Adverse Selection in Credit Certificates: Evidence from a P2P Platform

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Abstract

Certificates are widely used as a signaling device to resolve information asymmetry. Chinese Peer-to-Peer (P2P) lending platforms encourage borrowers to obtain various kinds of credit certificates, to promote information disclosure. As P2P markets continue to develop, it is plausible that certificates could play a pivotal role in ensuring investment efficiency. We perform the first empirical investigation into this issue, using unique data from Renrendai, one of China's largest P2P lending platforms. Surprisingly, we find loans with more credit certificates have worse payment performance with higher rates of delinquency and default. However, lenders remain attracted by higher certificates despite lower loan performance ex post, which results in distorted capital allocation and reduced investment inefficiency. Overall, we document a setting where credit certificates fail to serve as an accurate signal due to the adverse selection in certificates, where poor-quality borrowers use more certificates to boost their credit profiles and improve their funding success. Possible explanations for this phenomenon include differential marginal benefit of certificates for different borrower types, cognitive simplification, and borrower myopia.

Keywords: P2P lending; Credit allocation; Adverse selection; Certificate; Bounded rationality; Cognitive simplification

JEL code: G10, G20, G21, G23, G40

1. Introduction

Certificates have been widely used to signal quality when information is asymmetric[1]. For instance, job seekers signal their professional capacity by obtaining more educational certificates (Spence, 1973). Sustainable goods producers signal their uniqueness by acquiring third-party sustainability certificates (Brach et al., 2018). Gaining access to bank loans from financial institutions is another kind of certificate that signals the promising prospects of a firm (James, 1987; Lummer and McConnell, 1989; Best and Zhang, 1993). The corporate finance literature also documents that syndicated loans (Focarelli et al., 2008; Godlewski and Sanditov 2018), project loans (Gatti et al., 2013), stapled loans (Aslan and Kumar, 2017) and loan renegotiation (Godlewski, 2015) have similar certificate effects. In these studies, certificates convey better quality.

The Peer-to-Peer (P2P) lending platforms in China provide an ideal laboratory for investigating whether credit certificates help resolve the information asymmetry problem in the lending process. First of all, information asymmetry is of primary concern on online lending platforms. Lenders' ability to judge financial risk and information is crucial to the viability of these platforms (Iyer et al., 2009). However, most lenders on these platforms are small retail investors who are inexperienced and relatively new to the investment products on these platforms. They have little knowledge about either the borrowers' credit worthiness or the quality of the loan. As a result, they refer to these credit certificates as a convenient guide for quality, based on their past experiences (Gick and Holyoak, 1980; Duhaime and Schwenk, 1985; etc.). Many of the platforms attempt to boost lender confidence and provide assurance by using platform guarantee, which further results in lenders' lax screening and increased loan delinquencies due to moral hazard (Agarwal et al., 2015).

Second, credit certificates are an important feature of online P2P lending platforms. To promote information disclosure and facilitate investment decision-making, P2P platforms in China encourage borrowers to obtain various kinds of credit certificates, such as information on borrowers' employment, address proof, income level, car and property ownership, mortgage status, etc. Borrowers can voluntarily upload relevant documents for the platform to check by following simple instructions online. After passing the verification process, certificates are issued to borrowers and listed on their profile pages. As P2P

[1] The literature is abundant on signaling and information asymmetry. See Akerlof (1970), Spence (1973), Riley (1979), Crawford and Sobel (1982) and Austen-Smith and Banks (2000), among others.

markets continue to develop, it is plausible that certificates may play a pivotal role in ensuring investment efficiency.

Third, despite its rapid growth of investment and credit demand of Chinese individuals in recent years, P2P lending in China is still an emerging industry lack of regulatory monitoring. The P2P industry is considered one of the riskier and less regulated segment of China's $10 trillion shadow-banking system, and there was a large wave of platform collapse in the past years[2]. Hence, the issue of asymmetric information on Chinese P2P platforms is expected to be more severe compared to more developed P2P lending platforms internationally. To date, there is scant direct evidence on whether these peer-to-peer markets can effectively screen borrowers and allocate credit. As P2P lending and crowdfunding continues to develop, it is plausible that credit certificates may play a pivotal role in ensuring efficiency.

This study presents the first empirical investigation into this issue, using a unique dataset from one of the largest Chinese P2P platforms, Renrendai (RRD). Figure 1 Panel A presents a screenshot of a loan example from the platform webpage, and Panel B illustrates the basic lending and borrowing procedures, whereas Panel C reports the list of certificates and their frequencies in the sample. As shown in the Panel C frequency chart, platform training and ID information rank as the top two certificate types, which are compulsory information required in order to proceed with the loan application. The former indicates that a user has at least understood the loan procedure and skimmed through the basic policies of the platform, and the latter reveals the identity of the applicant.

RRD relies heavily on mobile phone information to facilitate debt collection. In the case of delayed payments, borrowers will be contacted via phone, and thus it is not surprising to see that mobile phone is ranked as the third most frequent certificate type. The platform also has other certificates covering borrowers' income and savings, social media, contact information and third-party endorsement (e.g. onsite authentication). To capture the heterogeneities among different types of certificates, we further classified them as important and voluntarily applied, and calculate the number of all, important, and voluntarily applied certificates of each loan respectively. The classification standard is discussed in the institutional background section.

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[2] Retrieved from Bloomberg "From China's Peer-to-Peer Lenders Are Falling Like Dominoes as Panic Spreads", July 20, 2018, https://www.bloomberg.com/news/articles/2018-07-20/china-s-p2p-platform-failures-surge-as-panic-spreads-in-market . In August 2016, 230 platforms collapsed. More recently, 118 Chinese P2P platforms collapsed in July 2018 alone.

[INSERT FIGURE 1 ABOUT HERE]

Using a comprehensive dataset on loan application[3] and repayment record from October 2010 to January 2016, we examine whether credit certificates serve as good investment guides for capital allocation, i.e., whether borrowers with more certificates indeed have better credit quality by examining detailed loan repayment records.

To our surprise, we find that loans with more important certificates actually perform worse and have a higher delinquency rate and higher default rate. Other things being equal, one additional important certificate increases delinquency rate by 22.6%. Figure 2 Panel A illustrates the Kaplan–Meier survival rate (i.e. on-time repayment without delinquency) across groups of loans with different important certificate levels, which offers direct evidence that more certificates are associated with higher delinquent hazard.

To reconcile the puzzling relationship between more certificates and higher delinquency, we next examine whether certain poor-quality borrowers self-select to obtain more certificates, to mimic the good-quality ones, to compete for funding in an opaque information environment. We analyze the determinants of important certificate usage and find that indeed the number of important certificates is negatively associated with the credit quality of borrowers. On average, a one-notch reduction in credit grade results in 0.119 more important certificates[4], other things being equal.

We then check whether investors are aware of the adverse selection of certificates by borrowers. We find that listings posted by borrowers with a higher number of credit certificates attract more capital investment. This suggests that investors are unaware of the lower performance associated with more certified loans, and still invest based on certificates.

Specifically, we divide the entire sample of listings into three equal groups based on the number of important certificates and compare the average funding probability of each group (Figure 2 Panel B). The funding success rate improves from 4.42% to 45.86% when a borrower moves from a low-certificate group to a high-certificate group. On average, one additional important certificate increases funding success by 88.3%, controlling for loan and borrower characteristics.

[INSERT FIGURE 2 ABOUT HERE]

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[3] A loan application is also known as a listing. We use these two names interchangeably.
[4] This is 3.0% increase compared with the funded loan sample mean number of certificate of 3.934.

This result suggests that lenders take it for granted that credit certificates on are positive signals, as they are more willing to invest in listings with more certificates, even with worse performance ex post. A crucial implication for investment efficiency is that credit certificates on P2P platforms fail to serve as an effective signal in capital allocation. Capital on this platform is misallocated, whereby low-quality borrowers receive preferential treatment over high-quality borrowers.

Ideally, certificates should serve as a distinguishing mechanism so that high-quality borrowers can assert priority in obtaining funds and therefore receive preferential treatment from lenders. In our case, certificates are unable to serve their signaling role, as they fail to distinguish the good from the bad, resulting in losses of both lenders and high-quality borrowers. Specifically, lenders take more uninformed risks without being compensated in return. Also, high-quality borrowers receive lower funding investment than they deserve. In a nutshell, credit certificates fail to serve as an accurate signal on credit quality, which results in distorted credit allocation and reduced investment efficiency of the platform.

To understand why lenders rely on certificates without conducting a thorough analysis of borrowers' credit quality, we first examine their investment experiences on the P2P platform. We find that most lenders are retail investors with limited experience of P2P investment. A median lender invests in 24 loans with a median amount of RMB 400 (about USD $58) and has 5 months of investment experience on the platform[5]. Faced with a myriad of information about loan applications and borrower profile, small retail P2P lenders may find it challenging to make optimal investment decisions. Instead, they resort to cognitive simplification (Schwenk, 1984). As shown in Schunn and Dunbar (1996), earlier life experience and prior knowledge can be applied to new situations using analogical reasoning. As credit certificates are conventionally associated with better quality and favorable attributes, lenders are likely to reason by analogy and regard certificates as a positive signal, and thus are more willing to invest in loan listings with more certificates.

To understand whether this credit distortion issue improves as lenders accumulate more experiences, we investigate how lenders learn from their past investment experiences over time. Our evidence shows that lenders do gradually realize the adverse selection in certificates and become less reliant on certificates in loan screening and improve their investment performance. However, the learning

[5] An average lender invests in 70 loans with an average amount of RMB 1143 (about USD $166) and has 8months of investment experience on the platform

speed is very slow. On average, lenders will invest in loans with 0.008 less important certificate with one additional year of investment experience on the platform. Lenders' slow learning explains the seemingly puzzle that lenders keep choosing loans based on high certificates and do not realize the inferior quality.

To ensure the robustness of our results, we conduct several additional tests. First, given that lenders tend to exercise less screening when investment return is guaranteed (Agarwal et al., 2015), we exclude loans with guaranteed repayment by the platform, to ensure our results are not driven by this platform guarantee. Second, to explore the linear combination of different types of certificates, we conduct principal component analysis by replacing the total number of certificates with the first main component as our main explanatory variable. Third, we use alternative definition of delinquency by changing the overdue length in month, and also adopt different estimation techniques including single-failure model and multiple-failure model.[6] Our results remain robust after these tests, confirming the main findings that more certificates attract more investment but have worse loan performance.

Next, we provide several possible mechanisms to explain our findings on borrowers' behaviors. Our main finding is that low-quality borrowers use more certificates to boost their credit profile, to mimic the behavior of high-quality borrowers. However, it is puzzling why high-quality borrowers do not apply the same strategy to obtain more certificates. Classic theory of certification posits that when good-quality agents enjoy lower cost of signaling, all good-quality borrowers will want to get certified, reaching separation equilibrium with full disclosure (Grossman and Hart, 1980, Grossman 1981, Milgrom 1981).

To explain this result, we argue that the marginal return of one more certificate is much higher for low-quality borrowers than high-quality ones. Low-quality borrowers can significantly improve their funding success by acquiring more certificates, however, the benefit to high-quality borrowers from more certificates is minimal. High-quality (AA) borrowers have less incentive to obtain more certificates, as their funding success rate is already high enough and hard to be further improved by having more certificates. On the other hand, borrowers with a High Risk (HR) credit grade experience a 193.9% increase in funding success rate for each additional important certificate.

In addition to differential marginal benefit, we also draw on the psychology and behavioral economics literature to offer explanations on borrowers' behavior. Borrowers' behavior may be subject

[6] For brevity, robustness results using different definitions of delinquency and different estimation models are omitted from the main text and are presented in Internet Appendix 2.

to bounded rationality. Instead of always achieving optimality, given limited knowledge and attention, they make satisficing decisions, that is, an action that exceeds a preset satisfactory level (Simon, 1955; Gigerenzer, 2008). While low-quality borrowers get additional certificates to improve their credit grade, the credit profile of high-quality ones is enough to attract the desired level of funding, and therefore it is the low-quality borrowers who would actively seek to obtain more certificates.

This research makes several important contributions. First and foremost, we document a setting where credit certificates fail to serve as an accurate signal in loan screening. These ineffective signaling results in distorted capital allocation and reduced investment efficiency, which contradicts the prevailing belief that credit certificates are always used to address information asymmetry and mitigate adverse selection. This could offer a partial explanation to the recent massive collapse of Chinese p2p platforms, wherein retail investors rely too much on inaccurate information such as credit certificates to guide their investment and lead to huge losses.

Our study offers new evidence on the role of certificates in credit allocation efficiency, adding to the literature on credit certificates. A related study on certificates by Auriol and Schilizzi (2015) questions the validity of certificates, but from a totally different angle. They focus on the seed market in developing countries, where the cost of obtaining a certificate is prohibitive. In the extreme case, the high certificate cost prevents producers from obtaining it, resulting in the collapse of the certificate market.[7]

This paper also contributes to the literature on P2P lending. Existing studies mainly focus on funding success rate, interest rate, default probability, and investors' bidding behavior (Duarte et al., 2012; Zhang and Liu, 2012; Lin et al., 2013; Liu et al., 2015; Dorfleitner et al., 2016, among others). Our study is able to examine loan performance (overdue and default) based on detailed monthly loan repayment record, thanks to the high granularity of monthly payment records. This enables us to conduct loan

[7] Our study has several distinctive differences from Auriol and Schilizzi (2015). First, their theory is framed under classical economics, with rationality as an important assumption. With more assumptions on cost and market structure, they show how certificates could be less effective or useless when the cost is too high. We relax the existing assumption of rationality, and instead place more emphasis on bounded rationality. Second, in contrast to Auriol and Schilizzi (2015), the credit certificates in our study are almost costless. Specifically, Auriol and Schilizzi (2015) demonstrate the prohibitive nature of high certificate cost, whereas we reveal how the low cost of certificates (along with bounded rationality) results in the misuse of them. Further, the economic consequences also differ. In their model, when the cost drives all producers away, certificates become useless and the market deteriorates into an initial pooling equilibrium, without any additional harm caused. In the P2P lending market, the certificates themselves distort the market by attracting more funds to low-quality borrowers, thus reducing credit allocation efficiency.

repayment analysis on a monthly basis using proportional hazard models. Our study also provides evidence on bounded rationality and cognitive simplification as possible causes of agents' behaviors on the P2P lending platform. Although our paper focuses on P2P lending, our conclusions also apply to other markets with amateur participants that place unduly trust on credit certificates.

We also offer practical implications for industry practitioners and policymakers in the P2P credit market. There has been waves of large-scale platform collapse in China p2p market in the past decade. Platforms have explored various ways to resolve information asymmetry without much success. Our paper offers some insights on this issue from two key channels: borrowers' adverse selection in certificates and lenders' bounded rationality. P2P platforms should take into account of potential misleading role of credit certificates and cognitive biases of investors when designing their certificate processes.

This paper proceeds as follows. Section 2 introduces the institutional background and Section 3 describes the data and sample. Section 4 presents the empirical results, revealing the influence of certificates on loan performance. Section 5 investigates the relationship between a borrower's credit quality and number of certificates he or she obtains, thereby presenting the prevalent adverse selection in credit certificates. Section 6 focuses on lenders' behavior and examines how certificates affect funding success. Section 7 provides evidence on the dynamic learning of the lenders. Robustness tests are presented in Section 8. Section 9 discusses the possible channels of our findings and Section 10 concludes.

2. Institutional Background

Established in 2010, RRD is one of the earliest and largest P2P lending platforms in China. To raise funds on this platform, a borrower needs to create an account by offering a telephone number that can receive an SMS verification code and submitting other basic information to the platform, such as a personal identification number. The platform then follows up with an authenticity check of the information provided and conduct a comprehensive assessment on borrowers' credit quality. Borrowers who are able to pass this verification process are eligible for post-loan requirements (aka loan listings), whereas those who provide fake or suspicious materials will be denied by the platform. The detailed lending and borrowing process is illustrated in Figure 1 Panel B.

All borrowers are classified into seven different credit grades by the platform, namely: AA, A, B, C, D, E, and HR, based on the Renrendai's proprietary credit rating system. To improve their credit profile, borrowers can voluntarily provide more information by displaying more credit certificates on the profile page of the platform. Credit certificates could also serve as an effective channel for the platform to collect additional information about an applicant.

RRD offers a wide array of certificates, including education level, marital status, income level, car and property ownership, housing loan, car loan, job industry, company size, job length, job type, job province, credit history, social media, and address, etc. To obtain each type of certificate, the applicant needs to prepare a list of required document proofs, according to platform guideline.

The total number of all certificates is defined as NCertif. As certificates that reveal an applicant's personal information, financial status, and credit history help the platform in risk management and debt collection in case of default, they are thus defined as important certificates. The number of the important certificates is defined as NCertif_Impt. Specifically, certificates that reveal the identity or the contact information of the borrowers are considered as important, e.g. ID number, ID card, mobile phone, phone bill, onsite authentication, residence proof, and remote video. In case of delinquency, these certificates can be used by the platform to locate the borrower and facilitate debt collection. As employment status, credit ration, and documentation on income and asset is often used in delinquency prediction (Arentsen et al., 2015), we also include credit report, occupation, bank statement, property ownership, and car ownership as important certificates.

The amount of voluntarily disclosed information shows the eagerness of a borrower to improve his or her credit profile. As certificates on platform training, ID number, mobile phone, loan description and ID card are compulsorily required, we define the rest of the certificates as voluntarily applied. The total number of the voluntarily applied certificates is defined as NCertif_Volun.

To obtain a certificate, an applicant simply needs to upload the required materials, most of which are as simple as photocopies of documents. Taking car certificate as an example, the applicant just needs to provide: 1) a photo of vehicle license, and 2) a photo of the applicant standing beside their car, with plate number being clear and identifiable. The platform staff will then manually check the materials and decide if the applicant should receive the certificate. With the help of technology, an applicant can obtain this certificate without much hassle, as most of the procedures are executed online. Therefore, the certification process is almost costless.

Once a loan application is posted, it becomes an ongoing loan listing, and its real-time funding percentage, bidding time remaining, loan characteristics, and borrower characteristics are available to all lenders for their reference. The bidding is on a first-come, first-served basis, where lenders can bid on any loan listing that is not fully funded. Once the total amount funded reaches the initial requested amount, the bidding process closes immediately. For each loan application, RRD platform sets a maximum fund raising duration. If the amount raised has not reached the requested amount in the end, the listing is deeded as unfunded and the previous invested fund will be returned to the bidders.

After getting funded, borrowers need to repay the fully-amortized loan in equal payment on a monthly basis. In case of overdue and default, RRD will contact the borrower to collect any outstanding balance along with any penalties. For each of the fully funded loan, our data includes detailed monthly repayment records, which enable us to identify the time and severity of delinquencies and default.

3. Data Description

3.1 Summary Statistics

The sample includes 742,292 loan listings on RRD from October 2010 to January 2016, with 163,152 funded and 579,140 unfunded. Both borrower and loan characteristics are available for all listings. With detailed monthly repayment records for each funded loan, we are able to accurately identify all types of payment issues (i.e. overdue payments and defaults) and pinpoint the exact time when they occur. Also, the repayment data allow for multiple delinquencies within one loan. For example, a borrower may accrue several overdue payments over the course of their loan.

Table 1 provides summary statistics of variables used in our analysis. All of the data are collected from RRD, and detailed definitions of variables are presented in Appendix 1. Our focal variable, NCertif_Impt, has large variation among borrowers. On average, borrowers on the platform obtain 2.773 important certificates. While some borrowers obtain no important certificates at all, the maximum number of obtainable important certificates is 11. A similar pattern is observed for NCertif and NCertif_Volun, which vary from 0 and 11, and 0 and 16 with a mean of 4.313 and 1.264 respectively. 40% of the borrowers own assets such as cars or houses, and the credit grade for the median borrower is the lowest, HR. The median borrower is 31 years old, post-tertiary educated, earns RMB 5,000 to RMB 10,000 a month from their employment, and has 1 to 3 years of working experience.

In terms of loan characteristics, the mean (median) loan duration is 17.69 (18) months in duration. While the maximum loan amount is as high as RMB 3 million, the smallest is only RMB 1,000, and the median amount is around RMB 40,000. Getting financed via RRD can be costly, as the average (median) interest rate is 13.11% (13.00%), and the average (median) interest premium is 7.38% (7.00%). 96.9% of loan sample are unsecured.

In terms of loan performance, 96.3% of the funded loans are completely repaid with no overdue record during the course of the loan. The rest 3.7% of problem loans have either late payments over some month or eventual default in the end. We further classified them into two categories: fully repaid loans with late payment records are categorized as overdue, which make up 1.2% of funded sample. And the rest 2.5% are default. The level of delinquency and default rates are similar to those in Hasan et al. (2017), which also used RRD data[8].

At bidding level, an average bidder has 0.729 year of investment experience on the platform. The means bid amount is around RMB 1,191, consisting of 2.2% of the loan amount requested. Consistent with the aforementioned higher interest rate and low default probabilities of P2P loans on this platform, the average realized annual internal rate of return of the bids is 11.1%, much higher than the benchmark rate on bank deposits during the sample period.

[INSERT TABLE 1 ABOUT HERE]

3.2 Univariate Analysis

3.2.1 By Funding Status

We next look at the differences in borrower and loan characteristics between funded and unfunded listings. In Panel A of Table 2, we report the number of observations and variable means in each group, and the mean differences are also presented with t-test statistics. The total records of funded and unfunded listings are 163,152 and 579,140 respectively.

[INSERT TABLE 2 ABOUT HERE]

Consistent with our hypothesis, the average number of important certificates for the funded listings is 3.934, which is significantly higher than that for unfunded listings. The number of all certificates and voluntarily applied certificates also differ significantly between the funded and unfunded loans. While the funded loans have 5.122 all certificates and 1.905 voluntarily applied certificates on average, the means

[8] Hasan et al. (2017) report 5% delinquency rate. The slight difference in average default rate may be caused by the different sample period. Also, data collection time affects the default rate, as some of the loans are still ongoing (i.e. still at the repayment period) at the data collection time. The ultimate repayment performances of those loans are thus unknown.

for unfunded loans are 4.085 and 0.306. Also, borrowers of funded loans have positive attributes, such as more advanced education, higher income, possession of assets, and higher credit grades.

Theoretically, the impact of having car and house loans is twofold. On the one hand, the existing liability increases the leverage of the borrower. On the other hand, as suggested by the banking literature, access to bank loans certifies banks' trust toward the borrower, thus signaling good quality (James, 1987; Lummer and McConnell, 1989; Best and Zhang, 1993). Our data indicate that the signaling effect plays the dominant role, as the funding success rate for borrowers with bank loans is higher. For loan characteristics, funded loans have a smaller loan amount, lower interest premium, and longer duration.

3.2.2 By High and Low Level of Certificates

Table 2 Panel B presents the differences in loans between high and low certificate levels, where the loans are equally partitioned into two groups by the number of important certificates. In general, the high certificate level is associated with relatively better borrower attributes and more favorable loan terms.

Specifically, borrowers with high certificate levels attain more advanced education and earn higher income. They also possess more assets compared to low-certificate borrowers and are more likely to obtain loans from financial institutions. Further, their track records indicate that they have previously applied for more loans. Borrowers with a high certificate level apply for 3.373 loans on average, which is around 1.68 times higher than that of borrowers with a low certificate level. In terms of cost, borrowers with a high certificate level also experience lower financing costs: with a mean of 7.221, they pay around 27 basis points less interest premium compared to low-certificate borrowers.

We focus on the funded subsample in Panel C. Notably, borrowers with a high certificate level have, on average, a lower credit grade, opposite to the patterns in Panel B, where high levels of certificates are associated with better credit ratings. The relationship between credit rating and number of certificates is driven by two distinct forces. On one hand, the adverse selection effect suggests that borrowers with a worse credit profile choose to get more certificates; on the other hand, certificates can boost credit profile, so they have a credit boosting effect on credit profile. The credit boosting effect differs among borrowers. While a low-quality borrower can boost his or her credit profile using more certificates, it is less rewarding for a high-quality one to do so.

As shown in Panel A, the average credit grade for funded borrowers is much higher than for those of the unfunded ones; hence, the credit boosting effect is much weaker for the funded group. Consequently, the negative relationship in Panel C is mainly driven by the adverse selection effect that we are interested in. The positive correlation in Panel B, however, captures a mixture of the aforementioned two effects. More importantly, the differences between funded sample and full sample also indicate that it is the low-quality borrowers that substantially boost their credit profile via certificates. Section 6 uses the funded subsample and analyzes this issue in depth.

The funded sample also allows us to investigate the performance of loans of different certificate level. We find that high certificate loans have significantly higher delinquencies. Specifically, compared with the low certificates group, loans with high certificates have, on average, 8.2 and 28 times chances of delinquencies and default.

4. Certificate and Loan Performance

In this section, we formally analyze how certificates affect the loan performance using multivariate regression, controlling for other relevant factors, such as loan characteristics, borrower characteristics, and borrower track records.

The analysis starts from a simple logit model, where the dependent variable is Delinquent, a dummy variable equals to 1 if the loans experienced either overdue or default) and 0 otherwise. Next we report the ordered logit regression results to capture the severity of delinquencies. The dependent variable is BadDebt, which equals to 0 is the loan is on time repaid for every period, and 1 if it is fully repaid but with overdue records, and 2 if it is unrepaid. A duration analysis is then adopted to further take the multiple delinquencies within one loan into consideration.

4.1 Logit Model

We first analyze loan performance using a logit regression, where all loans are classified into two categories by delinquency. Table 3 reports the coefficients from the logit regressions with standard errors in parentheses. The dependent variable, Delinquent, equals 1 if the loan is delinquent (i.e. overdue or default) and 0 if it is on time repaid for every period.

The specification in Models 1, 3, and 5 incorporate only our focal variables "NCertif_Impt," "NCertif," and "NCertif_Volun" along with credit grade and loan characters, and more control variables are included in Models 2, 4, and 6. Throughout our regression analysis, year quarter fixed effects are included in all specifications to control for unobserved time effects (Lin et al., 2013). Coefficients for number of all certificates are positive and statistically significant in both of the specifications, and the number of important and voluntarily applied certificates also have coefficients significantly larger than zero when the full set of control variables are included, suggesting that borrowers with more certificates, on average, are more likely to have worse performance. Models 2, 4, and 6 with full set of controls show that having one additional important certificate, all certificate, and voluntarily applied certificates increases the odds of having a deteriorated payment record by 3.3% (=exp(0.032)-1), 6.9% (=exp(0.067)-1), and 2.2% (=exp(0.022)-1) respectively.

4.2 Ordered logit Model

We then analyze loan repayment performance using an ordered logit regression, where all loans are classified into three ordered categories, namely: repaid (=0, loans repaid on time for each period), overdue (=1, loans with delayed payment records that are eventually repaid fully at the maturity of the loan), and default (=2, loans that are not fully repaid at the maturity of the loan). Table 3 reports the coefficients from the ordered logit regressions with standard errors in parentheses.

Consistent with prior results, coefficients for number of important certificates, all certificates are positive and statistically significant across all models, and the number of voluntarily applied certificates also has a significantly positive coefficient with the full set of control variables, suggesting that borrowers with more certificates, on average, are more likely to have worse performance. Models 2, 4, and 6 with full set of controls show that having one additional important certificate, all certificate, and voluntarily applied certificate increases the odds of having a deteriorated payment record by 4.3% (=exp(0.042)-1), 7.8% (=exp(0.075)-1), and 3.0% (=exp(0.030)-1) respectively.

[INSERT TABLE 3 ABOUT HERE]

4.3 Cox Proportional Hazard Model

A single loan may have multiple delinquency events, e.g. multiple delayed payments within the loan duration. We next construct a variance-corrected multiple-failure Cox proportional hazards model (Andersen-Gill model) to incorporate this multiple-failure attribute into our analysis (Anderson and Gill, 1982). Compared with a single-failure Cox proportional hazards model, the Andersen-Gill model not only fully utilizes all delinquency information in the data, but also corrects the estimation of the covariance matrix by taking the correlation between delinquencies into consideration (He et al., 2019).

We present the estimated coefficients from the variance-corrected multiple-failure Cox proportional hazards model in Table 4. In Panel A, delinquency is defined as any payment overdue for 1 month or longer. Panel B adopts a stricter definition in identifying delinquencies, in which only consecutive overdue records for 4 months or longer are recognized (Duarte et al., 2012).[9]

Consistent with prior results, the coefficients for the number of important certificates, all certificates, and voluntarily applied certificates are larger than 0 and significant in all models. After controlling for other relevant factors, a one unit increase in important, all, and voluntarily applied certificate number raises the conditional probability of delinquency by 22.6% (=exp(0.204)-1), 16.3% (=exp(0.151)-1), and 19.4% (=exp(0.177)-1). Defining delinquency as default or 4-month consecutive overdue payments as delinquency, these three ratios change to 20.0% (=exp(0.182)-1), 13.9% (=exp(0.132)-1), and 16.6% (=exp(0.154)-1) respectively.

[INSERT TABLE 4 ABOUT HERE]

Quantitatively, the coefficients in the duration analysis are much higher than those in the logit regression. The difference between these two models is that the variance-corrected multiple-failure Cox proportional hazards model takes the number of delinquencies into consideration, which results in the larger estimated impact. The higher coefficients indicate that certificates have a twofold impact on loan performance. They not only raise the probability of delinquency, but also increase the occurrences of delinquency events. To our best knowledge, this is also the first paper that uses a variance-corrected multiple-failure Cox model (Anderson and Gill, 1982) to examine the determinants of P2P lending delinquency, which not only fully utilizes the information of all delinquent events of each loan, but also adjusts the correlation between each event.

5. Determinants of Credit Certificates

To uncover the reason why certificates are inversely related to loan performance, we analyze the possible determinants of certificates related to borrower attributes. Table 5 presents the OLS estimation results with the number of important, all, and voluntarily applied certificates as the dependent variables,

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[9] As a robustness test, we present results using both the single failure model and changing the definition of delinquency to two-month consecutive overdue payments, following Lin et al. (2013). The results are qualitatively the same and are presented in Internet Appendix 2.

whereas credit grade, borrower characteristics, and borrowing experience are included as independent variables.

The number of important certificates, all certificates, and voluntarily applied certificates are used as the dependent variables in the first, middle, and last two columns of Table 5. Credit grade is the independent variable in Model 1, 3, and 5, and Model 2, 4, and 6 add other borrower characteristics and previous borrowing records as control variables. The coefficients on credit grade are significantly negative when number of important certificates and all certificates are used as dependent variable. Although statistically insignificant, the credit grade and number of voluntarily applied certificates are also inversely correlated. Quantitatively, a one-notch increase in credit grade is, on average, associated with a 0.119-unit reduction in the number of important certificates and 0.337 fewer all certificates.

We also find that single younger borrowers from large cities with a higher education level, higher income level, and shorter working experience tend to use more certificates. Borrowers who have housing or automobile assets are more likely to showcase these in certificates, potentially to serve as collateral or assurance. Previous borrowing experience is associated with more certificates, indicating that more experienced borrowers know better how to utilize certificates in boosting their credit profile.

The above estimates may be subject to reverse causality, as acquiring additional certificates also improves credit grades; we term this influence as credit boosting effect. And the estimated coefficients reflect the combination of two effects, i.e. adverse selection effect (negative) and credit boosting effect (positive). Therefore, the impact of the pure adverse selection effect should be even smaller than -0.119, indicating a stronger inverse correlation between borrower quality and number of certificates.

[INSERT TABLE 5 ABOUT HERE]

We have shown low-quality borrowers obtain more certificates to improve their credit profiles and attract investors. However, it is still necessary to understand why high-quality individuals obtain much fewer certificates. One possible cause is bounded rationality and satisficing decision.

Similar to lenders, borrowers also have limited expertise in investment and finance, and their behaviors may also be subject to bounded rationality. Instead of pursing optimality, they make satisficing decisions, i.e. using a preset satisfactory level as a key decision criterion (Simon, 1955; Simon 1979; Gigerenzer, 2008). A borrower only cares about their funding probability and financing cost. As long as the funding success reaches a preset satisfactory level, they will not bother to obtain more certificates, even if the process is nearly costless. In contrast, low-quality applicants, being unsatisfied with their credit profiles, continue to acquire certificates until their funding outcomes become satisfactory. In the end, we observe an adverse selection in certificates; namely borrowers with poor credit profiles choose to obtain more certificates.

6. Certificates and Funding Success Rate

While costless, voluntary, and unverifiable disclosures are unlikely to be credible sources of information, prior research demonstrates that lenders' investment decision on the P2P market can be influenced by this kind of uninformative content. Michels (2012) shows that an additional unverifiable disclosure in p2p loans on Propser.com is associated with a 1.27% reduction in interest rate and an 8% increase in bidding activity.

In Section 4 and 5 we have shown that more certificates are associated with poor ex-ante credit grade and higher ex-post delinquency rate in the market we study. A natural question is whether lenders are sophisticated enough to recognize the adverse selection in credit certificates, or do they still trust them and simply interpret them as positive signals and invest in loans with more certificates. To answer this question, we examine the impact of the number of certificates on funding probability.

Table 6 presents the logit regression model results, where the independent variable, Funding Success, is a dummy equal to 1 if the listing is funded and 0 otherwise. Panel A presents the full sample results and Panel B divides the loan applications by credit grade to reveal the heterogeneous impact across borrowers' qualities.

In Panel A, Model 1, 3, and 5 only include our focal variable, NCertif_Impt (NCertif or Ncertif_Volun), credit grade and loan characteristics. The full set of control variables consisting of loan characteristics, borrower characteristics, and prior borrowing records are added into Model 2, 4 and, 6.

We find all of the coefficients of our focal variables are highly positive and significant, indicating that more certificates improve funding success rate. Specifically, one additional important certificate, all certificate, and voluntarily applied certificate increases the funding odds by 88.3% (=exp(0.633)-1), 44.3% (=exp(0.367)-1), and 57.1% (=exp(0.452)-1).

Positive attributes, such as higher credit grade, advanced education level, higher income level, and longer working experience, are associated with higher funding success. In addition, interest premium as a comprehensive measure of risk is negatively related to funding probability. On average, a 1% increase in interest premium lowers funding odds by around 9.2% (=exp(-0.097)-1) to 10.0% (=exp(-0.105)-1) depending on specification. Prior loans from financial institutions also improve funding probability, consistent with the notion that bank loans can signal high borrower quality.

To uncover the reason why high-quality borrowers do not present a full set of certificates, we argue that it is possible that credit certificates boost funding success rate with varying degrees for high-quality and low-quality borrowers. Panel B presents the subsample regression outcomes, using the AA-rated loan sub sample in the first three columns, and HR-rated loans in the last three columns. The difference between the first and last three columns reflect the heterogeneous effect of the number of certificates on funding success between the highest and lowest quality borrowers.

We find that while certificates increase funding probability remarkably in the low credit grade group, the effect in the high rating group is very limited, indicating a diminishing effect of certificates in boosting borrower's credit quality. Take the number of important certificates as an example, while one more certificate increases funding odds by 88.3% in the full sample (Model 2 in Panel A), the effect is more than doubled in the HR subsample and reached 193.9% (=exp(1.078)-1) in Model 4 Panel B. The influence in the AA-rated sample, in contrast, is not significant.

[INSERT TABLE 6 ABOUT HERE]

7. Investors' Learning over Time

In the equilibrium documented above, the lenders are deceived by the inaccurate signals, i.e. certificates, and invest in loans of inferior qualities. This phenomenon can be baffling without a clear description of the lender's dynamic behaviors. In particular, we address the question do investors ever learn from their investment experience as a supplementary to the main finding.

As bidders accumulated their bidding experiences, they are expected to gradually realize the adverse selection in certificates and be less reliant on this inaccurate signal in selecting loans. Specifically, we expect that experienced borrowers on average invest in loans with fewer certificates and have better investment performance. Our bid level data capture the bidding behavior and performance heterogeneities among different lenders and among the same lender at different time, thus allowing us to examine the above hypothesis.

We conduct multivariate regression analysis to examine the role of experience on loan performance and return, where experience is measured by the years since the first investment on the platform. The dependent variables are the number of (important, all, or voluntarily applied) certificates, internal rate of return (IRR), and Delinquent in Model 1-5, respectively. After controlling for loan and borrower characteristics, experiences are associated with fewer certificates, suggesting that experienced bidders are less reliant on certificates in screening loans. Moreover, the investment performances improve with more experience, as experienced lenders have significantly lower default probabilities and higher IRRs.

Despite lenders do learn from their experiences, the learning speed is very slow. On average, lenders will invest in loans with 0.008 less important certificate with one additional year of investment experience on the platform. Especially considering the median investment experience of the borrowers is around half year, the impact of learning is quantitatively ignorable. With the expansion of the platform, inexperienced new bidders are attracted into the market, further diluting the effects of learning. And the slow learning speed justifies the observed investment inefficiency.

[INSERT TABLE 7 ABOUT HERE]

8. Robustness Checks

8.1 Removing Guaranteed Loans

Previous research has shown that deposit insurance reduces depositors' incentive to monitor a bank and encourages risk taking by the secured banks, which poses moral hazard risk (Grossman, 1992; Demirgüç-Kunt and Detragiache, 2002). In the same vein, P2P lenders invest in guaranteed repayment, they lose incentive to prudently screen the quality of the loan applications (Agarwal et al., 2015).

So far, we have shown that the number of certificates is positively related to funding success and loan delinquency, using the sample that includes both the secured loans and the unsecured loans. One potential concern is that the above results may be driven by the secured loans whose payments are guaranteed. For robustness check, we remove the secured loans from the sample, and re-estimate the main results.

Table 8 Panel A presents the number and funding success of loans by type. We can see that the secured loans (i.e. the collateral loans and loans guaranteed by the platform) only make up a small proportion in the full sample, 3.1%, so we expect the secured loan sample to have a low impact on our baseline findings. More directly, we re-estimate the main results using a subsample excluding the guaranteed loans, to see if the previous noted relationships still exist. Panel B of Table 8 shows estimation results using the unsecured loans subsample only.

As we can see, the outcomes in Table 8 Panel B are qualitatively similar to the full sample results in Table 4 and 6 respectively. Hence, we rule out the concern that the results are merely driven by secured loans and confirm the robustness of findings.

[INSERT TABLE 8 ABOUT HERE]

P2P platforms gradually allow lenders to set up autobids based on certain risk and return combination. We check whether and how will the existence of autobids affect the result on funding success rate and loan performance. To check the robustness, we remove all autobids from the sample, and redo the main analysis. The results using the human bid only sample are qualitatively similar to the main results in Table 4 and Table 6 and are reported in Internet Appendix 3.

8.2 Principal Components Analysis on Certificate Number

In the models above, we only use on the number of certificates as our focal variable, without focusing on the combination between certificates of different kind. The advantage of the simple sum of certificates is that it is intuitive, and the coefficients are easy to interpret.

However, assigning each certificate an equal weight may be a questionable assumption. To address this issue, we construct the linear combination of important, all, and voluntarily applied certificates, respectively, using principal components analysis (PCA). And the first principal components (Comp1_Impt, Comp1, and Comp_Volun) are used as the proxies for certificate level.

The eigenvectors and eigenvalues of the principal components for the important certificates, all certificates, and voluntarily applied certificates, along with proportions of variation explained are reported in the Internet Appendix 1. And the regression results using the principal components of certificates are presented in Table 9.

Consistent with our baseline results, the principal components of important, all, and voluntarily applied certificates are positively related to loan delinquency and funding odds, proving the robustness of our main findings.

[INSERT TABLE 9 ABOUT HERE]

9. Potential Channels

9.1 Bounded Rationality and Cognitive Simplification

So far, we have documented a situation where certificates are subject to adverse selection, which distorts credit allocation in P2P lending. Specifically, we find that lenders are more willing to invest in listings with higher certificates despite their poorer credit quality ex ante, higher delinquency rate ex post.

Biases in cognitive simplification provide a means of understanding the above irrational behavior of lenders. While reasoning by analogy allows lenders to assess the credit quality of borrowers in a simple manner, it is also subject to substantial biases. It is documented that when resorting to analogy, people tend to focus on superficial features without checking if the key underlying assumption is satisfied (Schwenk, 1984, 1988). As a result, the predictability of previous experiences is over-estimated, and representativeness bias is thus introduced into the decision process (Tversky and Kahneman, 1974). More directly, Simon (1959) describes this bias as "the distinction between the objective environment in which the economic actor 'really' lives and the subjective environment that he perceives and to which he responds."

The interaction between lenders and borrowers in P2P lending can be characterized by information asymmetry and adverse selection as posited in Akerlof (1970). Since the seminal works of Jaffee and Russell (1976) and Stiglitz and Weiss (1981) which document that high-quality individuals differentiate themselves (i.e. signaling) by choosing an action that cannot be imitated by low-quality individuals, there are more application of this line of theory on the credit market. Signaling by borrowers is known to be one of the solutions to alleviate information asymmetry (see Bester, 1985; Besanko and Thakor, 1987; Milde and Riley, 1988).

For costly signaling, the signaling cost is negatively related to one's quality (Spence, 1973), so that the high-quality individuals can differentiate themselves by signaling, which cannot be easily imitated by the low-quality ones. When signaling becomes costless, every rational agent will try to get as much certificates as they can, and the high-quality borrowers will differentiate themselves by having the most certificates (Grossman and Hart, 1980, Grossman 1981, Milgrom 1981). As we have discussed above, neither of these two assumptions are satisfied in our settings. As a result, certificates do not necessarily indicate high credit quality on this P2P platform.

There are plenty of real-life situations where certificates are used as a positive signal. For example, higher education level (i.e. an education certificate) reflects better ability (Spence, 1973), and more stars or certificates represent the high standard of a hotel or restaurant. Bidders, reasoning by analogy, directly relate certificates to positive attributes without carefully examining if the underlying assumptions are, in fact, true (Tversky, 1974; Tversky and Kahneman, 1974; Kahneman 1991; Kahneman 2003). Not realizing the subtle differences in underlying assumption, bidders simply interpret the existence of certificates as a positive signal and therefore invest in listings with a higher certificate level.

A large body of literature in cognitive psychology and decision science has revealed how people reason by analogy and exercise their judgments using simplifying heuristics when faced with complicated problems. Abundant laboratory and field experience evidence are documented in finance, economics, and management literature (Gick and Holyoak, 1980; Duhaime and Schwenk, 1985; Schwenk, 1986; Schwenk, 1988; Gavetti et al., 2005; Gavetti and Rivkin, 2005; Gary et al., 2012).

9.2 Difference in Marginal Benefits

As discussed in Section 5, one possible reason for the adverse selection in credit certificates is the difference in marginal benefit and the satisficing decision. High-quality borrowers are satisfied with their credit status and do not bother to apply for more certificates, the low-quality ones keep getting more certificates to beautify their credit profile.

Apart from the satisficing decision, another reason of the adverse selection is the difference in marginal return. For borrowers, the benefit of having certificates is to boost their credit profiles such that their funding success rate is improved. Given the near zero cost of obtaining certificates, the benefit of certificates is thus an important driving force determining a borrower's certificate level. Therefore, more prominent returns (i.e. when the borrower's credit grade is lower) should be associated with higher certificate level.

As shown in Table 6, this benefit from one additional certificate varies dramatically across borrowers in different credit grades, with lower rating ones enjoying much more prominent benefit. Although one certificate raises funding odds by 88.3% for all the groups, and the increase in HR-rated loans is as large as 193.9%, however, the benefit for the AA-rated group is insignificant. So, the low-quality borrowers have the strongest desire to obtain a high number of certificates. However, high-quality borrowers are not incentivized of getting additional certificates. Hence, this result, together with borrowers' bounded rationality and the satisficing decision, provides an explanation for the observed adverse selection in certificates.

9.3 Borrower Myopia and Debt Collection

Certificates may seem costless in terms of time, effort, and pecuniary expense; however, a large amount of personal information is revealed to the platform via certificates. Although the ramifications of this disclosure may be largely ignored or deemed innocuous during the early stages of RRD use, this disclosure may turn out to be considerably costly later on. In addition to concerns of identity theft, personal information such as address, employer name, and identity of spouse can be used for debt collection purposes by the P2P platform should any default or overdue payments occur.

Following RRD's debt collection policy, a borrower will first be reminded by SMS and phone call in the first five days when delayed payment occurs. After that, the borrower's designated contact person as recorded on the platform (e.g. relatives, colleagues, employers) will be notified that the specific borrower has defaulted on a P2P loan. Should the borrower still refuse to repay, the loan will be transferred to a third-party professional debt collection agency, which then pays the borrower a home visit or even resort to lawsuits.

As a typical borrower normally chooses their certificate level at the beginning stage of loan application, they may not be fully aware of the full cost of certificates in the debt collection stage. Not realizing the potential costs and being attracted by short-term benefits, borrowers' decision to submit more information to the platform for more certificates may be shortsighted.

We test this hypothesis of myopia by focusing on the different impact of certificates on loan delinquency between borrowers with and without prior default experience on the platform. Empirically, we measure this difference by an interaction term between number of certificates and a dummy variable, Default, which reveal if a borrower has previously defaulted. We argue that borrowers who have personally experienced defaults and the debt collection process should have a better understanding of the indirect cost, which allows us to examine whether the awareness of the long-term cost affects the impact of certificates on delinquent rate.

The regression results are presented in Table 10. Similar to Table 4, we use one-month overdue criterion and four-month consecutive overdue criterion in Panel A and B. Within each panel, the first, middle, and last two models focus on the number of important, all, and voluntarily applied certificates, respectively. The interaction terms are significantly negative in both panels across all models, suggesting that the impact of certificates in terms of raising delinquency rate is alleviated if the borrower has default records on the platform. Although important certificates increase delinquency rate, the delinquent hazard based on one-month overdue (Panel A) will be reduced by 20.1% (=exp(-0.225)-1) if the borrower has experienced prior defaults.

[INSERT TABLE 10 ABOUT HERE]

These findings reflect that the influence of certificates in terms of affecting delinquency hazard differs significantly between borrowers with and without default records. When borrowers decide on their certificate level, the indirect cost at the debt collection stage is not taken into consideration, implying the myopic behavior of borrowers. More importantly, borrower myopia is another important cause for the adverse selection in certificates. The negative relationship between certificates and loan performance is largely reduced (or vanishes) once myopia is corrected.

9.4 Intentional Default

It is possible that certain borrowers do not plan to repay after they receive funding from the platform. For this kind of borrowers, their gains are maximized if they default in the early stage of the loan. Also, they have a stronger incentive to improve their funding success rate by obtaining more certificates, which could result in a positive correlation between the number of certificates and delinquency hazard.

Although intentions cannot be observed directly from the data, we can infer intentions based on ex post performance. If a borrower has an early intention of default on a loan that is successfully funded via the platform, to maximize their gain, they should do so immediately after receiving the funds without any repayment, as any payment made to the platform will reduce their return.

We thus define early delinquency as delinquent behavior at the beginning stage of each loan and examine how the number of certificates affects early delinquent behavior. Table 11 shows the variance-corrected multiple-failure Cox proportional hazards model hazard ratios with early delinquent hazard as the dependent variable. While Panel A defines early delinquency as delinquent behavior within the first 3 months after granting of the loan, Panel B recognizes early delinquency as delinquent behavior within the first 1/6 period of the loan. Following the criterion in Table 4, delinquency includes default and any delayed payments. The results are similar when we adopt the four-month consecutive standard, i.e. define delinquency as default or consecutive delayed payments for four months or longer.

The coefficients are significantly positive for the number of important certificates, all certificates, and voluntary certificates when other factors are controlled, across all versions of definition of early delinquency. These results indicate that intentional default is another reason for the positive relationship between certificates and delinquency. However, the coefficients also become much smaller than those in the baseline models of Table 4, which suggests that intentional default is a quantitatively lower order channel.

[INSERT TABLE 11 ABOUT HERE]

It is also possible that some borrowers provide fake certificates in loan application to improve their credibility. Although we are not able to verify the authenticity of each of their certificates, we are able to infer from the actions taken by the platform on defaulted borrowers. After a borrower defaults, platform will contact the borrower based on the information provided. If a borrower uses fake certificates, the platform will realize it at the debt collection stage. Most likely those borrowers will be banned by the platform for good.

We then use a subsample excluding borrowers who never return the platform after default to address the concern on fake certificates. Although not all of the borrowers who never return to the platform have used faked certificates, we are able to exclude borrowers that defaulted and used fake certificates. Our results are robust using this subsample and are reported in Internet Appendix 4.

10. Conclusion

Certificates are widely used as a signaling device to resolve information asymmetry. The Peer-to-Peer (P2P) lending platforms in China provide an ideal laboratory for investigating whether credit certificates help resolve the information asymmetry problem in the lending process, as borrowers are encouraged to obtain various credit certificates to boost credit profiles. As P2P markets continue to develop, it is plausible that certificates could play a pivotal role in ensuring investment efficiency.

Using a large sample of detailed listings and repayment records on one of China's largest P2P platforms, Renrendai, we conduct the first empirical investigation into this issue. Surprisingly, we find loans with more credit certificates have worse payment performance with higher rates of delinquency and default, which suggest there is severe adverse selections in credit certificates. Poor-quality borrowers use more certificates to boost their credit profiles and improve their funding success, as the marginal benefit of one extra certificate is much higher compared with that for and high-quality borrowers.

Ideally certificates should serve as a distinguishing mechanism so that high-quality borrowers can assert priority in obtaining funds and therefore receive preferential treatment from lenders. Without realizing the adverse selection in certificates, lenders remain attracted by higher certificates despite poorer ex ante quality and higher ex post delinquency, which suggests that credit certificates fail to serve as an accurate signal on credit quality and lead to distorted capital allocation on the platform. That is, lenders take more uninformed risks without being compensated in return, and high-quality borrowers receive lower funding allocation than they deserve.

Although certificates are widely used as differentiating signals in resolving adverse selection as documented in Classical signaling literature, they may fail to serve this purpose when the signal itself becomes inaccurate due to adverse selection. Drawing inference from psychology literature, we propose lenders' cognitive simplification and borrowers' satisfying decision and myopia as possible explanations for our findings, besides marginal benefit differential for high- and low-quality borrowers.

Uninformed lenders exercise cognitive simplification and place too much trust on conventional wisdom and simply take certificates as positive signals for good credit quality (cognitive simplification). For borrowers, without realizing the potential costs at the debt collection stage, borrowers' decision to submit more information to the platform for more certificates may be shortsighted (borrowers' myopia). While low-quality borrowers get additional certificates to improve their credit grade, the credit profile of high-quality ones is enough to attract the desired level of funding, and therefore it is the low-quality borrowers who would actively seek to obtain more certificates (satisfying decision).

Overall, we document a setting where credit certificates fail to serve as an accurate signal due to the adverse selection in certificates. Although our setting is P2P lending platforms in China, we believe our findings and implications could apply to other markets where participants are amateur with bounded rationality. There are many situations where the cost of certificates is not inversely related to borrower quality and the market participants are not fully rational, which violate the key assumptions of signaling. As a result, there is no guarantee that certificates are always associated with positive attributes and favorable outcomes. If signal observers are not sophisticated enough to recognize this nuance, and simply interpret certificates as a positive sign based on cognitive simplification, we will observe similar equilibria in other contexts where low-quality individuals are selected and favored by means of mimicking high-quality individuals.

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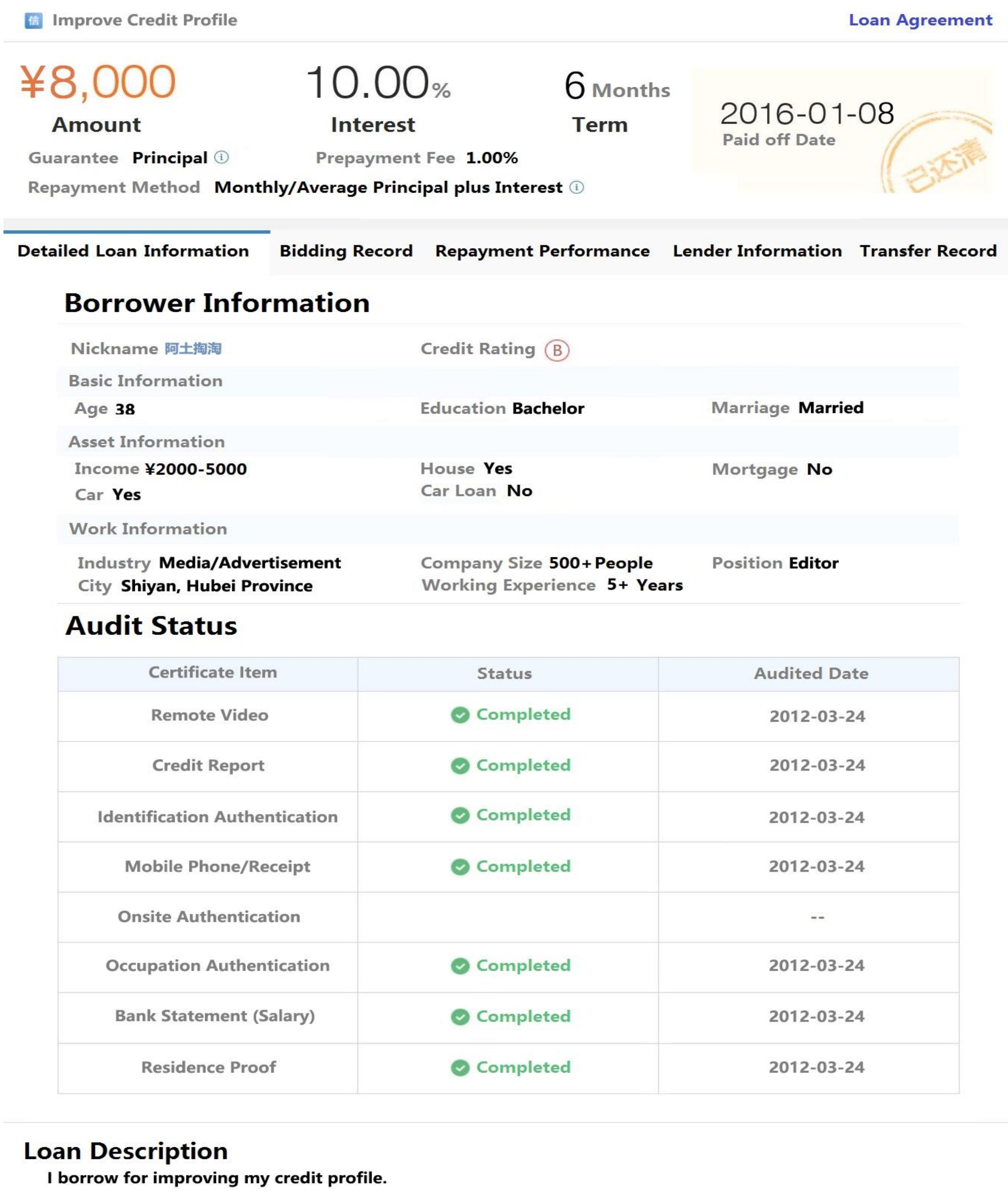
Figure 1: P2P Platform Lending Samples and Credit Certificates

Panel A presents the screenshot of a sample loan on the platform website, Panel B presents the lending and borrowing process flow chart on Renrendai, and Panel C presents the frequencies of the certificates in our data, collected from Renrendai. The definitions of all variables are presented in Appendix 1.

Panel A: Web Screenshot of a Sample Loan



Improve Credit Profile

Loan Agreement

¥8,000 Amount

10.00% Interest

6 Months Term

2016-01-08 Paid off Date

已还清

Guarantee Principal

Prepayment Fee 1.00%

Repayment Method Monthly/Average Principal plus Interest

Detailed Loan Information | Bidding Record | Repayment Performance | Lender Information | Transfer Record

Borrower Information

Nickname 阿土掏淘

Credit Rating B

Basic Information

Age 38

Education Bachelor

Marriage Married

Asset Information

Income ¥2000-5000

House Yes

Mortgage No

Car Yes

Car Loan No

Work Information

Industry Media/Advertisement

Company Size 500+People

Position Editor

City Shiyan, Hubei Province

Working Experience 5+ Years

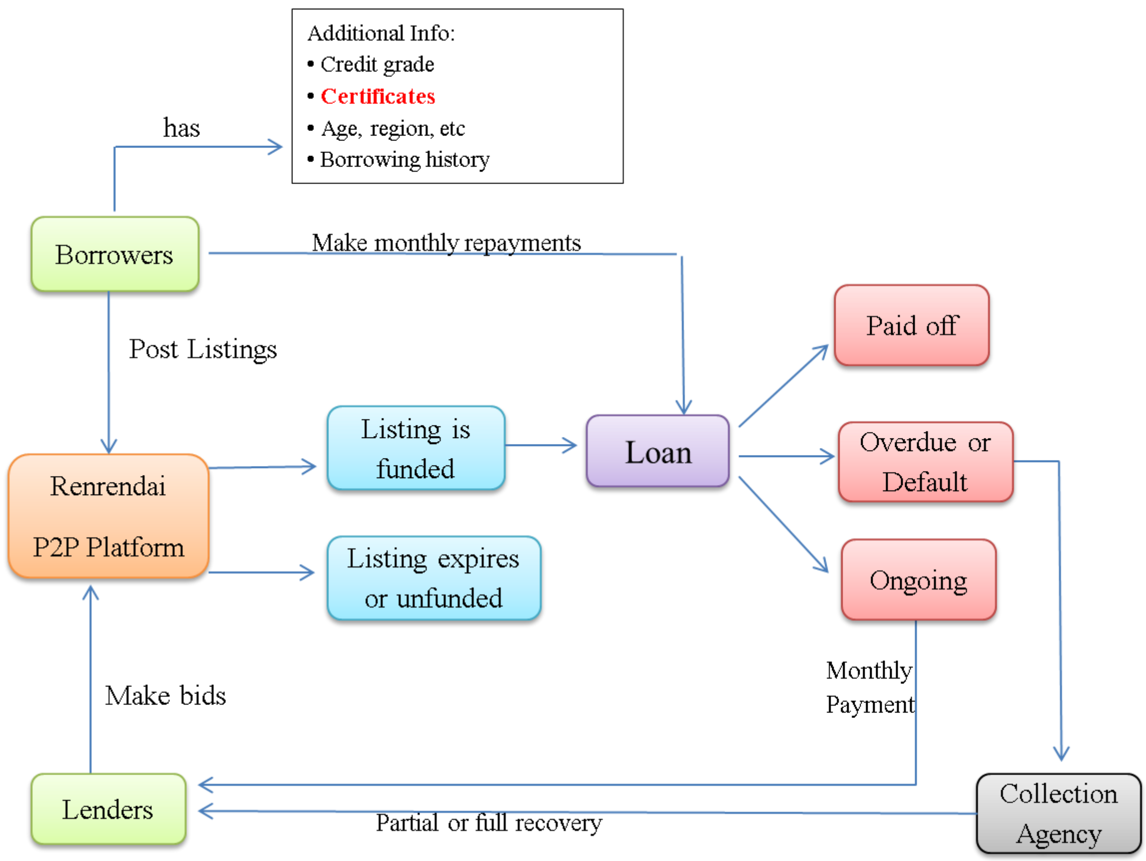
Audit Status

Certificate Item	Status	Audited Date
Remote Video	Completed	2012-03-24
Credit Report	Completed	2012-03-24
Identification Authentication	Completed	2012-03-24
Mobile Phone/Receipt	Completed	2012-03-24
Onsite Authentication		--
Occupation Authentication	Completed	2012-03-24
Bank Statement (Salary)	Completed	2012-03-24
Residence Proof	Completed	2012-03-24

Loan Description

I borrow for improving my credit profile.

Panel B: Lending and Borrowing Process



Panel C: List of Certificates

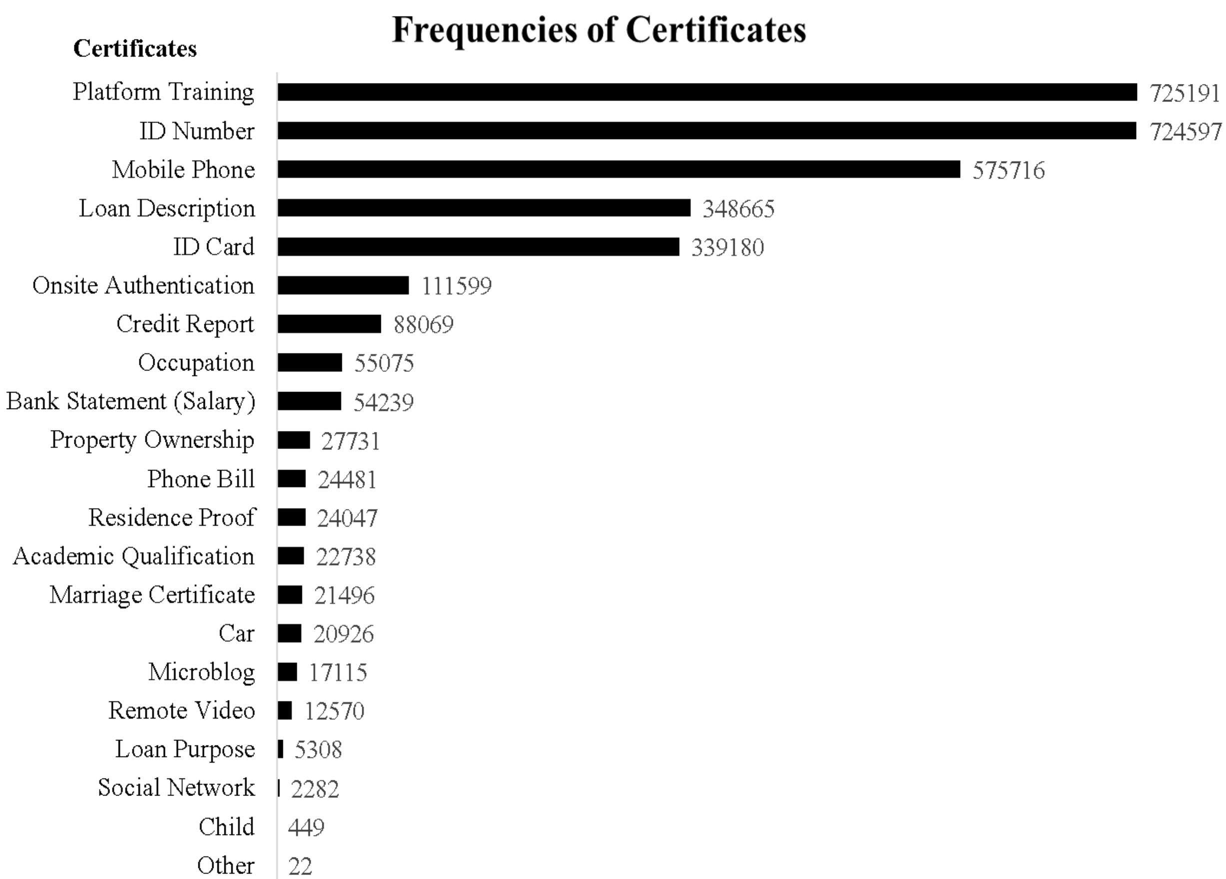
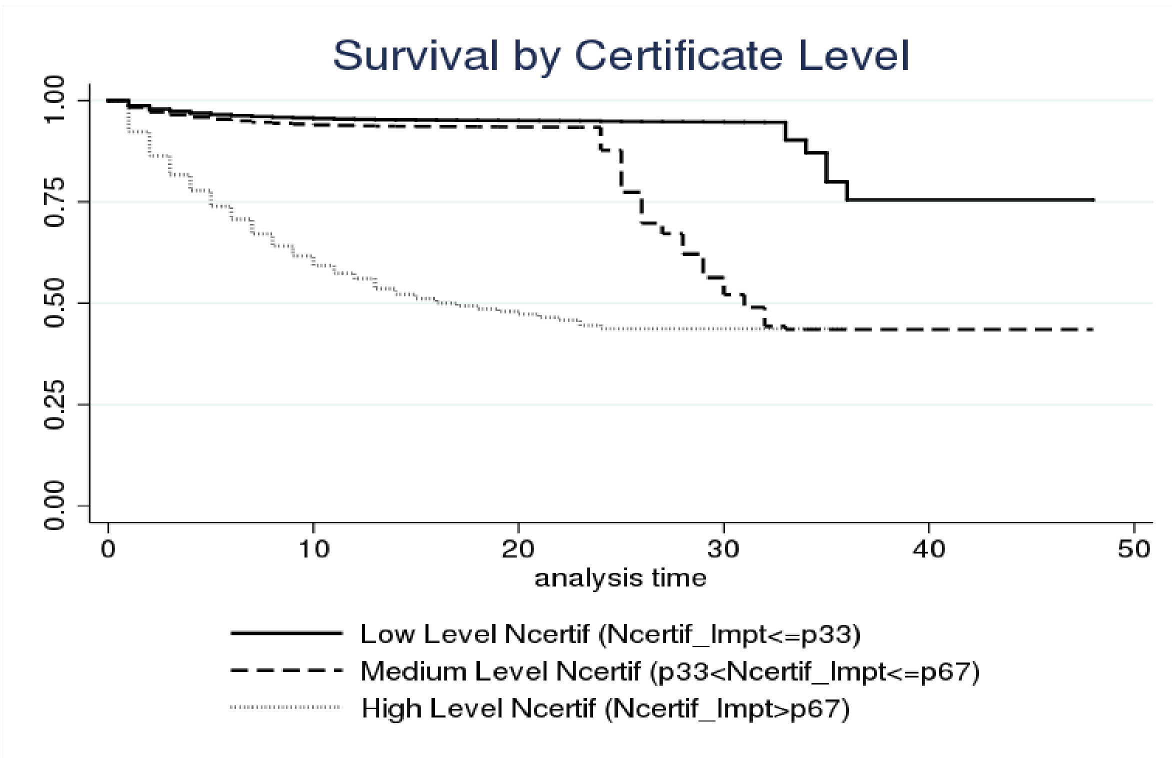


Figure 2: Loan Performance and Funding Success by Certificate Level

Panel A presents the performance of loans by certificate level, and Panel B presents the funding probability by certificate level. The sample is equally partitioned into three groups by the number of important certificates obtained by borrowers. Kaplan-Meier estimators of survival function and funding probability for the high-certificate group (above 67 percentile), medium-certificate group (33 percentile and 67 percentile), and low-certificate group (below 33 percentile) are presented.

Panel A: Loan Performance by Certificate Level



Panel B: Funding Success by Certificate Level

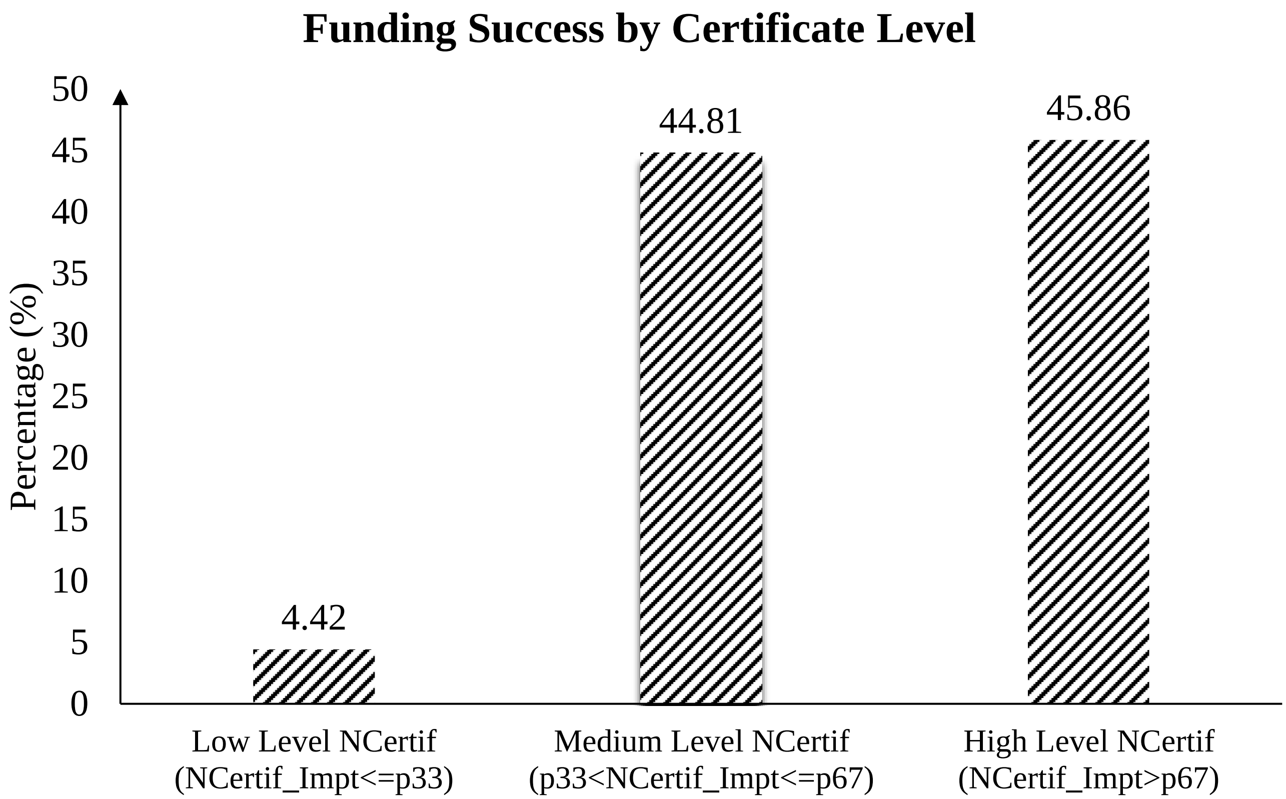


Table 1: Summary Statistics

Panel A reports the summary statistics of borrower characteristics. Panels B and C report the loan characteristics and repayment performance, respectively. Panel D report the bidding characteristics using bid level observations. A subsample of fully funded loans is used in Panel C and Panel D. The definitions of all variables are presented in Appendix 1.

Panel A: Borrower Characteristics (Full Sample)

Variable	N	mean	sd	p25	p50	p75	min	max
NCertif_Impt	742,292	2.773	1.318	2	2	3	0	11
NCertif	742,292	4.313	1.642	3	4	5	0	16
NCertif_Volun	742,292	0.658	1.264	0	0	1	0	11
CreditGrade	742,292	1.988	1.957	1	1	1	1	7
Age	742,276	33.529	7.373	28	31	37	18	89
EduLevel	670,294	1.857	0.780	1	2	2	1	4
JobIncomeLevel	594,206	4.068	1.218	3	4	5	1	7
JobLength	560,552	2.168	1.039	1	2	3	1	4
Single	723,459	0.521	0.500	0	1	1	0	1
Top20Province	560,663	0.562	0.496	0	1	1	0	1
HasAsset	742,292	0.400	0.490	0	0	1	0	1
HasLoan	742,292	0.166	0.372	0	0	0	0	1
NPriorLoan_Applied	742,291	2.416	3.741	1	1	3	1	148

Panel B: Loan Characteristics (Full sample)

Variable	N	mean	sd	p25	p50	p75	min	max
Loan_Amount (k)	742,292	59.648	86.885	12.000	40.000	62.000	1.000	3,000
Loan_Rate	742,292	13.113	2.674	12.000	13.000	13.200	3.000	24.400
Loan_Premium	742,039	7.376	2.547	6.000	7.000	7.750	-3.100	19.540
Loan_Duration (month)	742,292	17.689	10.005	12.000	18.000	24.000	1.000	48.000
Unsecured	742,292	0.969	0.172	1	1	1	0	1

Panel C: Loan Performance (Subsample of Funded Loans)

Variable	N	mean	sd	p25	p50	p75	min	max
Delinquent	163,152	0.037	0.188	0	0	0	0	1
BadDebt	163,152	0.062	0.329	0	0	0	0	2
BadDebt (=0)	163,152	0.963	0.188	1	1	1	0	1
BadDebt (=1)	163,152	0.012	0.107	0	0	0	0	1
BadDebt (=2)	163,152	0.025	0.156	0	0	0	0	1

Panel D: Bidding Characteristics

Variable	N	mean	sd	p25	p50	p75	min	max
Bidder Characteristics (Bid Level)								
Lender_Experience	7,546,182	0.729	0.774	0.101	0.503	1.083	0	5.272
IRR (%)	7,546,182	11.143	7.660	10.800	12.000	13.000	-100.000	24.400
Delinquent	7,546,182	0.018	0.132	0	0	0	0	1
BadDebt	7,546,182	0.029	0.225	0	0	0	0	2
NPriorBid	7,546,182	176.782	331.874	22	68	188	0	6,898
AveBidAmt (k)	7,546,182	1.622	2.992	0.460	0.827	1.722	0.050	1,200.000
BidAmt (k)	7,546,182	1.191	3.631	0.100	0.450	1.000	0.001	1,200.000
BidAmt/LoanAmt (%)	7,546,182	2.162	6.145	0.167	0.535	1.607	0.010	100.000
Loan Characteristics (Bid Level)								
Loan_Rate	7,546,182	11.930	1.214	10.800	12.000	13.000	3.000	24.400
Loan_Premium	7,546,182	6.263	0.943	5.650	6.150	7.050	-2.100	19.540
Loan_Duartion (month)	7,546,182	26.146	9.862	18	24	36	1	48
Loan_Amount (k)	7,546,182	78.871	92.857	46.700	69.100	94.200	3.000	3,000.000
Borrower Characteristics (Bid Level)								
NCertif_Impt	7,546,182	4.215	1.585	3	3	6	1	11
NCertif	7,546,182	5.285	1.744	4	4	7	2	16
NCertif_Volun	7,546,182	2.199	1.615	1	1	4	0	11
CreditGrade	7,546,182	5.719	1.062	6	6	6	1	7
Age	7,546,092	39.396	8.451	33	38	46	21	75
EduLevel	7,545,813	2.007	0.750	1	2	3	1	4
JobIncomeLevel	7,545,445	4.737	1.303	4	5	6	1	7
JobLength	7,533,194	1.586	0.995	1	1	2	1	4
Single	7,546,182	0.258	0.438	0	0	1	0	1
Top20Province	7,527,507	0.544	0.498	0	1	1	0	1
HasAsset	7,546,182	0.638	0.480	0	1	1	0	1
HasLoan	7,546,182	0.382	0.486	0	0	1	0	1
NpriorLoan_Applied	7,546,182	1.344	2.918	1	1	1	1	148

Table 2: Univariate Test

Panel A divides the full sample into funded and unfunded groups, demonstrating differences in borrower and loan characteristics between the funded and unfunded loans, while Panel B and C equally partition the full and funded sample by number of important certificates respectively. The number of observations, sample mean, difference in mean, and t-test significance are presented. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively. The definitions of all variables are presented in Appendix 1.

Panel A: Funded and Unfunded Loan Listings (Full Sample)

	Funded listings		Unfunded listings		Diff in mean
Variable	N	Mean	N	Mean	t-stat
Borrower Characteristics					
NCertif_Impt	163,152	3.934	579,140	2.446	1.489***
NCertif	163,152	5.122	579,140	4.085	1.037***
NCertif_Volun	163,152	1.905	579,140	0.306	1.599***
CreditGrade	163,152	5.360	579,140	1.038	4.322***
Age	163,149	38.417	579,127	32.152	6.265***
EduLevel	163,144	1.987	507,150	1.815	0.172***
JobIncomeLevel	163,145	4.504	431,061	3.903	0.601***
JobLength	162,952	1.737	397,600	2.344	-0.607***
Single	163,152	0.289	560,307	0.589	-0.300***
Top20Province	162,563	0.554	398,100	0.566	-0.012***
HasAsset	163,152	0.571	579,140	0.352	0.219***
HasLoan	163,152	0.320	579,140	0.122	0.198***
NPriorLoan_Applied	163,152	1.837	579,139	2.580	-0.742***
Loan Characteristics					
Loan_Amount (k)	163,152	55.067	579,140	60.937	-5.869***
Loan_Premium	163,074	6.357	578,965	7.663	-1.306***
Loan_Duration (month)	163,152	24.005	579,140	15.909	8.096***

Panel B: High Level and Low Level Certificate Loan Listings (Full Sample)

	High NCertif_Impt		Low NCertif_Impt		Diff in mean
Variable	N	Mean	N	Mean	t-stat
Borrower Characteristics					
Funding Success	319,251	0.453	423,041	0.044	0.408***
CreditGrade	319,251	3.004	423,041	1.221	1.784***
Age	319,248	35.255	423,028	32.227	3.028***
EduLevel	318,852	1.949	351,442	1.773	0.176***
JobIncomeLevel	318,411	4.224	275,795	3.887	0.337***
JobLength	317,979	2.089	242,573	2.271	-0.182***
Single	319,202	0.404	404,257	0.614	-0.209***
Top20Province	317,137	0.560	243,526	0.565	0.006***
HasAsset	319,251	0.570	423,041	0.272	0.298***
HasLoan	319,251	0.263	423,041	0.092	0.171***
NPriorLoan_Applied	319,251	3.373	423,040	1.694	1.679***
Loan Characteristics					
Loan_Amount (k)	319,240	59.780	423,034	59.549	0.231
Loan_Premium	319,125	7.221	422,914	7.493	-0.272***
Loan_Duration (month)	319,251	20.578	423,041	15.508	5.069***

Panel C: Loan Listings with High Level and Low Level Certificates (Subsample of Funded Loans)

Variable	High NCertif_Impt N	High NCertif_Impt Mean	Low NCertif_Impt N	Low NCertif_Impt Mean	Diff in mean t-stat
Borrower Characteristics					
CreditGrade	144,466	5.282	18,686	5.962	-0.680***
Age	144,463	38.154	18,686	40.451	-2.298***
EduLevel	144,458	1.986	18,686	1.994	-0.008
JobIncomeLevel	144,459	4.478	18,686	4.708	-0.230***
JobLength	144,266	1.678	18,686	2.190	-0.511***
Single	144,466	0.295	18,686	0.241	0.054***
Top20Province	143,880	0.566	18,683	0.460	0.106***
HasAsset	144,466	0.623	18,686	0.168	0.455***
HasLoan	144,466	0.350	18,686	0.086	0.264***
NPriorLoan_Applied	144,466	1.933	18,686	1.101	0.831***
Loan Characteristics					
Loan_Amount (k)	144,466	55.139	18.686	54.514	0.625
Loan_Premium	144,395	6.453	18,679	5.613	0.840***
Loan_Duration (month)	144,466	24.629	18,686	19.185	5.444***
Loan Performance					
Delinquent	144,466	0.041	18,686	0.005	0.036***
BadDebt	144,466	0.069	18,686	0.006	0.063***
BadDebt (=0)	144,466	0.959	18,686	0.995	-0.036***
BadDebt (=1)	144,466	0.013	18,686	0.003	0.009***
BadDebt (=2)	144,466	0.028	18,686	0.001	0.027***

Table 3: Number of Certificates and Delinquency

This table presents the logit regression results. Panel A reports the binary logit model results where dependent variable is Delinquent; a dummy equal to 1 if the loan is delinquent (i.e. overdue or default) and 0 otherwise. Panel B reports the ordered logit results where the dependent variable is a discrete variable BadDebt, which equals to 0 if the loan is on time repaid for every period, equals to 1 if the loan is fully repaid but with overdue records, and equals to 2 if the loan is unrepaid (i.e. defaulted). Within each panel, Specifications (1) and (2) focus on the number of important certificates, (3) and (4) focus on the number of all certificates, and (5) and (6) focus on the number of voluntarily applied certificates. Estimated coefficients are reported along with heteroskedasticity robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively. The definitions of all variables are presented in Appendix 1.

Panel A: Binary Logit Model

Dependent Variable: Delinquent	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt	0.019	0.032**				
	(0.014)	(0.014)				
NCertif			0.042***	0.067***		
			(0.010)	(0.010)		
NCertif_Volun					-0.004	0.022*
					(0.012)	(0.013)
CreditGrade	-1.463***	-1.475***	-1.458***	-1.470***	-1.462***	-1.478***
	(0.021)	(0.022)	(0.021)	(0.023)	(0.021)	(0.023)
logLoanAmount (k)	0.237***	0.094***	0.234***	0.095***	0.241***	0.095***
	(0.023)	(0.028)	(0.023)	(0.028)	(0.023)	(0.028)
Loan_Premium	0.067***	0.066***	0.066***	0.065***	0.067***	0.067***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
Loan_Duration (month)	0.029***	0.034***	0.029***	0.034***	0.029***	0.034***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age		0.024***		0.024***		0.024***
		(0.003)		(0.003)		(0.003)
EduLevel		-0.342***		-0.350***		-0.344***
		(0.021)		(0.021)		(0.021)
JobIncomeLevel		0.111***		0.104***		0.112***
		(0.016)		(0.016)		(0.016)
JobLength		0.047***		0.046**		0.048***
		(0.018)		(0.018)		(0.018)
Single		0.083**		0.094**		0.086**
		(0.037)		(0.037)		(0.037)
Top20Province		0.111***		0.108***		0.111***
		(0.033)		(0.033)		(0.033)
HasAsset		0.010		-0.003		0.015
		(0.041)		(0.041)		(0.041)
HasLoan		-0.372***		-0.385***		-0.371***
		(0.043)		(0.043)		(0.043)
NPriorLoan_Applied		-0.012		-0.016*		-0.012
		(0.008)		(0.008)		(0.008)
Constant	-0.803	-1.204**	-1.058*	-1.541***	-0.728	-1.160**
	(0.546)	(0.574)	(0.550)	(0.582)	(0.544)	(0.576)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	163,074	162,460	163,074	162,460	163,074	162,460
Pseudo R-squared	0.528	0.542	0.528	0.542	0.528	0.542

Panel B: Ordered Logit Model

Dependent Variable: BadDebt	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt	0.028**	0.042***				
	(0.013)	(0.014)				
NCertif			0.048***	0.075***		
			(0.009)	(0.010)		
NCertif_Volun					0.002	0.030**
					(0.012)	(0.013)
CreditGrade	-1.507***	-1.525***	-1.503***	-1.520***	-1.507***	-1.528***
	(0.021)	(0.023)	(0.021)	(0.023)	(0.021)	(0.023)
logLoanAmount (k)	0.256***	0.096***	0.254***	0.098***	0.261***	0.097***
	(0.023)	(0.028)	(0.023)	(0.028)	(0.023)	(0.028)
Loan_Premium	0.072***	0.073***	0.072***	0.072***	0.073***	0.074***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
Loan_Duration (month)	0.039***	0.045***	0.039***	0.045***	0.038***	0.045***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age		0.026***		0.026***		0.026***
		(0.003)		(0.003)		(0.003)
EduLevel		-0.376***		-0.386***		-0.379***
		(0.021)		(0.021)		(0.021)
JobIncomeLevel		0.123***		0.116***		0.124***
		(0.016)		(0.016)		(0.016)
JobLength		0.040**		0.038**		0.040**
		(0.018)		(0.018)		(0.018)
Single		0.076**		0.089**		0.080**
		(0.038)		(0.038)		(0.038)
Top20Province		0.121***		0.118***		0.121***
		(0.033)		(0.033)		(0.033)
HasAsset		-0.003		-0.015		0.002
		(0.041)		(0.040)		(0.041)
HasLoan		-0.366***		-0.379***		-0.365***
		(0.043)		(0.043)		(0.043)
NPriorLoan_Applied		-0.016**		-0.020**		-0.017**
		(0.008)		(0.008)		(0.008)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	163,074	162,460	163,074	162,460	163,074	162,460
Pseudo R-squared	0.469	0.484	0.528	0.485	0.469	0.542

Table 4: Hazard Model Estimation

This table investigates the impact of the number of certificates on the conditional probability (i.e. hazard) of delinquency. In Panel A, delinquency is defined as default or overdue payments for 1 month or longer, while in Panel B, default or overdue payments for 4 months or longer is regarded as delinquency. Within each panel, Specifications (1) and (2) focus on the number of important certificates, (3) and (4) focus on the number of all certificates, and (5) and (6) focus on the number of voluntarily applied certificates. Coefficients from the variance-corrected multiple-failure Cox proportional hazards model (i.e. Anderson-Gill model) are reported, along with standard errors in parentheses clustered at loan level. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively. The definitions of all variables are presented in Appendix 1.

Panel A: One-month Overdue Payment Criterion

Dependent Variable: Delinquency Hazard	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt	0.209***	0.204***				
	(0.006)	(0.006)				
NCertif			0.154***	0.151***		
			(0.004)	(0.004)		
NCertif_Volun					0.180***	0.177***
					(0.006)	(0.006)
CreditGrade	-0.927***	-0.900***	-0.898***	-0.871***	-0.951***	-0.922***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
logLoanAmount (k)	0.177***	0.172***	0.179***	0.175***	0.184***	0.177***
	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Loan_Premium	0.069***	0.090***	0.081***	0.101***	0.061***	0.083***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
Loan_Duration (month)	-0.024***	-0.026***	-0.025***	-0.027***	-0.022***	-0.025***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age		0.004***		0.004***		0.004***
		(0.000)		(0.000)		(0.000)
EduLevel		0.001		-0.003		-0.003
		(0.005)		(0.005)		(0.005)
JobIncomeLevel		0.009**		0.007*		0.011***
		(0.004)		(0.004)		(0.004)
JobLength		0.058***		0.059***		0.062***
		(0.004)		(0.004)		(0.004)
Single		0.021**		0.019**		0.018*
		(0.009)		(0.009)		(0.010)
Top20Province		0.012		0.011		0.012
		(0.008)		(0.008)		(0.008)
HasAsset		-0.029**		-0.024**		-0.024**
		(0.012)		(0.012)		(0.012)
HasLoan		-0.088***		-0.088***		-0.095***
		(0.010)		(0.010)		(0.010)
NPriorLoan_Applied		0.008*		0.007*		0.003
		(0.004)		(0.004)		(0.005)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,757,306	5,751,091	5,757,306	5,751,091	5,757,306	5,751,091
No. of Listings	220,606	219,924	22,0606	219,924	220,606	219,924
No. of Failures	398,790	398,105	398,790	398,105	398,790	398,105
Pseudo R-square	0.076	0.076	0.076	0.076	0.075	0.076

Panel B: Four-month Consecutive Overdue Payment Criterion

Dependent Variable: Delinquency Hazard	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt	0.186***	0.182***				
	(0.007)	(0.007)				
NCertif			0.134***	0.132***		
			(0.005)	(0.005)		
NCertif_Volun					0.156***	0.154***
					(0.007)	(0.007)
CreditGrade	-0.951***	-0.922***	-0.925***	-0.896***	-0.971***	-0.942***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
logLoanAmount (k)	0.183***	0.174***	0.185***	0.176***	0.189***	0.178***
	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)
Loan_Premium	0.058***	0.084***	0.070***	0.094***	0.050***	0.076***
	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)	(0.010)
Loan_Duration (month)	-0.010***	-0.013***	-0.010***	-0.014***	-0.008***	-0.012***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
Age		0.004***		0.004***		0.004***
		(0.000)		(0.000)		(0.000)
EduLevel		-0.010*		-0.013**		-0.013**
		(0.006)		(0.006)		(0.006)
JobIncomeLevel		0.018***		0.017***		0.020***
		(0.004)		(0.004)		(0.004)
JobLength		0.054***		0.056***		0.056***
		(0.004)		(0.004)		(0.004)
Single		0.032***		0.031***		0.031***
		(0.010)		(0.010)		(0.010)
Top20Province		0.013		0.012		0.013
		(0.008)		(0.008)		(0.008)
HasAsset		-0.018		-0.015		-0.014
		(0.012)		(0.012)		(0.012)
HasLoan		-0.102***		-0.102***		-0.107***
		(0.010)		(0.010)		(0.010)
NPriorLoan_Applied		0.002		0.002		-0.002
		(0.007)		(0.006)		(0.007)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,757,306	5,751,091	5,757,306	5,751,091	5,757,306	5,751,091
No. of Listings	220,606	219,924	220,606	219,924	220,606	219,924
No. of Failures	366,223	365,715	366,223	365,715	366,223	365,715
Pseudo R-square	0.067	0.068	0.067	0.068	0.067	0.067

Table 5: Determinants of Number of Certificates

This table presents the relationship between a borrower's credit grade and the number of certificates obtained. The independent variables are the number of important certificates, the number of all certificates, and the number of voluntarily applied certificates in specifications (1)-(2), (3)-(4), and (5)-(6) respectively. OLS regression coefficients are reported, along with heteroskedasticity robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively. The definitions of all variables are presented in Appendix 1.

	Dependent Variable: NCertif_Impt		Dependent Variable: NCertif		Dependent Variable: NCertif_Volun	
	(1)	(2)	(3)	(4)	(5)	(6)
CreditGrade	-0.118***	-0.119***	-0.325***	-0.337***	-0.005	-0.003
	(0.003)	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)
Age		-0.004***		-0.006***		-0.005***
		(0.000)		(0.000)		(0.000)
EduLevel		0.006**		0.062***		0.041***
		(0.003)		(0.005)		(0.003)
JobIncomeLevel		0.009***		0.003		0.008***
		(0.002)		(0.003)		(0.002)
JobLength		-0.050***		-0.110***		-0.048***
		(0.004)		(0.006)		(0.004)
Single		-0.028***		-0.077***		-0.060***
		(0.005)		(0.007)		(0.005)
Top20Province		0.065***		0.103***		0.066***
		(0.005)		(0.006)		(0.005)
HasAsset		0.395***		0.435***		0.403***
		(0.006)		(0.008)		(0.007)
HasLoan		0.026***		0.067***		0.049***
		(0.007)		(0.010)		(0.008)
NPriorLoan_Applied		0.040***		0.076***		0.060***
		(0.001)		(0.002)		(0.002)
Constant	4.524***	4.023***	9.474***	8.749***	3.282***	2.543***
	(0.111)	(0.099)	(0.215)	(0.213)	(0.169)	(0.165)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	163,152	162,538	163,152	162,538	163,152	162,538
Adj. R-squared	0.629	0.670	0.510	0.574	0.587	0.647

Table 6: Certificates and Funding Success

Panels A presents the logit regression results with dependent variable Funding Success; a dummy equal to 1 if the loan is successfully funded and 0 otherwise. Specifications (1) and (2) focus on the number of important certificates, (3) and (4) focus on the number of all certificates, and (5) and (6) focus on the number of voluntarily applied certificates. Panel B further divides the sample into two groups by credit grade: AA and A, and B and below. Estimated coefficients are reported along with heteroskedasticity robust standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Panel A: Certificates and Funding Success

Dependent Variable: Funding Success	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt	0.729***	0.633***				
	(0.005)	(0.006)				
NCertif			0.449***	0.367***		
			(0.004)	(0.004)		
NCertif_Volun					0.547***	0.452***
					(0.005)	(0.006)
CreditGrade	1.617***	1.553***	1.707***	1.637***	1.592***	1.528***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
logLoanAmount (k)	-0.612***	-0.889***	-0.572***	-0.865***	-0.542***	-0.854***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Loan_Premium	-0.114***	-0.105***	-0.109***	-0.100***	-0.103***	-0.097***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Loan_Duration (month)	0.015***	0.022***	0.012***	0.020***	0.012***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age		0.034***		0.037***		0.037***
		(0.001)		(0.001)		(0.001)
EduLevel		0.209***		0.187***		0.191***
		(0.010)		(0.010)		(0.010)
JobIncomeLevel		0.301***		0.316***		0.333***
		(0.007)		(0.007)		(0.007)
JobLength		0.092***		0.122***		0.128***
		(0.008)		(0.008)		(0.008)
Single		-0.151***		-0.124***		-0.117***
		(0.018)		(0.017)		(0.017)
Top20Province		-0.182***		-0.183***		-0.187***
		(0.016)		(0.015)		(0.015)
HasAsset		-0.104***		-0.009		-0.026
		(0.019)		(0.019)		(0.019)
HasLoan		0.005		0.050**		0.039*
		(0.021)		(0.021)		(0.021)
NPriorLoan_Applied		-0.079***		-0.080***		-0.076***
		(0.001)		(0.001)		(0.001)
Constant	-6.950***	-8.199***	-7.851***	-9.066***	-5.659***	-7.338***
	(0.226)	(0.211)	(0.247)	(0.229)	(0.244)	(0.225)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	742,021	556,538	742,021	556,538	742,021	556,538
Pseudo R-squared	0.809	0.801	0.802	0.794	0.797	0.792

Panel B: Certificates and Funding Success by Credit Grade

Dependent Variable: Funding Success	(1)	(2)	(3)	(4)	(5)	(6)
		AA			HR	
NCertif_Impt	0.028			1.078***		
	(0.050)			(0.008)		
NCertif		-0.051			0.740***	
		(0.037)			(0.006)	
NCertif_Volun			-0.025			0.855***
			(0.041)			(0.007)
logLoanAmount (k)	0.071	0.034	0.049	-0.943***	-0.913***	-0.901***
	(0.084)	(0.085)	(0.085)	(0.012)	(0.011)	(0.011)
Loan_Premium	0.058*	0.061*	0.060*	-0.084***	-0.083***	-0.076***
	(0.034)	(0.034)	(0.034)	(0.004)	(0.004)	(0.004)
Loan_Duration (month)	-0.065***	-0.061***	-0.063***	0.011***	0.010***	0.013***
	(0.012)	(0.012)	(0.012)	(0.001)	(0.001)	(0.001)
Age	0.026	0.019	0.022	0.022***	0.029***	0.030***
	(0.020)	(0.020)	(0.020)	(0.002)	(0.002)	(0.002)
EduLevel	0.250*	0.218	0.228*	0.261***	0.174***	0.192***
	(0.140)	(0.139)	(0.138)	(0.013)	(0.012)	(0.012)
JobIncomeLevel	0.044	0.058	0.055	0.343***	0.363***	0.371***
	(0.080)	(0.079)	(0.079)	(0.009)	(0.009)	(0.009)
JobLength	0.157	0.120	0.138	0.296***	0.307***	0.313***
	(0.111)	(0.113)	(0.113)	(0.011)	(0.011)	(0.011)
Single	-0.030	-0.148	-0.108	-0.157***	-0.081***	-0.072***
	(0.308)	(0.309)	(0.311)	(0.022)	(0.022)	(0.022)
Top20Province	-0.222	-0.293	-0.263	-0.229***	-0.219***	-0.236***
	(0.211)	(0.208)	(0.207)	(0.020)	(0.020)	(0.019)
HasAsset	-0.341	-0.302	-0.327	-0.162***	-0.030	-0.051**
	(0.342)	(0.343)	(0.342)	(0.024)	(0.024)	(0.024)
HasLoan	-0.000	0.015	0.020	-0.127***	-0.084***	-0.084***
	(0.195)	(0.193)	(0.194)	(0.027)	(0.027)	(0.027)
NPriorLoan_Applied	0.014***	0.015***	0.014***	-0.098***	-0.096***	-0.070***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)
Constant	-1.499	-0.382	-0.949	-6.949***	-8.240***	-5.160***
	(1.084)	(1.145)	(1.073)	(0.225)	(0.234)	(0.236)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	1,443	1,443	1,443	397,388	397,388	397,388
Pseudo R-squared	0.320	0.321	0.320	0.305	0.273	0.254

Table 7: Lender Experience, Number of Certificates and Investment Performance

This table investigates how bidders' experiences affect their investment decisions using bidding level data. The OLS regression results are presented below, where Lender_Experience is the measured by the year since the first investment. The dependent variable in specification (1) to (5) is number of important certificates, number of all certificates, and number of voluntarily applied certificates, IRR, and Delinquent, respectively. Coefficients are reported along with standard errors in parentheses clustered at lender level. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively. The definitions of all variables are presented in Appendix 1.

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	NCertif_Impt	NCertif	NCertif_Volun	IRR	Delinquent
Lender_Experience	-0.008***	-0.002	-0.006***	0.071***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.005)	(0.000)
logLoanAmount (k)	-0.126***	-0.372***	-0.009***	3.853***	0.011***
	(0.001)	(0.003)	(0.002)	(0.021)	(0.000)
Loan_Premium	0.068***	0.080***	0.035***	-0.556***	-0.003***
	(0.001)	(0.002)	(0.002)	(0.010)	(0.000)
Loan_Duration (month)	0.206***	0.156***	0.205***	1.002***	0.001***
	(0.003)	(0.004)	(0.004)	(0.018)	(0.000)
CreditGrade	-0.009***	-0.007***	-0.010***	-0.071***	-0.071***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)
Age	-0.003***	-0.003***	-0.003***	-0.009***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Edulevel	-0.007***	0.017***	0.008***	0.377***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.007)	(0.000)
JobIncomelevel	0.015***	0.002***	0.016***	-0.150***	0.002***
	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)
JobLength	-0.103***	-0.206***	-0.108***	0.059***	-0.001***
	(0.001)	(0.002)	(0.001)	(0.006)	(0.000)
Single	-0.001	-0.021***	-0.012***	0.088***	-0.001***
	(0.001)	(0.001)	(0.001)	(0.006)	(0.000)
Top20Province	0.035***	0.065***	0.041***	-0.096***	0.001***
	(0.001)	(0.001)	(0.001)	(0.005)	(0.000)
HasAsset	0.312***	0.347***	0.322***	0.365***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.010)	(0.000)
HasLoan	-0.051***	-0.029***	-0.029***	0.501***	-0.007***
	(0.001)	(0.002)	(0.001)	(0.011)	(0.000)
NPriorLoan_Applied	0.057***	0.101***	0.079***	-0.009***	0.000***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.000)
Constant	1.911***	7.338***	0.520***	-11.104***	0.371***
	(0.070)	(0.105)	(0.086)	(0.535)	(0.011)
Yr Qr FE	YES	YES	YES	YES	YES
Cluster Robust	Lender	Lender	Lender	Lender	Lender
Observations	7,523,012	7,523,012	7,523,012	7,523,012	7,523,012
Adj. R-squared	0.792	0.711	0.772	0.211	0.289

Table 8: Sub Sample Regression: Unsecured Loans

Panel A presents the decomposed funding success rate by loans of different types. Guarantee_Credit includes the credit-based loans, Guarantee_Onsite includes loans with onsite authentication by the platform, Guarantee_Collateral includes collateralized loans, and Guarantee_Platform includes platform guaranteed loans.[10] In Panel B, the first three specifications study the how the number of certificates affects the conditional probability (i.e. hazard) of delinquency, where delinquency is defined as default or overdue payments for 1 month or longer. The last three specifications investigate how the number of certificates affects funding success, where the dependent variable Funding Success equals 1 if the loan is successfully funded and 0 otherwise. Specification (1) and (3) focus on the number of important certificates, (2) and (5) focus on the number of all certificates, and (3) and (6) focus on the number of voluntarily applied certificates. Coefficients along with heteroskedasticity robust standard errors in parentheses are reported for logit regressions, Hazard models present coefficients along with standard errors clustered at loan level in parentheses clustered at loan level. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

Panel A: Loan Types by Guarantee Status

Guarantee Type	Full Sample			Funded Sample
	Number	Percentage	Funding Success	Number
Guarantee_Credit	605,773	81.6%	4.5%	27,136
Guarantee_Onsite	113,873	15.3%	99.8%	113,690
Guarantee_Collateral	89	0.0%	97.8%	87
Guarantee_Platform	22,557	3.0%	98.6%	22,239
Total	742,292	100.0%	22.0%	163,152

[10] According to the information on the platform, credit-based loans (Xinyong Renzheng Biao in Pinyin) are granted based on the borrower's credit quality, and neither the principal nor the interest are guaranteed. Loans with onsite authentication by the platform (Shidi Renzheng Biao in Pinyin) are similar to the credit-based loans with the only difference that the borrowers pass the onsite interview by the platform (or its business partners). Collateralized loans (Zhineng Licai Biao in Pinyin) are granted against the receivables of borrowers, who usually are small business owners. And platform-guaranteed loans (Jigou Danbao Biao in Pinyin) are loans to which the platform (or its business partners) holds joint liability of repayment. Thus the first two types of loans are unsecured and the last two types are secured.

Panel B: Number of Certificates, Delinquency and Funding Success

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Delinquency Hazard			Dependent Variable: Funding Success		
NCertif_Impt	0.212***			0.651***		
	(0.006)			(0.007)		
NCertif		0.163***			0.371***	
		(0.004)			(0.004)	
NCertif_Volun			0.183***			0.467***
			(0.006)			(0.007)
CreditGrade	-0.895***	-0.868***	-0.918***	1.557***	1.648***	1.536***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)	(0.007)
logLoanAmount (k)	0.171***	0.175***	0.176***	-0.913***	-0.880***	-0.873***
	(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Loan_Premium	0.086***	0.098***	0.079***	-0.101***	-0.097***	-0.093***
	(0.008)	(0.008)	(0.007)	(0.004)	(0.004)	(0.004)
Loan_Duration (month)	-0.027***	-0.028***	-0.026***	0.023***	0.021***	0.023***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Age	0.004***	0.004***	0.004***	0.034***	0.036***	0.036***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
EduLevel	-0.003	-0.009	-0.007	0.208***	0.187***	0.189***
	(0.005)	(0.005)	(0.006)	(0.010)	(0.010)	(0.010)
JobIncomeLevel	0.007**	0.005	0.010***	0.311***	0.325***	0.343***
	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.008)
JobLength	0.042***	0.039***	0.048***	0.104***	0.135***	0.141***
	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)	(0.009)
Single	0.023**	0.021**	0.020**	-0.143***	-0.118***	-0.108***
	(0.010)	(0.010)	(0.010)	(0.018)	(0.018)	(0.018)
Top20Province	0.012	0.012	0.011	-0.192***	-0.192***	-0.199***
	(0.008)	(0.008)	(0.008)	(0.016)	(0.016)	(0.016)
HasAsset	-0.022*	-0.015	-0.019	-0.095***	-0.006	-0.024
	(0.012)	(0.012)	(0.012)	(0.020)	(0.019)	(0.019)
HasLoan	-0.082***	-0.080***	-0.090***	-0.002	0.044*	0.030
	(0.010)	(0.010)	(0.010)	(0.023)	(0.023)	(0.023)
NPriorLoan_Applied	0.006	0.005	0.002	-0.080***	-0.081***	-0.077***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Constant				-8.326***	-9.190***	-7.453***
				(0.335)	(0.297)	(0.389)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,309,715	5,309,715	5,309,715	532,893	532,893	532,893
No. of Listings	5,309,715	195,374	195,374			
No. of Failures	195,374	390,964	390,964			
Pseudo R-squared	0.075	0.075	0.075	0.788	0.779	0.778

Table 9: Principal Component Analysis

The first three specifications study the how the principal component of certificates affects the conditional probability (i.e. hazard) of delinquency, where delinquency is defined as default or overdue payments for 1 month or longer. The last three specifications investigate how the principal component of certificates affects funding success, where the dependent variable, Funding Success, equals 1 if the loan is successfully funded and 0 otherwise. Specification (1) and (3) focus on the principal component of important certificates, (2) and (5) focus on the principal component of all certificates, and (3) and (6) focus on the principal component of voluntarily applied certificates. Coefficients along with heteroskedasticity robust standard errors in parentheses are reported for logit regressions, Hazard models present coefficients along with standard errors clustered at loan level in parentheses clustered at loan level. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Delinquency Default			Dependent Variable: Funding Success		
Comp1_Impt	0.153***			0.780***		
	(0.007)			(0.008)		
Comp1		0.053***			0.702***	
		(0.006)			(0.007)	
Comp1_Volun			0.093***			0.496***
			(0.005)			(0.007)
CreditGrade	-0.961***	-0.925***	-0.931***	1.315***	1.325***	1.535***
	(0.006)	(0.006)	(0.005)	(0.007)	(0.007)	(0.007)
logLoanAmount (k)	0.185***	0.194***	0.192***	-0.858***	-0.830***	-0.812***
	(0.011)	(0.011)	(0.011)	(0.009)	(0.008)	(0.008)
Loan_Premium	0.073***	0.063***	0.072***	-0.101***	-0.097***	-0.093***
	(0.008)	(0.008)	(0.008)	(0.004)	(0.003)	(0.003)
Loan_Duration (month)	-0.025***	-0.022***	-0.024***	0.016***	0.014***	0.015***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)
Age	0.004***	0.004***	0.004***	0.035***	0.033***	0.034***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
EduLevel	0.001	0.001	0.001	0.205***	0.217***	0.234***
	(0.005)	(0.006)	(0.005)	(0.010)	(0.010)	(0.010)
JobIncomeLevel	0.020***	0.023***	0.022***	0.397***	0.433***	0.406***
	(0.004)	(0.004)	(0.004)	(0.008)	(0.008)	(0.007)
JobLength	0.068***	0.069***	0.067***	0.148***	0.173***	0.186***
	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)	(0.008)
Single	0.027***	0.030***	0.031***	-0.169***	-0.177***	-0.176***
	(0.010)	(0.010)	(0.010)	(0.018)	(0.018)	(0.017)
Top20Province	0.014*	0.014	0.014*	-0.162***	-0.158***	-0.168***
	(0.008)	(0.008)	(0.008)	(0.016)	(0.016)	(0.016)
HasAsset	-0.004	0.002	0.004	0.057***	0.117***	0.121***
	(0.012)	(0.012)	(0.012)	(0.019)	(0.019)	(0.018)
HasLoan	-0.094***	-0.100***	-0.094***	0.101***	0.137***	0.140***
	(0.010)	(0.010)	(0.010)	(0.023)	(0.022)	(0.022)
NPriorLoan_Applied	0.019***	0.021***	0.025***	-0.047***	-0.036***	-0.041***
	(0.004)	(0.004)	(0.004)	(0.001)	(0.001)	(0.001)
Constant				-5.865***	-5.868***	-6.672***
				(0.270)	(0.251)	(0.279)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,751,091	5,751,091	5,751,091	556,538	556,538	556,538
No. of listings	219,924	219,924	219,924			
No. of failures	398,105	398,105	398,105			
Pseudo R-squared	0.075	0.075	0.075	0.808	0.804	0.794

Table 10: Alternative Channel: Borrower Myopia

This table investigates the how the number of certificates influences the conditional probability (i.e. hazard) of delinquency differently among borrowers with and without previous default records. In Panel A, delinquency is defined as default or overdue payments for 1 month or longer, while in Panel B, default or overdue payments for 4 months or longer is regarded as delinquency. Within each panel, Specifications (1) and (2) focus on the number of important certificates, (3) and (4) focus on the number of all certificates, and (5) and (6) focus on the number of voluntarily applied certificates. Coefficients from the variance-corrected multiple-failure Cox proportional hazards model (Anderson-Gill model) are reported along with standard errors in parentheses clustered at loan level. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively. The definitions of all variables are presented in Appendix 1.

Panel A: One-month Overdue Payment Criterion

Dependent Variable: Delinquency	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt*Default	-	-				
	(0.010)	(0.010)				
NCertif*Default			-	-		
			(0.008)	(0.008)		
NCertif_Volun*Default					-	-
					(0.010)	(0.011)
NCertif_Impt	0.299***	0.292***				
	(0.008)	(0.008)				
NCertif			0.218***	0.215***		
			(0.005)	(0.005)		
NCertif_Volun					0.277***	0.270***
					(0.007)	(0.007)
Default	2.035***	2.053***	1.884***	1.916***	1.509***	1.518***
	(0.061)	(0.062)	(0.068)	(0.070)	(0.039)	(0.040)
CreditGrade	-	-	-	-	-	-
	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
logLoanAmount (k)	0.163***	0.153***	0.162***	0.155***	0.172***	0.160***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.013)	(0.012)
Loan_Premium	0.056***	0.078***	0.067***	0.087***	0.051***	0.073***
	(0.008)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
Loan_Duration (month)	-	-	-	-	-	-
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age		0.003***		0.003***		0.003***
		(0.000)		(0.000)		(0.000)
EduLevel		0.036***		0.032***		0.033***
		(0.005)		(0.005)		(0.006)
JobIncomeLevel		0.002		-0.000		0.003
		(0.004)		(0.004)		(0.004)
JobLength		0.067***		0.068***		0.069***
		(0.005)		(0.005)		(0.005)
Single		0.016		0.013		0.014
		(0.010)		(0.010)		(0.011)
Top20Province		0.013		0.010		0.014
		(0.009)		(0.009)		(0.009)
HasAsset		-0.020		-0.021*		-0.017
		(0.013)		(0.013)		(0.013)
HasLoan		-		-		-
		(0.010)		(0.010)		(0.010)
NPriorLoan_Applied		0.011***		0.008**		0.009**
		(0.004)		(0.004)		(0.004)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,757,306	5,751,091	5,757,306	5,751,091	5,757,306	5,751,091
No. of Listings	220,606	219,924	220,606	219,924	220,606	219,924
No. of Failures	398,790	398,105	398,790	398,105	398,790	398,105
Pseudo R-square	0.078	0.079	0.078	0.078	0.078	0.078

Panel B: Four-month Consecutive Overdue Payment Criterion

Dependent Variable: Delinquency	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt*Default	-	-				
	(0.013)	(0.014)				
NCertif*Default			-	-		
			(0.010)	(0.011)		
NCertif_Volun*Default					-	-
					(0.014)	(0.015)
NCertif_Impt	0.293***	0.290***				
	(0.012)	(0.013)				
NCertif			0.218***	0.221***		
			(0.009)	(0.009)		
NCertif_Volun					0.277***	0.273***
					(0.011)	(0.012)
Default	3.574***	3.611***	3.429***	3.504***	3.068***	3.082***
	(0.087)	(0.090)	(0.095)	(0.100)	(0.062)	(0.064)
CreditGrade	-	-	-	-	-	-
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
logLoanAmount (k)	0.164***	0.146***	0.160***	0.144***	0.169***	0.150***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)
Loan_Premium	0.038***	0.066***	0.049***	0.075***	0.033***	0.062***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.010)	(0.011)
Loan_Duration (month)	-	-	-	-	-	-
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age		0.003***		0.003***		0.003***
		(0.000)		(0.000)		(0.000)
EduLevel		0.037***		0.036***		0.036***
		(0.006)		(0.006)		(0.006)
JobIncomeLevel		0.008**		0.007*		0.010**
		(0.004)		(0.004)		(0.004)
JobLength		0.069***		0.071***		0.070***
		(0.005)		(0.005)		(0.005)
Single		0.024**		0.022**		0.024**
		(0.011)		(0.011)		(0.011)
Top20Province		0.012		0.010		0.013
		(0.009)		(0.009)		(0.009)
HasAsset		-0.009		-0.014		-0.005
		(0.013)		(0.013)		(0.014)
HasLoan		-		-		-
		(0.010)		(0.010)		(0.011)
NPriorLoan_Applied		0.011*		0.004		0.011**
		(0.006)		(0.006)		(0.005)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,757,306	5,751,09	5,757,30	5,751,09	5,757,30	5,751,09
No. of Listings	220,606	219,924	220,606	219,924	220,606	219,924
No. of Failures	366,223	365,715	366,223	365,715	366,223	365,715
Pseudo R-square	0.073	0.073	0.073	0.073	0.073	0.073

Table 11: Intentional Default

This table investigates the impact of the number of certificates on the conditional probability (i.e. hazard) of early delinquency. In Panel A, early delinquency is defined as default or overdue payments for 1 month or longer within the first three months after the loan is granted, while in Panel B, default or overdue payments for 1 month or longer within the first 1/6 of the loan period is regarded as early delinquency. Within each panel, Specifications (1) and (2) focus on the number of important certificates, (3) and (4) focus on the number of all certificates, and (5) and (6) focus on the number of voluntarily applied certificates. Coefficients from the variance-corrected multiple-failure Cox proportional hazards model (Anderson-Gill model) are reported along with standard errors in parentheses clustered at loan level. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively. The definitions of all variables are presented in Appendix 1.

Panel A: Delinquent in the First Three Months

Dependent Variable: Delinquency Hazard	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt	0.011	0.029***				
	(0.009)	(0.009)				
NCertif			0.029***	0.050***		
			(0.007)	(0.007)		
NCertif_Volun					-0.003	0.020**
					(0.008)	(0.009)
CreditGrade	-	-	-	-	-	-
	(0.015)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
logLoanAmount (k)	0.083***	0.049***	0.080***	0.050***	0.085***	0.050***
	(0.015)	(0.018)	(0.015)	(0.018)	(0.015)	(0.018)
Loan_Premium	0.050***	0.045***	0.050***	0.044***	0.050***	0.045***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Loan_Duration (month)	-	-	-	-	-	-
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age		0.001		0.002		0.001
		(0.002)		(0.002)		(0.002)
EduLevel		-		-		-
		(0.014)		(0.014)		(0.014)
JobIncomeLevel		0.023**		0.019*		0.023**
		(0.011)		(0.011)		(0.011)
JobLength		0.033***		0.032***		0.033***
		(0.012)		(0.012)		(0.012)
Single		-0.056**		-		-0.059**
		(0.025)		(0.025)		(0.025)
Top20Province		0.069***		0.067***		0.070***
		(0.022)		(0.022)		(0.022)
HasAsset		0.086***		0.079***		0.090***
		(0.027)		(0.027)		(0.027)
HasLoan		-		-		-
		(0.030)		(0.030)		(0.030)
NPriorLoan_Applied		-		-		-
		(0.005)		(0.005)		(0.005)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,757,306	5,751,091	5,757,306	5,751,091	5,757,306	5,751,091
No. of Listings	220,606	219,924	220,606	219,924	220,606	219,924
No. of Failures	8,966	8,886	8,966	8,886	8,966	8,886
Pseudo R-square	0.189	0.192	0.189	0.192	0.189	0.192

Panel B: Delinquent in the First 1/6 Period

Dependent Variable: Delinquency	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt	0.021	0.040***				
	(0.014)	(0.015)				
NCertif			0.018*	0.039***		
			(0.010)	(0.011)		
NCertif_Volun					0.002	0.028**
					(0.013)	(0.013)
CreditGrade	-	-	-	-	-	-
	(0.022)	(0.023)	(0.022)	(0.023)	(0.022)	(0.023)
logLoanAmount (k)	0.191***	0.173***	0.191***	0.174***	0.194***	0.174***
	(0.023)	(0.028)	(0.023)	(0.028)	(0.023)	(0.028)
Loan_Premium	0.125***	0.117***	0.125***	0.117***	0.125***	0.118***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Loan_Duration (month)	0.096***	0.096***	0.096***	0.096***	0.096***	0.096***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age		0.005*		0.005*		0.005*
		(0.003)		(0.003)		(0.003)
EduLevel		-		-		-
		(0.019)		(0.019)		(0.019)
JobIncomeLevel		0.010		0.008		0.010
		(0.016)		(0.016)		(0.016)
JobLength		0.019		0.019		0.019
		(0.017)		(0.017)		(0.017)
Single		-0.026		-0.031		-0.028
		(0.034)		(0.035)		(0.035)
Top20Province		0.098***		0.098***		0.099***
		(0.031)		(0.031)		(0.031)
HasAsset		0.100***		0.102***		0.105***
		(0.037)		(0.037)		(0.037)
HasLoan		-		-		-
		(0.043)		(0.043)		(0.043)
NPriorLoan_Applied		-		-		-
		(0.008)		(0.008)		(0.008)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,757,306	5,751,091	5,757,306	5,751,091	5,757,306	5,751,091
No. of Listings	220,606	219,924	220,606	219,924	220,606	219,924
No. of Failures	5,518	5,496	5,518	5,496	5,518	5,496
Pseudo R-square	0.246	0.248	0.246	0.248	0.246	0.248

Appendix 1: Variable Definition

Variable	Definition
Borrower Characteristics	
NCertif_Impt	The number of important certificates.
NCertif	The number of all certificates.
NCertif_Volun	The number of voluntarily applied certificates.
NCertif_Impt*Default	The interaction between NCertif_Impt and Defaulted.
NCertif*Default	The interaction between NCertif and Defaulted.
NCertif_Volun*Default	The interaction between NCertif_Volun and Defaulted.
CreditGrade	Credit grade assigned by the platform, including seven grades AA, A, B, C, D, E, and HR. AA equals 7; A equals 6; B equals 5; C equals 4; D equals 3; E equals 2; and HR equals 1.
Age	Age of each borrower.
EduLevel	Education level. Equals 4 if the borrower's highest qualification is a master's degree or above; 3 if the borrower's highest qualification is a bachelor's degree; 2 if the borrower's highest qualification is post-tertiary; and 1 if the borrower's highest qualification is secondary or below.
JobIncomeLevel	Monthly income level. 7 means more than 50,000 RMB; 6 means between 20,000 and 50,000 RMB; 5 means between 10,000 and 20,000 RMB; 4 means between 5,000 and 10,000 RMB; 3 means between 2,000 and 5,000 RMB; 2 means between 1,000 and 2,000 RMB; and 1 means less than 1,000 RMB.
JobLength	Employment length in years. 4 indicates more than 5 years; 3 means between 3 and 5 years; 2 indicates between 1 and 3 years; and 1 indicates less than 1 year.
Single	Dummy variable that equals 1 if the marital status is single; and 0 otherwise.
Top20Province	Dummy variable that equals 1 if the borrower is from the top 20 provinces; and 0 otherwise.
HasAsset	Dummy variable that equals 1 if the borrower owns house or car; and 0 otherwise.
HasLoan	Dummy variable that equals 1 if the borrower has car loan or mortgage loan; and 0 otherwise.
NPriorLoan_Applied	Number of prior applied loans of each borrower.
Default	Dummy variable that equals 1 if the borrower has defaulted a loan on RRD.com and 0 otherwise.
Comp1_Impt	First principal component of important certificates.
Comp1	First principal component of all certificates.
Comp1_Volun	First principal component of voluntary certificates.
Loan Contract Terms	
Loan Amount (k)	Requested loan amount in thousands of RMB of each loan.
Loan_Rate	Loan interest rate of each loan.
Loan_Premium	Difference between the loan rate and the corresponding benchmark interest rate of each loan.
Loan_Duration (month)	Loan duration in months of each loan.

Loan Performance	
Delinquent	Dummy variable that equals 0 if the loan is repaid on time in each period; and 1 otherwise.
BadDebt	An ordered discrete variable which equals 0 if the loan is repaid on time in each period, 1 if the loan is completely repaid but with overdue records, and 2 if the loan is unrepaid.
BadDebt (=0)	Dummy variable that equals 1 if the loan is repaid on time in each period; and 0 otherwise.
BadDebt (=1)	Dummy variable that equals 1 if the loan is completely repaid but with overdue records; and 0 otherwise.
BadDebt (=2)	Dummy variable that equals 1 if the loan is unrepaid; and 0 otherwise.
Lender Characteristics	
Lender_Experience	A lender experience is measured by the year since the first investment.

Internet Appendix 1: Eigenvalues and Eigenvectors of Principal Components

Panel A presents the eigenvalues of the principal components for important certificates, all certificates, and voluntarily applied certificates, along with proportions of variation explained by each component. Panel B reports the corresponding eigenvector of each component. The definitions are presented in Appendix 1.

Panel A: Proportion of First Component (Comp1)

	Eigenvalue	Proportion (%)
Comp1_Impt	3.555	29.63
Comp1	3.668	17.47
Comp1_Volun	2.915	18.22

Panel B: Eigenvector of First Component (Comp1)

Certificate	Comp1_Impt	Comp1	Comp1_Volun
Onsite Authentication	0.377	0.381	0.343
Property Ownership	0.018	-0.024	-0.035
Loan Purpose		-0.012	-0.015
Remote Video	0.013	-0.021	-0.040
Bank Statement (Salary)	0.469	0.456	0.563
Credit Report	0.418	0.401	0.490
Other		-0.001	-0.002
ID Number	0.016	0.020	
Platform Training		-0.139	
Social Network		-0.018	-0.028
Phone Bill	0.011	-0.027	-0.038
Child		-0.011	-0.017
ID Card	0.320	-0.167	
Microblog		0.280	-0.032
Residence Proof	0.013	-0.024	-0.036
Occupation	0.468	-0.026	0.561
Academic Qualification		0.454	-0.018
Mobile Phone	-0.374	-0.017	
Marriage Certificate		-0.386	-0.042
Car	0.019	-0.027	-0.034

Internet Appendix 2: Robustness Tests Using Different Lengths of Overdue Payments

We examine the robustness of our findings by using alternative estimation technique and definition of delinquency. Panels A and B repeat the estimation of Table 4 using the single-failure model, where each loan observation after the first delinquency is ignored. In Panel C, we change the definition of delinquency to default or consecutive overdue for 2 months or longer, and re-estimate the multiple-failure model. Coefficients from the variance-corrected multiple-failure Cox proportional hazards model (Anderson-Gill model) are reported along with standard errors in parentheses clustered at listing level. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively. The definitions of all variables are presented in Appendix 1.

Panel A: One-month Overdue Payment Criterion (Single-Failure)

Dependent Variable: Delinquency Hazard	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt	0.110***	0.100***				
	(0.006)	(0.006)				
NCertif			0.093***	0.086***		
			(0.004)	(0.004)		
NCertif_Volun					0.106***	0.097***
					(0.006)	(0.006)
CreditGrade	-0.951***	-0.924***	-0.932***	-0.906***	-0.966***	-0.937***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
logLoanAmount (k)	0.194***	0.179***	0.195***	0.182***	0.199***	0.183***
	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)
Loan_Premium	0.069***	0.087***	0.077***	0.094***	0.070***	0.088***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Loan_Duration (month)	-0.026***	-0.027***	-0.027***	-0.027***	-0.026***	-0.026***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age				0.007***		0.006***
				(0.001)		(0.001)
EduLevel				0.014*		0.015*
				(0.008)		(0.008)
JobIncomeLevel				0.004		0.007
				(0.006)		(0.006)
JobLength				0.077***		0.078***
				(0.007)		(0.007)
Single				0.013		0.012
				(0.012)		(0.012)
Top20Province				0.024**		0.024**
				(0.011)		(0.011)
HasAsset				0.012		0.012
				(0.018)		(0.018)
HasLoan				-0.080***		-0.084***
				(0.013)		(0.013)
NPriorLoan_Applied				0.014***		0.013***
				(0.003)		(0.004)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,571,323	5,565,412	5,571,323	5,565,412	5,571,323	5,565,412
No. of Listings	220,612	219,930	220,612	219,930	220,612	219,930
No. of Failures	53,923	53,784	53,923	53,784	53,923	53,784
Pseudo R-square	0.079	0.079	0.079	0.079	0.079	0.079

Panel B: Four-month Consecutive Overdue Payment Criterion (Single-Failure)

Dependent Variable: Delinquency Hazard	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt	0.076***	0.072***				
	(0.007)	(0.007)				
NCertif			0.056***	0.055***		
			(0.005)	(0.005)		
NCertif_Volun					0.066***	0.064***
					(0.007)	(0.007)
CreditGrade	-0.846***	-0.818***	-0.834***	-0.806***	-0.856***	-0.827***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
logLoanAmount (k)	0.243***	0.220***	0.243***	0.221***	0.245***	0.222***
	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)
Loan_Premium	0.079***	0.107***	0.084***	0.112***	0.077***	0.105***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Loan_Duration (month)	-0.008***	-0.009***	-0.008***	-0.010***	-0.007***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age		0.008***		0.008***		0.008***
		(0.001)		(0.001)		(0.001)
EduLevel		-0.001		-0.002		-0.002
		(0.007)		(0.007)		(0.007)
JobIncomeLevel		0.018***		0.017***		0.018***
		(0.006)		(0.006)		(0.006)
JobLength		0.064***		0.066***		0.065***
		(0.007)		(0.007)		(0.007)
Single		0.041***		0.041***		0.041***
		(0.012)		(0.012)		(0.012)
Top20Province		0.032***		0.031***		0.032***
		(0.010)		(0.010)		(0.010)
HasAsset		-0.009		-0.009		-0.008
		(0.017)		(0.017)		(0.017)
HasLoan		-0.089***		-0.089***		-0.091***
		(0.014)		(0.014)		(0.014)
NPriorLoan_Applied		0.005		0.005		0.003
		(0.006)		(0.006)		(0.006)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,643,990	5,637,598	5,643,990	5,637,598	5,643,990	5,637,598
No. of Listings	220,612	219,930	220,612	219,930	220,612	219,930
No. of Failures	46,560	46,496	46,560	46,496	46,560	46,496
Pseudo R-square	0.063	0.064	0.063	0.064	0.063	0.064

Panel C: Two-month Consecutive Overdue Payment Criterion (Multiple-Failure)

Dependent Variable: Delinquency Hazard	(1)	(2)	(3)	(4)	(5)	(6)
NCertif_Impt	0.197***	0.193***				
	(0.007)	(0.007)				
NCertif			0.143***	0.141***		
			(0.005)	(0.005)		
NCertif_Volun					0.167***	0.165***
					(0.007)	(0.007)
CreditGrade	-0.945***	-0.918***	-0.918***	-0.891***	-0.967***	-0.939***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
logLoanAmount (k)	0.184***	0.178***	0.186***	0.180***	0.190***	0.182***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Loan_Premium	0.067***	0.089***	0.079***	0.100***	0.058***	0.082***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Loan_Duration (month)	-0.015***	-0.018***	-0.016***	-0.019***	-0.014***	-0.017***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age		0.004***		0.004***		0.004***
		(0.000)		(0.000)		(0.000)
EduLevel		-0.007		-0.010*		-0.010*
		(0.005)		(0.005)		(0.006)
JobIncomeLevel		0.014***		0.012***		0.015***
		(0.004)		(0.004)		(0.004)
JobLength		0.055***		0.056***		0.057***
		(0.004)		(0.004)		(0.004)
Single		0.027***		0.026***		0.025***
		(0.010)		(0.010)		(0.010)
Top20Province		0.013		0.012		0.013
		(0.008)		(0.008)		(0.008)
HasAsset		-0.024**		-0.020*		-0.020
		(0.012)		(0.012)		(0.012)
HasLoan		-0.096***		-0.097***		-0.102***
		(0.010)		(0.010)		(0.010)
NPriorLoan_Applied		0.004		0.003		-0.001
		(0.006)		(0.005)		(0.006)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,757,306	5,751,091	5,757,306	5,751,091	5,757,306	5,751,091
No. of Listings	220,606	219,924	220,606	219,924	220,606	219,924
No. of Failures	378,150	377,586	378,150	377,586	378,150	377,586
Pseudo R-square	0.071	0.071	0.071	0.071	0.070	0.071

Internet Appendix 3: Subsample Regression: Human Bids Only

This table reports the relationship between loan performance, funding success and number of certificates using the human funded sample only. The first three specifications study the how the number of certificates affects the conditional probability (i.e. hazard) of delinquency, where delinquency is defined as default or payment overdue for 1 month or longer. The last three specifications investigate how the number of certificates affects funding success, where the dependent variable Funding Success equals 1 if the loan is successfully funded and 0 otherwise. Specification (1) and (3) focus on the number of important certificates, (2) and (5) focus on the number of all certificates, and (3) and (6) focus on the number of voluntarily applied certificates. Coefficients along with heteroskedasticity robust standard errors in parentheses are reported for logit regressions, Hazard models present coefficients along with standard errors clustered at loan level in parentheses clustered at loan level. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Delinquency Dummy			Dependent Variable: Funding Success		
NCertif_Impt	0.050***			0.641***		
	(0.007)			(0.007)		
NCertif		0.064***			0.378***	
		(0.005)			(0.005)	
NCertif_Volun			0.043***			0.463***
			(0.006)			(0.007)
CreditGrade	-1.283***	-1.279***	-1.289***	1.333***	1.407***	1.303***
	(0.015)	(0.015)	(0.015)	(0.007)	(0.008)	(0.007)
logLoanAmount (k)	0.010	0.012	0.010	-0.880***	-0.859***	-0.848***
	(0.014)	(0.014)	(0.014)	(0.009)	(0.009)	(0.008)
Loan_Premium	0.033***	0.032***	0.034***	-0.094***	-0.089***	-0.086***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)
Loan_Duration (month)	-0.002	-0.002	-0.002	0.013***	0.012***	0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.005***	0.006***	0.006***	0.031***	0.034***	0.034***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EduLevel	-0.157***	-0.164***	-0.162***	0.241***	0.215***	0.219***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
JobIncomeLevel	0.067***	0.062***	0.066***	0.280***	0.297***	0.312***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
JobLength	0.008	0.008	0.008	0.138***	0.164***	0.171***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Single	-0.040**	-0.049***	-0.045***	-0.154***	-0.121***	-0.115***
	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)	(0.018)
Top20Province	0.049***	0.047***	0.049***	-0.200***	-0.201***	-0.204***
	(0.015)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)
HasAsset	0.033*	0.029	0.036**	-0.120***	-0.017	-0.038**
	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)
HasLoan	-0.187***	-0.194***	-0.187***	0.017	0.066***	0.055**
	(0.020)	(0.020)	(0.020)	(0.024)	(0.023)	(0.023)
NPriorLoan_Applied	-0.014***	-0.017***	-0.015***	-0.069***	-0.070***	-0.066***
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Constant				-7.704***	-8.590***	-6.819***
				(0.289)	(0.342)	(0.333)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	864,870	864,870	864,870	445,574	445,574	445,574
No. of Listings	51,452	51,452	51,452			
No. of Failures	83,520	83,520	83,520			
Pseudo R-squared	0.136	0.136	0.136	0.600	0.586	0.582

Internet Appendix 4: Subsample Regression: Excluding Loans with Suspected Fake Certificates

This table reports the relationship between loan performance, funding success and number of certificates using a subsample excluding loans from bidders who never borrow on the platform again after delinquency. The first three specifications study the how the number of certificates affects the conditional probability (i.e. hazard) of delinquency, where delinquency is defined as default or payment overdue for 1 month and longer. The last three specifications investigate how the number of certificates affects funding success, where the dependent variable Funding Success equals 1 if the loan is successfully funded and 0 otherwise. Specification (1) and (3) focus on the number of important certificates, (2) and (5) focus on the number of all certificates, and (3) and (6) focus on the number of voluntarily applied certificates. Coefficients along with heteroskedasticity robust standard errors in parentheses are reported for logit regressions, Hazard models present coefficients along with standard errors clustered at loan level in parentheses clustered at loan level. ***, **, and * denote significance at the 1%, 5%, and 10% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable: Delinquency Dummy			Dependent Variable: Funding Success		
NCertif_Impt	0.156***			0.549***		
	(0.006)			(0.008)		
NCertif		0.124***			0.300***	
		(0.005)			(0.006)	
NCertif_Volun			0.150***			0.368***
			(0.006)			(0.009)
CreditGrade	-0.957***	-0.931***	-0.975***	1.690***	1.775***	1.686***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
logLoanAmount (k)	0.130***	0.132***	0.133***	-0.835***	-0.810***	-0.802***
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)
Loan_Premium	0.027**	0.037***	0.026**	-0.107***	-0.100***	-0.098***
	(0.010)	(0.010)	(0.010)	(0.005)	(0.005)	(0.005)
Loan_Duration (month)	-0.022***	-0.023***	-0.022***	0.013***	0.010***	0.012***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Age	0.003***	0.003***	0.003***	0.029***	0.031***	0.031***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
EduLevel	0.038***	0.037***	0.037***	0.292***	0.276***	0.279***
	(0.005)	(0.005)	(0.005)	(0.012)	(0.012)	(0.012)
JobIncomeLevel	0.012***	0.011***	0.012***	0.248***	0.261***	0.280***
	(0.004)	(0.004)	(0.004)	(0.009)	(0.009)	(0.009)
JobLength	0.070***	0.073***	0.071***	0.071***	0.103***	0.110***
	(0.004)	(0.004)	(0.004)	(0.011)	(0.010)	(0.010)
Single	0.039***	0.039***	0.038***	-0.153***	-0.134***	-0.128***
	(0.009)	(0.009)	(0.009)	(0.021)	(0.021)	(0.021)
Top20Province	0.008	0.007	0.008	-0.181***	-0.185***	-0.187***
	(0.008)	(0.008)	(0.008)	(0.019)	(0.019)	(0.019)
HasAsset	-0.026**	-0.027**	-0.026**	-0.123***	-0.032	-0.044**
	(0.011)	(0.011)	(0.011)	(0.023)	(0.023)	(0.022)
HasLoan	-0.071***	-0.071***	-0.073***	0.134***	0.172***	0.166***
	(0.010)	(0.010)	(0.010)	(0.028)	(0.027)	(0.027)
NPriorLoan_Applied	0.026***	0.025***	0.022***	-0.072***	-0.073***	-0.070***
	(0.005)	(0.005)	(0.005)	(0.001)	(0.001)	(0.001)
Constant				-8.321***	-9.035***	-7.631***
				(0.395)	(0.456)	(0.447)
Yr Qtr FE	YES	YES	YES	YES	YES	YES
Observations	5,658,034	5,658,034	5,658,034	543,397	543,397	543,397
No. of Listings	212,649	212,649	212,649			
No. of Failures	338,550	338,550	338,550			
Pseudo R-squared	0.060	0.060	0.060	0.844	0.840	0.839