.311*** (15.292)	58.850*** (18.848)
Average term	−1511.450*** (81.007)	−1667.602*** (100.004)	36.327 (28.514)	67.886** (34.191)
Average interest rate ×market risk	−2103.143*** (291.364)	−3177.454*** (438.009)	−64.747 (50.141)	−22.958 (60.285)
Average term ×market risk	3724.816*** (230.355)	3966.520*** (279.971)	−137.922 (87.572)	−293.827*** (105.942)
Constant term	−2060.226 (2191.305)	−2480.977 (7495.160)	−465.656* (274.520)	−889.043*** (307.060)
Number of samples	27266	20239	7027	6229
R^2	0.025	0.030	0.032	0.042
Number of platforms	575	412	163	161
Platform fixed effect	YES	YES	YES	YES
Weekly fixed effect	YES	YES	YES	YES

The samples listed in column (1) of the table contain all the platforms. It can be seen that the average interest rate linear term with a significantly positive coefficient indicates that higher interest rates do attract more investment. However, the coefficient of the interaction term between the average interest rate and market risk is also significant, and its symbol is just opposite to the linear term. This shows that when the overall industry risk in the online lending market increases, the effect of platform raising interest rate on attracting investor funds will be significantly weakened. This verifies Hypothesis 2, indicating that, in general, investors' investment behavior will respond to the overall market risk. The variable of average product term is similar, which also reflects that investors become more cautious about short-term products when market risk increases. The regression of column (2) in Table 6 contains only a sample of the normal platforms, and the results are consistent with those of the full sample.

The regression of column (3) contains only the potentially problematic platforms, and it can be seen that there are more obvious differences between the investors of the problematic platforms and those of the normal platforms. At this point, of the four coefficients we are concerned about, only the coefficient of interest rate linear item is significantly positive, and it is relatively small, indicating that the effect of the problematic platforms to attract investment by raising interest rates is relatively limited, so investors of potentially problematic platforms have some awareness of the risks of the platforms. However, the interaction term between interest rates and market risk in column (3) is not significant, and our guess is that investors who invest in potentially problematic platforms are likely to be a more specific group that are attracted to invest by the platforms' high interest rates, but they have a strong risk perception of the platforms. So the volatility of the overall market risk during our sample period is not sufficient to make a significant change in their investment behaviour. By examining the raw data, we find that the characteristics of the potentially problematic platforms change significantly when they are about to become problem platforms (such as an increase in the dispersion of variables such as average interest rates). To this end, we further limit the sample of potentially problematic platforms to three months before the problem occurs in the regression of column (4). It can be seen that the regression results of interest rates and their interaction terms are basically consistent with those in column (3). In the above test of Hypothesis 2, if we measure market risk by the proportion of new problematic platforms to all platforms during the week, the results are still similar. Therefore, through the test of Hypothesis 2, we find that investors will be more cautious in investing in high-interest products when the overall industry risk of the online lending market increases, and this understanding of market risk is mainly reflected in the investors of normal platforms.

4. Conclusions

This paper uses micro data from the P2P online lending platforms to study whether investors can identify potential risks in the absence of effective regulation. By obtaining the operational data of 575 P2P online lending platforms, we measure the individual risk of specific platforms by deciding whether they are potentially problematic platforms, and by using the difference between product interest rate or term of platform and industry product interest rate or term, and measure the overall market risk by the proportion of problematic platforms in the market. We find that while investors are attracted by the higher interest rates of online lending products, their investment behavior still shows a certain risk awareness to the individual risk of the platform and the overall market risk of the industry. Investors' risk awareness of the platform manifests itself as follows: (1) It is more difficult for potentially problematic platforms to attract investment through high interest rates (short term); (2) Investors become more cautious about products with high interest rate when the platform operation risk increases, that is, when the platform interest rate (or duration) gets increasingly higher than (or shorter than) the industry average interest rate (or term); (3) When the overall market risk of the industry increases, the appeal of high interest rate (short-term) products to investors will also be significantly reduced.

The findings of this paper provide an empirical basis for us to understand the risk consciousness of investors in the P2P online lending market. As P2P lending is one of the important business forms of Internet finance, the findings of this paper can help us understand the investment risks in the context of the rapid development of Internet finance and investors' perception of Internet financial risks in the absence of regulation. This paper provides a policy basis for understanding the development of the emerging form of financial industry. This paper has confirmed that even in the absence of regulation, investors still show a clear risk awareness of the individual risks of specific platforms and the overall market risks of the online lending industry. This means that although the government has regulatory responsibilities, it should not easily take the responsibility for investors' losses. In addition, the basic idea of future regulatory policy should be to conform to the financial innovation of the market, standardize the market, and at the same time, draw on investors' risk awareness and market competition to achieve the survival of the fittest online lending platforms.

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