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Seeking Excess Returns under a Posted Price Mechanism:
Evidence from a Peer-to-Peer Lending Market

Abstract

This study examines the performance of a new online peer-to-peer (P2P) lending platform in China that relies on non-expert individuals to screen for loans. Using the bank deposit rate as a benchmark, positive excess returns exist under the posted price mechanism, which indicates that P2P markets provide lenders with adequate profit opportunities to compensate for investment risks. Moreover, we find that loans with higher excess returns are more likely to be funded and are bid on more quickly than other loans. Finally, voluntarily disclosed soft information in the listing's description plays a significant moderating role in the lenders' decision-making process. Borrowers who promise to repay on time are more likely to be funded and to be funded faster, but those who claim economic hardship have a lower probability of being funded. Our results provide evidence that lenders have the ability to seek excess returns in P2P lending markets and highlight that aggregating the views of peers can improve market efficiency.

Keywords: Peer-to-Peer lending market; excess returns; voluntary information disclosure; moderating effect; information asymmetry

1. Introduction

Two important functions of a lending market are to screen borrowers and to allocate credit efficiently based on each borrower's creditworthiness (Iyer et al., 2016). However, the market might break down due to information asymmetry between borrowers and lenders (Stiglitz & Weiss, 1981). With their financial expertise to evaluate borrowers and intermediate capital, banks traditionally have played a dominant role in reducing information asymmetry and allocating credit (Diamond, 1984). The 2008 banking crisis has highlighted the shortcomings of traditional bank lending models, particularly in allocating credit to smaller borrowers (e.g. Christine & Guillaume, 2008; Houston et al., 2010; Parlour & Winton, 2013). The diffusion of the Internet has driven the emergence of peer-to-peer (P2P) lending platforms, which offer a new way to match supply and demand for capital and some valuable insights. On P2P lending platforms, borrowers can present themselves and their planned projects and seek financing directly from individual lenders. Based on the information disclosed, individual lenders invest in loans for projects that they like. However, the downside of P2P lending markets is that individual lenders in these markets typically have limited experience and no formal training in judging borrowers' creditworthiness. Some information (e.g. identification, gender, education and income) disclosed by borrowers can be verified by the platform, but not all of it. If lenders pursue only high interest rates but ignore default risks, this will increase the systematic risk of P2P lending markets. Therefore, whether lenders can earn excess returns is of great significance to the P2P lending market so that it can efficiently allocate capital and survive.

The purpose of this study is to investigate whether lenders can collectively screen out high-quality loans in a P2P lending market. This article addresses the following related questions: (1) Do excess returns exist in the P2P lending market? (2) Do lenders have the ability to identify excess returns? (3) Can voluntary soft information disclosure improve the efficiency of lenders' decision-making process?

We utilise transaction-level data from a leading Chinese online P2P lending platform, Renrendai.com. Without banks as intermediaries, the transaction costs and transaction time in the P2P market are reduced, but the problems associated with information asymmetry may become more pronounced (Ivashina, 2009). Compared to the developed markets (e.g. US and UK), in which borrowers' credit scores are directly provided by independent credit rating agencies, the trustworthiness of borrowers are assessed by the P2P platform in China. Thus, our study offers a more direct lens to observe the extent to which information disclosed by borrowers on the P2P platform reduces information asymmetry faced by lenders. Moreover, different from a Dutch auction, in which the platforms allow the lender and borrowers to reach the final loan interest rate (i.e., borrower starts the auction with a maximum interest rate and multiple lenders bid that rate down until the auction times out), Renrendai.com employs a posted-price mechanism where the platform assigns each loan application an interest rate, and lenders bid for an amount. Loans are more likely to be funded and funded faster under this posted-price mechanism (Wei & Lin, 2017).

Our study provides some new findings about mispricing in the P2P lending market. Considering the listing's default risks and posted prices (interest rates), we measure each listing's expected returns and compare them with the risk-free interest rate to calculate each loan's excess returns. The results show that this P2P lending market has loans with positive excess returns and provides lenders with abundant opportunities to make profits. Furthermore, we investigate lenders' screening ability. For listing-level data, the probability of listings being funded increases with excess returns. For loan-level data, loans with higher excess returns are funded faster. Finally, we explore the moderating role of the voluntary information in the lenders' screening process and find that the voluntary soft information disclosed by lenders plays a significant moderating role. Borrowers who promise to repay on time are more likely to receive funding quickly, but those who claim economic hardship have a lower probability of being funded even when their excess returns are the same.

Our study makes several contributions to the literature. First, our study contributes to the ongoing debate about whether P2P lending markets compensate lenders for their investment risks. Some studies claim that the entire P2P lending market generates a loss for all lenders by measuring the realized mean returns (Mild et al., 2015). However, Emekter et al. (2015) and Krumme and Herrero (2009) find that high-quality loans offer lenders positive excess returns by measuring the excess returns as the difference between the interest rate and the expected interest rate. We extend the literature by considering both the benefits and risks of a loan to measure excess returns in the online P2P lending market. We also provide new evidence that loan's posted rates and default risks exhibit a U-shaped relationship, which indicates that posted rates do not fully reflect the loan's default risks.

Second, our study also contributes to the debate on whether lenders have the ability to screen high-quality loans. Some studies (e.g. Iyer et al., 2015; Liao et al., 2014) find that lenders have the ability to screen high-value listings but they are also found to suffer from cognitive limitations and bias (e.g. Andrei & Hasler, 2015; Burtch et al., 2014; Lin & Viswanathan, 2016), which inhibit the ability of lenders to convert the available information into correct screening behaviour. Our results support that lenders have the ability to seek excess returns and highlight that aggregating the views of peers can enhance capital allocation in the market.

Finally, in contrast to existing studies (Dorfleitner et al., 2016; Herzenstein et al., 2011) that focus on the effect of voluntary information disclosure on borrowers' default risks, we enrich the moderating role of voluntary information in the lenders' screening process. We find that voluntary information disclosure in a listing's description plays a significant moderating role in reducing the information asymmetry faced by lenders in the investment decision-making process.

Overall, our study enriches the knowledge about the distribution of risk-adjusted returns and lenders' screening abilities under a posted price mechanism, the current mainstream online P2P lending market pricing mechanism. These results also highlight the important role of voluntary soft information disclosure in enabling lenders to screen high-quality loans and borrowers to secure funding from the P2P lending markets successfully.

The remainder of this paper is organised as follows: In Section 2, we review the related literature and present our testable hypotheses. Section 3 presents the methods to measure of loan's excess returns and reports the descriptive statistics. Section 4 provides evidence that individual lenders can seek higher excess returns. Finally, Section 5 presents the conclusions.

2. Literature Review and Hypothesis Development

In this section, we review two strands of literature related to our research questions: the distribution of excess returns in P2P lending markets and lenders' ability to screen high-quality loans.

As an emerging lending market, P2P lending platforms advertise high interest rates to attract lenders. However, the existing empirical studies have not reached a conclusion on whether P2P lending markets compensate lenders for their investment risks. Some argue that P2P lending markets as a whole generate losses for lenders. Mild et al. (2015) demonstrate that myc4.com fails to price adequately a loan's default risks under the Dutch auction. Wei and Lin (2017) compare different P2P market pricing mechanisms and find that loans that are funded under posted prices are more likely to default, which generate losses for lenders.

Other research finds that high-quality loans offer excess returns. Using data from Lending Club, Emekter et al. (2015) find that the actual interest rates are higher than the theoretical interest rates for lower risk borrowers. Employing data from Prosper.com, Berkovich (2011) finds that high-quality loans offer lenders excess returns.

If positive excess returns do not exist in the market, lenders who can identify excess returns will switch to other P2P platforms. Fewer listings can be funded in the platform in question, which will lead to borrowers to leave the platform and the platform to fail. Therefore, if a platform runs steadily, the market should provide investors with non-negative excess returns and even positive excess returns. Thus, we hypothesise that positive excess returns exist in the P2P lending market and formally state this as Hypothesis 1:

H1: On average, investors earn positive excess returns in a P2P lending market.

In P2P markets, individual lenders screen borrowers and allocate their capital. To increase efficiency and maximise profits, funds must be distributed and invested in listings with high excess returns. Some research shows evidence that lenders can identify high-quality loans. Iyer et al. (2015) find that lenders can predict borrowers' default probability on a loan and demand lower interest rates from borrowers with lower default risks. Lin et al. (2013) show that lenders can allocate funds to loans with lower ex post default rates based on the borrowers' online friendship. Liao et al. (2014) find that lenders can distinguish different default risks of listings with the same interest rates using the listing information. Similarly, Hu & Song (2017) prove that there are optimal interest rates that lenders most prefer when they assess interest rates and risks simultaneously.

However, individual lenders also suffer from some cognitive limitations and biases, which affect their investment decision-making. Investment decisions are influenced by attention (Andrei & Hasler, 2015; Barber & Odean, 2008) and herding behaviour (Andreas & Hamid, 2011; Burtch et al., 2014; Liu et al., 2015; Park & Sgroi, 2012; Zhang & Liu, 2012). Further, such decisions are affected by home bias (Lin & Viswanathan, 2016), age discrimination (Pope & Sydnor, 2011), appearance discrimination (Duarte et al., 2012), cultural discrimination (Burtch et al., 2014) and market sentiment (Cen et al., 2013). These factors make it more difficult for lenders to screen high-quality loans. Mild et al. (2015) prove that lenders cannot convert the available information into the correct market behaviour that they should adopt. Lenders in P2P markets are more likely to have limited experience and no formal training in estimating default risks. Figure 1 reports the distribution of lenders in our sample and their investments. We divide lenders according to the frequency of their investments. Of all the lenders, 78% invested only 1-10 times, but their investments accounted for 23% of the total investments in the P2P market; therefore, they account for the largest proportion of funding sources.

If lenders have the ability to identify listings with excess returns, listings with higher excess returns should attract more interest from lenders and be fully financed faster. Thus, we posit Hypothesis 2:

H2: Listings with higher excess returns have a greater chance of successful financing and are fully financed faster.

Information disclosure reduces adverse selection (Bourveau & Schoenfeld, 2017; Riordan et al., 2013) and information asymmetry (Thomas et al., 2018). Some information, such as the borrower's personal information can be verified by the platform but the voluntary soft information disclosed by the borrowers, despite not being verified by the platform, can indicate borrowers' commitment to repaying on time and their economic hardship based on whether they state that the money is in an urgent need (Abbasi et al., 2008; Abbasi & Chen, 2008; Hassan et al., 2013).

Using data from Prosper.com, Iyer et al. (2015) find that lenders rely on voluntarily disclosed information in their screening process. The effect of voluntary, unverifiable information extends beyond the influence of objective, verifiable information on reducing the interest rate and increasing funding probability (Herzenstein et al., 2011; Michels, 2012).

For listings in which borrowers emphasize their willingness to repay on time (*Honesty*) and listings in which borrowers clearly state their economic difficulty (*Hardship*), we expect a higher degree of efficiency in the lenders' decision-making process. Thus, in Hypothesis 3, we hypothesize that voluntary information disclosure exhibits a moderating effect:

H3: For listings with the same excess returns, those in which borrowers indicate their willingness to repay on time (*Honesty*) are more likely to receive funding and be funded more quickly. However, listings in which borrowers indicate their economic difficulty (*Hardship*) have a lower probability of being funded.

3. Data and Methodology

3.1 Data from Renrendai.com

To study the excess returns on the P2P market and lenders' ability to screen loan listings, we obtain the listing data from Renrendai.com, which was founded in 2010 and has become a leader in the industry. It was designated as an AAA (the highest level) online lending platform in 2014 and in 2015. By the end of February 2018, the platform's total transaction volume exceeded 50 billion (RMB).

Transactions on Renrendai.com are typical examples of P2P lending. Borrowers are required to disclose purpose and personal information when they submit applications, including identification, age, income, education, and assets. Specifically, Renrendai.com provides verification services for standard information, such as national identification cards, credit reports, phone numbers, education, houses, and cars. Furthermore, borrowers voluntarily provide a "loan description", in which they disclose specific information regarding their jobs, income, investment projects, and other personal information in a freeform text field. Based on the information above and users' borrowing and lending histories, the platform assigns a credit score to each borrower and sets the interest rate for each listing. On Renrendai.com, borrowers can request funding for any amount ranging from RMB 3,000 to RMB 500,000 and decide the debt term, which is usually one of the following: 3, 6, 9, 12, 15, 18, 24, or 36 months.

Once a listing is posted online, lenders may place bids by stating the amount they want to invest. With a minimum bid amount of RMB 50, a listing typically requires multiple bids to become fully funded. Within seven days of fundraising, a listing that achieves 100% funding is successful and becomes a formal loan. If this deadline is not met, the listing cannot continue to accept lenders' bids. If lenders fail to provide enough money in the required time, the borrower receives no funding. Renrendai.com loan repayments occur in a phased manner that matches the return of the monthly loan interest.

We study loan listings on Renrendai.com for the period of January 1, 2011 to December 31, 2015. The starting point of the study period is chosen to avoid the initial launch period. We end our sample period as of December 2015, as we need to observe the entire credit cycle, in some cases 36 months, to estimate the loan's default risks. Following Chen et al. (2018), we keep listings with credit guarantees. The principal is guaranteed for credit loans, which is more suitable for estimating lenders' ability to seek excess returns. Listings with credit guarantees were banned in October 2016. The other types of loans are institutional guarantees and field certification, which guarantee the payment of the original investment and interest. In addition, we also drop listings funded by the platform's financial plans.

As a result, our final sample includes 454,913 listings, among which approximately 5.7% were successfully funded, and 16.4% of the loans were defaults. We winsorise all the data at both the upper and lower 1% levels to mitigate the impact of outliers.

3.2 Measuring Excess Returns

From the lenders' perspective, the main concern is whether they are compensated for default risks. We first evaluate the probability of default for each listing and calculate the corresponding expected returns. Then, we employ the benchmark rate to adjust the risks. Finally, the difference between the expected return and the benchmark rate is defined as the excess return.

To evaluate a listing's default risks, we employ probit regression and examine the factors that determine the likelihood of a loan's default. The dependent variable is the probability that an event will occur—here, the probability that the loan is not repaid either entirely or partially. We run the regression with loans that have completed the entire credit cycle and obtain the estimated coefficients $\widehat{\beta_n}$. Then, using these estimated coefficients and the following expressions, we estimate the probability of default for each listing that is not yet due:

$$Dmy\_Default = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \varepsilon$$

$$defaltratio = \widehat{\beta_0} + \widehat{\beta_1} x_1 + \widehat{\beta_2} x_2 + \cdots + \widehat{\beta_n} x_n \quad (1)$$

where $Dmy\_Default$ is an indicator variable for loans that have completed the entire credit cycle, which equals one if the loan defaulted and equals zero if the loan was fully repaid. $x_1, x_2, \ldots, x_n$ are a series of loan's characteristics, such as the loan rate, squared loan rate, duration, amount, number of words in a loan's description and borrowers' credit, age and income. $defaultratio$ is the estimated default risk. ε denotes for the error term.

Given the posted rates and the guaranteed principal repayment on Renrendai.com, we calculate the corresponding expected return as follows:

$$Ereturn = loanrate * (1 - defaultratio) \quad (2)$$

where $Ereturn$ is a listing's expected return, and $loanrate$ is the rate priced by the platform. When a loan defaults, the return will be zero, because the principal will be repaid by the platform. In normal circumstances, $Ereturn$ is the posted rate when the loan is repaid on time.

Following the capital asset pricing model (Sharpe, 1964), to measure the excess returns, we compare the expected return of each listing with a benchmark return (Eq.(3)). As the benchmark rate, we employ the bank deposit rate ($Bank\ Rate$), which represents the risk-free interest rate of the entire financial environment in the same period. If the expected returns of most listings are lower than the bank deposit rate, lenders should put their money into banks rather than listings.

$$ExcessReturn = Ereturn\ \ - Bank\ \ Rate \quad (3)$$

where $ExcessReturn$ is the excess return adjusted by the bank deposit rate.

3.3 Empirical Strategy

To investigate whether lenders have the ability to identify loans with higher excess returns, we run the following probit regression.

$$Dmy\_Funded = \beta_0 + \beta_1 ExcessReturn + c'X + \varepsilon \quad (4)$$

where Dmy_Funded is an indicator variable that equals one if the listing was successfully funded and equals zero otherwise. X is a vector of time effects.

For each loan, we measure the $Financing\_Speed$ to explore whether lenders can rapidly screen high-quality loans in Eq. (5).

$$Financing\_Speed = \frac{ln\_loanamount}{Completion\ \ time\ \ of\ \ financing} \quad (5)$$

where $Completion\ \ time\ \ of\ \ financing$ is the seconds that it takes for a loan to be fully funded. Furthermore, to test whether listings with higher excess returns will complete financing in less time, we run the following OLS regression:

$$Financing\_Speed = \beta_0 + \beta_1 ExcessReturn + c'X + \varepsilon \quad (6)$$

Last, we test the moderating effect of the voluntary soft information disclosure on the relationship between excess returns and the probability of being funded in Eq. (7) and financing speed in Eq. (8). We construct regression models as follows:

$$dmy\_funded = \beta_0 + \beta_1 ExcessReturn + \beta_2 Honesty\ (Hardship) + \beta_3 Honesty\ (Hardship) * ExcessReturn + c'X + \varepsilon \quad (7)$$

$$Financing\_Speed = \beta_0 + \beta_1 ExcessReturn + \beta_2 Honesty\ (Hardship) + \beta_3 Honesty\ (Hardship) * ExcessReturn + c'X + \varepsilon \quad (8)$$

where $Honesty$ is an indicator variable that equals one if the borrower mention words about honesty, such as 'reliable', 'no overdue', or 'must repay', in the loan description and zero otherwise. $Hardship$ is an indicator variable that equals one if the borrower mention words about economic hardship, such as 'urgently required', 'funding difficulty', or 'lack of money', in the loan description and zero otherwise. β_3 measures the magnitude of the moderating effect.

3.4 Variables and Summary Statistics

Each listing in our sample is associated with a large number of variables, Table 1 shows a complete list of all variables that were obtained can be found. Table 2 provides descriptive statistics of all the variables used in this study. Based on our full sample, in Panel A, the average interest rate charged in the listings on Renrendai.com is 13.6%, the average loan amount is RMB 58,811.4 (USD 8,401.63), and the average term is approximately 16 months. In Prosper.com, a leading P2P lending platform in the US, the listings' average interest rate is lower (17.29%), the average loan amount is USD 8,160, and the average term is 36 months (Hildebrand et al., 2016). With respect to the borrowers' information, the borrowers' average age is approximately 31 and their average education level is undergraduate. Approximately

0.4% of borrowers have an income of less than RMB 1,000 (USD 142.86) per month, 5.3% of borrowers have a car loan and 12.9% have an existing mortgage. For loan descriptions, the average word count is 41.58.

[Insert Table 1 Here]

Moreover, 5.7% of listings are fully funded and become loans (Dmy_Funded). For the loans in our sample, the average financing completion time is 1106.69 seconds (18.5 minutes). The financing speed shows that loans receive approximately RMB 1.16 per second. 20,817 loans have completed the entire credit cycle. Among them, 16.4% default ($Dmy\_Default$).

[Insert Table 2 Here]

To investigate whether lenders screen listings at the entire market level, we also compare the characteristics of loans and listings in Panel B in Table 2. Funded loans have significantly lower posted interest rates, smaller amounts, and shorter terms and the corresponding borrowers have better credit and higher levels of education. These significant differences indicate that lenders can screen listings based on the available information rather than selecting them at random.

4. Empirical Results

4.1 Excess Returns in the Market

4.1.1 Default Ratio

As discussed in subsection 3.2, we estimate each listing's default risks based on Eq. (1). In Column (2) in Table 3, *Loan Rate* and default risks exhibit a U-shaped relationship, which means that the default risks first decline and then rise with the interest rate. This relationship indicates that the interest rates set by the platform do not fully reflect each loan's default risks. This is in line with Mild et al. (2015), who find that the P2P lending market fails to price listings' default risks adequately.

[Insert Table 3 Here]

Regarding loan and borrower characteristics, the longer the term is, the larger the amount and the greater the likelihood of default. In addition, the coefficient of credit grade is negative ($\beta = -0.884, z - statistic = -35.87$), suggesting that the higher a borrower's credit grade, the lower the default risk. This is consistent with the results of previous studies (Emekter et al., 2015) that credit ratings are negatively correlated with default. We also find that older borrowers with less education, no car, a car loan, no mortgage, and longer descriptions tend to default. This result is consistent with that of Liao et al. (2014) who find that borrowers' education is negatively correlated with the default probability in Chinese P2P lending markets. These results again document that borrowers' public information contains a large amount of information that is not included in the interest rate to predict the default probability of borrowers and that default risks are not fully reflected in interest rates.

4.1.2 Excess Return

Next, we use the estimated listing default ratio to calculate expected returns and excess returns using Eqs. (2) and (3). Table 4 provides a detailed statistical analysis of the excess returns in the Chinese P2P market.

In Panel A, we compare the excess returns, expected returns and market benchmark interest rates. The results show that the average expected return on loans is 10.07%, which is significantly higher than the expected return on listings (7.34%). When $Bank\ Rate$ is used as the market benchmark interest rate, the average excess return for loans (7.28%) is significantly greater than the average excess return (4.41%) for listings. This preliminary result indicates that the quality of successfully loans is significantly better than that of listings and lenders have the ability to screen out high-quality listings. Thus, Hypothesis 1 is supported.

[Insert Table 4 Here]

Further, we investigate the distribution of excess returns over the years in Panel B. As Renrendai.com expands, the average excess returns decrease. Listings with positive excess returns are abundant in the market, which provides a good opportunity for lenders to obtain profits that are greater than the average market rates.

4.2 Can Lenders Seek Excess Returns?

Having found that listings with positive excess returns are abundant in this P2P lending market, we now focus on whether lenders have the ability to seek loans with higher excess returns.

Controlling for the time effects, excess returns are significantly and positively correlated with the probability of successful financing in Column (1) in Table 5. As regards loans, column (2) reports that the greater the excess returns are, the faster the speed of financing. The result supports Hypothesis 2 and confirms that lenders can select high-quality loans from the market, which is in line with the results of Iyer et al. (2015), that lenders can select loans with lower default risks and price them at lower rates, and of Hu & Song (2017), that individual lenders can balance default risks and the loan rate assigned by the platform.

[Insert Table 5 Here]

4.3 The Role of Voluntary Information Disclosure in Lender Decision-Making

Since the analyses above show that lenders have the ability to identify loans with higher excess returns, we turn to another question. Does voluntarily disclosed soft information affect lenders' decision-making? We test whether soft information disclosure has a moderating effect on the process through which lenders seek excess returns.

In Table 6, we find that $Honesty$ and $Hardship$ have a significant moderating effect on the relationship between loan excess returns and the probability of being funded, which supports Hypothesis 3. The coefficient of $ExcessReturn * Honesty$ ($\beta = 0.003, t-statistic = 1.78$) is significantly positive, which indicates a positive moderating effect of honesty on the relationship between excess returns and the probability of listings being funded. These results are consistent with those of Michels (2012) that voluntary information promotes bidding activity and thus increases the probability of listings being successfully funded. In addition, $Hardship$ has a negative moderating effect, that is, for listings with the same excess returns, those in which borrowers claim $Hardship$ in the loan description have a lower probability of being funded.

[Insert Table 6 Here]

Further, we test the moderating effects of soft information disclosure on the relationship between loans' excess returns and financing speed, with the results presented in Columns (3) and (4) in Table 6. The coefficient of the interaction term with $Honesty$ is significantly positive, which means that, for listings with the same excess returns, those in which borrowers indicate their $Honesty$ exhibit a faster financing speed. In contrast, for listings with the same excess returns, those in which borrowers claim $Hardship$ need a longer time to be funded.

[Insert Figure 2 Here]

To illustrate the moderating effect better, we also report the marginal effects of $Honesty$ and $Hardship$ in Figure 2. In Panel A, the impact of $Honesty$ on the probability of listings being funded and the financing speed of loans increases with an increase in excess returns. Panel B shows that the impact of $Hardship$ decreases with an increase in excess returns. These results indicate that the moderating effect of voluntary information disclosure is more pronounced for loans with higher rather than lower excess returns.

4.4 Robustness Checks

4.4.1 The Effect of Time on Loans' Default Risks

In Section 4.1.1, we employ a probit regression to evaluate a listing's default risks in Eq. (1), which may ignore the non-linear effect of time on risks. Weibull regression (Peto & Lee, 1973; Weibull, 1939) is a parametric model that assumes that the distribution function changes with time. Using a Weibull regression, we evaluate loans' default risks in any given month and measure excess returns again as an alternative measure.

[Insert Table 7 Here]

Table 7 reports the results of the Weibull regression. Loan interest rates and default risks still exhibit U-shaped relationships, which suggests that posted prices do not fully reflect loans' default risks. $\mathrm{P} > 1$ indicates that the failure probability increases with time ($ln(p) = 0.48, t - statistic = 94.72$). Based on the new default ratios estimated by the Weibull regression and the new excess returns, we run Eq. (6) and Eq. (8) again. Table 8 shows that financing speed increases as a loan's excess returns increase and *Honesty* still has a positive moderating effect on the process through which lenders seek excess returns. These results are consistent with our main results.

[Insert Table 8 Here]

4.4.2 Potential Endogenous Problems

We employ two-stage least squares (2SLS) regression analysis to allow for potential endogeneity that may be caused by omitted variable bias in Section 4.2 and Section 4.3.

Our instrumental variables are borrowers' cumulative number of successfully financed loans ($Fundnum$) and cumulative number of defaults ($Defaultnum$) before they apply for the current loan. These instruments are significantly related to current excess returns, as shown in Column (1) in Table 9, but not related to the current regression residuals. To explore lenders' screening ability, we run the regressions (Eq. (6) and (8)) again. When instrumental variables are used, loans' financing speed significantly increases as excess returns increase in Table 9, and $Honesty$ still has a positive moderating effect in Table 10.

[Insert Table 9 Here]

We also conduct a Hausman test ($Chi^2 = 1245.64, p = 0.00$) to detect the existence of endogenous, and perform the Stock and Yogo (2005) test and the Hansen (1982) over-identification test to ensure that our instruments are valid. Overall, our main results are robust after controlling for endogeneity using 2SLS estimation.

[Insert Table 10 Here]

5. Conclusions

This study employs data from Renrendai.com to investigate whether lenders have the ability to seek excess returns. Our results show that there are many listings with positive excess returns in this P2P lending market, which provide lenders with adequate profit opportunities. We further find that listings with higher excess returns have a greater probability of being successfully financed and that loans with higher excess returns complete their financing faster. These results highlight that even non-expert individuals can effectively screen borrowers better to obtain excess returns. Individuals collectively perform well at solving this problem, which is generally thought to be best left to experts with access to standard information. Finally, voluntarily disclosed soft information in the listing's description plays a significant moderating role in lenders' investment decision-making process. Borrowers who promise to repay on time are more likely to receive funding quickly, but those who declare economic difficulty have a lower probability of being funded. Moreover, the moderating effect of voluntary information is more pronounced for loans with higher rather than lower excess returns.

Due to problems of adverse selection and information asymmetry, a lending market may break down, if lenders can't seek excess returns, which compensate for their investment risk. Without traditional banks' intermediary, the P2P platform plays an important role in reducing the information asymmetry faced by lenders. The P2P platform in China takes the responsibility to verify information disclosed by borrowers and assign a credit score for each loan. Although soft information cannot be verified, it plays an important role on promoting lenders' screening process. The excess returns made up of the risk premium for expected default plus the economic rent from informational asymmetry can be sustainable in the medium/long-run if the P2P platform matures (i.e. prices the default risks effectively and provides timely and accurate information to lenders). Only when P2P markets can effectively filter borrowers can such markets offer a potential capital source for small borrowers who may be restricted to more expensive sources of finance, such as payday lenders and credit card debt (Morse, 2011). As individuals generate more information than ever before, and technology drastically reduces P2P transaction costs, such mechanisms have the great potential to improve the effectiveness of financial markets.

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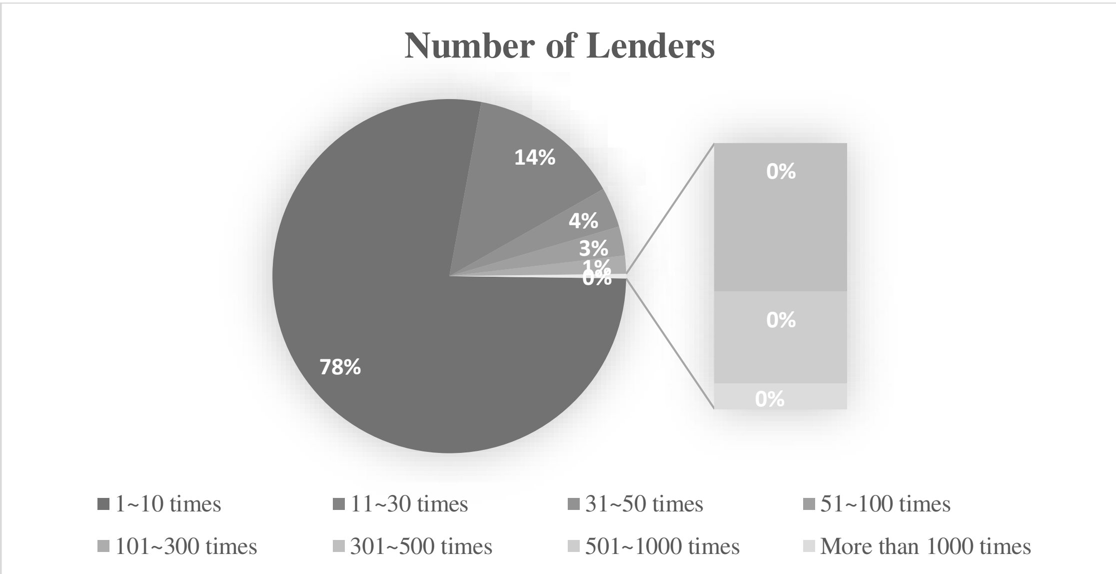
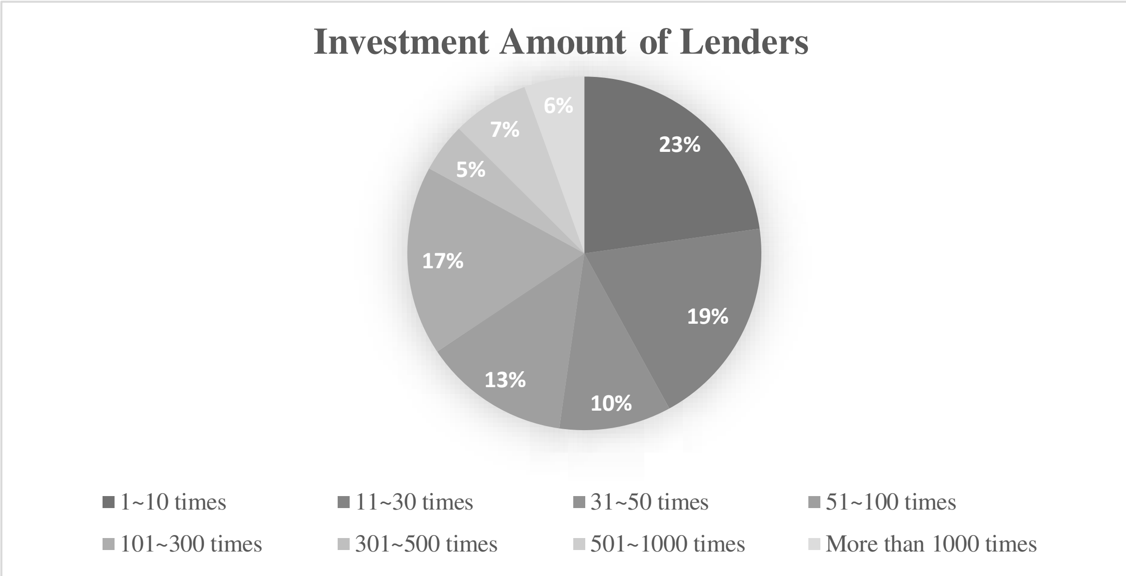
Figure 1. Lenders and Investment Amounts in Groups with Different Investments Frequency
Panel A. Proportion of the Number of Lenders



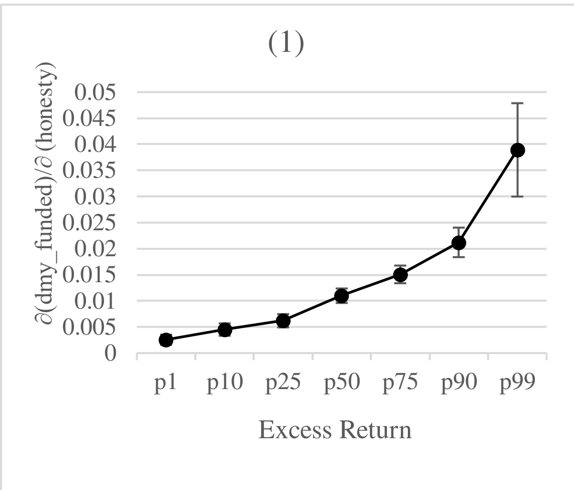
Panel B. Proportion of the Investment Amount

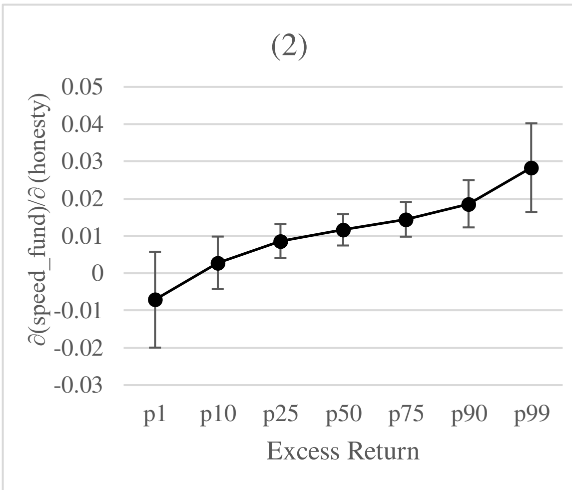


In this figure, we divide the sample by the frequency of lenders' investments and separately count the number of investors and the total investment amount in each group. Panel A reports the proportion of lenders in different groups. Panel B shows the proportion of total investment amounts in different groups.

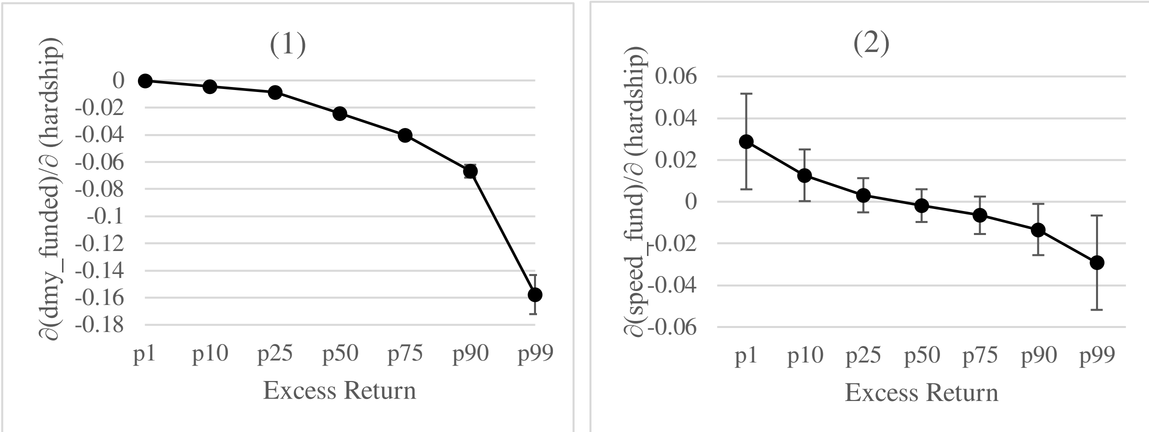
Figure 2. The Marginal Effect of Voluntary Information as a Moderator

Panel A. Marginal Effect of Honesty





Panel B. Marginal Effect of Hardship



This figure reports the impact of voluntary information on the probability of listings being funded and financing speed when excess returns change. Panel A and Panel B show the marginal effect of *Honesty* and *Hardship* on the process through which lenders seek excess returns.

Table 1 Definitions of all variables

Variable Name	Variable Definition
Loan Rate	The rate that a borrower pays on a loan and the platform prices.
ln_loanamount	The natural logarithm of the requested loan amount.
Loan Duration	The duration in months from the date that borrowers receive loans to the date when the principal and interest of the loan should be fully repaid.
Dmy_Default	An indicator variable for loans that have gone through the whole credit cycle, which equals one if the borrower defaulted and zero otherwise.
Dmy_Funded	An indicator variable that equals one if the listing was funded and zero otherwise.
defaultratio	The probability of default of listings, which is estimated using loans that finished the whole credit cycle.
Ereturn	The expected return on a listing, which is calculated using the promised interest rate and the probability of default.
ExcessReturn	The excess return on a listing based on the bank deposit rate which is in the same month as the listings and with the same maturity time.
Financing_Speed	The loan financing speed, which equals the natural logarithm of borrowers receive money in per second.
Credit Grade	Credit grade of the borrower takes on values between 1 (high risk) and 7 (low risk).
Age	Age of the borrower at the time the listing is created.
Income	An indicator variable that equals one if the borrowers' income is less than RMB 1000 per month at the lowest level and zero otherwise.
Education level	Education level of the borrower takes on values between 1 (low level) and 4 (high level).
Car	An indicator variable that equals one if the borrower is verified to own a car and zero otherwise.
Car Loan	An indicator variable that equals one if the borrower is verified to have a car loan and zero otherwise.
House	An indicator variable that equals one if the borrower is a verified homeowner and zero otherwise.
Mortgage	An indicator variable that equals one if the borrower is verified to have a house loan and zero otherwise.
Number of Words	The number of Chinese words in the loan description.
Honesty	An indicator variable that equals one if the borrower mentions words about honesty, such as 'reliable', 'no overdue', or 'must repay', in the loan description and zero otherwise.
Hardship	An indicator variable that equals one if the borrower mentions words about economic difficulty, such as 'urgently required', 'funding difficulty', or 'lack of money', in the loan description and zero otherwise.
Year	The year when the loan listing was posted, which takes on values from 2011 to 2015.
Month	The month when the listing was posted, which takes on values from 1 (January) to 12 (December).
Week	Day of week when the listing was posted, which takes on values from 0 (Sunday) to 6 (Saturday).
Hour	Hour of the day when the listing was posted, which takes on values from 0 to 23.

Table 2 Summary Statistics

Panel A: All Loans and Listings in the Full Sample

Variable	N	Mean	SD	p1	p50	p99
Loan Rate	454,913	13.601	2.955	10	13	24
Loan Amount	454,913	58811.420	89791.780	3000	30000	500000
Loan Duration	454,913	15.774	9.269	3	12	36
Dmy_Funded	454,913	0.057	0.232	0	0	1
Completion time of financing	26,020	1106.691	4342.712	9	115	35741
Financing_Speed	26,020	0.149	0.185	0.0003	0.083	1.001
Dmy_Default	20,817	0.164	0.370	0	0	1
Credit Grade	454,913	1.100	0.534	1	1	4
Age	454,913	31.121	6.378	23	29	52
Income	454,913	0.004	0.062	0	0	0
Education level	454,913	1.849	0.791	1	2	4
Car	454,913	0.231	0.422	0	0	1
Car Loan	454,913	0.053	0.224	0	0	1
House	454,913	0.398	0.490	0	0	1
Mortgage	454,913	0.129	0.336	0	0	1
Number of Words	454,913	41.581	30.332	6	31	186

Panel B: Difference between Loans and Listings

	Loans (N=26,020)		Listings (N=428,893)		Loans-Listings	
	Mean	**SD**	**Mean**	**SD**	**MeanDiff**	**t-stat**
Loan Rate	12.686	2.281	13.657	2.982	-0.970***	-60.528
Loan Amount(¥ hun)	22.398	33.644	61.020	91.639	-38.622***	-111.301
Loan Duration	12.169	8.252	15.993	9.282	-3.824***	-65.779
Credit Grade	2.060	1.517	1.042	0.322	1.018***	89.792
Age	33.403	6.578	30.983	6.339	2.420***	54.355
Income	0.000	0.019	0.004	0.063	-0.004***	-24.137
Education level	2.149	0.818	1.831	0.786	0.317***	56.997
Car	0.392	0.488	0.221	0.415	0.171***	52.214
Car Loan	0.086	0.280	0.051	0.221	0.034***	19.315
House	0.555	0.497	0.389	0.488	0.166***	49.770
Mortgage	0.229	0.420	0.123	0.329	0.106***	38.636
Number of Words	47.641	34.412	41.214	30.028	6.427***	28.977

Table 3 Estimation of the Default Ratio

	(1) Dmy_Default	(2) Dmy_Default
Loan Rate	-0.017***	-0.040***
	(-2.98)	(-5.23)
Loan Rate^2		0.007***
		(4.57)
Loan Duration	0.069***	0.072***
	(37.31)	(35.76)
Credit Grade	-0.889***	-0.897***
	(-35.82)	(-35.81)
ln_loanamount	0.199***	0.209***
	(11.31)	(11.78)
Age	0.015***	0.015***
	(7.01)	(7.19)
Education level	-0.270***	-0.273***
	(-16.34)	(-16.49)
Car	-0.185***	-0.184***
	(-5.72)	(-5.71)
Car Loan	0.179***	0.173***
	(3.46)	(3.33)
Mortgage	-0.230***	-0.238***
	(-6.11)	(-6.31)
House	0.022	0.022
	(0.71)	(0.71)
Number of Words	0.001***	0.001***
	(2.71)	(2.71)
Income	-0.011	-0.016
	(-0.02)	(-0.02)
Constant	-2.333***	-2.532***
	(-14.46)	(-15.08)
Pseudo R^2	0.327	0.328
N	20,817	20,817

Notes: This table reports the relationship between loan characteristics and default. The t statistics are in parentheses. * $p<0.1$ ** $p<0.05$*** $p<0.01$.

Table 4 Detailed Summary Statistics of Excess Returns

Panel A: Excess Returns in the Market

	Loans		**Listings**		**Loans-Listings**	
	Mean	**SD**	**Mean**	**SD**	**MeanDiff**	**t-stat**
Bank Rate	2.791	0.579	2.933	0.612	-0.142***	-37.329
Ereturn	10.068	3.361	7.341	4.092	2.727***	98.990
ExcessReturn	7.283	3.488	4.408	4.359	2.875***	99.816
N	428,893	428,893	26,020	26,020		

Panel B: Excess Returns for Different Issuance Years

	Year	**N**	**Mean**	**SD**	**p1**	**p50**	**p99**
ExcessReturn	2011	20,271	9.592	5.299	-3.655	10.455	18.978
	2012	27,429	7.417	4.702	-1.937	7.428	17.873
	2013	53,119	6.690	4.830	-1.846	6.715	18.039
	2014	154,286	3.841	4.757	-3.877	4.500	16.226
	2015	199,808	3.700	2.938	-1.490	3.687	9.022

Table 5 Regression of the Probability of Listings being Funded and Excess Returns

	(1) Dmy_Funded	(2) Financing_Speed
ExcessReturn	0.083***	0.012***
	(94.71)	(34.93)
Year	Yes	Yes
Month	Yes	Yes
Week	Yes	Yes
Hour	Yes	Yes
Constant	-3.251***	-0.115***
	(-67.69)	(-6.41)
Adjusted R^2	0.172	0.198
N	454,913	26,020

Notes: This table reports the relationship between the probability of listings being funded, financing speed and excess returns. The t statistics are in parentheses. * p<0.1, ** p<0.05, and *** p<0.0.

Table 6 The Moderating Effect of Voluntary Information

	(1) Dmy_Funded	(2) Dmy_Funded	(3) Financing_Speed	(4) Financing_Speed
ExcessReturn *Honesty	0.003*		0.002***	
	(1.78)		(2.98)	
ExcessReturn *Hardship		-0.030***		-0.003***
		(-11.69)		(-2.66)
Honesty	0.105***		-0.002	
	(8.21)		(-0.39)	
Hardship		-0.118***		0.021**
		(-5.81)		(2.33)
ExcessReturn	0.082***	0.086***	0.011***	0.012***
	(78.11)	(93.59)	(26.92)	(34.49)
Year	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes
Week	Yes	Yes	Yes	Yes
Hour	Yes	Yes	Yes	Yes
Constant	-3.273***	-3.218***	-0.114***	-0.116***
	(-67.74)	(-66.63)	(-6.35)	(-6.48)
Adjusted R^2	0.174	0.177	0.199	0.199
N	454,913	454,913	26,020	26,020

Notes: This table reports the moderating effect of voluntary information. The t statistics are in parentheses. * p<0.1, ** p<0.05, and *** p<0.01.

Table 7 Results of the Weibull Regression

	Dmy_Default
Loan Rate	-0.449***
	(-56.57)
Loan Rate^2	0.085***
	(62.80)
Credit Degree	-1.983***
	(-70.28)
ln_loanamount	-1.332***
	(-10.52)
Age	0.019***
	(19.93)
ln_jobincome	0.311***
	(38.55)
Education Level	-0.447***
	(-49.14)
Car	-0.121***
	(-6.68)
Car Loan	0.051*
	(1.76)
House	0.182***
	(11.87)
Mortgage	-5.038***
	(-23.82)
Number of Words	0.002***
	(11.92)
Constant	0.266*
	(1,90)
Ln (p)	0.481***
	(94.72)
No. of failures	22,394
N	316,626
Log likelihood	-70241.78

Notes: This table reports the coefficients of Weibull regression which are in log hazard form, and the t statistics are in parentheses. * p<0.1, ** p<0.05, and *** p<0.01.

Table 8 Loans' Speed and Excess Returns Estimated by the Weibull Regression

	(1) Financing_Speed	(2) Financing_Speed	(3) Financing_Speed
ExcessReturn2	0.005***	0.004***	0.005***
	(13.72)	(9.79)	(13.25)
ExcessReturn2 *Honesty		0.001**	
		(2.02)	
Honesty		0.015***	
		(3.18)	
ExcessReturn2 *Hardship			0.0001
			(0.05)
Hardship			-0.002
			(-0.23)
Year	Yes	Yes	Yes
Month	Yes	Yes	Yes
Week	Yes	Yes	Yes
Hour	Yes	Yes	Yes
Constant	0.007	0.001	0.008
	(0.24)	(0.04)	(0.25)
Adjusted R^2	0.075	0.076	0.075
N	26,020	26,020	26,020

Notes: This table reports the moderating effect of voluntary information on loans' financing speed and excess returns (ExcessReturn2), which was estimated by Weibull regression. The t statistics are in parentheses. * p<0.1, ** p<0.05, and *** p<0.01.

Table 9 Instrumented Excess Returns and Financing Speed

	(1) First Stage Excess Return	(2) Second Stage Financing_Speed
Instrumented Excess Return		0.007*
		(1.82)
Fundnum	-0.031***	
	(-13.29)	
Defaultnum	-0.491**	
	(-3.20)	
Year	YES	YES
Month	YES	YES
Week	YES	YES
Hour	YES	YES
Constant	11.230***	-0.057
	(35.57)	(-1.20)
R^2	0.218	0.187
N	20,817	20,817

Notes: This table reports the relationship between instrumented excess returns and financing speed. The t statistics of column (1) and z statistics of column (2) are in parentheses with robust standard errors. * p<0.1; ** p<0.05; *** p<0.01.

Table 10 Instrumented Excess Returns and Voluntary Information

	(1)	(2)
	speed_fund	Financing_Speed
Instrumented Excess Return*Honesty	0.026**	
	(2.20)	
Honesty	-0.193**	
	(-2.09)	
Instrumented Excess Return*Hardship		-0.0003
		(-0.04)
Hardship		0.003
		(0.04)
Instrumented Excess Return	0.003	0.008**
	(0.49)	(2.02)
Year	YES	YES
Month	YES	YES
Week	YES	YES
Hour	YES	YES
Constant	-0.047	-0.065
	(-0.93)	(-1.42)
R^2	0.152	0.189
N	20,817	20,817

Notes: This table reports the 2SLS results of the moderating effect of voluntary information. The z statistics are in parentheses with robust standard errors. * p<0.1; ** p<0.05; *** p<0.01.