Seeking Excess Return and Moderation Effect of Voluntary Information Disclosures in Peer-to-peer Lending Market*

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Abstract

This paper examines the performance of new online Peer-to-Peer (P2P) lending markets that rely on non-expert individuals to screen loans. Using data from renrendai.com we find that there are about 75% loans with positive excess return in this P2P lending market, which means it could provide lenders with adequate opportunities to profit. Moreover, we find loans with higher excess return were bidden quicker than the other loans, which suggests that lenders may have the ability to seek excess returns in P2P lending market. In lenders' decision-making process, voluntary information disclosures, in loan description, plays a positive moderating role. Our results highlight aggregating over the views of peers and leveraging voluntary information disclosures can improve market efficiency.

Keywords: Peer-to-Peer lending; excess return; voluntary information

1. Introduction

An important function of credit lending markets is to screen borrowers and allocate credit efficiently based on borrowers' loan risk (Iyer et al. 2015). Lenders' expected profit depend not only on lending rates, but also on the loan's risks. If the loan's risk is independent of the loan's rate, when the loan demand is greater than the loan supply, lenders can increase profits by raising loan's rates, and anyone who demands fund can get a loan. However, as the existence of asymmetric information, the lender can't observe the borrowers' all the information and repay behavior when considering bid or not, blindly pursuing higher rates would make low-risk borrowers out of the market lead to adverse selection. Alternatively, inducing the borrower to invest a riskier project caused moral hazard behavior. As a result, the average risk in the credit market increased and expected earnings fell.

Traditionally, banks have played the dominant role in allocating credit partly due to their financial expertise to evaluate borrowers and effectively intermediate capital (Diamond, 1984). While there is a broad consensus on the importance of banks in financial intermediation, the recent banking crisis has highlighted shortcomings in the traditional lending models, particularly in allocating credit to smaller borrowers. While there is increasing debate in how these short-comings can be addressed, a variety of new lending models offer potentially valuable insights. The diffusion of the internet has enabled a new form of matching supply and demand for capital, peer-to-peer (P2P) lending platforms. On such platforms, individuals and companies can present themselves and their planned projects and seek financing from private lenders. Individual lenders have to integrate standard and nonstandard financial information and price the risk of not getting their money back

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and factor the default risk in the interest rate at which they are willing to lend money.

However, the downside is that lenders in such markets typically have limited experience and no formal training in judging borrower creditworthiness. Further, the nonstandard information is self-reported by borrowers and not readily verifiable. Given these types of markets dominated by non-financial experts in the lending industry, whether lenders can identify the excess return is the key to the viability of the peer-to-peer lending market. If lenders can't identify excess return, they will only pursue high interest rates and ignore high default risk, which increases the risk of P2P lending market system, or too much focus on risk and income is too low, which loss the efficiency of the market credit allocation.

The purpose of this study is to investigate that whether lenders have the ability to seek excess return of loans from one of the largest P2P platforms in China, renrendai.com, which is significance that the P2P lending market efficiently play an intermediary role in private lending and helpful to improve matching efficiency of capital supply and demand and regulate P2P industry. There are there related questions this article will address: (1) Does excess return exist in P2P lending market? Is the higher interest rate generated from the riskier borrower large enough to compensate for the incremental risk? (2) Do lenders have the ability to identify excess return? (3) What role does the specific voluntary information disclosures of P2P lending market play in lenders' decision-making process?

In contrast to the papers that we consider the benefits and risks of the loan at the same time to explore loan screening problem in the P2P lending marketplaces. Second, we employ the Weibull regression to evaluate each loan's the probability of repayment in each month, which include the impact of time factor. Third, we investigate the whole situation that interest rates compensate probabilities of potential loss in P2P lending market. Finally, we associate excess return of loan with completion time of bidding to investigate lenders' ability to filter high quality loans and the moderation effect of voluntary information disclosures.

We use loan-level data from a Chinese leading online peer-to-peer market, namely Renrendai, to examine whether multiple lenders can collectively seek loans with higher excess return. With Weibull function, we estimate excess return and find that there are about 75% loans with positive excess return in market, which provide lenders with adequate opportunities to profit. In addition， loans with higher excess return are completed bidding in less time, suggesting that lenders have the ability to seek excess returns. As well as, in lenders decision-making process, voluntary information disclosures in loan description plays a positive moderating role. The results highlight how aggregating over the views of peers and leveraging voluntary information disclosures can enhance credit market efficiency.

The remainder of the paper is organized in the following way. After a review of the literature, we describe our data and summarizes and descriptive statistics of online P2P from Renrendai.com. Next, we present descriptions of methodologies and empirical results for measuring seeking excess return and moderation effect of voluntary information disclosures. The final section presents our work's conclusions and proposes directions for future research.

2. Related Research and Hypothesis Development

In this section, we review the literature relevant to the subject of excess return and voluntary information to derive the testable hypotheses.

Peer-to-peer (P2P) lending platform is the emerging lending market without banks as intermediaries, advertising high interest rate attracting lenders. However, empirical studies suggestion that many P2P lending platforms do not meet lenders' the high expectations. Research that relates the excess return of the online P2P loan listings is very limited. Using data from Lending Club, Emekter et al. (2015) find that higher interest rate charged on the high-risk borrowers are not enough compensate for higher probability of the loan default, but the actual interest rate is higher compared to theoretical interest rates for the highest credit grade category.

Employing the loans data from Prosper, Krumme and Herrero (2009) analyze the distribution of lender preferences for investing in different borrower risk classes and find strong heterogeneity among lenders. For the aggregate, they find that lenders over invest in high risk classes and thus exhibit suboptimal lending in terms of performance. Similarly, Klafft (2008) found that only prime category loans exhibit positive returns and clearly outperform comparable AAA US treasuries. Berkovich (2011) found that high quality loans offer excess return . For myc4.com, Mild et al. (2015) demonstrate the market itself fail to price the risk of default at all. Chen（2016）builds a borrower credit market measure model of pricing efficiency, and find that the market rate rates significantly lower than the actual interest rate on Renrendai loan(Chen and Ye, 2016).

Thus, we hypothesis excess return exists in the P2P lending market, and are positively correlated with credit, formally stated as Hypothesis 1.

H1: Excess return exists in the P2P lending market.

In P2P lending market, individual lenders play the dominant role in screen borrowers and allocating credit. To efficiently allocate capital, funds must be allocated to listings with high excess return, that is to say, the determination of acceptable interest rates must take the risk of default into account. While there is scant direct evidence on lenders without knowing the borrower personally be capable of seeking excess return, mostly research only analysis lenders screen borrowers by their risk of default.

Some research supports that individual can choose high quality loans. Iyer et al. (2015) find that lenders have ability to screen loan listings. They predict borrowers' likelihood of defaulting on a loan, and price lower rates for borrower with lower default risk. Liao et al. (2014) investigate bidding behavior in P2P lending market with not-fully-marketized interest rate. They find that lenders are able to distinguish the different default risk at the same interest rate with listing information. It takes longer and needs more lenders to complete a bidding with higher default risk. Similarly, Hu and Song (2017) prove that there exist an optimal interest rate that lenders prefer most when they face the interest rate and risk simultaneously. Moreover, the optimal rate will be affected by other information of loan listings.

The proper completion of this selection, however，can suffer from some cognitive limitations and biases. First, lenders in such markets obviously have limited experience and no formal training in estimate default risk. Second, investment decisions are influenced by attention (Andrei and Hasler, 2015; Barber and Odean, 2008) and herding behavior(Zhang and Liu, 2012). Further, various kinds of discrimination exist in P2P lending market. such as racial discrimination (Herzenstein et al., 2011), age discrimination (Pope and Sydnor, 2011), appearance discrimination (Duarte et al., 2012). Some discriminations due to the different default risk behind the group, while others depend entirely on individual taste. These factors make it harder for lenders to screen high-quality loans. Mild et al. (2015) prove that lenders cannot covert the available information into the correct market behavior.

It is necessary to the viability of the peer-to-peer lending market that lenders can identify the excess return. If lenders are not able to seek excess return, they will only pursue high interest rates and ignore high default risk, which increases the risk of P2P lending market system, or too much focus on risk and lose income, which reduces the efficiency of the market credit allocation. Therefore, we hypothesis lenders have ability to choose loan listings with excess return. More money allocated to the loan listings with higher excess return, which completed biddings in less time, formally stated as Hypothesis 2.

H2: Loan listings with higher excess return completed biddings in less time.

Although the specific content is various, all P2P lending platforms demand prospective borrowers to provide information about themselves and loan purpose. If investors are able to seek excess returns and choose high-quality loans, then what information affects lenders' decisions?

Using data from Prosper.com, Iyer et al. (2015) differentiate this information between standard banking variables and nonstandard variables. They find that lenders rely on non-standard or soft sources of information in their screening process and that such information appears to be relatively more important when screening borrowers of lower quality. Herzenstein et al. (2011) prove that unverifiable information affects lending decisions and beyond the influence of objective, verifiable information. As the number of identity claims in narratives increases, so does loan funding, whereas loan performance suffers, because these borrowers are less likely to pay back the loan. In addition, identity content plays an important role. Identities focused on being trustworthy or successful are associated with increased loan funding but ironically are less predictive of loan performance than other identities (i.e., moral and economic hardship). Thus, some identity claims aim to mislead lenders, whereas others provide true representations of borrowers. Michels (2012) demonstrate an economically large effect of voluntary, unverifiable disclosures in reducing interest rate and increasing in bidding activity. In two leading European P2P platforms, Dorfleitner et al. (2016) find spelling errors, text length and the mentioning of positive emotion evoking keywords predict the funding probability on the less restrictive of both platforms, which even accepts applications without credit scores. Conditional on being funded, text-related factors hardly predict default probabilities in P2P lending. In Renrendai, one of largest Chinese P2P lending market， Li et al. (2014) find that borrowers with low credit ratings tend to provide more personal characteristic information in their descriptions, which will increase the probability of getting a loan and completed biddings in less time. Different feature information have influence on investment decision, and a stable income contribute to success. Wang and He (2015) show that loan listings with more personalities in description are easier the access to borrowing, attract more bidders, completed in less time and lower default risk.

These literatures show that voluntary information relieve the asymmetric information between the borrower and the lender. While some information raises the possibility of financing success, it also means higher credit risk. We associate voluntary information with excess returns and put forward hypothesis 3.

H3: Voluntary information disclosure can promote the recognition of excess return.

3.Data

3.1 Data from Renrendai

The data are obtained from Renrendai platform, founded in 2010, one of the largest P2P lending platforms in China. After years of steady development, Renrendai platform has become a leader in the industry. It has twice entered the list of China's top 100 Internet companies in 2015 and 2016, and was awarded the level of an AAA (the highest level) online lending platform in 2014 and 2015. By the end of February 2018, the total transaction volume of Renrendai platform exceeded 50 billion.

The transactions taking place at Renrendai platform are typical examples of P2P lending. On Renrendai platform, borrowers can submit a loan application with the loan title, amount of borrowing, loan term, description of loan usage. They voluntarily disclose personal information on loan listings, including age, income, education, gender, marriage status, estate, mortgage, car, car loans etc. And specifically, Renrendai platform provides verification services for standard/hard information, such as national identification cards, credit reports, mobile, education, house, car, borrowers' addresses and so on. What's more, borrowers fill out "loan description", where they disclose specific information regarding personal job, income, investment project and other personal information in a freeform text field. Given the above information and users' borrowing and lending history, the platform assigns a credit score to each borrower, according to the score from high to low, divided into AA, A, B, C, D, E and HR. In addition, it also establishes loan interest rate for each loan listing. On Renrendai platform, borrowers can fund any amount ranging from 3,000 yuan and 500,000 yuan and decide the term of debt, usually has the following terms: 3 months, 6 months,9 months, 12 months, 15 months, 18 months, 24 months, 36 months.

Once a loan listing is posted online, lenders may place bids by stating the amount they want to fund. With a minimum bid amount of RMB 50, a listing typically requires multiple bids to become fully funded, and each bid amount varies. Within seven days of fundraising, a listing that achieves 100% funding is a successful fundraising. Even if the deadline is not met, the loan cannot continue to accept investors' investment. If lenders fail to provide enough money in the required time, the borrower receives no funding. Repayment of loans using phased manner, matching the return of monthly loan interest.

To study the excess return of loan listings and accurately judge loan defaults, we only use loans that successfully funded and completed repayment or defaults in January 1, 2011 to December 31, 2015. We eliminate the data earlier and later than this period to avoid the initial launch period and leave enough time for repayment, respectively. To estimate lenders' ability to seek excess return, we keep loan with credit guarantee which only guaranteeing payment of the original investment, and drop loan with institutional guarantee and field certification which guaranteeing payment of the original investment plus interest.

As a result, our sample includes 21,416 loan listings, 14.6% of loan defaults. Among them, there were 2,615 loan applications in 2011, 3,295 loan applications in 2012, 2,612 loan applications in 2013, 7,231 loan applications in 2014, and 5,681 loans in 2015.

3.2 Key variables and summary statistics

Each loan in our sample is associated with a lot of variables either that are provided by Renrendai platform or that we compute using information in loans. These variables fall into three groups. The first group is the information of loans, including the loan amount, loan interest rate, and speed of bids, etc. The second group is personal standard information, such as credit rating, income, age, mortgage and car loans, etc. The third group is self-report information in loan description, such as the number of words and some characters. Moreover, we also control the year effect. A complete list of all variables derived from Renrendai platform can be found in Table 1.

[Insert Table 1 Here]

We report summary statistics in Table 2. Table 2 provides summary statistics of all variables used in this study. As indicated by Table 2, average completion time of bidding is 8922.281 seconds, loan description average contains 51.417 Chinese words and 2.287 numbers. We winsorize data at both the upper and lower 1% levels to mitigate the impacts of outliers.

[Insert Table 2 Here]

3. Methodology

3.1 Measuring Excess Return of Loan

From a lender's perspective the most important concern is whether they are getting enough compensation for default risk on a loan. To have an empirical measure, we use the difference between real return and expected return of a loan to estimate excess return. We first evaluate the probabilities that a loan will repay in any given month. Using the given loan interest rate, we calculate the corresponding expected cash flows for every month during the loan life. Then, real return and expect return are calculated based on real cash flow and expected cash flow, respectively. Finally, the difference between the two is the excess return.

We utilize Weibull regression, which is parameter analysis in survival analysis, to calculate the probabilities that a loan will repay in any given month. Survival analysis is able to handle delete data, thus it can dynamically identify and measure the various factors that affect the default risk of loan. In addition, Weibull regression is a parameter model, which assuming the distribution function changes with time, and the time factor is included in the estimation of the probability of repayment. The risk function is:

$$\mathrm{h(k)} = \theta(\mathrm{k})\exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_m x_m) \tag{1}$$

Where $\mathrm{h(k)}$ is the hazard rate at time k; in our case it is the probability that the loan will default in month k. If $\theta(k) = \frac{1}{\sigma} \cdot k^{(\frac{1}{\sigma}-1)}$, $\theta(\mathrm{k})$ is Weibull distribution and σ is the scale parameter of the distribution. A value of $\sigma > 1$ indicates that the failure rate increases with time. A value of $\sigma < 1$ indicates that the failure rate decreases with time. A value of $\sigma = 1$ indicates that the failure rate is constant over time. Further, we estimate survival function to evaluate the probability of repayment in any given month.

$$\mathrm{S(k)} = \exp\{-\{\mathrm{k}^{1/\hat{\sigma}} \cdot \exp(\widehat{\beta_0} + \widehat{\beta_1} x_1 + \cdots + \widehat{\beta_m} x_m)\}\} \tag{2}$$

where $\mathrm{S(k)}$ is the survival probability of a loan on month k, $\widehat{\beta_0}, \widehat{\beta_1}, \dots, \widehat{\beta_m}$ is coefficients estimated in Eq.(1), $x_1, \dots, x_m$ is a vector characteristics of loan i. For simplicity, the subscript of loan i is omitted in the equation. Using the interest rate promised to the lenders, we calculate the corresponding expected cash flows for every month during the loan life, based on the following specification:

$$\mathrm{LoanAmount}_i = \sum_{k=1}^{K} \frac{E[CashFolw_{ik}]}{(1+EIRR_i/12)^k} \tag{3}$$

where $\mathrm{LoanAmount}_i$ is the requested amount on loan i, $\mathrm{E[CashFolw}_{ik}]$ is monthly expected payment on loan i on month k, EIRR_i is the expected internal rate of return on loan i. The monthly principal amount and interest payment are utilized to calculate real internal rate of return, based on the following equation (4).

$$\mathrm{LoanAmount}_i = \sum_{k=1}^{K} \frac{CashFolw_{ik}}{(1+IRR_i/12)^k} \tag{4}$$

where $\mathrm{LoanAmount}_i$ is the requested amount on loan i, $\mathrm{CashFolw}_{ik}$ is real monthly payment on loan i on month k, IRR_i is the real return on loan i. Finally, we get the excess return of loan i,

$$Excessreturn_i = IRR_i - EIRR_i \tag{5}$$

3.2 Analyzing Borrowers' Description

To test the role of voluntary information in lender decision making, especially content, it is necessary to identify key features in voluntary information. Firstly, we statistics the number of Chinese characters and numbers in loan description. Number represents a more precise in narratives (specific income amount, the value of car, etc.) or organized to help lenders to read. We reading a lot of loan description, and mine the following seven features based on the frequency of mention and relevant literatures: honesty, success, hardship, family, entrepreneurship, help and thanks. In Panel B of Table 1, we provide definitions and illustrative key words of each feature. We code each feature as a dummy variable that receives the value of 1 if the corresponding key words was present in loan description and 0 if otherwise by programming.

4. Empirical Results

In this section, we first investigate the distribution of excess return in P2P lending market. And whether loan listings with higher excess return complete biddings in less time to examine lenders' ability to seek excess return. Next, we investigate the role of the features of loan description on lender decision making.

4.1 Excess Return in Market

As discussed in subsection 3.1, we use Weibull regression to estimate each loan's the probability of repayment in any given month. In regression (1), the time-dependent variable was the number of months passed from the issuance date of the loan until the current date if the loan is fully paid off.

Table 3 reports the Weibull regress estimates in log relative hazard form. All the estimated coefficients are significant at 1% level. For the likelihood of the loan being default, the coefficient on the credit degree of the borrowers is negative, suggesting that the higher borrowers' credit, the lower default risk of loan. Loan interest rate and default risk are U shaped relationship, suggesting that the default risk rises first and then increases with the increase of interest rate. In addition, $\ln(\frac{1}{\sigma})$ is 0.831, not equal to 0 and significant, proving that the default risk varies with time. This also illustrates that the rate assigned by Renrendai platform does not fully reflect the borrower's risk level. The default risk increases with loan amount. We also examine the relationship between borrower characteristics and default risk. We find that borrowers with older, higher income, lower level of education, no car, have car loan, have real estate and no mortgage are tend to default.

[Insert Table 3 Here]

Next, we use coefficients β to estimate survival function (eq. (2)), and calculate excess return of loan with eq.(3)-(5). We make a summary statistical analysis on excess return in the market in Table 4. Excess return is 0.068 in the first quartile, indicating that about 75% of loan in P2P lending market have positive excess return. Further, we investigate the distribution of excess returns in different credit ratings and different issue year. Table 4 also shows that loans in credit category of 'E', higher risk, have highest excess return in the market (Panel B), and the standard deviation of excess return becomes larger as the market expands (Panel C). In sum, loans with excess return are abundant in the market.

[Insert Table 4 Here]

4.2 Do Lenders Seek Excess Returns?

We now test whether lenders have ability to seek loans with higher excess return. If the majority of lenders in P2P lending market can bid on the loan with higher excess return, these loans will complete bidding in less time. We use the fixed time to measure completion time of bid for eliminating the impact of loan amount, and fixed time is defined as:

$$\text{Fixed Time} = \frac{Completion\ Time\ of\ Bidding}{Loan\ Amount} \tag{6}$$

Table 5 shows the result of OLS regression of completion time of bid and excess return of loan. The OLS regression has the following specification:

$$\text{Fixed Time}_i = \beta_0 + \beta_1 Excess\ Return_i + c'X_i + \varepsilon_i \tag{7}$$

where ExcessReturn_i is excess return on loan i, and X_i is a vector of loan characteristics.

[Insert Table 5 Here]

Table 5 reports results corresponding to the test in the previous subsections. We control for borrower demographics and financial characteristics, and find that completion time of bid is reduced with the increase of excess return. Loan interest rate and completion time of bid are U shaped relationship, suggesting that the completion time of bid rises first and then increases with the increase of interest rate. The completion time of bid is negative with loan amount and credit degree. We also examine the relationship between borrower characteristics and completion time of bid. We find that borrowers with older, higher income, lower level of education, have real estate and no mortgage finance quickly.

4.3 Role of Voluntary Information on Lender Decision Making

We have proved that lenders are able to screen loans with higher excess return. Now, we turn to another fundamental question: What role does the specific voluntary information play in lenders' decision making? Unlike standard information can reflect the borrowers' ability to repay (i.e. income, level of education, car, real estate, etc.), voluntary information cannot be verified. We assume that voluntary information plays a moderating variable in the process that lenders seek excess return. The relationship between them is reported in figure1.

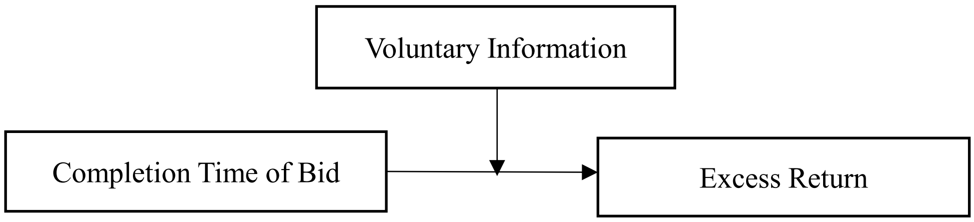

Figure 1 The Moderation Effect of Voluntary Information in the Process of Lenders Recognizing Excess Return

Table 6 presents the results. As the characteristics of voluntary is dummy variable, we use group regression to explore the moderating effect. We find that the coefficient on excess return is negative and significant in loans with honesty ($\beta = -0.00214, \mathrm{t-statistic} = -3.26$), which is no significant in loans without honesty ($\beta = -0.000299, \mathrm{t-statistic} = -0.64$). This finding suggesting honesty of voluntary information disclosures promote the recognition of excess return. In addition, loans with hardship and without entrepreneurship, family, thank, help in voluntary information are completed bidding in less time.

[Insert Table 6 Here]

5.Conclusions

On P2P lending platforms, individual lenders play the dominant role in allocating fund. This study employs the data from Renrendai to investigate lenders' ability to seek excess return. Our results show that there are about 75% loans with positive excess return in market, which provide lenders with adequate opportunities to profit. We further find that loans with higher excess return are completed bidding in less time. In lenders decision-making process, voluntary information disclosures in loan description plays a positive moderating role.

Our results highlight that even markets with non-expert individuals can effectively screen for better borrower to get excess return. Individuals collectively perform well in solving a problem that is generally thought to be best left to experts with access to standard information. In effect, given the nuances of human behavior, peers likely have an advantage in interpreting nonstandard information to seek better loan than market average level. Our study shows the value of harnessing peer-evaluation mechanisms, and those that use voluntary information disclosures to speed up the process of seeking loans with higher excess return.

Given peer-to-peer markets' ability to effectively screen borrowers, and given their non-collateral-based lending structure, such markets can offer a potential capital source for small borrowers who may otherwise be limited to more costly sources of finance, such as payday lenders and credit-card debt. It is necessary to design better mechanisms to incorporate voluntary information in banking systems. As individuals generate more information than ever before and technology drastically reducing peer-to-peer transaction costs, such mechanisms has great potential to improve the effectiveness of financial markets.

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Table 1 Definition of all variables

Variable Name	Viable Definition
Loan Rate	The rate that borrower pays on the loan.
ln_loanamount	The natural logarithm of the requested loan amount.
Default Per Month	An indicator variable that equals one if the borrower is not repay money in that month and is zero otherwise.
IRR	IRR is the real internal rate of return on a loan. If the loan is repaid every month, IRR is equal to the loan interest rate. $LoanAmount = \sum_{t=1}^{T} \frac{CashFlow_t}{(1+IRR/12)^t}$
EIRR	EIRR is the expected return on a loan, given the promised interested rate and the probability of monthly payment. $LoanAmount = \sum_{t=1}^{T} \frac{E[CashFlow_t]}{(1+EIRR/12)^t}$
Excess Return	Excess Return=IRR-EIRR
Fixed Time	Fixed Time $= \frac{Completion\,Time\,of\,\,Bidding}{Loan\,\,Amount}$
Number of Bids	The number of bids is the total number of bids placed on a listing.
Credit Grade	Credit grade of the borrower.Credit grade takes on values between 1 (high risk) and 7 (low risk).
Age	Age of borrower at the time the listing is created.
ln_jobincome	The natural logarithm of borrower's job income at the time the listing is created.
Education level	Education level of borrower at the time the listing is created. Education level takes on values between 1(low level) and 4 (high level)
Car	An indicator variable that equals one if the borrower is verified to have a car at the time the listing is created and is zero otherwise.

Table 1, continued.

Variable Name	Viable Definition
Car Loan	An indicator variable that equals one if the borrower is verified to have a car loan at the time the listing is created and is zero otherwise.
House	An indicator variable that equals one if the borrower is a verified homeowner at the time the listing is created and is zero otherwise.
Mortgage	An indicator variable that equals one if the borrower is verified to have a house loan at the time the listing is created and is zero otherwise.
Year	The year which loan listing was post in.
Number of Words	The number of Chinese words used by the borrower in the loan description.
Number of digits	The number of digits used by the borrower in the loan description.
Honesty	An indicator variable that equals one if the borrower mention words about honesty, such as ‘good credit’, ‘good faith’, ‘the 'reliable’, ‘no overdue’, ‘must repay’, in the loan description and is zero otherwise.
Success	An indicator variable that equals one if the borrower mention words about success, such as ‘award’, 'car', ‘house’ in loan description, and is zero otherwise.
Hardship	An indicator variable that equals one if the borrower mention words about hardship, such as ‘urgently required’, ‘funding press’, ‘life press’, ‘lack of money’, in the loan description and is zero otherwise.
Family	An indicator variable that equals one if the borrower mention words about family, such as ‘family’, ‘son’, ‘father’, ‘mother’, ‘wife’, ‘daughter’, ’parents’ in the loan description and is zero otherwise.
Entrepreneurship	An indicator variable that equals one if the borrower mention words about entrepreneurship, such as ‘entrepreneurship’, ‘Taobao shop’, ‘Tianmao shop’, ‘business’ in the loan description and is zero otherwise.
Thanks	An indicator variable that equals one if the borrower mention words about thanks, such as ‘thanks’, ‘thank you’ in the loan description and is zero otherwise.
Help	An indicator variable that equals one if the borrower mention words about help, such as ‘need help’in the loan description and is zero otherwise.

Table 2 Summary statistics

variable	N	mean	sd	p1	p10	p25	p50	p75	p90	p99
loanrate	21416	12.715	2.543	9	10	11	12	14	15	22
default	21416	0.146	0.353	0	0	0	0	0	1	1
credit_cd	21416	2.206	1.651	1	1	1	1	3	5	7
ln_loanamount	21416	9.549	1.018	8.006	8.006	8.854	9.393	10.127	10.820	12.429
ln_jobincome	21416	9.109	1.105	7.313	7.824	7.824	8.923	10.463	10.820	10.820
Education level	21416	2.113	0.825	1	1	1	2	3	3	4
Car	21416	0.432	0.495	0	0	0	0	1	1	1
Car loan	21416	0.088	0.283	0	0	0	0	0	0	1
House	21416	0.565	0.496	0	0	0	1	1	1	1
Mortgage	21416	0.226	0.418	0	0	0	0	0	1	1
Number of Words	21416	51.417	44.090	9	19	24	41	60	93	252
Number of digits	21416	2.287	5.834	0	0	0	0	2	7	25
Entrepreneurship	21416	0.355	0.479	0	0	0	0	1	1	1
Honesty	21416	0.346	0.476	0	0	0	0	1	1	1
Hardship	21416	0.073	0.260	0	0	0	0	0	0	1
Family	21416	0.081	0.273	0	0	0	0	0	0	1
Success	21416	0.194	0.396	0	0	0	0	0	1	1
Thanks	21416	0.202	0.402	0	0	0	0	0	1	1
Help	21416	0.085	0.279	0	0	0	0	0	0	1
Completion Time of Bidding	21416	8922.281	46263.720	9	26	50	130	643	4192	260406
Fixed Time	21416	1.304	10.252	0.001	0.002	0.004	0.010	0.043	0.309	34.837

Table 3 Weibull regression results

	Coef.	Std. Err.	z	P>z
cloanrate	-0.367	0.006	-59.840	0.000
cloanratesq	0.037	0.001	52.010	0.000
credit_cd	-1.459	0.020	-71.700	0.000
ln_loanamount	0.055	0.010	5.500	0.000
age	0.009	0.001	12.210	0.000
ln_jobincome	0.181	0.006	27.800	0.000
Education Level	-0.315	0.007	-44.750	0.000
Car	-0.108	0.014	-7.460	0.000
Car Loan	0.105	0.023	4.550	0.000
House	0.110	0.012	9.410	0.000
Mortgage	-0.351	0.016	-21.430	0.000
_cons	-7.339	0.089	-82.410	0.000
$1/\sigma$	0.831	0.003	241.940	0.000
No. of subjects	217,848			
No. of failures	37,214			
Number of obs	217,848			
Log likelihood	-56255.613			

Table 4 Detail Summary Statistics of Excess Return

	N	mean	sd	p1	p10	p25	p50	p75	p90	p99
Panel A：Excess Return in Market										
IRR	21416	-44.75452	188.3509	-1091.69	-127.7503	9.097099	11.02149	12.97555	14.99998	20.02313
EIRR	21416	0.248532	15.31427	-50.5223	-19.19637	-6.764005	5.216252	10.24513	14.00805	19.22238
Excess Return	21416	-45.00305	183.3438	-1065.287	-118.06	0.0675664	2.360073	11.42933	21.86162	43.3946
Panel B: Excess Return in Different Credit Degree										
AA	1148	-0.120	4.212	0.000	0.001	0.001	0.002	0.004	0.009	0.041
A	279	-11.071	91.760	-706.747	0.001	0.003	0.006	0.013	0.026	0.101
B	740	-0.083	3.541	0.003	0.009	0.017	0.037	0.059	0.095	0.216
C	1253	-2.597	39.051	-62.439	0.029	0.071	0.151	0.263	0.408	0.955
D	3648	-1.205	32.123	0.040	0.175	0.445	0.828	1.292	1.856	3.532
E	3524	-0.033	50.269	-177.144	2.278	3.325	4.685	6.553	8.861	15.211
HR	10824	-87.710	244.652	-1065.287	-373.561	-21.913	10.755	19.476	28.251	43.395
Total	21416	-44.846	181.441	-1065.287	-118.060	0.068	2.360	11.429	21.862	43.395
Panel C: Excess Return in Different Issue Year										
2011	2615	-9.366	88.567	-591.691	0.001	0.007	0.122	1.808	6.318	38.299
2012	3295	-16.372	111.423	-775.884	0.001	0.041	0.484	2.257	12.798	25.973
2013	2612	-26.223	148.253	-1002.647	0.001	0.148	1.382	10.447	18.927	39.399
2014	7213	-49.241	190.209	-1065.287	-164.744	0.432	6.311	17.500	26.216	43.395
2015	5681	-80.676	233.988	-1065.287	-333.493	1.000	4.422	11.432	24.020	43.395
Total	21416	-44.846	181.441	-1065.287	-118.060	0.068	2.360	11.429	21.862	43.395

Table 5 Seek Excess Return

	(1) Fixed Time	(2) Fixed Time	(3) Fixed Time	(4) Fixed Time	(5) Fixed Time	(6) Fixed Time	(7) Fixed Time	(8) Fixed Time	(9) Fixed Time	(10) Fixed Time	(11) Fixed Time
Excess Return	-0.000416***	-0.000403***	-0.000416***	-0.000436***	-0.000416***	-0.000418***	-0.000415***	-0.000407***	-0.000417***	-0.000407***	-0.000415***
	(-2.79)	(-2.71)	(-2.79)	(-2.93)	(-2.79)	(-2.80)	(-2.78)	(-2.73)	(-2.80)	(-2.73)	(-2.79)
Number of Words		0.00366***									0.00213***
		(5.85)									(2.99)
Number of digits			0.0185***								0.00948*
			(4.08)								(1.92)
Entrepren-eurship				0.387***							0.321***
				(6.60)							(5.33)
honesty					0.0506						0.0164
					(0.91)						(0.29)
hardship						0.335***					0.319***
						(3.29)					(3.13)
family							0.0364				-0.0464
							(0.37)				(-0.47)

Notes:***indicates significance at the 1% level , ** indicates significance at the 5% level and * indicated significance at the 10% level.

Table 5, continued.

	(1) Fixed Time	(2) Fixed Time	(3) Fixed Time	(4) Fixed Time	(5) Fixed Time	(6) Fixed Time	(7) Fixed Time	(8) Fixed Time	(9) Fixed Time	(10) Fixed Time	(11) Fixed Time
success								0.198***			0.150**
								(2.90)			(2.16)
thanks									-0.134**		-0.189***
									(-1.98)		(-2.75)
help										0.321***	0.329***
										(3.36)	(3.37)
						control standard information					
_cons	9.442***	9.471***	9.448***	9.839***	9.405***	9.390***	9.435***	9.395***	9.531***	9.345***	9.730***
	(29.03)	(29.13)	(29.05)	(29.77)	(28.68)	(28.84)	(28.94)	(28.85)	(29.03)	(28.62)	(28.87)
r2_a	0.131	0.132	0.131	0.133	0.131	0.131	0.131	0.131	0.131	0.131	0.134
N	21416	21416	21416	21416	21416	21416	21416	21416	21416	21416	21416

Notes: ***indicates significance at the 1% level , ** indicates significance at the 5% level and * indicated significance at the 10% level.

Table 6 Seek Excess Return

	entrepreneurship=0	entrepreneurship=1	honesty=0	honesty=1	hardship=0	hardship=1	family=0	family=1
	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)
	Fixed Time	Fixed Time	Fixed Time	Fixed Time	Fixed Time	Fixed Time	Fixed Time	Fixed Time
Excess Return	-0.00162***	-0.000128	-0.000299	-0.00214***	-0.000738*	-0.00376**	-0.00101**	-0.000665
	(-3.29)	(-0.21)	(-0.64)	(-3.26)	(-1.93)	(-2.00)	(-2.47)	(-0.68)
Year	-1.822***	-1.796***	-1.680***	-1.987***	-1.701***	-3.097***	-1.741***	-2.273***
	(-21.10)	(-15.12)	(-20.14)	(-16.11)	(-25.04)	(-7.62)	(-24.23)	(-9.16)
_cons	17.14***	25.24***	17.97***	20.51***	17.54***	37.17***	18.41***	26.60***
	(15.55)	(18.30)	(18.06)	(13.36)	(21.20)	(8.27)	(21.22)	(8.42)
				control standard information				
r2_a	0.0766	0.0824	0.0718	0.0774	0.0702	0.137	0.0726	0.0940
N	13811	7605	14001	7415	19855	1561	19682	1734

Notes: ***indicates significance at the 1% level, ** indicates significance at the 5% level and * indicated significance at the 10% level.

Table 6, continued.

	success=0	success=1	thanks=0	thanks=1	help=0	help=1
	(1)	(2)	(1)	(2)	(1)	(2)
	Fixed Time	Fixed Time	Fixed Time	Fixed Time	Fixed Time	Fixed Time
Excess Return	-0.00103**	-0.000704	-0.00112***	-0.000316	-0.000949**	-0.00119
	(-2.24)	(-1.12)	(-3.04)	(-0.25)	(-2.54)	(-0.63)
Year	-1.783***	-1.813***	-1.672***	-2.131***	-1.631***	-3.307***
	(-22.76)	(-12.34)	(-23.97)	(-10.63)	(-24.34)	(-9.04)
_cons	19.38***	14.93***	16.70***	25.60***	16.70***	40.61***
	(20.64)	(8.24)	(19.99)	(10.40)	(20.60)	(9.20)
			control standard information			
r2_a	0.0713	0.0889	0.0729	0.0722	0.0677	0.122
N	17252	4164	17082	4334	19597	1819

Notes: ***indicates significance at the 1% level, ** indicates significance at the 5% level and * indicated significance at the 10% level.