Sharing borrower default information via central depository

–Evidence from two randomized field experiments*

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Abstract

This study conducted two randomized field experiments on an online lending platform in China aiming to examine the effect of default information sharing among lenders on hidden information and hidden action problems. In the first experiment, we sent a text message to randomly selected borrowers with approved loan applications before they made a take-out decision, informing that loan default will be reported to the central credit bureau and affect their credit ratings. Two types of lenders provide funding to the lending platform–one lender, by regulation, reports borrower default to the credit bureau (reporting lender, RL) and the other lender does not (non-reporting lender, NRL). We randomly assigned RL and NRL to approved loans. We report two key findings. First, borrowers with prior experience at the lending platform (old borrowers) are 9.01% less likely to take out a loan funded by RL. Old borrowers are 1.5% less likely to default on loans funded by RL than on loans funded by NRL. However, receiving the message does not affect their default likelihood, suggesting that old borrowers might have learned about the two lenders' reporting policy from their prior experience and therefore text messages do not alter their prior or influence their decisions. Second, among borrowers without prior experience at the lending platform (new borrowers), those who received the message are 2.81% more likely to take out the loan and 2.65% less likely to default than those who did not receive the message. Among these new borrowers, we don't find any difference in default likelihood between RL loans and NRL loans, suggesting that new borrowers, without text messages, are not aware of the difference in two lenders' reporting policy. Our follow-up phone interviews confirm that some borrowers learned about the default consequence on credit ratings via the credit warning message.

The second experiment is conducted among loans funded by RL. The key difference from the first experiment is that the credit warning message was sent to pseudo-randomly selected borrowers only after they took out a loan, when adverse selection does not have a role. We find that borrowers receiving the text message are less likely to default than borrowers not receiving such a message, and this effect concentrates on new borrowers (the default rate is 5.12% for message receivers and 11.6% for non-receivers). Taken in tandem, our findings suggest that awareness of lenders' sharing default information mitigates borrowers' moral hazard but might exacerbate adverse selection problems in the consumer credit market in emerging economies. Our study provides empirical evidence on the causal effect of information sharing among lenders on borrower moral hazard and adverse selection. Our research has important policy implications on consumer lending and contributes to the growing literature on Fintech.

I. Introduction

A large body of theoretical research shows that information sharing among lenders attenuates adverse selection and moral hazard, and thus can foster lending and reduce default rates.[1] The idea is that 1) exchange of borrower information improves lenders' knowledge of applicants' characteristics and permits more accurate prediction of repayment probability. This allows lenders to target and price their loans better, easing adverse selection problems; 2) knowing that if he defaults, his reputation with all potential lenders is damaged, incentivizes borrowers to repay, reducing moral hazard. Convincing empirical evidence about the importance of credit information sharing is not only relevant for the theoretical literature but also has policy implications. Extant empirical evidence largely relies on a cross-country setting (Jappelli and Pagano, 2002), where it is difficult to discern causality from correlation, and to disentangle adverse selection from moral hazard. The goal of this study is to provide direct evidence on whether sharing borrowers' default information with other lenders has any effect on borrowers' taking out and default decisions using two randomized field experiments via an internet lending platform.

We theoretically derive that if borrowers know that lenders share their default information *before* taking out a loan, then 1) adverse selection problems will be alleviated (exacerbated) if the expected penalty for default is greater (smaller) for borrowers with low credit rating; 2) borrowers' expected effort for loan repayment will improve. We further argue that if borrowers are made aware of lenders sharing their default information *after* taking out a loan, their effort of making repayment will rise (ex-post hidden action by Karlan and Zinman 2009), reducing the default probability.

[1] For example, Pagano and Jappelli (1993) show that information sharing mitigates adverse selection, Padilla and Pagano (2000) demonstrate that information sharing reduces moral hazard by improving borrowers' effort to repay loans, and Bennardo et al. (2007) find that information sharing reduces banks' moral hazard by avoiding excessive lending.

We focus on an internet lending platform which connects institutional lenders with retail borrowers in China. Lenders in the consumer lending market can be broadly categorized into two types: financial institutions (banks and financial firms) and P2P lenders (high tech companies). One key distinction between the two, among many, is that financial institutions are required by regulation to report borrower default experience to the central bank – People's Bank of China, whereas P2P lenders are not.[2] We label financial institutions as reporting lenders (RLs) and high tech companies that provide consumer loans as non-reporting lenders (NRLs). We conducted two field experiments at Liang Hua Pai (LHP), an internet lending platform, over the period of March to April of 2017, detailed in Section 2. Two institutional lenders participated in this experiment, Hua Rong (HR), a reporting lender, and Yang Qian Guan (YQG), a non-reporting lender.

For the first experiment, by randomly assigning loans to these two lenders after the approval of loan applications, we ensure no selection bias with respect to the matching between lenders and borrowers. Subsequent to the loan approval, we sent a text message (credit warning) to randomly-selected RL and NRL borrowers, respectively, informing that their loan default will be reported to the central bank.[3] We then observed whether borrowers took out a loan, and the repayment behavior if the loan was taken out, comparing the decisions of borrowers receiving the credit warning message with those not receiving the message.

We separately analyze borrowers with prior experience at the lending platform (old borrowers) and those without prior experience (new borrowers) because old borrowers likely have learned about the credit reporting policy of the two types of lenders from past experience. Consequently

[2] The central bank serves as a credit bureau collecting borrowers' default information and sharing this information with other lenders. Acquiring this information is free for RLs but with a fee for NRLs. In practice, NRLs do not acquire this information in making lending decisions.

[3] The wording in the text message to RL borrowers is slightly different from that to NRL borrowers for practical reasons. We discuss this difference in details in Section III.

credit warning might not incrementally influence their decisions. We have two main findings. First, among old borrowers, those borrowing from RL are less likely to take out a loan, particularly for those low credit risk borrowers. Old borrowers funded by RL are also less likely to default than those who take out loans from NRL. However, there is no difference in the take-out or default rate between message receivers and non-receivers. Second, among new borrowers, the default likelihood is lower for message receivers than for non-receivers. However, the default likelihood is comparable between RL and NRL borrowers. These results suggest that 1) old borrowers learned the two lenders' reporting policy from prior experience while new borrowers acquired that information from the text message; 2) borrowers' awareness of information sharing among lenders reduces moral hazard but it may exacerbate or mitigate adverse selection problems.

For the second experiment, we randomly-selected 2,804 borrowers who took out a loan from RL. None of these 2,804 RL borrowers received a credit warning message before taking out the loan. Borrowers of this experiment have characteristics similar to borrowers of the first experiment, but the two groups do not overlap. We sent a credit warning message to 709 randomly-selected borrowers. We then record the loan repayment history for borrowers receiving the credit warning message and borrowers not receiving the message. We find that the credit warning reduces the default rate and this effect concentrates on new borrowers, who likely learn about the default reporting policy of RL via the credit warning message. The evidence suggests that credit warning improves borrowers' effort for loan repayment, thereby reducing moral hazard. Taken in tandem, our study provides causal evidence that default information sharing among lenders reduces moral hazard but exacerbates adverse selection problems.

Our study makes three contributions. First, we demonstrate a causal relationship of lender information sharing with adverse selection and moral hazard problems. Our findings support the theoretical prediction that information sharing mitigates moral hazard problems (Pagano and Jappalli, 1991; Jappalli and Pagano, 2002). However, we find that information sharing likely exacerbates adverse selection, which is contrary to the theoretical prediction (Pagano and Jappalli, 1993; Jappalli and Pagano, 2002). This might happen if the perceived default cost resulting from information sharing is much higher for low credit risk borrowers than their high risk counterparts.

Second, our results are informative to policy makers in emerging markets, where personal loans and small business loans are growing exponentially aided by recent advancement in lending technologies. Policy makers are concerned about systemic risk imposed by this rapid growth because information sharing is less developed in these markets, particularly in Asian and Latin American countries (Jappelli and Pagano 2002). Our findings suggest that sharing borrower default information among lenders, on the one hand, can mitigate borrowers' moral hazard problem, thereby reducing systematic risk induced by coordinated strategic defaults as seen in the residual mortgage markets during the 2008 financial crisis. On the other hand, we find that information sharing might exacerbate adverse selection. Therefore, an effective policy might combine default reporting with subsidies on loan interest rate, loan guarantees, information coordination, and enhanced screening strategies (Karlan and Zinman, 2009).

Third, our study is also related to the growing literature on Fintech. Large amount of information on individuals become available on the internet in recent years, coupled with increased capacity of information processing, makes it possible to depict individuals' traits and predict their behavior. Access to digital footprints can help reduce information asymmetry between borrowers and lenders in the consumer lending market (Berg, et al., 2017). Improved screening technology enables financial intermediaries (banks, financial firms, and information technology companies) to expand their reach to consumers and foster financial inclusion. Moreover, based on improved information, we can design more effective incentive mechanisms (a combination of rewards and penalty) at different stages of lending to improve lending outcomes. Sharing borrower default information among lenders (directly or via the central credit bureau) and educating borrowers on such information sharing are essential for the incentive mechanisms to function properly. In a setting of randomized field experiments, we show that warning borrowers default information sharing among lenders via text messaging is an effective and inexpensive approach to improve lending outcomes in the consumer credit market.

II. Literature review and background

Literature review on information sharing among lenders

A large body of literature documents that asymmetry information between borrowers and lenders can prevent the efficient credit allocation. Recent theoretical research suggests sharing borrower information among lenders can help overcome these informational problems. First, information sharing among lenders improves the effectiveness of bank screening. Banks can acquire more knowledge of applicants' characteristics via information sharing and thus predict repayment probability with a greater precision. This leads lenders to better screen loan applicants, easing adverse selection problems (Pagano and Jappelli 1993). Second, information sharing reduces the informational rents that banks could otherwise extract from their borrowers, thereby forcing lenders to price loans more competitively. The resulting lower interest rates improve borrowers' incentive to perform (Padilla and Pagano 1997). Third, information sharing can discipline borrowers for repayment. This is because borrowers know that if they default their reputation with all potential lenders will be tarnished, resulting in either an increase in interest rates or credit rationing. This mechanism enhances borrowers' incentive to repay, reducing moral hazard (Vercammen, 1995; Padilla and Pagano, 2000; Klein, 1992).

A growing body of empirical evidence largely supports the theoretical predictions above. For example, recent studies find that credit reporting reduces the selection costs of lenders by allowing them to more accurately predict individual loan defaults (Barron and Staten, 2003; Kallberg and Udell, 2003; Powell et al., 2004; Luoto et al., 2007). In a lab experiment, Brown and Zehnder (2010) show that both adverse selection and lender competition affect lenders' voluntary information sharing − asymmetric information in the credit market increases the frequency of information sharing between lenders significantly while stronger competition between lenders reduce information sharing.

The impact of information sharing on aggregate credit market performance has been tested by two cross-country studies. Based on a survey of credit reporting in 43 countries, Jappelli and Pagano (2002) show that bank lending to the private sector is larger and default rates are lower in countries where information sharing is extensive and more solidly established. Djankov et al. (2007) confirm that private sector credit relative to GDP is positively correlated with information sharing in their study of credit market performance and institutional arrangements in 129 countries for the period 1978–2003. Love and Mylenko (2003) combine cross-sectional firm-level data from the 1999 World Business Environment Survey with aggregate data on private and public registries collected in Miller (2003). They find that private credit bureaus are associated with lower perceived financing constraints and a higher share of bank financing (while public credit registries are not), and that these correlations are particularly strong for small and young firms that are informationally opaque. Brown, Jappelli, and Pagano (2009) focusing on transition economies provide firm-level evidence that information sharing is associated with improved availability and lower cost of credit to firms. This correlation is stronger for opaque firms than for transparent ones and stronger in countries with weak legal environments than in those with strong legal environments.

Literature review on online consumer lending and Fintech

Over the past 10 years, P2P lending has become an increasingly important method of providing small loans to individual borrowers. Most existing studies on P2P lending rely on Prosper.com. For example, Iyer, Khwaja, Luttmer, and Shue (2009) show that lenders effectively use soft and non-standard information to evaluate borrowers' creditworthiness. Lin, Prabhala, and Viswanathan (2013), Michels (2012), Kawai and Onishi (2016), and Hertzberg, Liberman and Paravisini (2017) document that friendship networks, voluntary disclosure, posting reservation interest rate, and maturity choices help reduce information asymmetry in the P2P lending markets. Recent research starts examining information contents in individuals' digital footprints and compares their discriminatory power with that of credit bureau information (Berg et al., 2017). Berg et al. suggests potential use of Fintech to mitigate information asymmetry and transform the business model of consumer lending.

Consumer credit market in China

As China transitions from a planned economy to a market-oriented economy that began in 1978, the country changed from a strictly "cash-based" system to "credit-based" system. In the 1980s the Bank of China (BOC) began issuing credit cards, marking a major innovation and the beginning of a major revolution in providing credit to consumers. Since then the number of credit cards issued in China has grown at an astonishing annual rate of over 30%. The underlying economic forces are the rapid development of the Chinese economy and the deepening reform of the financial system since 1998 (i.e., housing market reform). The main lenders to consumers in China in early 2000 are commercial banks and a number of auto financing corporations. With the recent technology advancement, the Internet-enabled consumer finance segment (P2P) has grown rapidly after 2013. P2P lending platforms mushroomed from only 200 in 2012 to more than 3,000 in 2015, and P2P loans reached RMB982.3 billion in 2015 (Wang and Dollar, 2018).

The Internet-based P2P lending platforms employs two major business models. One is that the lending platform servers as an intermediary between lenders and borrowers without bearing borrowers' credit risk; and the other is that the lending platform bears borrowers credit risk besides matching lenders with borrowers. Majority lending platforms in China belong to the latter. The one used in our experiment falls into this category. Absence of regulation sparked the boom but also might have contributed to a market brimming with scams and high-risk financial models.[4,5] The concern of fraud in the P2P market has moved Chinese authorities to impose stricter regulations and establish a national credit reporting system. Yet, the Chinese government's public credit register, the Credit Reference Center of the People's Bank of China (hereafter Central Bank) has fallen short in achieving such a system.[6,7]

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[4] The main concern of Chinese regulators is the funding of P2P lending by Chinese banks. These banks delegate credit risk management to online lending platforms, which may create systematic risk to the Chinese financial system.

[5] The most headline-grabbing case was the collapse of Ezubao, a platform that lured investors with promises of double-digit annual returns. It attracted $7.6 billion from nearly one million lenders in just 18 months before it was identified as a Ponzi scheme, with more than 95 percent of its borrowers being fictitious. In 2016, about 1,300 platforms were pegged as problematic, and over 900 closed by the end of the year. In November 2017, approvals for online lending companies came to a complete halt, a measure that further chilled this fast-growing sector.

[6] Although it claims to have credit profiles for over 20 million businesses and over 850 million individuals, only a quarter of China's population of 1.4 billion has a documented credit history. In comparison, nearly 90 percent of the adult population in the United States has a credit score.

[7] The credit report at the central credit bureau contains credit information on individuals. It includes credit card, mortgage, and other loan information. For credit cards, for example, the report includes the number of credit cards, the number of credit cards in use, the number of credit cards with overdue balance, the number of credit cards with balance overdue over 90 days, the credit limit for each card, and the card's expenses in the previous month. There could also be information on unpaid taxes, civil lawsuit filing, administrative penalty, and unpaid phone bills over the past five years. Moreover, all inquiries over the past two years are listed: the date of the inquiry, the inquirer, and the

With reams of user data, China's largest Fintech firms spearheaded setting up their own credit measurements (e.g., private credit bureaus). For example, Alibaba, the world's largest e-commerce firm, rolled out Sesame Credit in 2015.[8] Sesame Credit assigns users a score ranging from 350 to 950 based on five criteria: credit history, online transactional habits, personal information, ability to honor an agreement, and social network affiliations. Our study attempts to provide direct empirical evidence on whether credit reporting (via central credit registry or data sharing among Fintech lenders) affects borrowing behavior with the hope that our findings are informative to policy makers in China and other developing economies.

III. Experimental design and testable predictions

Lending platform−LHP

The lending platform used in our field experiment (LHP) is an independent Fintech firm that matches a large number of borrowers of micro loans with lenders. It was founded in 2014. As of August 28, 2017, LHP has made cumulatively 7,765,536 loans, which amounts to 16.55 billion CNY. LHP's main function is to use its comprehensive database and sophisticated risk modeling to screen borrowers and match them with lenders. Typical LHP borrowers are males in their late 20s, employed, and heavy smart phone users. With a rapid growth of the borrower base, on average, 85% of borrowers are first-time borrowers (new borrowers) at LHP. The rejection rate of loan applications is approximately 90% for new borrowers and 30% for repeated (old) borrowers.

purpose for the inquiry (e.g., credit card approval, and loan management). An individual can request his or her credit report for a given number of times each year, free of charge. Lenders can access individuals' credit reports with their permissions.

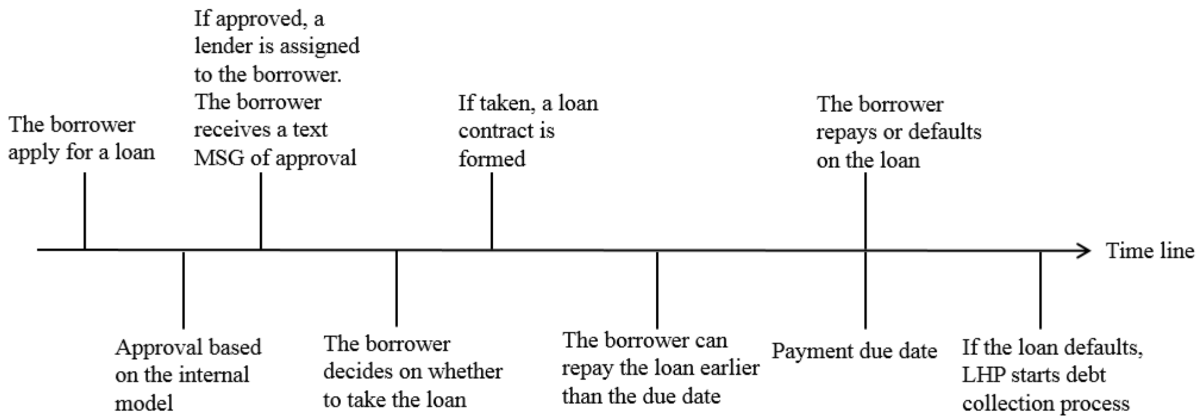
[8] Sesame Credit has direct access to data related to the more than 500 million consumers who use Alibaba's Taobao and Tmall marketplaces on a monthly basis, as well as payment histories of the more than 400 million registered users on its mobile payment app Alipay.

Default on a loan forbids a borrower from taking any loan from the platform in the future. With repayment history at LHP, borrowers are qualified for larger and longer-term loans. Repeated borrowers tend to borrower three to four times a year, with an average amount of *** Yuan.

Lenders at LHP include banks (e.g., banks' wealth management funds) and financial firms such as Hua Rong, as well as P2P lender such as Yang Qian Guan. Defaults on loans backed by banks and financial firms (reporting lenders or RLs) are required to be reported to the credit bureau at the Central Bank, and will affect the borrowers' credit reports. In contrast, defaults on loans funded by P2P lenders (non-reporting lenders, or NRLs) are not subject to the same reporting requirement and thus will not affect the borrowers' credit reports. LHP bears borrowers' default risk—if a borrower does not repay the loan, LHP will step in for the repayment of loan principal and interests. Thus, LHP imposes hefty monthly service fees on top of the interests charged by fund providers to offset the risk it bears.

Lending procedure at LHP

The lending procedure works as follows. (1) A borrower submits a loan application to LHP along with permission to access her phone records. (2) LHP approves or rejects the application based on borrower characteristics including age, gender, income, education, social security, Sesame credit score, LHP credit score, self-reported credit card information, and mortgage. (3) If approved, a lender is assigned to the borrower and an approval notification was sent to the borrower's mobile phone via a text message. The message contains a link to an APP for inputting the bank account information for fund transfer. There is a loan contract in the APP that a borrower can click and review. The contract includes the lender's name. (4) The borrower decides whether to take out the loan by inputting bank account information to receive the funds.[9] (5) If taking out a loan, the borrower either repays amortized principal plus interest and service fee monthly or defaults on the loan. The borrower has an option to repay the loan before its due date for the principal, full interests and service fees.



Experimental design

We conducted two experiments at LHP over the period of March to April, 2017. In the first experiment, among approved loan applications, we randomly selected 4,700 borrowers with an odd birthday and assign them to the financial firm (RL), and randomly selected 4,700 borrowers with an even birthday and assign them to the P2P lender (NRL).

Among RL borrowers, we randomly selected half of them and manipulated the test message in step (3) so that their message displayed a credit warning that − default on the loan *will be* reported to the central bank and affect the borrower’s credit report. The text message received by the

[9] The link for inputting bank account information is valid for 10 minutes and is re-sent to the borrower five times in a month if the borrower fails to act on it. Without receiving a response, LHP considers such an approved loan discarded.

remaining borrowers did not contain such information. The randomization of the text message was determined by an independently generated random number between zero and one. If the random number was greater than 0.5, the borrower received a warning (Group RL1). If the random number was less than 0.5, the borrower's text message did not contain a warning (Group RL2).

For borrowers in Group NRL, we manipulate the text message received in step (3) in a similar way with one exception. That is, roughly half of the borrowers' message contained a line stating that default on the loan *will possibly be* reported to the central bank and affect the borrower's credit report (Group NRL1). The division between these two subgroups is also determined by the random number generated for each borrower. We added "possibly" to the warning message that NRL1 borrowers received to ensure that such warning is not simply a lie for at least two practical reasons. First, lying might adversely affect LHP's reputation. Second, lying is not acceptable for the purpose of academic research. However, the subtle difference in the warning message between RL1 and NRL1 borrowers might affect their borrowing decisions differently. The text message of the remaining borrowers did not contain such warning information (Group NRL2).

We summarize in Figure 1 that borrowers in Group RL1 received a warning that is consistent with the reporting regulation, while borrowers in Group RL2 did not receive such warning albeit they are subject to the same regulation. In contrast, borrowers in Group NRL1 received a warning of the possible credit effect even though such effect does not exist, while borrowers in Group NRL2 did not receive such warning, consistent with the reporting regulation.

We design the experiment to include a financial firm (RL) and a P2P lender (NRL) for three purposes. First, though there is a clear distinction in credit reporting between the two by regulation, borrowers may not be aware of it. Given that the awareness of reporting regulation might undermine the incremental effect of credit warning, the inclusion of RL funding serves to gauge the extent to which borrowers were already aware of the credit reporting regulation. Second, whether the credit reporting difference by regulation has an effect on borrower behavior is important in its own right. Third, this design allows us to compare the credit warning effect with the regulatory reporting effect, which may suggest different mechanisms of implementing information sharing among lenders.

We conduct a second experiment around the same time of the first experiment. The sample of the two experiments do not overlap with each other. In the second experiment, we randomly selected 2,804 borrowers who took out a loan from RL. We then randomly assigned these borrowers into two groups (M1: 709) and (M2: 2095). We sent a credit warning message to M1 but not to M2. The message informs borrowers that default on the loan will be reported to the central credit bureau and affect their credit report.

Testable predictions

Appendix A includes a simple model that illustrate the effect of an increase in the default reporting probability on the take-out and repayment decisions. Recall that lenders are concerned about asymmetric information on borrower risk types and moral hazard problems when making a lending decision. If a borrower (regardless of type) knows that she is likely to default and default will adversely affect her credit report via lender reporting before taking out a loan, then she is less likely to take out the loan. This leads to H1a:

H1a: The awareness of default consequence on credit reporting before taking out the loan is negatively associated with the likelihood of taking out a loan.

The effect of awareness of default reporting before taking out a loan on default rate depends on two factors. The first factor is its effect on the composition of borrowers who take out a loan – the ratio of high credit risk borrowers relative to low credit risk borrowers. The composition effect further depends on default cost (the default probability * the penalty for reported default (e.g., increases in future funding costs)) and the change in unobservable expected effort. In the cross section, if the net effect is stronger (lesser) for high credit risk borrowers than for lower credit risk borrowers, then high credit risk borrowers are more (less) likely to drop out as the reporting probability increases, mitigating (exacerbating) adverse selection, resulting in lower (higher) default likelihood. The second factor is the default reporting effect on unobservable effort. According to our model, an increase in default reporting probability will improve borrowers' effort for loan repayment because of an increased marginal benefit of effort in reducing default penalty, leading to a decline in default likelihood. Overall, the awareness of default reporting on default likelihood before taking a loan is the net effect of two factors (compositional effect and unobservable effort effect). Because these two effects can go in the same or the opposite direction, the prediction of default reporting on loan default is unclear ex ante. The association is negative if and only if adverse selection is mitigated, or the effect of hidden actions dominates the exacerbation of adverse selection.

H1b: The awareness of default consequence on credit reporting before taking out the loan is not associated with the likelihood of default.

If a borrower learns that default will adversely affect her credit report after taking out a loan, based on moral hazard argument, she will exert greater effort to repay the loan than otherwise. The increased effort will reduce the default probability. This line of reasoning generates the prediction below:

H2: The awareness of default consequence on credit reporting after taking out the loan is negatively associated with the likelihood of default.

The awareness of default reporting may come from two sources. The first is regulation because RL (NRL) is (not) mandated to report borrowers' default to the central credit register. In other words, if a borrower knows this regulatory difference, then she understands that she will bear default consequence if her lender is RL but not if her lender is NRL. Intuitively, borrowers with prior borrowing experience with LHP is more likely to know the regulatory difference between the two types of lenders than new borrowers. Thus in the empirical analysis, we differentiate new borrowers from old borrowers based on their past experience with LHP. The second is via warning message. In other words, if a borrower receives a warning message, then she knows her default will bear the consequence. Whether these two sources of information will affect borrowers similarly and/or how they interact with each other are open empirical questions.

Data collection

LHP collected personal information o borrowers during the loan application process. It includes borrowers' Sesame score, LH score, age, gender, education, and income, as well as whether they have borrowed from LHP before (old vs. new borrower). We also obtained data on their loan characteristics consisting of interest rate, service fee, maturity, and loan amount, and their decision to take out a loan, default on the loan, and the time stamp of default over the course of duration.

Post-borrowing survey

After the due date of all loans in our first experiment, we randomly selected 1,500 applicants (18% of the 8,281 borrowers whose loan applications were approved by LHP and participated in that experiment) to administer a short post-borrowing survey. In the survey, we collected information about reasons for not taking out a loan, the probability of future borrowing, the main source of funding, the awareness of default consequence on the credit report, the source of the awareness, and how borrowers perceive the effect of the warning text message on their take-out and default decisions.

IV. Empirical results

4.1 Descriptive statistics

Table 1 Panel A reports the summary statistics of main variables used for testing H1 based on the first experiment. Our sample includes 8,281 approved loan applications, out which 4,700 (i.e., 56.8%) are funded by HR, a RL, and 3,581 loans are funded by YQG, a NRL.[10] The first panel shows that 82.2% applicants took up a loan and among them, out of which 7% borrowers defaulted. On average, 46.9% of borrowers received a text message before deciding on whether to take out a loan. If the funding source is RL, the text message states that default of the loan will be reported to the credit bureau. If the funding source is NRL, the text message states that loan default may affect their credit report. 6,803 (82.2% of) approved applications took out loans, out of which 7.1%

[10] In our experiment, 4,700 approved loan applications were assigned to HR, and the remaining 4,700 were assigned to YQG. However, some of the YQG loans were reassigned from HR, because HR does not allow any borrower who took out a loan in the previous three months to take out another loan, regardless whether the previous loan was paid off at the time of loan application. To make the two sub-samples of borrowers more comparable, we leave out 1,419 loans in the YQG pool of which the borrowers took out a loan from HR in the previous three months, regardless of whether the loan was originally assigned to YQG in our experiment, or it was reassigned from HR to YQG. This approach leaves us with 3,581 loans from YQG.

defaulted. A typical loan matures in three months.[11] Both the average and median loan amounts are 4,000 Yuan. The average (median) monthly interest rate is 6% (7%), most of which is monthly service fee, averaging at 4.9% (with a median of 6%).

We use two measures for borrowers' credit quality. *Sesame Score* (*Zhimafen*), the most widely used credit scores in China, provided by the Ant Financial. *LH Score* is generated by the LHP platform using a proprietary model, incorporating the borrowing and repayment history of individuals at LHP. The average (median) Sesame score of LHP borrowers is 653.49 (651) with a standard deviation of 37, indicating that approved borrowers, by and large, have fair credit quality. The average (median) LH score is 674.21 (675) mirror-imagining the Sesame score.[12] The correlation between Sesame score and LH score is 0.409. Among all LHP borrowers, 55.2% borrowed from LHP for the first time (i.e., new borrowers), 23.7% are female, and the average (median) age is 29.64 (28) years old. Untabulated, we find that characteristics of RL borrowers and NRL borrowers are comparable in all dimensions.

Panel B breaks up the sample into old and new borrowers. We observe significant differences between the two subsamples. For example, new borrowers are less likely to take up a loan but more likely to default compared with old borrowers. Fewer new borrowers received the credit warning. Loans to new borrowers are smaller, and have shorter maturity and higher interest rate. Furthermore, new borrowers have lower Sesame score and LH score, implying that they have

[11] 259 loans from HR have a maturity of six months, while all remaining loans mature in three months. The results of our empirical analyses remain unchanged if we leave out those 259 loans.

[12] Sesame Score is provided by Sesame Credit, a private credit bureau under Ant Financial that processes approximately 70% of online transactions in China. Sesame score is calculated based on an individual's credit history, online transaction habits, ability to honor agreements, personal information, and social network affiliations. Sesame Score ranges from 350 to 950. Sesame Score of 700 or above is considered excellent, Sesame Score between 650 and 700 is good, Sesame Score between 600 and 650 is fair, and Sesame Score below 600 is considered poor credit quality. https://baike.baidu.com/item/%E8%8A%9D%E9%BA%BB%E4%BF%A1%E7%94%A8/15870746?fr=aladdin&fromid=16696800&fromtitle=%E8%8A%9D%E9%BA%BB%E5%88%86

lower credit quality than old borrowers. New borrowers have slightly lower female presence and are marginally older in age than old borrowers.

We have information on the highest degree obtained by borrowers. In our sample, 19.09% borrowers do not report their education information. There are eight categories for reported degrees: Master or above (0.41%), College (13.13%), Junior college (30.54%), Vocational secondary school (16.68%), Vocational high school (1.7%), High school (13.36%), Middle school (5.06%), and Elementary school or below (0.04%). Given the distribution, we combine Master or Above with College into a category of *Bachelor or above*. Furthermore, we combine Middle school and Elementary school or below into *Below high school*.

Table 1 Panel C presents summary statistics for the 2,804 loans from the second experiment. All these loans were already taken up by borrowers and were funded by RL. Among these 2,804 loans, 1,340 are taken by old borrowers and 1,464 by new borrowers. The proportion of new borrowers (52%) is comparable to that in Panel A among borrowers who took up the loan funded by RL (52%). 6.9% borrowers defaulted, slightly lower than the 7.1% default rate for the first experiment sample. 25.3% borrowers received the credit warning. The sample from the second experiment preserves similar loan and borrower characteristics as the one from the first experiment. For example, loan size, maturity, and interest rate are comparable across the two samples. We also break down the second experiment sample into old and new borrowers. Mirroring Panel B, Panel D shows that new borrowers have higher default rate, received higher interest rate, and have lower Sesame score and LH score than old borrowers of the second experiment. Lower percentage of new borrowers received the credit warning.

[Insert Table 1]

For the second experiment, Table 6 Panel A reports the summary statistics for old and new borrowers separately. When comparing warning receivers (treated) with non-warning receivers (control) among old borrowers, their loans were charged with similar service fee and they have similar credit scores. Their gender composition and age are also comparable. The only difference is that the loan size is slightly smaller for warning receivers than non-warning receivers. For the borrower and loan characteristics among new borrowers, the treated and control only differ in gender composition – warning receivers have higher female representation. Overall, borrowers who received the warning message have very similar observable credit risk profile (such as Service fee, Sesame score and LH score) with those who did not receive the message.

Pearson correlation coefficients are reported in Table 2 with p-values placed in brackets. Panel A, based on the sample from the first experiment, shows that take-out likelihood is negatively associated with whether a lender reports borrower default information but positively associated with whether a borrower received the credit warning. Thus, we find mixed evidence for H1a at the univariate level. Default likelihood is negatively associated with loan size, maturity, Sesame score, LH score, and whether a borrower is female while positively associated with the interest rate and whether a borrower is new to LHP. Our univariate evidence is largely consistent with the findings in prior research that borrowers taking out large size loans, and loans with longer maturity are safer (Michels, 2012), and females are less risky than their male counterparts (Kevane and Wydick, 2001; D'Espallier, Guerin and Mersland, 2011). Receiving a credit warning message and whether a lender reports borrower default information are both negatively associated with default incidence, implying that being aware of default reporting has a net effect of reducing default likelihood. Receiving a credit warning message is also negatively associated with loan size, whether a borrower is new, and borrower age. Loans funded by RL have a longer maturity, higher interest rate, but charge a lower service fee. Interestingly, loans given to female borrowers are larger and have lower service fee, and female borrowers tend to be repeated borrowers at LHP, and have higher Sesame score and LH score.

Panel B, based on loans from the second experiment, depicts a similar picture of correlation coefficients. More importantly, we find a negative correlation between MSG and default, consistent with H2 that credit warning reduces borrower moral hazard.

[Insert Table 2]

4.2 Testing H1

In testing H1, we analyze borrowers' take-out and default decisions separately, using Experiment 1.

4.2.1 Take-out decision

In this subsection, we analyze borrowers' loan take-out decisions observed in the first experiment to test the effect of information sharing on adverse selection. We conduct analysis for old and new borrowers separately because of the possible difference between the two groups in their knowledge of the lenders' reporting policy before the experiment.

Among old borrowers, column 1 of Table 3 shows that those funded by RL are less likely to take out a loan than those funded by NRL, as indicated in the negative and significant coefficient on *RL*. The coefficient on *MSG* is statistically insignificant. This evidence is consistent with H1a—awareness of default reporting reduces borrowers' likelihood to take out a loan. In addition, the evidence supports our maintained assumption that old borrowers are aware of the default reporting policy of RL and NRL. The marginal effect of RL implies that an old borrower is 9.01%

less likely to take out a loan if the loan is funded by a RL relative to a NRL. This magnitude is economically large given the 10% unconditional withdraw rate reported in Table 1 Panel A. With respect to control variables, Sesame score and interest rate are both negatively associated with take-out likelihood, suggesting that borrowers with higher credit score might be less financially constrained and higher interest rate discourages applicants to borrow. Regarding education, we find that borrowers with high school or lower diplomas are more likely to take out a loan, possibly due to financial constraint.

For new borrowers, column 2 shows that the coefficient on RL is negative but statistically insignificant at a conventional level. The coefficient on MSG is positive and significant, indicating that credit warning increases new borrowers' propensity to take out a loan. This might happen because credit warning sent a positive signal to new borrowers who are not familiar with LHP that it is safe to give bank account information to LHP because it is a legitimate business. This might also happen because some borrowers realized that the penalty for default if more civilized than expected. The marginal effect of MSG is 2.81%, indicating that a new borrower is more likely to take out a loan if she receives a credit warning message than otherwise. This magnitude is economically meaningful given the 24% unconditional withdraw rate reported in Table 1 Panel A. Overall, we find evidence that the awareness of information sharing among old (new) borrowers reduces (increases) their propensity to take out a loan.

[Insert Table 3]

4.2.2 Default decision

Our measure of default is a dummy variable indicating whether a loan defaults during its lifetime. We again separate old borrowers from new borrowers. Within each group, we examine whether the default likelihood differs between loans funded by RL differ and loans funded by NRL, and between borrowers receiving credit warning and those not received the warning. Table 4 reports the regression results for old and new borrowers, respectively.

Column 1 shows a negative and significant coefficient on RL, implying that old borrowers funded by RL are less likely to default relative to those funded by NRL. This suggests that 1) old borrowers are aware of the reporting difference between RL and NRL; 2) Being aware of information sharing among lenders reduces ex ante moral hazard and/or adverse selection. The coefficient on MSG is positive but statistically indistinguishable from zero. Therefore, we do not find any effect of credit warning on old borrowers. This is consistent with our prior – credit warning might not sway borrowers' decision when they already know lenders' reporting policy. From an economic perspective, among old borrowers, the default likelihood is reduced by 1.50% if the lender is a RL instead of NRL. This magnitude is large given the 4.4% unconditional default rate reported in Table 1 Panel B.

In column 2 when we focus on new borrowers, we find a negative and significant coefficient on MSG while insignificant coefficient on RL, implying that 1) credit warning reduces new borrowers' default likelihood; 2) new borrowers are on average unaware of the reporting difference between RL and NRL. Economically, the default likelihood is reduced by 2.65% if a new borrower received a credit warning message. This magnitude is economically meaningful given the 9.6% unconditional default rate reported in Table 1 Panel B.

Regarding control variables, Sesame score is negatively associated with default likelihood for both old and new borrowers. However, its coefficient is only statistically significant for new borrowers. In addition, interest rate is positively associated with default likelihood for both columns. Therefore, it is possible that the presence of interest rate as a control subsumes the explanatory power of Sesame score for old borrowers because interest rate might contain more lending-platform specific credit relevant information for old borrowers than for new borrowers. Among old borrowers, females are less likely to default than their male counterparts. We don't find such difference among new borrowers. Taken together, Table 4 provides evidence supporting H1b that knowing information sharing among lenders ex ante reduces borrower default likelihood, due to reduced expected moral hazard and/or adverse selection. In addition, the evidence validates our rationale of separating old borrowers from new borrowers on the ground that old (new) borrowers are aware (unaware) of the reporting difference between RL and NRL.

[Insert Table 4]

4.3 Testing H2

In testing H2, we rely on the sample from the second experiment. Among 1,340 old borrowers, 377 received the credit report warning while 963 did not. For 1,464 new borrowers, 332 received the credit warning while 1,132 did not. The left panel of Table 5 reports Probit regression results for old and new borrowers separately based on the second experiment sample. The model specification is the same as our previous tests reported in Table 4. Note we do not include RL as an independent variable because all loans in Experiment 2 were funded by RL. To ease comparison we also tabulate the results in the right panel based on loans funded by RL from the first experiment.

Column 1shows that among old borrowers MSG is loaded with a negative sign but statistically indistinguishable from zero. Therefore, the evidence suggests that credit warning following take-out does not affect the default rate for old borrowers. In contrast, the coefficient on MSG is negative and statistically significant at the one percent level for new borrowers as evidenced in column 2. The marginal effect of MSG is 2.51%, which is economically significant compared to the unconditional default probability of 10% (Table 1 Panel D). The coefficients on control variables are largely consistent with those reported in Table 4. Taken together, we find that credit warnings reduce new borrowers' moral hazard, supporting our prediction in H2.

In the right panel based on the RL borrowers from the first experiment, we find that the coefficient on MSG is insignificant for old borrowers but negative and statistically significant for new borrowers, consistent with that reported in Table 4. The marginal effect of MSG for new borrowers is 3.43%, smaller than that reported for its counterpart in the left panel. To test if the MSG effect differs between the first and second experiment among new borrowers, we pool the two subsamples together and interact a dummy variable (E1), taking values of one if the new borrower comes from the first experiment, with MSG. Using OLS estimate we find that the coefficient on MSG is negative (coefficient = -0.036) and statistically significant at the one percent level. The coefficient of the interaction term (MSG*E1) is positive (coefficient = 0.019) but statistically indistinguishable from zero. Recall the coefficient on MSG from the first experiment (right panel) reflects its net effect on adverse selection and unobservable expected effort while the MSG coefficient from the second experiment (left panel) reflects its effect on unobservable effort. The insignificant interaction term suggests that credit warning does not affect adverse selection significantly.

[Insert Table 5]

Though we show that treated borrowers who received credit warning and control borrowers (who did not receive the warning) are very similar in observable credit risk profile in Table 6 Panel A, they do differ in loan size and gender composition. To ensure that these two groups of borrowers are comparable across all covariates, we use Mahalanobis matching method for old and new borrowers separately. More specifically, we find three matched non-receivers for each receiver based on Sesame Score, Interest rate, Female, Age, and Education dummies.

Table 6 Panel B presents the result of covariate balance. The left panel focuses on old borrowers while the right panel focuses on new borrowers. The difference between the treated and control borrowers in all variables used in the matching is statistically insignificant, suggesting that the matching quality is satisfactory in removing systematic observable difference between the two groups. The top row shows that default rate does not differ between warning receivers and non-warning receivers among old borrowers. Therefore, credit warning does not have any effect on moral hazard among old borrowers. This is consistent with our expectation because old borrowers already know that RL will report their default information if they default on the loan and credit warning does not provide additional information.

In the right panel when we focus on new borrowers, borrowers receiving the credit warning are less likely to default (5.1%) compared to borrowers who did not receive the warning (11.6%). The difference of 6.5% is both statistically and economically significant. Overall, we find evidence supporting H2 that knowing information sharing among lenders after taking out a loan reduces moral hazard of borrowers.

[Insert Table 6]

IV. Survey evidence

To gauge the importance of P2P lending for LHP borrowers, and to see what affect their take-out and default decisions, LHP conducted a survey in October, 2017 on our behalf. The survey includes 11 questions (see the list in Appendix B). LHP randomly selected 1,500 borrowers among those used in the first experiment and conducted phone interviews. Out of these 1,500 borrowers, 1,244 (82.9%) borrowers took out the loan and 256 (17.1%) borrowers did not. The take out rate approximates the one in the first experiment (82.2% reported in Table 1 Panel A). Among borrowers who took out LHP loans, 284 (a participation rate of 22.8%) participated in the survey and 273 completed the survey. This response rate is considered good compared with other studies which have the average response rate of 11% (Graham, Harvey and Puri, 2015). Among borrowers who did not take out LHP loans, 43 (a participation rate of 16.8%) participated the survey and 36 borrowers completed the survey. We summarize the survey results below, first contrasting borrowers who took out the loan with those who did not. We find that

(1) Borrowers who took out the loan rely more on P2P lending for financing (37%) than borrowers who did not take out the loan (23%).

(2) Credit cards represent a major source of external financing for both applicants who took out the loan (36%) and those who did not take out the loan (40%). This evidence validates that information sharing increases default cost to borrowers.

(3) Applicants who did not take out the loan are more likely to apply for a credit card in the next three years than those who took out the loan.

(4) Borrowers who took out the loan rely more on LHP to obtain information about lending reporting policy, borrowers who did not take out the loan search Baidu (the Chinese counterpart of Google).

(5) Among borrowers who received the text message, few have any question or doubt about this message (10% for borrowers who did not take out the loan and 6% for borrowers who took out the loan), suggesting that borrowers are likely to take the text message at face value.

(6) Among borrowers who did not take out the loan, 20% indicate that the reason for not taking out the loan is the concern about their bank account security. This evidence renders some support to our interpretation of why receiving the text message increases new borrowers' propensity to take up a loan (discussed in Section III and reported in Table 3).

Furthermore, for all borrowers as a group, we find that

(7) Post borrowing, approximately 90% of borrowers knew that loan default would affect their credit scores.

(8) Borrowers who knew the consequence of loan default were less likely to default (inferred), confirming our evidence reported in Table 4.

(9) Approximately 20% of borrowers believed that the text message affects their take-out decision, and approximately 20% of borrowers believed that the text message affects their repayment decision.

V. Conclusion

This study investigates the effect of awareness of default information sharing among lenders on borrower take-out and default decisions. We conducted two field experiments via an online lending platform with two lenders–one lender reports borrower default information (RL) and the other does not (NRL). In the first experiment we sent a text message to a randomly selected group of borrowers informing that their loan default will (possibly) be reported to the central credit bureau. The message was sent out before borrowers made the take-out decision. In the second experiment, we sent the same text message to a randomly selected group of borrowers who have already taken out a loan. We have two major findings. First, knowing that lenders share borrowers' default information attenuate moral hazard problem. Second, the awareness of information sharing among lenders unlikely has any material effect on adverse selection.

Our study provides evidence on the causal effect of information sharing among lenders on adverse selection and moral hazard problems. It is hard to separate the two based on observational data. Our experimental setting allows us to do so by manipulating the timing when borrowers became aware of information sharing. Our study has significant implications for policy makers who are concerned about adverse selection and moral hazard problems. Our findings suggest that information sharing has a large effect on limiting moral hazard problem but not so much on adverse selection. Therefore, an effective policy might combine default reporting with subsidies on loan interest rate, loan guarantees, information coordination, and enhanced screening strategies (Karlan and Zinman, 2009). The evidence sheds lights on how to improve lending outcomes using readily available, inexpensive technology—sending text messages, which is of interest to Fintech lenders. Our findings contribute to the nascent Fintech literature, particularly on how to use digital footprints and machine learning to foster financial inclusion and improve efficiency in the segment of consumer credit market.

Appendix A. Two Simple Models

In this Appendix, we present two models to illustrate the effect of adverse selection and moral hazard on loan take-out and default decisions. We show the effect of a positive shock to the probability of reporting loan default (e.g., via learning about the RL or receiving the text message) on the adverse selection and moral hazard problems.

Assumptions

There are two types of borrowers, those with high credit rating, *h* (high type or low credit risk), and those with low credit rating, *l* (low type or high credit risk). All borrowers are risk neutral and do not engage in strategic default (to make economic insight more transparent). Suppose that both types of borrowers need a fixed amount, F. The interest rate charged for borrowers with low and high credit ratings are r_l and r_h, respectively, where $r_l > r_h$. Without loss of generality, we assume the value of the loan to be *g(F)* for all borrowers. *g(F)* is increasing in F, and $g(F) \geq F(1 + r_l) > F(1 + r_h)$. The probability of a project failure: $0 \leq p_h < p_l \leq 1$. If the project fails, the payoff is normalized to zero and the borrower defaults on the loan. Suppose the probability of reporting the default to the central credit bureau is $0 < \alpha \leq 1$. It is reasonable to assume that the penalty for a reported default is larger for high type borrowers than low type borrowers: $0 < k_l < k_h$, because high type borrowers more likely to apply for credit cards, home mortgage, and car loans in the future when credit scores play an important role. Thus, a negative credit report to the central credit bureau will adversely affect funding sources and costs to a larger extent for the high type borrowers.

<u>Model I:</u> Adverse Selection

<u>The expected utility for high type borrowers:</u>

$U_h = g(F) - (1 - p_h)F(1 + r_h) - p_h\alpha\, k_h \geq U_h^0$ (reservation utility);

Taking the first-order derivative with respect to α, the reporting probability, we obtain the effect of changing the reporting probability on the borrower's expected utility: $\frac{\partial U_h}{\partial \alpha} = -p_h k_h < 0$.

<u>The expected utility for low type borrowers:</u>

$U_l = g(F) - (1 - p_l)F(1 + r_l) - p_l\alpha\, k_l \geq U_l^0$, and the effect of changing the default reporting probability on the borrower's expected utility is $\frac{\partial U_l}{\partial \alpha} = -p_l k_l < 0$.

As the probability of reporting default increases, borrowers' utility decreases. Which type of borrowers is more sensitive to the increased reporting probability depends on the relationship between $p_h k_h$ and $p_l k_l$ ($0 \leq p_h < p_l$ and $0 < k_l < k_h$). If $p_h k_h > p_l k_l$, high type borrowers are more likely to drop out as the reporting probability increases, exacerbating the adverse selection problem. On the other hand, if $p_h k_h < p_l k_l$, low type borrowers are more likely to drop out. As a result, the effect of adverse selection on the take-out decision is mitigated.

<u>Model II:</u> Adverse Selection and Moral Hazard

We introduce effort choices to the model above. A borrower's effort reduces the default probability in a linear fashion, and the cost of effort is quadratic. For simplicity, the unit cost of effort is 1. For high type borrowers, the default probability is $p_h(e_h) = p_h - e_h$ (e.g., $p_h'(e_h) = -1$). The cost of effort is $0.5e_h^2$. The expected utility of high-credit borrowers is $U_h = g(F) - \big(1 - p_h(e_h)\big)F(1 + r_h) - p_h(e_h)\alpha k_h - \frac{1}{2}e_h^2 = -g(F) - F(1 + r_h) + p_h(e_h)(F(1 + r_h) - \alpha k_h) - \frac{1}{2}e_h^2$, concave in effort. The FOC yields:

$$\frac{\partial U_h}{\partial e_h} = -(F(1 + r_h) - \alpha k_h) - e_h = 0.$$

The optimal effort level is $e_h^* = \alpha k_h - F(1 + r_h)$. Given optimal effort, default probability is $p_h - \ \alpha k_h + F(1 + r_h)$; decreasing in α, and more sensitive to an increase in α for high type borrowers.

Plugging in the optimal effort level into the borrower's expected utility function, we obtain:

$$U_h = g(F) - F(1 + r_h) + p_h(F(1 + r_h) - \alpha k_h) + \frac{1}{2}\big(\alpha k_h - F(1 + r_h)\big)^2.$$

The sensitivity of the expected utility to the reporting probability is

$\frac{\partial U_h}{\partial \alpha} = -p_h k_h + k_h\big(\alpha k_h - F(1 + r_h)\big) = -k_h p_h(e_h^*) < 0$ for high type borrowers and

$\frac{\partial U_l}{\partial \alpha} = -p_l k_l + k_l\big(\alpha k_l - F(1 + r_l)\big) = -k_l p_l(e_l^*) < 0$ for low type borrowers.

Thus, as the reporting probability increases, both types of borrowers are less likely to take out loans.

The first term reflects the effect of different types. The second term makes the high type borrowers' utility less sensitive to the increased probability of reporting default, because the higher marginal cost of default $k_h > k_l$ motivates high type borrowers to work harder to avoid default. If high type borrowers were more sensitive to the reporting probability due to adverse selection (that is, $p_h k_h > \ p_l k_l$), their greater effort reduces the sensitivity to reporting.

Model Predictions on Take-Out

Model II predicts that as reporting probability increases, the take-out rate decreases. Cross-sectional predictions on take-out rates depend on the relative magnitude of $-p_h k_h + k_h\big(\alpha k_h - F(1 + r_h)\big)$ and $-p_l k_l + k_l\big(\alpha k_l - F(1 + r_l)\big)$. If the former is more negative than the latter, low credit risk borrowers are more likely to drop out, and adverse selection problem is exacerbated as a result.

Model Predictions on Default

Model II predicts that as reporting probability increases, default probability (1) decreases for all borrowers who take out a loan, and (2) decreases to a larger extent for high type borrowers. Due to changes in the composition of borrowers (who take out a loan), the overall default rate will decrease if the expected penalty for reported default is not much larger for low credit risk borrowers than for high credit risk borrowers (e.g., adverse selection does not dominate moral hazard problems).

Appendix B. Survey Following Experiment 1

Below is the list of our survey questions and summary of answers from LHP borrowers.

1. *What is your key external financing source? Borrowing from 1. Banks, 2. Credit cards, 3. P2P lending, 3. Family and friends, 5. Others.*

    - [14%: 39.5%: 23.3%: 4.65%: 18.6%] for 43 borrowers who did not take out the loan, [7.39%: 35.9%: 37.3%: 7.75%: 11.6%] for 284 borrowers who took out the loan.
    - One important financing source for both groups is credit cards.
    - Borrowers who take out the LHP loan rely on P2P lending significantly more than borrowers who do not take out the loan (statistically significant at the 10% level).

2. *How likely you are going to borrow from banks or other financial institutions in the next three years? 1. Very unlikely, b. Unlikely, 3. Likely, 4. Very likely.*

    - An average of 2.38 for 39 borrowers who did not take out the loan, and 2.65 for 280 borrowers who took out the loan

Q2		N	Percent	N	Percent
1. Very unlikely	1	13	33.33	67	23.93
2. Unlikely	2	9	23.08	57	20.36
3. Likely	3	6	15.38	63	22.5
4. Very likely	4	11	28.21	93	33.21
Total		39	100	280	100

3. *How likely you are going to apply for credit cards in the next three years? 1. Very unlikely, b. Unlikely, 3. Likely, 4. Very likely.*

    - An average of 3.05 for 38 borrowers who did not take out the loan, and 2.46 for 277 borrowers who took out the loan.
    - Borrowers who do not take out the LHP loan are significantly more likely to apply for a credit card in the near future (statistically significant at the 1% level).

4. *Do you know the lender's identity when deciding on whether to take out the loan? 1. Yes, 2. No.*

    - [25%: 75%] for 36 borrowers who did not take out the loan, and [38.1%: 61.9%] for 273 borrowers who took out the loan.
    - The majority of LHP borrowers do not read the loan contract which contains information on lender's identity.

5. *If you do know the lender's identity, do you find reviewing the loan contract helps you decide on whether to take out the loan? 1. Yes, 2. No.*

    - [100%: 0%] for 9 borrowers who did not take out the loan, and [96.2%: 3.8%] for 104 borrowers who took out the loan.

6. *Do you know default on the loan will affect your credit score? 1. Yes, 2. No.*

- [88.9%: 11.1%] for 36 borrowers who did not take out the loan, and [88.9%: 11.1%] for 271 borrowers who took out the loan.

7. If you do know, where did you learn about the information? From 1. Prior P2P lending experiences, 2. Baidu forums, 3. Family and friends, 4. The text message sent by LHP, 5. Other sources.

- [9%: 47%: 0: 21.9%: 21.9%] for 32 borrowers who did not take out the loan,
  [18%: 11.8%: 7.56%: 33.6%: 29%] for 238 borrowers who took out the loan;
- Borrowers who did not take out the loan rely on Baidu to learn about default consequence (Difference in 7b is statistically significant at the 1% level);
- Borrowers who took out the loan rely more on the text message (difference in 7d is not statistically different at a conventional level, unfortunately).

8. *Do you have any question on the LHP text message (for borrowers receiving the text message)? 1. Yes, 2. No.*

- [8.33%: 91.7%] for 12 borrowers who did not take out the loan, and [5.81%: 94.2%] for 86 borrowers who took out the loan.

9. *If you do have questions on the text message, how did you answer the question? 1. Read Baidu forum, 2. Inquire friends or family, 3. Talk to LHP customer service, 4. Others.*

- [1: 100%, 0, 0, 0] for 1 borrower who did not take out the loan, and [5: 20%, 20%, 60%, 0] for 5 borrowers who took out the loan.

10. *Did the text message affect your decision to take out the loan (for borrowers receiving the text message)? 1. Yes, 2. No.*

- [18.2%: 81.8%] for 11 borrowers not taking out the loan, and [25.6%: 74.4%] for 86 borrowers taking out the loan.

11a. *Did the text message affect your decision to repay the loan (for borrowers receiving the text message and taking out the loan)? 1. Yes, 2. No.*

- [21.2%: 78.8%] for 85 answers. Surprise!

11b. *Please specify the main reason for not taking out the loan (for borrowers who did not take out the loan): 1. No longer needed the fund or found alternative sources, 2. Concerns about the security of the bank account (needed for depositing the loan), 3. Knowing the lender's identify, are concerned about the adverse effect on the credit report, 4. Others.*

- [47.6%: 19%: 9.5%: 23.8%] for 21 answers.

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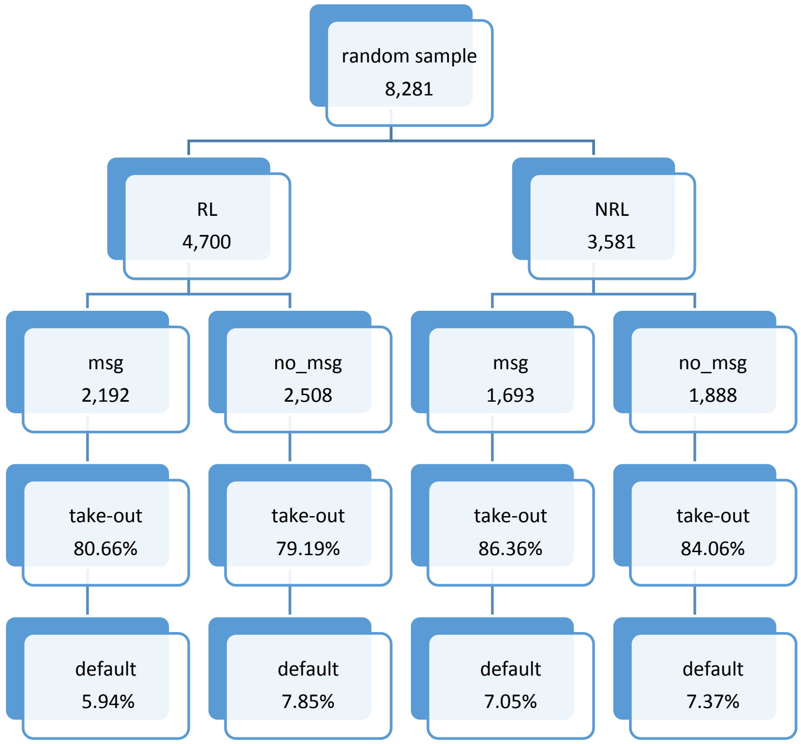
Figure 1. Description of Experiment 1.



Description of Experiment 2.

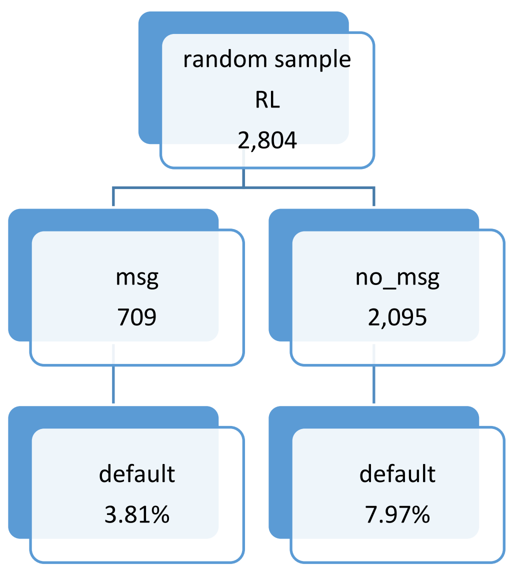


Table 1. Summary statistics

This table reports summary statistics on take-out and default outcomes of two experiments, credit warning message, lender types, loan characteristics, and borrower characteristics. Panels A and B focus on the sample of Experiment 1, while Panels C and D focus on the sample of Experiment 2. *RL* is an indicator that takes the value of one if the lender reports default lender and zero otherwise. *MSG* is an indicator that takes the value of one if the borrower received a credit warning message and zero otherwise. *Interest rate* is the sum of monthly interest rate and service fees.

Panel A. Sample for Experiment 1

Variable	*N*	Mean	Min	*p*25	*p*50	*p*75	Max	St. Dev.
Default	6,803	0.071	0	0	0	0	1	0.256
Take-out	8,281	0.822	0	1	1	1	1	0.383
MSG	8,281	0.469	0	0	0	1	1	0.499
RL	8,281	0.568	0	0	1	1	1	0.495
Amount (Yuan)	8,281	3,736.75	2,000	2,000	4,000	6,000	6,000	1,750.16
Maturity (months)	8,281	3.094	3	3	3	3	6	0.522
Interest rate (monthly)	8,281	0.060	0.032	0.050	0.070	0.072	0.072	0.013
New	8,281	0.552	0	0	1	1	1	0.497
Sesame score	8,281	653.68	584	625	651	678	753	37.38
LH score	8,281	674.21	532	640	675	706	772	40.98
Female	8,281	0.237	0	0	0	0	1	0.425
Age	8,281	29.641	20	25	28	33	55	6.193
Bachelor or above	8,281	0.135	0	0	0	0	1	0.342
Junior college	8,281	0.305	0	0	0	1	1	0.461
Vocational secondary school	8,281	0.167	0	0	0	0	1	0.373
Vocational high school	8,281	0.017	0	0	0	0	1	0.129
High school	8,281	0.134	0	0	0	0	1	0.34
Below high school	8,281	0.051	0	0	0	0	1	0.22

Panel B. Experiment 1: old vs. new borrowers

	Old borrowers		New borrowers		Diff
Variables	*N*	Mean	*N*	Mean	
Default	3,339	0.044	3,464	0.096	-0.052***
Take-out	3,707	0.901	4,574	0.757	0.143***
MSG	3,707	0.489	4,574	0.453	0.037***
RL	3,707	0.558	4,574	0.575	-0.017
Amount (Yuan)	3,707	4,561.1	4,574	3,068.6	1492.5***
Maturity (months)	3,707	3.197	4,574	3.01	0.186***
Interest rate (monthly)	3,707	0.052	4,574	0.067	-0.016***
Sesame score	3,707	659.5	4,574	649.0	10.48***
LH score	3,707	703.46	4,574	650.50	52.96***
Female	3,707	0.246	4,574	0.23	0.016*
Age	3,707	29.253	4,574	29.956	-0.703***
Bachelor or above	3,707	29.253	4,574	29.956	-0.703***
Junior college	3,707	0.148	4,574	0.125	0.023***
Vocational secondary school	3,707	0.32	4,574	0.294	0.026***
Vocational high school	3,707	0.114	4,574	0.21	-0.096***
High school	3,707	0.013	4,574	0.02	-0.006**
Below high school	3,707	0.131	4,574	0.136	-0.004

Panel C. Sample for Experiment 2

Variable	*N*	Mean	Min	*p*25	*p*50	*p*75	Max	St. Dev.
Default	2,804	0.069	0	0	0	0	1	0.254
MSG	2,804	0.253	0	0	0	1	1	0.435
Amount (Yuan)	2,804	3,715.407	2,000	2,000	4,000	6,000	6,000	1,722.953
Maturity (months)	2,804	3	3	3	3	3	3	0
Interest rate (monthly)	2,804	0.061	0.042	0.052	0.072	0.072	0.072	0.013
New	2,804	0.522	0	0	1	1	1	0.5
Sesame score	2,804	650.729	584	623	647	674	748	36.896
LH score	2,804	676.198	610	640	675	712	772	40.449
Female	2,804	0.241	0	0	0	0	1	0.428
Age	2,804	29.845	20	25	28	33	55	6.278
Bachelor or above	2,804	0.122	0	0	0	0	1	0.327
Junior college	2,804	0.307	0	0	0	1	1	0.461
Vocational secondary school	2,804	0.177	0	0	0	0	1	0.381
Vocational high school	2,804	0.02	0	0	0	0	1	0.139
High school	2,804	0.139	0	0	0	0	1	0.346
Below high school	2,804	0.065	0	0	0	0	1	0.246

Panel D. Experiment 2: old vs. new borrowers

Variables	Old borrowers		New borrowers		Diff
	N	Mean	*N*	Mean	
Default	1,340	0.036	1,464	0.1	-0.064***
MSG	1,340	0.281	1,464	0.227	0.055***
Amount (Yuan)	1,340	4,453.7	1,464	3,039.6	1414.1***
Maturity (months)	1,340	3	1,464	3	0
Interest rate (monthly)	1,340	0.053	1,464	0.068	-0.015***
Sesame score	1,340	657.59	1,464	644.45	13.146***
LH score	1,340	704.31	1,464	650.47	53.84***
Female	1,340	0.274	1,464	0.212	0.062***
Age	1,340	29.861	1,464	29.829	0.032
Bachelor or above	1,340	0.11	1,464	0.133	-0.022*
Junior college	1,340	0.316	1,464	0.298	0.017
Vocational secondary school	1,340	0.114	1,464	0.234	-0.119***
Vocational high school	1,340	0.023	1,464	0.016	0.007
High school	1,340	0.148	1,464	0.132	0.016
Below high school	1,340	0.051	1,464	0.077	-0.026***

Table 2. Pearson correlation coefficients

Pearson correlation coefficients are provided with p-values below each coefficient testing the prob > |r| under H_0: $\rho = 0$.

Panel A: sample for Experiment 1

	1	2	3	4	5	6	7	8	9	10	11	12
1. Default	1											
2. Take-out	-	1										
	-											
3. MSG	-0.023	0.024	1									
	(0.054)	(0.027)										
4. RL	-0.005	-0.068	-0.006	1								
	(0.674)	(0.000)	(0.564)									
5. Amount (Yuan)	-0.100	0.074	-0.027	0.006	1							
	(0.000)	(0.000)	(0.015)	(0.619)								
6. Maturity (months)	-0.039	-0.049	0.006	0.157	0.232	1						
	(0.001)	(0.000)	(0.570)	(0.000)	(0.000)							
7. Interest rate (monthly)	0.108	-0.113	0.003	0.042	-0.774	-0.304	1					
	(0.000)	(0.000)	(0.755)	(0.000)	(0.000)	(0.000)						
8. New	0.101	-0.186	-0.036	0.017	-0.424	-0.177	0.595	1				
	(0.000)	(0.000)	(0.001)	(0.119)	(0.000)	(0.000)	(0.000)					
9. Sesame score	-0.110	-0.100	0.017	-0.002	0.422	0.086	-0.346	-0.140	1			
	(0.000)	(0.000)	(0.117)	(0.840)	(0.000)	(0.000)	(0.000)	(0.000)				
10. LH score	-0.150	0.133	0.004	-0.011	0.582	0.154	-0.629	-0.643	0.409	1		
	(0.000)	(0.000)	(0.703)	(0.321)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
11. Female	-0.043	0.002	0.011	-0.018	0.099	0.006	-0.086	-0.019	0.120	0.071	1	
	(0.000)	(0.874)	(0.299)	(0.105)	(0.000)	(0.593)	(0.000)	(0.084)	(0.000)	(0.000)		
12. Age	0.026	-0.007	-0.025	-0.007	0.065	-0.032	-0.045	0.057	-0.009	0.037	0.034	1
	(0.032)	(0.516)	(0.023)	(0.543)	(0.000)	(0.004)	(0.000)	(0.000)	(0.396)	(0.001)	(0.002)	

Table 2. Continued.

Panel B: Sample for Experiment 2

	1	2	3	4	5	6	7	8	9
1. Default	1								
2. MSG	-0.071	1							
	(0.000)								
3. Amount (Yuan)	-0.117	-0.013	1						
	(0.000)	(0.509)							
4. Interest rate (monthly)	0.122	-0.011	-0.749	1					
	(0.000)	(0.568)	(0.000)						
5. New	0.126	-0.063	-0.410	0.581	1				
	(0.000)	(0.001)	(0.000)	(0.000)					
6. Sesame score	-0.115	0.044	0.480	-0.390	-0.178	1			
	(0.000)	(0.019)	(0.000)	(0.000)	(0.000)				
7. LH score	-0.154	0.038	0.585	-0.629	-0.665	0.461	1		
	(0.000)	(0.045)	(0.000)	(0.000)	(0.000)	(0.000)			
8. Female	-0.065	0.040	0.121	-0.095	-0.073	0.135	0.103	1	
	(0.001)	(0.035)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
9. Age	0.027	-0.014	0.107	-0.097	-0.003	0.039	0.103	0.057	1
	(0.148)	(0.448)	(0.000)	(0.000)	(0.893)	(0.038)	(0.000)	(0.003)	

Table 3. The effect of awareness of information sharing on take-out decisions

This table examines borrowers' take-out decision in Experiment 1. Column1 focuses on old borrowers, and column 2 focuses on new (first-time) borrowers of LHP. The dependent variable is an indicator that takes the value of one if a borrower takes out an approved loan and zero otherwise. *RL* is an indicator that takes the value of one if the lender reports default lender and zero otherwise. *MSG* is an indicator that takes the value of one if the borrower received a credit warning message and zero otherwise. *Interest rate* is the sum of monthly interest rate and service fees. We report t-statistics based on heteroscedasticity robust standard errors in the parentheses below the corresponding regression coefficients. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Probit regression: Dependent variable = take-out		
	Old borrowers	New borrowers
	(1)	(2)
RL	-0.578***	-0.034
	(-9.147)	(-0.812)
MSG	0.020	0.092**
	(0.348)	(2.203)
Sesame score	-0.002**	-0.008***
	(-2.271)	(-12.194)
Interest rate	-3.839*	-14.648***
	(-1.704)	(-5.005)
Female	0.003	0.047
	(0.048)	(0.938)
Age	-0.001	-0.003
	(-0.141)	(-1.065)
Education dummies (base group: do not report)		
Bachelor or above	0.094	0.009
	(0.980)	(0.118)
Junior college	0.077	0.065
	(1.006)	(1.027)
Vocational secondary school	0.145	0.066
	(1.377)	(0.964)
Vocational high school	0.073	0.281*
	(0.286)	(1.699)
High school	0.273***	0.258***
	(2.606)	(3.273)
Below high school	0.322*	0.297***
	(1.881)	(2.776)
Constant	3.046***	6.646***
	(4.958)	(12.334)
Observations	3,707	4,574
Pseudo R^2	0.0443	0.0405

Table 4. The effect of awareness of information sharing ex ante on default decisions

This table examines borrowers' take-out decision in Experiment 1. Column1 focuses on old borrowers, and column 2 focuses on new (first-time) borrowers of LHP. The dependent variable is an indicator that takes the value of one if a loan defaults and zero otherwise. *RL* is an indicator that takes the value of one if the lender is a reporting lender and zero otherwise. *MSG* is an indicator that takes the value of one if the borrower received a credit warning message and zero otherwise. *Interest rate* is the sum of monthly interest rate and service fees. We report t-statistics based on heteroscedasticity robust standard errors in the parentheses below the corresponding regression coefficients. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Probit regression: Dependent variable = default		
	Old borrowers	New borrowers
	(1)	(2)
RL	-0.172**	0.020
	(-2.211)	(0.323)
MSG	0.091	-0.170***
	(1.168)	(-2.773)
Sesame score	-0.001	-0.005***
	(-1.242)	(-4.994)
Interest rate	7.456**	8.680*
	(2.486)	(1.702)
Female	-0.224**	-0.092
	(-2.207)	(-1.196)
Age	0.003	0.006
	(0.510)	(1.291)
Education dummies (base group: do not report)		
Bachelor or above	-0.390**	-0.429***
	(-2.536)	(-3.047)
Junior college	-0.066	-0.176*
	(-0.639)	(-1.866)
Vocational secondary school	-0.147	-0.085
	(-1.041)	(-0.874)
Vocational high school	0.070	-0.024
	(0.232)	(-0.117)
High school	-0.053	-0.054
	(-0.419)	(-0.512)
Below high school	0.143	0.134
	(0.814)	(1.073)
Constant	-1.072	1.430
	(-1.267)	(1.611)
Observations	3,339	3,464
Pseudo R^2	0.0299	0.0424

Table 5. The effect of awareness of information sharing on borrower default: ex post vs. ex ante

This table examines borrowers' default decisions. The dependent variable is an indicator that takes the value of one if a loan defaults and zero otherwise. Columns 1 and 2 use the sample of Experiment 2, while columns 3 and 4 use the sample of Experiment 1 (only loans funded by RL are used for this analysis). Columns 1 and 3 focus on borrowers who previously took out loans from LHP (old borrowers), and columns 2 and 4 focus on first-time (new) borrowers of LHP. *MSG* is an indicator that takes the value of one if the borrower received a credit warning message and zero otherwise. We report t-statistics based on heteroscedasticity robust standard errors in the parentheses below the corresponding regression coefficients. ***, **, * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Probit regression: Dependent variable = default				
	Experiment 2		Experiment 1	
	Old borrowers	New borrowers	Old RL borrowers	New RL borrowers
	(1)	(2)	(3)	(4)
MSG	-0.192	-0.426***	0.092	-0.217***
	(-1.213)	(-3.290)	(0.806)	(-2.664)
Sesame score	0.001	-0.006***	-0.002	-0.005***
	(0.294)	(-3.819)	(-1.056)	(-3.850)
Interest rate	7.649	16.242*	9.889**	2.487
	(1.490)	(1.915)	(2.333)	(0.393)
Female	-0.360**	-0.211*	-0.215	-0.087
	(-2.056)	(-1.650)	(-1.434)	(-0.856)
Age	0.015	0.008	0.012	0.007
	(1.460)	(1.060)	(1.325)	(1.114)
Education dummies (base group: do not report)				
Bachelor or above	-0.199	-0.021	-0.404*	-0.529***
	(-0.775)	(-0.112)	(-1.882)	(-2.765)
Junior college	-0.199	-0.211	-0.249*	-0.212*
	(-1.103)	(-1.290)	(-1.674)	(-1.680)
Vocational secondary school	-0.055	0.000	-0.483**	-0.091
	(-0.243)	(0.002)	(-2.087)	(-0.708)
Vocational high school		0.097		0.064
		(0.272)		(0.240)
High school	-0.104	0.002	-0.157	-0.186
	(-0.490)	(0.014)	(-0.893)	(-1.307)
Below high school	0.208	0.024	0.162	0.087
	(0.784)	(0.116)	(0.704)	(0.519)
Constant	-2.848*	1.512	-1.281	1.938*
	(-1.943)	(1.073)	(-1.027)	(1.678)
Observations	1,309	1,464	1,761	1,973
Pseudo R^2	0.0334	0.0602	0.0444	0.0442

Table 6. The effect of awareness of information sharing ex post on borrower default—Experiment 2

This table reports summary statistics of main variables in Experiment 2, including default outcome, credit warning message, loan characteristics, and borrower characteristics. We contrast borrowers who received the credit warning message (treated) with borrowers who did not receive the message (control). Panel A present the results of covariate balance before matching, and Panel B presents the results after the propensity score matching (for each treated loan, we allow three untreated loan using the Mahalanobis approach).

Panel A: Differences in observables (pre match)

	Old borrowers				New borrowers			
	Control (*N*=963)	Treated (*N*=377)	Diff	*t*-stats	Control (*N*=1132)	Treated (*N*=332)	Diff	*t*-stats
Outcome variables:								
Default	0.039	0.027	0.013	1.15	0.114	0.051	0.063	3.37***
Control variables:								
Sesame score	656.9	659.4	-2.49	-1.12	643.7	646.9	-3.182	-1.42
Interest rate (monthly)	0.052	0.054	-0.001	-1.62	0.056	0.057	0	-0.48
Female	0.270	0.284	-0.014	-0.51	0.199	0.256	-0.057	-2.25**
Age	29.90	29.76	0.121	0.32	29.90	29.59	0.305	0.77
Bachelor or above	0.114	0.101	0.013	0.70	0.133	0.133	0.000	0.00
Junior college	0.317	0.313	0.004	0.13	0.303	0.283	0.020	0.70
Vocational secondary school	0.112	0.119	-0.007	-0.37	0.233	0.235	-0.002	-0.07
Vocational high school	0.028	0.011	0.017	1.91*	0.020	0.003	0.017	2.19**
High school	0.139	0.170	-0.031	-1.42	0.123	0.163	-0.040	-1.89*
Below high school	0.055	0.040	0.015	1.14	0.077	0.078	-0.001	-0.09
Other variables								
Amount (Yuan)	4,508	4,312	195.83	1.97**	3,063	2,958	105.8	1.12
LH score	704.7	703.4	1.334	0.70	650.3	651.0	-0.673	-0.37

Table 6. Continued.

Panel B: Differences in observables (post match: Mahalanobis distance matching (1:3))

	Old borrowers				New borrowers			
	Control	Treated	Diff	*t*-stats	Control	Treated	Diff	*t*-stats
Outcome variables:								
Default	0.038	0.027	0.012	0.93	0.116	0.051	0.065	3.51***
Control variables:								
Interest rate (monthly)	0.053	0.054	0.001	0.41	0.069	0.068	0.000	0.21
Sesame score	658.4	659.4	-1.01	0.41	646.5	646.9	-0.374	-0.15
Female	0.277	0.284	-0.007	-0.23	0.252	0.256	-0.004	-0.13
Age	29.49	29.76	-0.283	0.68	29.37	29.59	-0.226	-0.50
Bachelor or above	0.101	0.101	0.000	0.00	0.133	0.133	0.000	0.00
Junior college	0.313	0.313	0.000	0.00	0.283	0.283	0.000	0.00
Vocational secondary school	0.119	0.119	0.000	0.00	0.235	0.235	0.000	0.00
Vocational high school	0.011	0.011	0.000	0.00	0.003	0.003	0.000	0.00
High school	0.170	0.170	0.000	0.00	0.163	0.163	0.000	0.00
Below high school	0.040	0.040	0.000	0.00	0.078	0.078	0.000	0.00
Other variables								
Amount (Yuan)	4,412	4,312	99.03	0.87	3,026	2,958	68.27	0.66
LH score	705.4	703.4	2.050	0.98	650.1	651.0	-0.902	-0.420