What If borrowers were Informed about Credit Reporting? Two Randomized Field Experiments*

Li Liao, Xiumin Martin+, Ni Wang, Zhengwei Wang, Jun Yang

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* Li Liao is from Tsinghua University, email: liaol@pbcsf.tsinghua.edu.cn; Xiumin Martin is from Washington University, email: xmartin@wustl.edu; Ni Wang is from Quant Group, email: cjtop10@gmail.com; Zhengwei Wang is from Tsinghua University, email: wangzhw@pbcsf.tsinghua.edu.cn; Jun Yang is from Indiana University, email: jy4@iu.edu.

+Corresponding author.

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Abstract

Using two randomized field experiments, we examine how warning borrowers that their loan performance will be reported to a public credit registry affects their loan take-up and repayment decisions. We show that credit warnings increase loan take-up rates. The main drivers appear to be anticipation of reduction in incumbent lenders' informational rents and improvement in access to informal or formal credit. Moreover, credit warnings reduce default rates by 3.7–5.9 percentage points. This reduction is comparable for borrowers who receive the credit warning before and after the loan take-up, which suggests that credit warnings have little net effect on borrowers' credit-risk composition due to selection.

Keywords: Credit reporting, Loan take-up, Default, Incentive, Selection, Field experiment

JEL: G10, G21, G23

1. Introduction

Information asymmetry and the resulting adverse selection and moral hazard impede efficient credit allocation. Theories suggest that sharing loan performance information helps lenders address these imperfections and fosters lending. Information sharing improves lender screening by reducing information asymmetry between borrowers and lenders (Pagano and Jappelli 1993). It also improves borrowers' repayment efforts by narrowing incumbent lenders' informational advantage and reducing their rents (Padilla and Pagano 1997), and by restricting default borrowers' access to future credit (Padilla and Pagano 2000). These mechanisms have different implications for borrower welfare and policy. However, in a setting where credit reporting is pervasive, as in the U.S., it is challenging to empirically identify these causal relationships, to separate the demand-side from the supply-side effect, and to disentangle the incentive effect from the selection effect. We conduct a pair of randomized field experiments in the consumer credit market in China, where credit reporting has limited coverage but nevertheless plays an important role, because legal enforcement of consumer loan repayment is almost non-existent.

Both of our experiments focus on borrowers who have already obtained a loan approval. This choice allows us to hold credit supply constant and focus on the demand-side effect of lender information sharing with the Credit Reference Center at the People's Bank of China (hereafter "the public credit registry"). More specifically, we investigate how informing borrowers that their loan performance will be reported to the public credit registry (hereafter "credit warnings") affects their loan take-up and repayment decisions. We show that credit warnings increase loan take-up rates by 3.3 percentage points and reduce loan default rates by 3.7–5.9 percentage points.

We conducted the experiments in early April 2017 on a large online lending platform in China, the Quant Group. Lending platforms are Fintech companies that were unregulated at the time and cannot report loan performance to the public credit registry. The platform assigns institutional lenders to individual borrowers and makes small uncollateralized consumer loans. According to credit-reporting policy in 2017, there are two types of institutional lenders: reporting lenders (e.g., financial institutions) and non-reporting lenders (e.g., Fintech companies). Reporting lenders are required to report loan repayments and defaults to the public credit registry, but there is no such reporting channel for non-reporting lenders. Half of the platform's lenders are reporting lenders, and the other half are not. The language on the reporting policy used by non-reporting lenders also closely resembles that used by reporting lenders (see Appendix B for details). Thus, borrowers at Quant, especially first-time borrowers, might not know whether their loan performance will be reported to the public credit registry. Questions posted in major online forums on consumer credit (e.g., Baidu Post Bar) confirm this conjecture. Importantly, to hold constant lenders' underlying reporting policy, we conducted both of our experiments using loans made by a single *reporting lender*.

We describe the two experiments in greater detail below. In the first experiment (see Figure 1), we randomly selected 1,464 new borrowers among those who had decided to take out a loan. We then sent a text message to these borrowers confirming fund transfer to their bank account. Among them, we randomly chose 332 borrowers and appended credit warnings to the same message, stating that their loan repayment or default would be reported to the public credit registry. These borrowers are classified as treated and the rest as control. Notably, all borrowers in this experiment received the same loan-approval message before they decided to take out the loan, as well as the same repayment reminder one week before the due date. We conjecture that credit warnings reduce default rates because they improve borrowers' repayment effort for at least two reasons. First, upon receiving credit warnings, borrowers increase their estimated likelihood of credit reporting. The borrowers understand that if they default on the loan, the increased likelihood that the default will be reported to the public credit registry could jeopardize their access to the credit market in the future (Padilla and Pagano 2000); thus, they will likely exert more effort to repay the loan. This impact of credit warnings is called the *disciplinary effect*. Second, borrowers who received credit warnings might expect that if they take out and repay the loan, they will have a positive record at the public credit registry. The positive record will reduce the information asymmetry with other lenders, which helps borrowers gain access to future credit and cut the incumbent lender's informational rents (Padilla and Pagano 1997). This impact is called the *informational rents effect*. We show that the default rate, defined based on the industry standard of two months overdue, is 5.9 percentage points lower for the treatment group who received credit warnings than for the control group who did not. Given the unconditional default rate of about 10%, the credit-warning effect on default rates is economically large. The evidence supports our conjecture that credit reporting improves borrowers' repayment incentives.

The second experiment differs from the first in that we sent credit warnings to borrowers *before* they decided to take out a loan. Specifically, we randomly selected 2,631 new borrowers whose loan applications were approved (there was no overlap with those in the first experiment). We sent a loan-approval message to all 2,631 borrowers. Among them, we randomly selected 1,189 borrowers to receive messages with credit warnings stating that their loan repayment or default would be reported to the public credit registry. We argue that the effect of credit warnings on loan take-up rates is unclear a priori. On the one hand, the disciplinary effect of credit warnings predicts a lower loan take-up rate among credit-warning recipients, because credit reporting increases the expected cost of default. On the other hand, the informational rents effect predicts a higher loan take-up rate. This is because credit-warning recipients expect to gain future access to the credit market at a lower borrowing cost by taking out and repaying the current loan in full. Ultimately, the net effect of credit warnings on loan take-up rates is an empirical question.

In the second experiment, we compare loan take-up rates between the borrowers in the treatment group who received credit warnings and those in the control group who did not. We find that the loan take-up rate is 3.3 percentage points higher for the treatment group than for the control group. This magnitude is economically meaningful, given that unconditionally, 25% of borrowers did not take out a loan. These results suggest that on average, the informational rents effect dominates the disciplinary effect of credit warnings in affecting a borrower's loan take-up propensity.

To further probe the informational rents mechanism that explains the higher take-up rates among credit-warning recipients, we conduct cross-sectional tests based a novel measure of the incumbent lender's informational rents (this measure is discussed in detail in section 5.5). We find that credit-warning recipients are more likely to take out a loan when the lender is likely to have higher informational rents. The evidence suggests that the dampening effect of credit reporting on lenders' information rents might explain the higher loan take-up rates among credit-warning recipients.

In addition to comparing loan take-up rates, we examine the difference between the default rates of the treatment and control groups in the second experiment. We argue that the effect of credit warnings on default rates is unclear a priori. Credit warnings affect the composition of the borrower pool through the borrowers' take-up decisions (selection effect). The overall credit risk of the borrower pool depends on the credit risk of the marginal borrowers who are affected by credit warnings. If we hold the composition of borrowers constant, credit warnings are likely to dampen the default rate due to the improved repayment incentives from the disciplinary effect and the informational rents effect. Consequently, the net effect of credit warnings on default rates is an empirical question. We show that the default likelihood is 3.7 percentage points lower for the treatment group than for the control group, suggesting that the net effect of credit warnings received before taking out a loan is to dampen the default rates.

In the final set of analyses, we compare the credit-warning effect on default rates between the two experiments, which allows us to disentangle the selection effect from the incentive effect. In the first experiment involving credit warnings after loan take-up, the difference in default rates between the treatment and control groups captures the incentive effect only. In the second experiment involving credit warnings before loan take-up, the difference in default rates between the treatment and control groups captures both the incentive effect and the selection effect. Thus, the difference in the credit warning effect on loan default between the second and first experiments captures the selection effect of credit warnings. We find that the credit-warning effect on default is similar across the two experiments, which implies that borrowers' selection has no measurable impact on the credit risk of the borrower pool.

Although the lending platform used in our field experiments is from China, the institutional features of the consumer credit market, especially those pertaining to credit reporting and credit access, are similar in many developing countries (Powell, Mylenko, Miller, and Majnoni 2004; Luoto, McIntosh, and Wydick 2007; Peria and Singh 2014; Liberman 2016; Liberman, Neilson, Opazo, and Zimmerman 2018; World Bank Group 2019). Therefore, our findings have direct implications for those economies. Equally important, the insights of our study are informative about credit market policies in developed economies where it is impossible to disentangle different economic mechanisms due to universal credit reporting.

Our study departs from prior empirical research on the effects of credit information sharing in three important ways. First, prior association studies in cross-country settings (Jappelli and Pagano 2002; Djankov, McLiesh, and Shleifer 2007) face challenges in making causal inferences. Even studies using natural experiments (Doblas-Madrid and Minetti 2013) cannot separate the demand-side and supply-side effects, because information sharing can affect both sides simultaneously.[1] Randomized field experiments allow us to identify the causal effects on the demand side cleanly by holding credit supply constant. This separation not only contributes to academic research, but also has important implications for policies related to financial inclusion.

Second, by comparing the default rate of the experiment in which credit warnings were sent before loan take-up and that of the experiment in which credit warnings were sent after loan take-up, we can determine the selection effect of borrowers in response to credit warnings. Thus, on the credit-demand side, we can further distinguish the incentive effect from the selection effect, which is challenging with archival data.

Third, prior research focuses mainly on the effect of information sharing on borrower default decisions (Doblas-Madrid and Minetti 2013). To the best of our knowledge, we are the first to examine its effect on borrowers' loan take-up decisions. We can identify the effect of credit reporting on borrower selection due to borrowers' desire to reduce lenders' informational rents and to gain access to formal credit (e.g., mortgages, car loans, and credit cards). Our findings provide empirical support for Padilla and Pagano's (1997) theory and confirm the value of credit reputation (Liberman 2016). In this regard, our study complements that of Sutherland (2018), who provides empirical evidence that information sharing among lenders via a credit bureau reduces relationship-switching costs, particularly for firms that are young, small, or have had no defaults.

[1] Using 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 is positively correlated with information sharing using 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 credit bureaus and public registries and find that the presence of private credit bureaus is associated with lower perceived financing constraints and a higher share of bank financing (whereas the presence of public credit registries is not). Focusing on transitional economies, Brown, Jappelli, and Pagano (2009) provide firm-level evidence that information sharing is associated with improved availability and lower cost of credit to firms.

Our study relates to the recent accounting literature that examines the impact of credit reporting on lenders. Balakrishnan and Ertan (2021) show that both the initiation of a public credit registry and the expansion of a registry's coverage improve lenders' understanding of borrowers' credit risk, which improves the quality of lenders' loan loss recognition. Our evidence that credit warnings increase borrowers' propensity to take out a loan complements their findings, highlighting that credit reporting reduces information asymmetry and mitigates adverse selection.

2. Institutional background on consumer credit markets in China

The rapid development of the Chinese economy and the deepening reforms of its financial system since 1998 (e.g., housing market reform) have contributed to precipitous growth in the consumer credit markets. Financial institutions (comprising commercial banks and non-depository financial institutions such as financial trust and investment corporations, financial leasing companies, auto-financing companies, and loan companies) dominate consumer credit markets, which are termed formal credit markets. Since 2005, Chinese regulators have required financial institutions to report repayment/default information on both business and individual loans to the Credit Reference Center at the People's Bank of China (i.e., the public credit registry). A formal credit report containing loan-performance information is shared with all financial institutions on a complimentary basis.[2] The number of reporting financial institutions has increased over time (from 23 in 2005 to 1,811 in 2014). The public credit registry's coverage of individual borrowers was, however, very limited at the time of our experiments—approximately 25% of the population.

[2] A formal credit report contains an individual's information on formal credit, such as the history of credit card, mortgage, and other types of loan applications; the use, repayment, and outstanding and overdue balances; the number of guarantee activities; and the individual's social security status. A default that is fully repaid stays on the record for five years. Repayment stays on the record for two years.

With recent advances in technology, and in the absence of regulation, online marketplace lending (known as informal credit markets) has grown rapidly since 2013. The number of lending platforms mushroomed from 200 in 2012 to around 3,000 in March 2017, and loans reached 2.8 trillion yuan (over $400 billion) in 2017 (https://shuju.wdzj.com/industry-list.html; Wang and Dollar 2018). Concerns about fraud and systemic risk due to lack of regulation in these markets prompted Chinese authorities to consider imposing stricter regulations and establishing a nationwide credit-reporting system. [3]

Given the public credit registry's limited coverage of individuals and the soaring growth in informal consumer credit markets, China's largest Fintech firms have started to set up their own credit measurements, leveraging their reams of user data. One such measure is the Sesame score (known as the informal credit score), which was rolled out in 2015 by Sesame Credit, a quasi-private credit bureau under Ant Financial. Sesame Credit assigns users a score ranging from 350 to 950 based on five criteria: credit history (including payments of credit cards and utility bills), personal information, repayment ability, social networks, and behaviors.[4]

Sesame Credit covers much more of the Chinese population than the public credit registry, and Sesame scores are available to legitimate companies upon clients' authorization, with a nominal cost of 0.4 yuan per inquiry. Sesame scores have been widely used in both retail business decisions (e.g., waivers on car rental deposits, expedited airport security checks) and informal credit markets. Thus, Sesame scores are a reasonable measure of an individual's credit quality. When banks allocate credit, however, they ignore informal credit scores and rely solely on credit reports from the public credit registry. Because formal credit markets still play a dominant role in the consumer

[3] The new regulation for FinTech lenders was not passed till September 2019 requiring these lenders to share credit information at the public credit register. Therefore, at the time of our study, no FinTech lenders report credit information to the public credit registry.
[4] Berg, Burg, Puri, and Vanjak (2019) analyze the information content of a digital footprint and show that it complements credit bureau information. A digital footprint affects access to credit and reduces default rates.

credit supply (e.g., only banks can issue credit cards and originate mortgages),[5] establishing credit files at the public credit registry is crucial for many individuals who have good credit and want to gain access to the formal credit markets.

Although the Sesame score is widely used by lenders in the informal credit market, Quant Group also developed its own credit score (i.e., the Quant score) based on its proprietary data and models. Our study uses these scores to capture lenders' private information and construct a measure of lenders' informational rents to examine the argument that credit reporting improves borrower repayment effort by lowering the incumbent lenders' informational rents.

3. Background information on Quant Group and experimental design

Lending platform—Quant Group

Quant Group, the lending platform used in our field experiment, is an independent Fintech firm founded in 2014 that matches a large number of borrowers with institutional lenders of microloans. Each loan has one lender only. As of August 28, 2017, Quant Group had made 7,765,536 loans totaling 16.55 billion yuan (roughly $2.5 billion). Quant Group's main function is to use its comprehensive database and sophisticated risk modeling to screen borrowers and match them with lenders (fund providers). A lending platform may serve as an intermediary between lenders and borrowers without bearing borrowers' credit risk; alternatively, it may choose to assume this credit risk. Quant Group, along with most lending platforms in China, falls into the latter category. If a borrower does not repay a loan, Quant Group steps in to repay the principal and interest. Thus,

[5] "The credit card market is completely dominated by China UnionPay, the state-owned bank card network founded in 2002. China UnionPay controls more than 90% of the market," David Robertson said in his interview with CNN on August 3, 2018. Importantly, China UnionPay allocates credit based solely on borrowers' formal credit scores. https://money.cnn.com/2018/08/03/news/companies/mastercard-visa-amex-china/index.html

Quant Group has developed a rigorous screening model, and it imposes hefty monthly service fees on top of the interest charged by lenders to offset the credit risk it bears.

Quant Group receives funding from both reporting financial institutions (reporting lenders) and non-reporting marketplace lenders (non-reporting lenders). As discussed previously, repayments and defaults on loans backed by reporting lenders must be reported to the public credit registry and thus affect borrowers' credit reports. However, there is no such reporting channel for non-reporting lenders.

Typical Quant Group applicants are males in their late 20s, employed with decent incomes—4,000 yuan/month (approximately $600) on average—and heavy smartphone users. They have fair credit scores (the average Sesame score is 602) and high education levels (three-year college degree, on average). Loans are often used to pay down other debt or for consumption. The borrower base is growing rapidly: on average, 85% of applicants are first-time borrowers. The rejection rate for loan applications is approximately 90% for new borrowers and 30% for repeat borrowers, suggesting that credit rationing is prevalent among new borrowers. Even after strict screening, the default rates for new borrowers are as high as 10%. Quant Group incentivizes borrowers to repay on time by barring defaulters from taking out loans on the platform in the future, while offering those with a sound repayment history larger loans with lower interest rates. On average, repeat borrowers borrow from Quant Group three to four times a year, with an average loan amount of 4,500 yuan.

Quant Group's lending procedure

Figure 1 depicts Quant Group's lending procedure. Each borrower submits a loan application containing information regarding age, gender, and social security, which can be verified by her residence ID card.[6] The borrower also needs to provide income, education, and credit card and house ownership information, which is largely unverifiable. Quant Group approves or rejects the application based on the borrower's characteristics contained in the application, along with the borrower's Sesame score purchased from Ant Financial, and its own assessment of the borrower's creditworthiness, the Quant score. The Quant score is generated using a proprietary model that incorporates individuals' Sesame scores, phone book information, and borrowing and repayment histories at Quant Group.

If the application is approved, a lender is assigned to the borrower and an approval notification is sent to the borrower's mobile phone via a text message. The message contains a link to an app where the borrower can input bank account information to receive funds. The app also includes a loan contract specifying the lender's name, loan amount, monthly payment of principal, interest charged by the lender, and service fees charged by Quant Group, as well as clauses on late payments, credit reporting, and collection. The borrower decides whether to take out the approved loan by inputting bank account information for a fund transfer. The same bank account is set up for automatic withdrawal of funds to repay the loan. If the borrower chooses to take out the loan, she will receive a text message stating that the funds have been deposited to her bank account and that Quant Group encourages her to repay on time.

One critical factor for our experiment design is that lender information is buried in a seven-page loan contract, making it very difficult to tell whether the lender is a reporting lender. For example, for a reporting-lender-funded loan, the contract states that loan performance will be reported to "the *People's Bank of China's* Financial Credit Information Foundational Database." However, a loan contract for a non-reporting lender uses similar language: "loan performance will

[6] A loan applicant needs to provide the front and back sides of her residence ID card and make facial expressions as instructed in front of a camera, holding her residence ID, to verify her identity.

be reported to the Financial Credit Information Foundational Database and affect credit rating," although there was no channel for the non-reporting lender to report loan performance to the public credit registry or any other agency. Appendix B provides the credit reporting clauses of a loan contract with a reporting lender and one key clause of a loan contract with a non-reporting lender.

The borrower can either repay the amortized principal, interest, and service fees monthly or default on the loan. In our empirical analysis, we use the effective interest rate that combines the interest rate with the service fee. The borrower also has the option to repay the entire loan—including the principal, full interest, and service fees—before the scheduled payment dates. If a borrower is late on a payment, Quant Group will send a first reminder via text message three days past the due date, and then follow up with a call to the borrower's mobile phone. If no repayment is received after these attempts, Quant Group will reach out to the frequently called phone numbers on the borrower's contact list to disseminate the late payment information among the borrower's friends, hoping to recover the loan through this "social shaming" mechanism. In this study, we follow industry practice and label a loan as being in default if it is not repaid two months after the due date. Very little money can be recovered after a loan default in the Chinese consumer credit market.

Experimental design

We conducted two experiments at Quant Group between April 4 and April 7, 2017. In both experiments, we focus on loans funded by a reporting lender, because sending a credit-warning message to a borrower who takes out a loan from a non-reporting lender would compromise our research integrity. We choose to focus on new borrowers for two reasons. First, new borrowers are unlikely to be aware of a particular lender's reporting policy. Second, the information asymmetry problem is arguably more severe for new borrowers. Even after the platform's screening, credit qualities are still dispersed, and their default rates are much higher than those of repeat borrowers (10% vs. 4%). Importantly, the subjects of the two experiments do not overlap.

In the first experiment, we started by randomly selecting 1,464 subjects from new borrowers who had just taken out a loan (Figure 1A shows the design of the first experiment). We then randomly divided them into two groups of 332 and 1,132. Notably, borrowers in both groups received a text message confirming fund deposit. The message sent to the 332 borrowers in the treated group also included credit warnings stating, "Your loan repayment and default information will be instantaneously shared with the Credit Reference Center at the People's Bank of China." The standard text message for the remaining 1,132 borrowers (control group) did not contain this credit warning (see Figure 2A for the sample split). Quant Group designed and conducted this experiment as part of its regular operations, and it chose to randomize the credit warnings in a stratified manner to minimize the potential adverse impact of warnings on its business.[7]

We conducted the second experiment using loans funded by the same reporting lender during the same week as the first experiment. The second experiment started with 2,631 borrowers who were randomly selected among those whose loan applications were approved by Quant Group but had not yet decided to take out the loan (Figure 1B shows the design of the second experiment). In the loan-approval text message sent to these borrowers, we sent the same credit warning that we used in our first experiment to a group of 1,189 randomly selected borrowers. The standard loan-approval text message sent to the remaining 1,442 borrowers did not contain this information (see Figure 2B for the sample split). Like the first experiment, the second experiment used a

[7] More specifically, Quant group sent the credit-warning message to 25% of borrowers with loans of 2,000 yuan, and to 20% of borrowers with loans of 4,000 and 6,000 yuan. Given the different treatment rates used in the randomization procedure, we consider the stratum (by using a large loan indicator: amount exceeding 2,000 yuan) when checking the covariate balance. We further verify the robustness of the regression analysis results with and without the stratum.

stratified randomization algorithm.[8] In both experiments, the text message reminding borrowers to repay the loan before the due date was identical for the borrowers in the treated and controlled groups.

Data collection

We collected borrower characteristics, Sesame score, and Quant score, as well as information on whether borrowers had taken out loans from Quant Group before (repeat vs. new borrowers). We also obtained data on borrowers' loan characteristics: loan amount, maturity, interest rate, and service fee. Finally, we tracked borrowers' loan take-up decisions and any loan defaults, including the time stamp for each repayment. We do not have information on these borrowers' subsequent borrowing behavior.

4. Results

4.1 Descriptive statistics

Table 1 reports the summary statistics on the variables used in our empirical analyses. All variables are defined in Appendix A. Panel A focuses on the sample for the first experiment, and Panel B partitions this sample into credit-warning recipients (CW=1) and non-recipients (CW=0) and compares the two groups to assess the validity of Quant Group's randomization design. Panel A shows that 10% of loans ultimately defaulted; 22.7% of borrowers received the fund-deposit message with a credit warning, and the rest received the fund-deposit message without a credit warning. All loans in the first experiment mature in three months. The mean and median loan amounts are approximately 3,000 yuan (roughly $450) and 2,000 yuan (roughly $300). The

[8] For loans of 2,000 yuan, Quant Group implemented a randomization rate of 50% using a random number generator. For loans of 4,000 and 6,000 yuan, Quant Group chose a lower randomization rate of 40% to "soften" the experiment's impact on its valuable high-credit-quality borrowers.

average (median) monthly interest rate is 6.8% (7.2%), most of which is the monthly service fee (mean: 5.6%, median: 6%).[9]

Regarding borrower characteristics, the average (median) borrower's *Sesame score* is 644.45 (640), indicating that approved borrowers have much better credit scores than the overall applicant population (an average of 602). The average (median) *Quant score* is 650.47 (640), with a minimum of 610 and a maximum of 772.[10] The average (median) borrower age is 29.83 (28) years old, and 21.2% of borrowers are female. Regarding education, 43.1% of borrowers have junior college (a three-year associate degree) or higher degrees, 45.9% of borrowers report education below junior college, and the remaining 11% do not report education information.

Panel B partitions the sample into credit-warning recipients and non-recipients and compares the two groups' loan and borrower characteristics. Given the different treatment ratios for small loans (of 2,000 yuan) and large loans (of 4,000 or 6,000 yuan), we add a large loan fixed effect in the regression of a loan (borrower) characteristic measure on the credit warning (Bertrand, Djankov, Hanna, and Mullainathan 2007; Bruhn and McKenzie 2009). Columns (7) and (8) show that overall, the characteristics are fairly well balanced across the two groups, except for one difference—the fraction of women is greater for the warning recipients (25.6% vs. 19.9%). In the following empirical analysis, we directly control for gender (as well as other loan and borrower characteristics) because prior research shows that female borrowers are less likely to default than their male counterparts (Kevane and Wydick 2001; D'Espallier, Guerin, and Mersland 2011).

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[9] *Amount* and *Interest rate* are highly correlated, with a correlation coefficient of -0.749. To avoid multi-collinearity, we include the interest rate and leave out the loan amount in all analyses.

[10] The correlation between *Quant score* and *Sesame score* is 0.544. *Interest rate* has a correlation of -0.488 with *Quant score* and a correlation of -0.426 with *Sesame score*. To avoid multi-collinearity and draw meaningful inferences from the results, we retain *Sesame score* and *Interest rate* as control variables to measure borrowers' credit risk while omitting *Quant score*. However, all results are similar if we include *Quant score* (untabulated).

Panel C reports the summary statistics of the main variables for the second experiment sample. It includes 2,631 approved loan applications funded by the reporting lender. The table shows that 75% of applicants took out loans, 9.8% of which ultimately defaulted.[11] Regarding credit warnings, 45.2% of borrowers received a loan-approval message with a credit warning before taking out a loan. The rest received a standard approval message without a credit warning.

Similar to Panel B, Panel D compares loan and borrower characteristics of credit-warning recipients with those of non-recipients in Experiment 2. Columns (7) and (8) show that the characteristics are in general balanced across the two groups with one exception: *Sesame score* is higher for the credit-warning recipients (651 vs. 648). To address the covariate imbalance problem, we directly control for loan and borrower characteristics, including *Sesame score*, in the regression analysis that follows.

[Insert Table 1]

4.2 Credit warnings and borrower repayment effort

Recall that we wish to examine the effect of credit reporting on repayment incentives using the first experiment. We argue that credit warnings likely increase the borrowers' estimated likelihood of lenders' credit reporting. In response, credit-warning recipients will exert greater effort to repay their loans because of the disciplinary effect and/or informational rents effect, as discussed previously. Therefore, we predict that credit-warning recipients will have a lower loan default rate than non-warning recipients.

Table 2 reports the results of the (univariate and multivariate) regression analyses based on the OLS estimation. Column (1) shows that the default rate for borrowers receiving a credit warning is 6.3 percentage points lower than that for borrowers not receiving the warning (5.1% vs. 11.4%).

[11] According to our follow-up phone interviews, the top two reasons borrowers did not take out an approved loan are (1) they no longer needed the funds, and (2) they were concerned about the safety of their bank accounts.

Column (2) shows a negative and statistically significant coefficient on *CW*, implying that awareness of lender information sharing reduces borrower default likelihood by 5.9 percentage points.[12] The economic magnitude of the credit-warning effect on the borrower repayment incentive is substantial, given the control group's default rate of 11.4%. Results are nearly identical if we add the large loan indicator in the regression. Regarding control variables, we find that the default likelihood is negatively correlated with *Sesame score*, which suggests that borrowers with better credit quality are less likely to default. Taken together, these results suggest that credit warnings improve borrowers' incentives to repay their loans.

[Insert Table 2]

4.3 Credit warnings and borrower selection

We find robust evidence that credit warnings received *after* taking out a loan dampen the default rates. We next investigate whether credit warnings received *before* taking out a loan affect borrowers' loan take-up and default decisions. The evidence of this investigation will help us address two questions. First, does the dampening effect of credit warnings on default rates come from the disciplinary effect, the informational rents effect, or both? Second, do credit warnings affect borrowers' selection, and consequently their risk composition?

As we discussed earlier, credit reporting involves both benefits (the informational rents effect) and costs (the disciplinary effect) for a borrower. As a borrower becomes aware of credit reporting, the change in her utility of taking out a loan depends on the net effect of the benefits and costs associated with credit warnings. For example, the take-up rates will increase if and only if the informational rents effect exceeds the disciplinary effect. Ultimately, how credit warnings affect borrowers' loan take-up decisions is an empirical question.

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[12] The effects of credit warnings on default and take-up decisions are robust to other regression specifications. For example, all results hold when we use probit regressions. We report the OLS regression results because that makes it easier to interpret the economic magnitude of the credit warning effect.

We analyze the credit warning effect on loan take-up decision and report the OLS regression results in columns (1) and (2) of Table 3. The univariate analysis in column (1) shows that the take-up likelihood is 2.1 percentage points higher (76.1% vs. 74.0%) for the warning recipients, implying that the credit warning increases take-up likelihood, even though the difference between the two groups is statistically insignificant (*t*-stat = 1.209). The multivariate analysis in column (2) shows a marginal effect of *CW* (3.3 percentage points), which indicates that a new borrower is more likely to take out a loan if she receives a credit warning than otherwise. This magnitude is economically meaningful, given that 26% of non-warning recipients did not take out a loan. This result implies that, on average, the expected benefit (the informational rents effect) dominates the expected cost (the disciplinary effect) of credit reporting. With respect to control variables, *Interest rate* has a significant negative association with the take-up decision, suggesting that borrowers are sensitive to loan costs when deciding whether to take out a loan. In addition, *Sesame score*, *Junior college or above* and *Edu missing* are negatively associated with take-up likelihood, suggesting that borrowers with better credit profiles are likely to have better outside options.

Next, we use the Experiment 2 sample to examine how credit warnings received *before* borrowers take out a loan affect the average default rate, which is the net effect of two factors: (1) the risk composition of borrowers who take out a loan, and (2) borrowers' effort to repay loans given their risk. Table 2 presents evidence suggesting that credit reporting improves borrowers' repayment effort and thus reduces the likelihood of default. However, the effect of credit warnings on borrowers' composition depends on the relative change in the expected utility of risky and safe borrowers. Two scenarios are possible. If the increase in take-up is greater for safe borrowers than for risky borrowers, credit warnings will tilt the borrower pool towards safer borrowers. Because credit warnings also improve borrowers' repayment effort, the aggregate of these two effects would result in a decrease in defaults—borrowers who received the credit warning ex ante would default less frequently than those who did not. Conversely, if the increase in take-up is greater for risky borrowers than for safe borrowers, we expect credit warnings to tilt the borrower pool towards riskier borrowers. However, because credit warnings also improve borrowers' repayment effort, the overall effect on defaults is unclear ex ante.

Column (3) of Table 3 reports the univariate analysis results. The default likelihood is 3.9 percentage points lower for the warning recipients (7.7% vs. 11.6%), suggesting that the credit warning reduces the default likelihood. Column (4) reports the multivariate OLS regression result. The default likelihood is negatively associated with *CW*, consistent with the evidence from column (3). When we aggregate the composition effect and the repayment-incentive effect, ex-ante credit warnings reduce the default likelihood by 3.7 percentage points. This magnitude is economically large, representing 37.8% of the 11.6% unconditional default rate. Of the control variables, *Sesame score* and education level are negatively associated with default likelihood. Overall, Table 3 provides evidence that the aggregate effect of credit warnings on borrower selection and incentive reduces loan default likelihood.

[Insert Table 3]

4.4 Differentiating the selection effect from the incentive effect

To assess the selection effect of credit warnings on borrower risk composition, we compare the effect of credit warnings on default rates across the two experiments. Recall that the effect of credit warnings in the first experiment comes from the incentive effect alone, whereas their effect in the second experiment comes from the net effect of selection and incentives. Consequently, the comparison across the two experiments allows us to separate the two effects.

The assumption underlying this comparison is that the two experiments draw subjects from a similar pool of borrowers and offer similar loan contracts given borrower characteristics. To assess the assumption's validity, we compare the loan and borrower characteristics from the first and second experiments. We restrict borrowers in the second experiment to those who took out a loan without receiving the credit warning, because their information set is comparable to that of the borrowers in the first experiment when they were deciding whether to take out the loan. Columns (7) and (8) of Table 4, Panel A show that all borrower characteristics are comparable across the two groups. Loan characteristics differ in the amount and term: loans are smaller and loan term is shorter (the first experiment involves only three-month loans, whereas 5.5% of loans in the second experiment have a six-month term) for borrowers in the first experiment. Thus, we control for loan characteristics in the regression analysis.

Next, we conduct regression analyses on default by pooling the samples of the two experiments and interacting *CW* with a dummy variable (*E2*), which takes a value of 1 if the borrower is a participant in the second experiment. Column (1) of Table 4, Panel B reports the results of the univariate analysis. The coefficient on *CW* is negative (-0.063) and statistically significant at the 1% level, consistent with the results in column (1) of Table 2. Column (2) reports the results of a multivariate analysis using OLS estimation. The coefficient on *CW* is negative (-0.059) and statistically significant at the 1% level, consistent with the results in column (2) of Table 2. The default rate for borrowers who did not receive a credit warning is similar for *E1* and *E2*, as evidenced by the insignificant coefficient estimate on *E2*. This result again confirms that the randomly selected borrowers in the two experiments are similar. More importantly, the coefficient of the interaction term (*CW*E2*) is positive (0.022) but statistically indistinguishable from zero, suggesting that awareness of credit reporting ex ante does not materially affect the average risk level of borrowers. In other words, credit warnings do not exacerbate or alleviate borrowers' adverse selection. In summary, the reduction in default likelihood in Experiment 2 is driven by the incentive effect of credit warnings. Overall, our evidence suggests that lenders benefit from sending credit warnings since they improve borrowers' repayment incentive without inducing adverse selection. We acknowledge that the lack of selection effect could be partially due to Quant Group's screening, which rejects most loan applications from first-time borrowers. On the other hand, the lender's high rejection rate might reflect the impact of information asymmetry on the extensive margin of credit allocation, which helps explain the prevalence of credit constraints.

[Insert Table 4]

4.5 Exploration of the mechanisms for the credit-warning effect on loan take-up decisions

We find a significantly higher take-up rate in Experiment 2 when borrowers are informed about credit reporting. In this subsection, we conduct cross-sectional analyses to explore the mechanisms for the effect. Taking out a loan and repaying it on time establishes a positive record in the public credit registry and enhances a borrower's formal credit profile. Such enhancement likely enables borrowers with fair credit quality but poor informal credit profiles (i.e., low Sesame score) to access other lenders in the informal credit market, which in turn reduces the incumbent lender's informational rents. The formal credit-profile enhancement could also help borrowers with good informal credit profiles to graduate to the formal credit market. We explore both mechanisms below.

Lenders' informational rents are clear in theory: when the incumbent lender possesses private information about a borrower (e.g., through repeated transactions) that other lenders do not have, the incumbent can expropriate the borrower by charging an interest rate higher than the borrower's commensurate credit risk would justify. However, measuring lenders' informational rents is challenging in practice, because researchers do not observe incumbent lenders' private information. Fortunately, we have loan interest rates and the borrowers' credit scores assigned by the lender (Quant score). The Quant score is Quant Group's internal rating of borrowers' credit risk, which presumably reflects both *public* and *private* information possessed by the lender, Quant Group.

Taking advantage of these two variables along with other observable borrower characteristics, we develop a novel measure of lenders' informational rents.

We use the following example to illustrate our measure. Consider two individuals, A and B, who have similar credit risk but different observable characteristics: A has a higher Sesame score and a higher level of education than B. If these observable characteristics have statistical predictability for loan defaults, A likely has easier access to credit with lower financing costs than B.

Assume that both A and B have borrowed from Quant Group in the past and repaid the loan in full. If the positive repayment history significantly alleviated information asymmetry with the lender (Diamond 1989), we expect the lender's credit risk assessment to converge to the true credit risk for both borrowers, which implies that the two individuals' Quant scores would become comparable when they repeatedly borrow from the lender. However, due to lack of lenders' credit reporting, the two individuals' past repayment history is not observable to other lenders in the credit market. Thus, the incumbent lender can exploit her informational rents by charging B a higher interest than A, due to B's limited outside options. The interest-rate difference between B and A is thus deemed the lender's informational rents. With this example in mind, we construct the measure for lenders' informational rents in three steps.

In the first step, we regress the interest rate on the Quant score among *repeat* borrowers such as A and B, and we obtain the regression residual, *e*, as shown in equation (1):

$$Interest\ rate = a_1 + b_1 * Quant\ score + e. \quad (1)$$

The rationale for using *repeat* borrowers is that Quant Group likely possesses private information on repeat borrowers as it observes the borrowers' repayment history. To validate this argument, we regress the default likelihood on *Quant score*, *Sesame score*, and other publicly observable borrower characteristics separately for repeat and first-time borrowers from

Experiment 2. Table 5, Panel A presents the results. Column (1), which focuses on repeat borrowers, indicates that *Quant score* is incrementally informative about borrower credit risk, as evidenced by the negative and statistically significant coefficient on *Quant score*. By contrast, the coefficient on *Sesame score* is indistinguishable from zero, suggesting that *Sesame score* does not contain incremental credit-risk information over and above that contained in the *Quant score*. The evidence supports our argument that Quant Group incorporates both *private* information (not reflected in *Sesame score*) and *public* information (e.g., *Sesame score*) into *Quant score* as it learns more about borrowers' credit quality through repeated lending relationships.

Column (2) presents the results based on first-time borrowers, indicating that both *Sesame score* and *Quant score* contain credit-risk information incremental to each other. Furthermore, we find that the simple correlation between *Quant score* and *Sesame score* is 0.3485 for repeat borrowers, much smaller than 0.4659 for new borrowers. This finding suggests that Quant Group relies more on public information in assessing the credit risk of new borrowers due to lack of private information (e.g., borrowers' repayment history). In sum, the evidence supports our argument that Quant Group has private information about repeat borrowers and reflects the information in *Quant score*.

The regression residual, *e*, from equation (1) captures interest rates that are unrelated to borrower credit risk assessed by Quant Group. We consider *e* the lender's informational rents for repeat borrowers. In our example, B has a higher *e* than A. One concern is that *e* may capture borrowers' soft information or other credit-relevant information not reflected in *Quant score*. However, if this were the case, we would expect that the greater *e*, the higher the default rates. We will examine this possibility later in this section and show that it is not the case.

The above informational-rents measure, *e*, is derived from repeat borrowers. To explore how informational rents affect the extent to which credit warnings affect first-time borrowers' loan take-up decisions, we need to construct a measure for new borrowers. If it is reasonable to argue that borrowers' observable characteristics (e.g., Sesame score and education) affect their outside options and the extent to which they are exploited by the incumbent lender, we can use the estimated relationships of these characteristics for e based on repeat borrowers and apply them to new borrowers to derive the corresponding informational-rents measure.

In the second step, we use observable borrower characteristics to predict e based on repeat borrowers and obtain the estimated coefficients on borrower characteristics, ($\widehat{b_2}, \widehat{b_3}, \widehat{b_4}, \widehat{b_5}$ and $\widehat{b_6}$), as shown below:

$$e = a_2 + b_2 * Sesame\ score + b_3 * Female + b_4 * Age\ + b_5 * Junior\ college\ or\ above\ + b_6 * Edu\ missing + \varepsilon. \quad (2)$$

The results in column (2) of Table 5, Panel B show that repeat borrowers with a high *Sesame score* and *Junior college or above* education (i.e., Borrower A) have lower lenders' informational rents. Interestingly, borrowers with *Edu missing* also have lower e. Overall, the evidence is consistent with our argument that borrowers' observable characteristics affect informational rents: borrowers with less favorable observable characteristics (lower *Sesame score* and lower level of education) and thus fewer outside options (i.e., Borrower B) suffer higher informational rents.

At this point, we can address the possibility that our measure of lenders' informational rents captures borrowers' soft information or other credit-relevant information not reflected in *Quant score*. We partition *repeat* borrowers into three groups: high, medium, and low, based on the predicted value from equation (2). Table 5, Panel C reports the results comparing *Quant score*, *Default*, *Interest rate*, *Sesame score*, and other borrower characteristics across the three groups. Both *Quant score* and *default rate* are comparable across groups, highlighting that Quant Group's ex-ante assessment of borrowers' credit risk is, on average, consistent with their actual rate of default. This evidence is inconsistent with the argument that the informational-rents measure captures credit-relevant information not reflected in *Quant score*, because if it did, we would observe a higher default rate for the high-informational-rents group. More importantly, borrowers in the high-informational-rents group are charged a significantly higher interest rate (5.5%) than those in the low-informational-rents group (4.8%) in spite of their comparable credit risk ex ante and ex post. Unsurprisingly, borrowers in the high-informational-rents group (i.e., Borrower B) have a lower *Sesame score* and lower education levels than borrowers in other groups. In sum, the evidence presented in Panel C helps validate our informational-rents measure, which is unlikely to capture borrowers' credit risk.

In the third step, we calculate lenders' informational rents for new borrowers by multiplying $(\widehat{b_2}, \widehat{b_3}, \widehat{b_4}, \widehat{b_5}$ and $\widehat{b_6})$, estimated from equation (2) based on repeat borrowers, by the corresponding characteristics of new borrowers. We then apply the cutoffs of the three informational-rents groups based on repeat borrowers to new borrowers. Panel D shows that new borrowers have a higher concentration in the low- and medium-informational-rents groups. This finding is again consistent with the notion that Quant Group has less private information about new borrowers than about repeat borrowers and thus is more likely to approve loans to borrowers with better observable characteristics (i.e., those in the low- or medium-informational-rents group).

[Insert Table 5]

To test the informational rent channel, we run the take-up analysis for the three groups separately. The results are reported in Table 6. Notably, the coefficient on *CW* is positive across the three groups, but it is statistically significant only for the high-informational-rents group (as column (3) shows). This evidence supports the informational rent argument that borrowers who are more likely to be expropriated by the lender are more likely to take out a loan. Given the low rejection rate (15.9%) for non-warning recipients in the high group, a reduction of 5.4% is economically large. The finding suggests that reporting to the public credit registry reduces lenders' informational rents. The coefficients on control variables indicate that only borrowers in the low-informational-rents group are sensitive to interest rates: they are less likely to take out a loan with a higher interest rate. This evidence is again consistent with these borrowers having more outside opportunities to borrow at lower costs.

We next explore the second mechanism to explain the take-up result: the formal-credit-access channel. Arguably, borrowers with better credit profiles (e.g., Borrower A in the low-informational-rent group) are more eager to gain access to the formal credit market, which includes mortgages, car loans, and credit cards. Furthermore, within this group, borrowers who do not report education information when applying for a loan might be less concerned about not obtaining the loan approval, possibly because they have better access to credit in the informal market. These borrowers, however, might be more eager to enhance their credit profiles at the public credit registry to gain access to the formal credit market. We find some supportive evidence for this argument. For example, column (1) of Table 3 shows that borrowers with missing education information are less likely to accept the Quant Group loan offer, as evidenced by the negative and significant coefficient on *Edu missing*, than are borrowers with a low level of education (statistically significant at the 1% level) and borrowers with a high level of education, though this difference is statistically insignificant (-0.072 vs. -0.054). In addition, column (1) of Table 5, Panel B shows that Quant Group charges borrowers with missing education a lower interest rate than those with either high or low education levels, which again suggests that borrowers with missing education information might have better credit access and thus might be less financially constrained.

We now examine how credit warnings affect the take-up likelihood of borrowers in the low-informational-rents group with missing education information, who, we conjecture, are ready to graduate to the formal credit market. Column (4) of Table 6 reports a positive and statistically significant coefficient on *CW*, supporting the formal-credit-access argument. From an economic perspective, informing about credit reporting increases take-up rate by 12 percentage points among borrowers who are less financially constrained in the informal credit market. This increase is economically large given the average borrower rejection rate of 36.8% for this subsample, for which $CW = 0$. Furthermore, the economic magnitude of the motive to gain formal-credit access (12%/36.8% = 33% in column (4)) is comparable to that of the motive to circumvent the lenders' informational rents (5.4%/15.9%=34% in column (1)). Overall, our evidence suggests that the desire to reduce lenders' informational rents for future loans and the desire to access the formal credit market might represent the underlying mechanisms for the higher loan take-up rates among credit-warning recipients.

[Insert Table 6]

5. Additional discussions

5.1 Placebo tests on repeat borrowers

We focus on new borrowers in both of our experiments because these borrowers are unlikely to be aware of lender reporting policies; thus, we expect them to react to credit warnings. By contrast, repeat borrowers are likely to have discovered lenders' reporting policies during their previous borrowing experiences; thus, credit warnings should not affect their take-up decision (if they are sent before the take-up) or repayment likelihood (whether they are sent before or after the take-up). To validate this assumption, we conduct the same two experiments for repeat borrowers, randomly selecting 1,340 and 2,069 borrowers for Experiment 1 and Experiment 2, respectively. We report the summary statistics on loan and borrower characteristics for Experiment 1 in Panel A and for Experiment 2 in Panel C of Table 7.

Comparing Panel A of Table 7 with Panel A of Table 1, we find significant differences between repeat and new borrowers for Experiment 1. For example, repeat borrowers have higher Sesame scores (658 vs. 644) and Quant scores (704 vs. 650) than new borrowers. They are slightly more likely to be female (27.4% vs. 21.2%) and are better educated (33.6% vs. 45.9% have below a junior college degree). Repeat borrowers are less likely to default (3.6% for repeat borrowers vs. 10% for new borrowers, on average). These results are not surprising, given Quant Group's policy of not extending loans to borrowers who have defaulted on a Quant Group loan in the past. Loans to repeat borrowers are larger (4,454 yuan vs. 3,040 yuan) and have lower interest rates (5.3% vs. 6.8%). More repeat borrowers received the credit warning (28.1% vs. 22.7%).

The contrast between repeat and new borrowers for Experiment 2 is similar: see the comparison between Panel C of Table 7 and Panel C of Table 1. Repeat borrowers are more likely to take out a loan (86% for repeat borrowers vs. 75% for new borrowers) and are less likely to default (3.8% vs. 9.8%).

Panel B reports the results of the covariate balance tests for Experiment 1. All loan and borrower characteristics are comparable between the treatment and control groups. [13] For Experiment 2, Panel D shows that all loan characteristics are comparable between the treatment and control groups. Regarding borrower characteristics, the Sesame score and education level are similar. Borrowers who received a credit warning, however, have slightly lower Quant scores and are younger than those who did not. Thus, we control for loan and borrower characteristics in the following regression analysis.

[13] In implementing the first experiment, Quant Group staff sent the credit-warning text to a smaller fraction of new borrowers than repeat borrowers because they were concerned about losing the business of new borrowers. For loans of 2,000 yuan, 25% of new borrowers received the credit warning, whereas 33.3% of repeat borrowers received it. For loans of 4,000 and 6,000 yuan, 20% of new borrowers, whereas 25% of repeat borrowers received the credit-warning message. Given that the treatment ratio varies with loan amount, we include large loans (i.e., loans of 4,000 or 6000 yuan) as a control.

In Panel E, we report the results of regression analyses on default in columns (1) and (2) for Experiment 1 and in columns (3) and (4) for Experiment 2, and those on take-up in columns (5) and (6) for Experiment 2. Columns (1) to (4) show that credit warnings do not affect repeat borrowers' default decisions, regardless of whether they are sent after or before loan take-up. Columns (5) and (6) show that credit warnings do not affect repeat borrowers' take-up decisions.

Our evidence that new and repeat borrowers respond to credit warnings differently is consistent with our assumption that repeat borrowers are aware of lenders' reporting policies from their previous borrowing experiences and thus remain largely unaffected by credit warnings. By contrast, new borrowers gain novel information from credit warnings, which affects their take-up and default decisions. However, we acknowledge the possibility that the differential responses of repeat and new borrowers might be driven by unobservable differences that are not captured by the observables controlled for in the regression model.

[Insert Table 7]

5.2 An alternative explanation

Credit warnings undoubtedly informed borrowers about credit reporting in both experiments. However, one might argue that these text messages not only offered information but also provided borrowers with a salient reminder that may have increased their sense of duty to repay the loan, which might drive the CW effect. This alternative explanation is not plausible for at least three reasons. First, all borrowers received text messages informing them of the fund deposit in the first experiment and informing them of loan approval in the second experiment. The only difference between the treatment and control borrowers was whether the message contained credit-warning information. Therefore, the presence of a text message per se cannot explain our results. Second, if credit warnings produce a saliency effect, the results observed among new borrowers should also hold for repeat borrowers: a priori, we have no reason to believe that the saliency effect should differ between the two groups. Given that credit warnings do not affect either take-up or default decisions for repeat borrowers, the saliency argument is unlikely to explain our findings. Third, subsequent text messages that borrowers received when they were late on repayment were identical for the treatment and control groups in both experiments, which rules out the possibility that credit warnings affect borrowers' repayment behavior by acting as loan-repayment reminders.

6. Conclusion

This study investigates how credit reporting affects borrowers' loan take-up and default decisions. We argue that credit warnings increase borrowers' awareness of lenders' credit reporting to the public credit registry. To cleanly identify the causal effect of credit warnings and to separate the effect on borrowers' repayment incentive from the effect on borrowers' selection, we conduct a pair of randomized field experiments, starting with all loans approved by the lender for the first-time borrowers from an online lending platform. In the first experiment, we altered the fund-deposit confirmation message sent to randomly selected borrowers informing them about credit reporting after their loan take-up. We show that credit warnings reduce default rates by 5.9 percentage points, which accounts for approximately 52% of the baseline default rates. This evidence suggests that credit warnings substantially improve borrowers' repayment effort.

In the second experiment, we altered the loan-approval message sent to randomly selected borrowers informing them about credit reporting before loan take-up. We show that the take-up rate is 3.3 percentage points higher for borrowers who received the credit warning than for those who did not receive the credit warning. The effect of credit reporting on take-up is stronger for borrowers who are eager to access formal credit. Furthermore, using a novel measure of lenders' information rents, we show that the effect of credit warnings on take-up is more pronounced for borrowers who are more likely to be exploited by incumbent lenders' informational advantage. This evidence supports the theoretical argument that credit reporting improves borrowers' repayment effort by correcting lenders' incentive problems (Padilla and Pagano 1997). Finally, credit warnings have a similar effect on default rates (3.7 percentage points) when borrowers receive the credit warning before versus after loan take-up. This finding suggests that credit warnings do not materially affect borrowers' risk composition due to selection. An interesting question is whether credit warnings would affect borrowers' selection if they were sent before the borrowers submitted a loan application. Evidence on this question might shed light on the signaling effect of credit warnings. We leave this question for future research.

To the best of our knowledge, our paper is the first to examine the effect of credit reporting on borrowers' take-up decisions. Our findings reveal that lenders' information reporting has significant benefits for borrowers: it allows underbanked consumers to establish or improve formal credit files. In addition, our experimental setting allows us to cleanly distinguish the causal effect of lender information sharing on borrowers' repayment effort from its effect on borrowers' selection, which has not been possible in prior studies (Jappelli and Pagano 2002; Djankov et al. 2007; Doblas-Madrid and Minetti 2013). Our findings provide insight into the cost-benefit tradeoffs of establishing a public credit registry in the consumer credit markets and thereby inform policy debates in countries deliberating whether to establish such a registry.

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Figure 1. Timeline for lending procedure

This figure depicts the process of a loan from the application to the repayment, and the timeline of the two experiments.

Panel A. Experiment 1

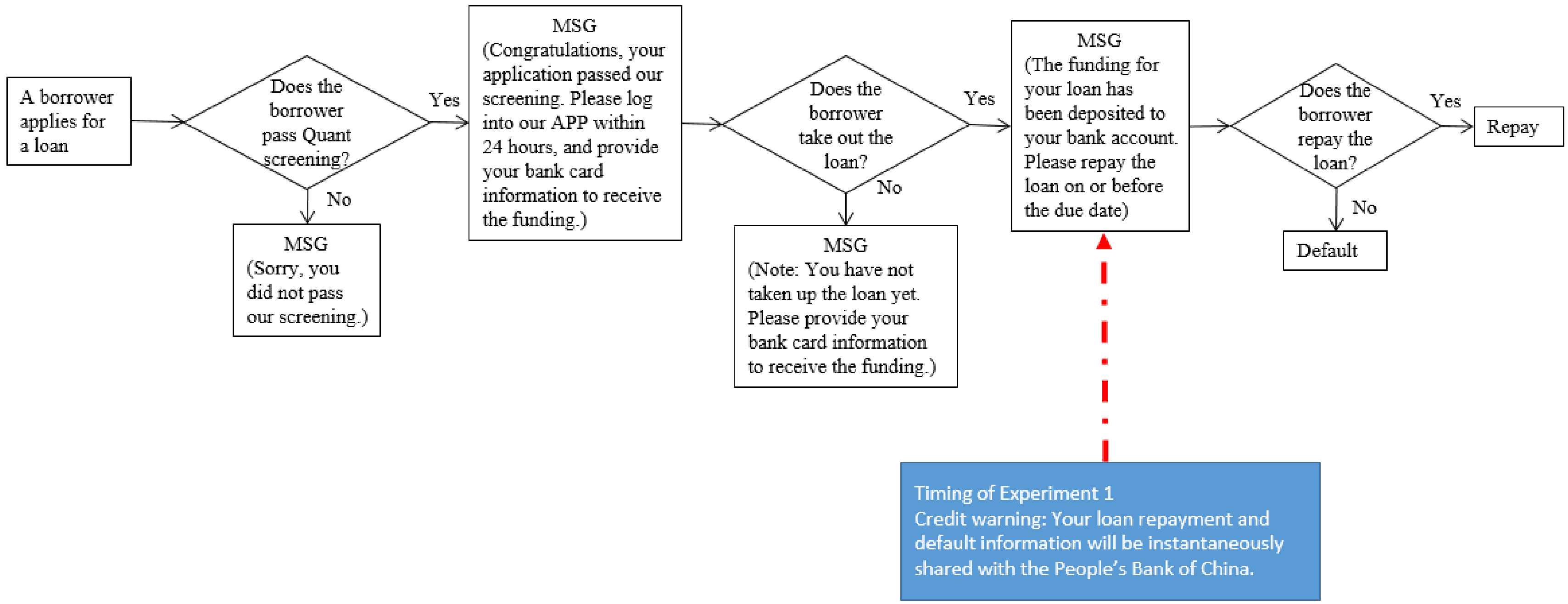

Figure 1. (Continued)
Panel B. Experiment 2

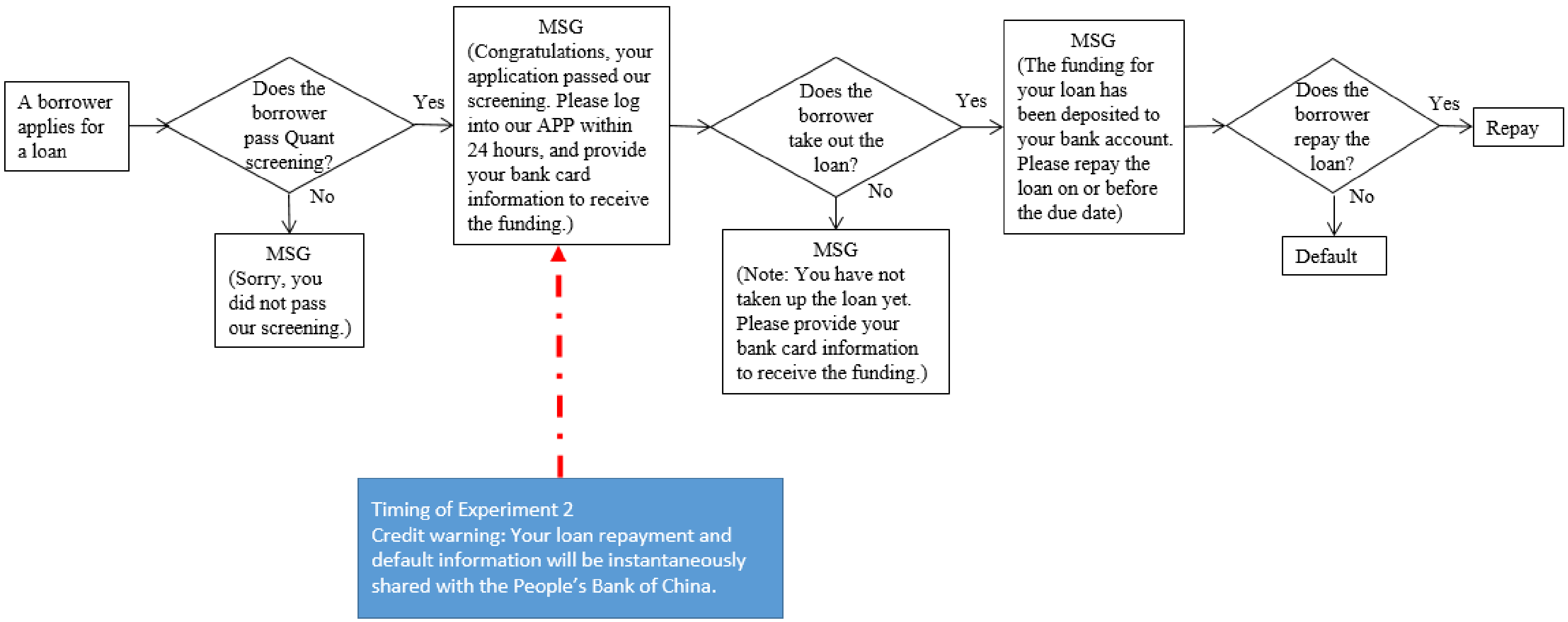

Figure 2. Sample description of the two field experiments

Panel A describes the procedure of Experiment 1 and the default rates of its two subsamples: credit-warning recipients and non-recipients. Panel B describes the procedure of Experiment 2 and the take-up or default rates of its four subsamples: credit-warning recipients who took out a loan, credit-warning recipients who did not, non-recipients who took out a loan, and non-recipients who did not.

Panel A. Description of Experiment 1

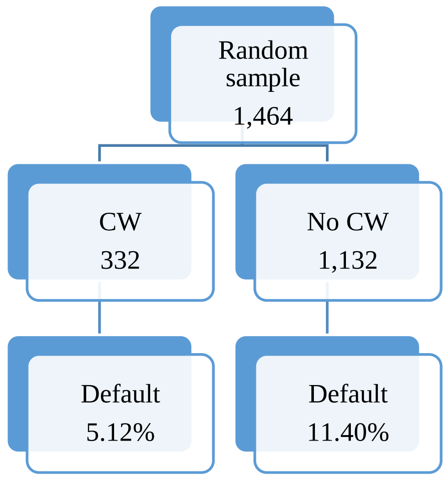

Figure B. Description of Experiment 2

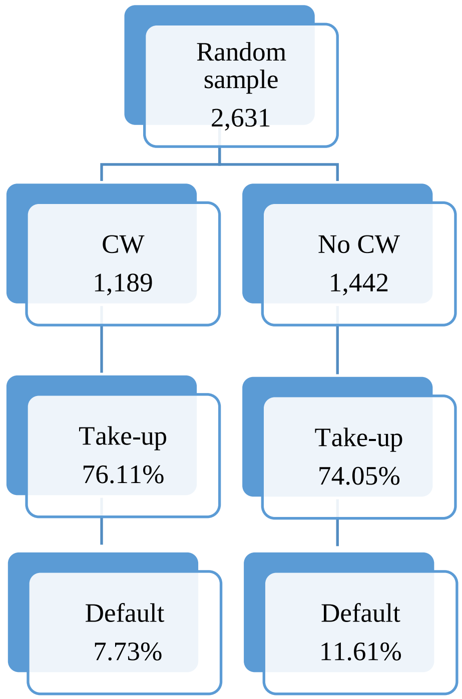

Table 1. Summary statistics and univariate analyses

This table reports summary statistics on the outcome variables as well as loan and borrower characteristics for the two experiments. The table also compares these measures between borrowers who received a credit warning and borrowers who did not. Panels A and B focus on the sample for Experiment 1, and Panels C and D focus on the sample for Experiment 2. Variable definitions are included in Appendix A.

Panel A: Summary statistics for Experiment 1

Variables	*N*	Mean	St. Dev.	Min	*p*10	*p*25	*p*50	*p*75	*p*90	Max
Default	1,464	0.1	0.3	0	0	0	0	0	0	1
CW	1,464	0.227	0.419	0	0	0	0	0	1	1
Amount (yuan)	1,464	3,039.6	1,511.34	2,000	2,000	2,000	2,000	4,000	6,000	6,000
Maturity (months)	1,464	3	0	3	3	3	3	3	3	3
Interest rate (monthly)	1,464	0.068	0.008	0.042	0.052	0.072	0.072	0.072	0.072	0.072
Sesame score	1,464	644.45	35.966	584	603	617	640	666	696	748
Quant score	1,464	650.47	29.318	610	620	625	640	665	695	772
Female	1,464	0.212	0.409	0	0	0	0	0	1	1
Age	1,464	29.829	6.361	22	23	25	28	33	39	55
Junior college or above	1,464	0.431	0.495	0	0	0	0	1	1	1
Below junior college	1,464	0.459	0.498	0	0	0	0	1	1	1
Edu missing	1,464	0.110	0.313	0	0	0	0	0	1	0

Panel B: Covariate balance tests for Experiment 1

	CW = 0			CW = 1			Balance test	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	*N*	Mean	St. Dev.	*N*	Mean	St. Dev.	Coef. CW	*t*-statistics
Amount (yuan)	1,132	3,063.60	1,520.69	332	2,957.83	1,478.35	-0.000	-1.182
Maturity (months)	1,132	3.000	0.000	332	3.000	0.000	0.000	-
Interest rate (monthly)	1,132	0.068	0.008	332	0.068	0.008	-3.715	-0.883
Sesame score	1,132	643.724	35.518	332	646.907	37.401	0.001	1.431
Quant score	1,132	650.315	28.743	332	650.988	31.238	0.000	0.722
Female	1,132	0.199	0.399	332	0.256	0.437	0.059**	2.172
Age	1,132	29.898	6.301	332	29.593	6.566	-0.001	-0.676
Junior college or above	1,132	0.436	0.496	332	0.416	0.494	-0.021	-0.880
Below junior college	1,132	0.453	0.498	332	0.479	0.500	0.026	0.471
Edu missing	1,132	0.111	0.315	332	0.105	0.308	-0.017	-0.471

Panel C: Summary statistics for Experiment 2

Variables	*N*	Mean	St. Dev.	Min	*p*10	*p*25	*p*50	*p*75	*p90*	Max
Default	1,973	0.098	0.298	0	0	0	0	0	0	1
Take-up	2,631	0.75	0.433	0	0	0	1	1	1	1
CW	2,631	0.452	0.498	0	0	0	0	1	1	1
Amount (yuan)	2,631	3,074.88	1,551.19	2,000	2,000	2,000	2,000	4,000	6,000	6,000
Maturity (months)	2,631	3.018	0.233	3	3	3	3	3	3	6
Interest rate (monthly)	2,631	0.068	0.008	0.042	0.052	0.072	0.072	0.072	0.072	0.072
Sesame score	2,631	649.177	37.551	584	604	621	645	673	702	753
Quant score	2,631	650.64	31.590	550	620	625	645	670	695	760
Female	2,631	0.225	0.417	0	0	0	0	0	1	1
Age	2,631	29.905	6.345	22	23	25	28	33	39	55
Junior college or above	2,631	0.43	0.495	0	0	0	0	1	1	1
Below junior college	2,631	0.428	0.495	0	0	0	0	1	1	1
Edu missing	2,631	0.141	0.348	0	0	0	0	0	1	1

Panel D: Covariate balance tests for Experiment 2

	CW = 0			CW = 1			Balance test	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	*N*	Mean	St. Dev.	*N*	Mean	St. Dev.	Coef. CW	*t*-statistics
Amount (yuan)	1,442	3,202.497	1,601.281	1,189	2,920.101	1,474.077	0.000	0.120
Maturity (months)	1,442	3.015	0.209	1,189	3.023	0.260	0.088	1.587
Interest rate (monthly)	1,442	0.068	0.008	1,189	0.069	0.007	5.501	0.508
Sesame score	1,442	647.723	37.090	1,189	650.941	38.045	0.001***	3.796
Quant score	1,442	651.087	32.497	1,189	650.098	30.458	0.000	-1.008
Female	1,442	0.221	0.415	1,189	0.230	0.421	0.010	0.419
Age	1,442	29.929	6.462	1,189	29.876	6.203	0.001	0.734
Junior college or above	1,442	0.433	0.496	1,189	0.427	0.495	-0.014	-0.653
Below junior college	1,442	0.428	0.495	1,189	0.429	0.495	-0.002	-0.061
Edu missing	1,442	0.139	0.346	1,189	0.144	0.351	0.002	0.061

Table 2. The effect of credit warnings after loan take-up on default decisions

This table examines the effect of credit warnings received *after* loan take-up on borrowers' default decisions in Experiment 1 based on OLS estimation. The dependent variable is an indicator that takes the value of 1 if a loan defaults, and 0 otherwise. *CW* is an indicator that takes the value of 1 if the borrower received a credit-warning message, and 0 otherwise. We report coefficient estimates and t-statistics in parentheses based on heteroscedasticity-robust standard errors. Variable definitions are included in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	Default	
	(1)	(2)
CW	-0.063***	-0.059***
	(-3.366)	(-3.185)
Interest rate		1.742
		(1.565)
Sesame score		-0.001***
		(-3.607)
Female		-0.027
		(-1.401)
Age		0.001
		(1.042)
Education dummies		
(Base group: Below junior college)		
Junior college or above		-0.027
		(-1.587)
Edu missing		0.003
		(0.101)
Intercept	0.114***	0.537***
	(12.837)	(2.600)
Observations	1,464	1,464
R^2	0.008	0.032

Table 3. The effect of credit warnings on take-up and default decisions

This table examines the effect of credit warnings received before loan take-up on borrowers' take-up and default decisions in Experiment 2. All tests use OLS estimation. In columns (1) and (2), the dependent variable is an indicator that takes the value of 1 if the borrower takes out the loan, and 0 otherwise. In columns (3) and (4), the dependent variable is an indicator that takes the value of 1 if the loan defaults, and 0 otherwise. *CW* is an indicator that takes the value of 1 if the borrower received a credit-warning message, and 0 otherwise. We report coefficient estimates and t-statistics in parentheses based on heteroscedasticity-robust standard errors. Variable definitions are included in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	Take-up		Default	
	(1)	(2)	(3)	(4)
CW	0.021	0.033*	-0.039***	-0.037***
	(1.209)	(1.950)	(-2.886)	(-2.734)
Interest rate		-4.525***		0.377
		(-3.864)		(0.396)
Sesame score		-0.002***		-0.001***
		(-9.193)		(-4.066)
Female		0.010		-0.012
		(0.505)		(-0.759)
Age		0.000		0.001
		(0.334)		(1.186)
Education dummies (Base group: Below junior college)				
Junior college or above		-0.054***		-0.030**
		(-2.937)		(-2.024)
Edu missing		-0.072***		0.015
		(-2.838)		(0.747)
Intercept	0.741***	2.549***	0.116***	0.615***
	(64.936)	(11.876)	(12.763)	(3.442)
Observations	2,631	2,631	1,973	1,973
R^2	0.001	0.042	0.004	0.024

Table 4. The effect of credit warnings on default decisions: Before vs. after loan take-up

This table compares the default likelihood of borrowers who received credit warnings before taking out a loan with the default likelihood of borrowers who received warnings after taking out a loan. In Panel A, we compare loan and borrower characteristics for borrowers in the first experiment and borrowers in the second experiment who did not receive a credit warning and took out the loan. These two groups of borrowers have the same information at the time of making the take-up decisions. In Panel B, we run multivariate OLS regressions. The dependent variable is an indicator that takes the value of 1 if a loan defaults, and 0 otherwise. *CW* is an indicator that takes the value of 1 if the borrower received a credit warning, and 0 otherwise. *E2* is an indicator that takes the value of 1 for loans from the second experiment, and 0 otherwise. We report coefficient estimates and t-statistics in parentheses based on heteroscedasticity-robust standard errors. Variable definitions are included in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Comparison of the E1 sample with the sample of E2 having CW = 0 and Take-up = 1

	E1			E2&CW=0&Take-up=1			Balance test	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	*N*	Mean	St. Dev.	*N*	Mean	St. Dev.	Coef. E2	*t*-statistics
Amount (yuan)	1,464	3039.617	1511.338	1,068	3181.648	1601.534	0.000*	1.863
Maturity (months)	1,464	3.000	0.000	1,068	3.017	0.224	0.184***	2.679
Interest rate (monthly)	1,464	0.068	0.008	1,068	0.068	0.008	0.728	0.298
Sesame score	1,464	644.446	35.966	1,068	643.785	35.210	-0.000	-1.322
Quant score	1,464	650.468	29.318	1,068	652.043	29.698	0.000	0.457
Female	1,464	0.212	0.409	1,068	0.219	0.414	0.010	0.432
Age	1,464	29.829	6.361	1,068	30.081	6.516	0.001	0.639
Junior college or above	1,464	0.431	0.495	1,068	0.416	0.493	-0.013	-0.602
Below junior college	1,464	0.459	0.498	1,068	0.457	0.498	-0.037	-1.153
Edu missing	1,464	0.110	0.313	1,068	0.127	0.334	0.037	1.153

Panel B: Regression analysis

Dependent variable:	Default	
	(1)	(2)
CW	-0.063***	-0.059***
	(-3.375)	(-3.216)
E2	0.002	0.002
	(0.169)	(0.171)
CW*E2	0.024	0.022
	(1.045)	(0.978)
Interest rate		0.958
		(1.324)
Sesame score		-0.001***
		(-5.452)
Female		-0.018
		(-1.496)
Age		0.001
		(1.568)
Education dummies (Base group: Below junior college)		
Junior college or above		-0.028**
		(-2.544)
Edu missing		0.010
		(0.642)
Constant	0.114***	0.582***
	(12.871)	(4.305)
Observations	3,437	3,437
R^2	0.006	0.027

Table 5. Validation of the informational-rents measure

Panel A compares the ability of the Quant score and the Sesame score to predict default for repeat and new borrowers, respectively. Panel B tabulates the results of regressing interest rates and informational rents on borrower characteristics. Panel C reports the comparison of borrower characteristics across high-, medium-, and low-informational-rents groups for repeat borrowers. Informational rents are calculated in two steps. First, we regress the interest rate on the Quant score based on repeat borrowers and obtain the regression residual, *e*. Second, we regress *e* on observable borrower characteristics based on repeat borrowers and obtain the predicted values and coefficient estimates on borrower characteristics. The predicted value serves as a measure of informational rents for repeat borrowers. We partition repeat borrowers into low, medium, and high terciles based on the predicted value (i.e., the measure of informational rents). For new borrowers, we multiply the coefficients estimated from repeat borrowers by new borrowers' characteristics to obtain the informational-rents measure. We then partition new borrowers into low, medium, and high groups based on the informational rents. The higher the value, the higher the informational rents. We apply the two cutoffs of repeat borrowers to new borrowers. Panel C reports loan and borrower characteristics for repeat borrowers in the low-, medium-, and high-informational-rents groups, and Panel D reports those for new borrowers. We report coefficient estimates from OLS and t-statistics in parentheses based on heteroscedasticity-robust standard errors.

Panel A: Default analyses contrasting repeat and new borrowers

Dependent variable:	Default	
	Repeat borrowers	New borrowers
	(1)	(2)
Sesame score	-0.00005	-0.001***
	(-0.403)	(-3.023)
Quant score	-0.001***	-0.001**
	(-4.709)	(-2.389)
Female	-0.017	-0.013
	(-1.605)	(-0.831)
Age	0.001*	0.001
	(1.796)	(1.397)
Education dummies (Base group: Below junior college)		
Junior college or above	-0.005	-0.028*
	(-0.469)	(-1.883)
Edu missing	0.019	0.014
	(1.529)	(0.698)
Intercept	0.544***	0.907***
	(4.788)	(5.551)
Observations	1,781	1,973
R^2	0.020	0.023

Panel B: Analyses of interest rates and residual for repeat borrowers

Dependent variable:	Interest rate	*e*
	(1)	(2)
Sesame score	-0.0001***	-0.0001***
	(-12.701)	(-7.330)
Female	-0.0002	-0.0004
	(-0.247)	(-0.631)
Age	-0.0002***	-0.0001
	(-3.357)	(-1.567)
Education dummies (Base group: Below junior college)		
Junior college or above	-0.0018***	-0.0014**
	(-2.672)	(-2.112)
Edu missing	-0.0032***	-0.0028***
	(-3.988)	(-3.699)
Intercept	0.1260***	0.0411***
	(23.685)	(8.073)
Observations	2,069	2,069
R^2	0.098	0.0386

Panel C: Comparison of borrower and loan characteristics across low-, medium-, and high-informational-rents groups for repeat borrowers

	Low (N=689)		Medium (N=690)		High (N=690)		t-test (p-value)		
Variables	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	L vs. M	M vs. H	L vs. H
Quant score	703.303	34.901	704.094	30.738	702.477	28.553	0.655	0.312	0.631
Default	0.040	0.197	0.032	0.176	0.041	0.198	0.464	0.404	0.931
Interest rate	0.048	0.012	0.052	0.014	0.055	0.014	0.000	0.000	0.000
Sesame score	695.017	29.139	654.683	21.633	628.083	20.994	0.000	0.000	0.000
Female	0.296	0.457	0.238	0.426	0.180	0.384	0.015	0.008	0.000
Age	31.038	6.461	28.858	5.712	27.778	4.822	0.000	0.000	0.000
Junior college or above	0.573	0.495	0.509	0.500	0.328	0.470	0.017	0.000	0.000
Below junior college	0.099	0.298	0.213	0.410	0.586	0.493	0.000	0.000	0.000
Edu missing	0.328	0.470	0.278	0.448	0.087	0.282	0.045	0.000	0.000
Take-up	0.829	0.377	0.867	0.340	0.887	0.317	0.050	0.259	0.002

*N = 571, 598, and 612 for the default row across low-, medium-, and high-informational-rents groups.

Panel D: Comparison of borrower and loan characteristics across low-, medium-, and high-informational-rents groups for new borrowers

	Low (N=1,089)		Medium (N=959)		High (N=583)		t-test (p-value)		
Variables	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	L vs. M	M vs. H	L vs. H
Quant score	654.899	34.219	648.651	30.285	645.957	27.357	0.000	0.079	0.000
Default	0.073	0.261	0.099	0.299	0.133	0.340	0.077	0.061	0.001
Interest rate	0.066	0.009	0.069	0.007	0.071	0.004	0.000	0.000	0.000
Sesame score	680.022	32.236	635.292	21.432	614.401	19.083	0.000	0.000	0.000
Female	0.286	0.452	0.214	0.410	0.129	0.335	0.000	0.000	0.000
Age	30.294	6.713	30.360	6.366	28.431	5.307	0.820	0.000	0.000
Junior college or above	0.574	0.495	0.438	0.496	0.149	0.357	0.000	0.000	0.000
Below junior college	0.193	0.395	0.443	0.497	0.844	0.363	0.000	0.000	0.000
Edu missing	0.233	0.423	0.119	0.324	0.007	0.083	0.000	0.000	0.000
Take-up	0.653	0.476	0.790	0.407	0.864	0.343	0.000	0.000	0.000

*N = 711, 758, and 504 for the default row across low-, medium-, and high-informational-rents groups.

Table 6. Take-up analysis in the cross section for Experiment 2

This table reports loan take-up results across low-, medium-, and high-informational-rents groups. The informational-rents partition is detailed in Table 5. The dependent variable is an indicator that takes the value of 1 if a borrower takes out a loan, and 0 otherwise. *CW* is an indicator that takes the value of 1 if the borrower received a credit-warning message, and 0 otherwise. We report coefficient estimates from OLS regressions and t-statistics in parentheses based on heteroscedasticity-robust standard errors. Variable definitions are included in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	Take-up			
	Low	Medium	High	Low & Edu missing
	(1)	(2)	(3)	(4)
CW	0.039	0.012	0.054*	0.120**
	(1.362)	(0.453)	(1.854)	(2.115)
Interest rate	-5.564***	-0.957	-0.008	-3.589
	(-3.287)	(-0.464)	(-0.002)	(-0.922)
Sesame score	-0.001***	0.000	-0.002*	-0.003***
	(-2.588)	(0.083)	(-1.905)	(-3.143)
Female	0.059*	-0.042	0.048	-0.021
	(1.838)	(-1.296)	(1.125)	(-0.305)
Age	0.002	0.001	0.004	0.006
	(1.122)	(0.474)	(1.382)	(1.474)
Junior college or above	-0.056	0.023	0.016	
	(-1.456)	(0.758)	(0.393)	
Edu missing	-0.002	-0.020	-0.110	
	(-0.052)	(-0.379)	(-0.638)	
Constant	1.841***	0.774	1.685***	2.626***
	(4.298)	(1.194)	(2.628)	(3.247)
Observations	1,089	959	583	254
R^2	0.024	0.004	0.024	0.081

Table 7. Repeat borrowers: Summary statistics, covariate balance tests, default decisions, and take-up decision for E2

Panels A and B report summary statistics on loan and borrower characteristics and conduct covariate balance checks for Experiment 1; Panels C and D do the same for Experiment 2. Panel E presents the results of OLS regressions on default decisions for E1 and E2, and on loan take-up decisions for E2.

Panel A: Summary statistics for Experiment 1

Variables	*N*	Mean	St. Dev.	Min	*p*10	*p*25	*p*50	*p*75	*p*90	Max
Default	1,340	0.036	0.186	0	0	0	0	0	0	1
CW	1,340	0.281	0.450	0	0	0	0	1	1	1
Amount (yuan)	1,340	4,453.7	1,635.16	2,000	2,000	4,000	4,000	6,000	6,000	6,000
Maturity (months)	1,340	3	0	3	3	3	3	3	3	3
Interest rate (monthly)	1,340	0.053	0.013	0.042	0.042	0.042	0.042	0.072	0.072	0.072
Sesame score	1,340	657.59	36.689	584	612	630.5	655	681	709	748
Quant score	1,340	704.31	31.163	615	660	685	706	730	742	766
Female	1,340	0.274	0.446	0	0	0	0	1	1	1
Age	1,340	29.861	6.189	20	23	25	29	33	39	53
Junior college or above	1,340	0.426	0.495	0	0	0	0	1	1	1
Below junior college	1,340	0.336	0.472	0	0	0	0	1	1	1
Edu missing	1,340	0.238	0.426	0	0	0	0	0	1	1

Panel B: Covariate balance tests for Experiment 1

	CW = 0			CW = 1			Balance test	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	*N*	Mean	St. Dev.	*N*	Mean	St. Dev.	Coef. CW	*t*-statistics
Amount (yuan)	963	4,508.827	1,609.055	377	4,312.997	1,694.065	10.365	0.203
Maturity (months)	963	3.000	0.000	377	3.000	0.000	0.000	-
Interest rate (monthly)	963	0.052	0.013	377	0.054	0.014	0.000	0.294
Sesame score	963	656.892	36.508	377	659.382	37.138	2.490	1.117
Quant score	963	704.684	31.453	377	703.350	30.431	0.033	0.018
Female	963	0.270	0.444	377	0.284	0.451	0.017	0.638
Age	963	29.895	6.175	377	29.775	6.230	-0.049	-0.131
Junior college or above	963	0.431	0.495	377	0.414	0.493	-0.009	-0.297
Below junior college	963	0.334	0.472	377	0.340	0.474	-0.002	-0.062
Edu missing	963	0.235	0.424	377	0.247	0.432	0.011	0.411

Panel C: Summary statistics for Experiment 2

Variables	*N*	Mean	St. Dev.	Min	*p*10	*p*25	*p*50	*p*75	*p*90	Max
Default	1,781	0.038	0.190	0	0	0	0	0	0	1
Take-up	2,069	0.861	0.346	0	0	1	1	1	1	1
CW	2,069	0.485	0.500	0	0	0	0	1	1	1
Amount (yuan)	2,069	4,597.39	1,623.93	2,000	2,000	4,000	6,000	6,000	6,000	6,000
Maturity (months)	2,069	3.352	0.966	3	3	3	3	3	6	6
Interest rate (monthly)	2,069	0.052	0.014	0.032	0.042	0.042	0.042	0.072	0.072	0.072
Sesame score	2,069	659.244	36.641	584	614	633	656	683	709	753
Quant score	2,069	703.291	31.498	615	660	685	706	730	742	772
Female	2,069	0.238	0.426	0	0	0	0	0	1	1
Age	2,069	29.224	5.860	20	23	25	28	32	37	55
Junior college or above	2,069	0.470	0.499	0	0	0	0	1	1	1
Below junior college	2,069	0.299	0.458	0	0	0	0	1	1	1
Edu missing	2,069	0.231	0.422	0	0	0	0	0	1	1

Panel D: Covariate balance test for Experiment 2

	CW = 0			CW = 1			Balance test	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	*N*	Mean	St. Dev.	*N*	Mean	St. Dev.	Coef. CW	*t*-statistics
Amount (yuan)	1,066	4,592.871	1,644.826	1,003	4,602.193	1,602.230	-51.778	-1.427
Maturity (months)	1,066	3.355	0.969	1,003	3.350	0.963	0.001	1.090
Interest rate (monthly)	1,066	0.051	0.014	1,003	0.052	0.014	-0.013	-0.310
Sesame score	1,066	659.926	36.929	1,003	658.518	36.337	-1.857	-1.200
Quant score	1,066	704.602	30.531	1,003	701.898	32.450	-3.099**	-2.335
Female	1,066	0.226	0.418	1,003	0.250	0.433	0.023	1.255
Age	1,066	29.566	5.976	1,003	28.860	5.716	-0.727***	-2.836
Junior college or above	1,066	0.478	0.500	1,003	0.461	0.499	-0.020	-0.895
Below junior college	1,066	0.293	0.455	1,003	0.306	0.461	0.016	0.777
Edu missing	1,066	0.229	0.420	1,003	0.233	0.423	0.004	0.217

Panel E: Regression analyses

Dependent variable:	Default (E1)		Default (E2)		Take-up (E2)	
	(1)	(2)	(3)	(4)	(5)	(6)
CW	-0.013	-0.014	0.006	0.006	-0.001	-0.002
	(-1.145)	(-1.194)	(0.631)	(0.699)	(-0.049)	(-0.128)
Interest rate		0.613		0.846**		0.140
		(1.500)		(2.441)		(0.238)
Sesame score		0.000		-0.000		-0.001**
		(0.077)		(-1.263)		(-2.382)
Female		-0.023**		-0.017		-0.005
		(-2.004)		(-1.612)		(-0.274)
Age		0.001		0.001		-0.000
		(1.645)		(1.478)		(-0.241)
Education dummies (Base group: Below junior college)						
Junior college or above		-0.010		-0.006		-0.034*
		(-0.861)		(-0.549)		(-1.843)
Edu missing		0.004		0.019		-0.061***
		(0.258)		(1.542)		(-2.872)
Intercept	0.039***	-0.032	0.035***	0.070	0.861***	1.247***
	(6.587)	(-0.289)	(5.548)	(0.743)	(81.187)	(7.791)
Observations	1,340	1,340	1,781	1,781	2,069	2,069
R^2	0.001	0.009	0.000	0.011	0.000	0.008

Appendix A. Variable definitions

Outcome variables:	
Take-up	Indicator that equals 1 if a borrower takes out an approved loan, and 0 otherwise.
Default	Indicator that equals 1 if a loan defaults (more than two months overdue), and 0 otherwise.
Lenders' informational rents	We calculate lenders' informational rents in three steps. (1) We regress the interest rate on the Quant score based on repeat borrowers in Experiment 2 and obtain the regression residual, *e*. (2) We regress *e* on observable borrower characteristics based on repeat borrowers and obtain the predicted values and coefficient estimates on borrower characteristics. (3) The predicted values serve as the measure of informational rents for repeat borrowers. Repeat borrowers are partitioned into high, medium, and low groups of informational rents based on tercile cutoffs. For new borrowers, we multiply the coefficient estimates (obtained from repeat borrowers) by new borrowers' characteristics to obtain the informational-rents measure. New borrowers are partitioned into high, medium, and low groups using repeat borrowers' tercile cutoffs.
Policy variable:	
CW	Indicator that equals 1 if a borrower receives the credit-warning text message stating that loan repayment and default information will be instantaneously shared with the Credit Reference Center at the People's Bank of China (i.e., the public credit registry), and 0 otherwise.
Loan characteristics:	
Amount (yuan)	Loan amount in yuan ($1=6.89 yuan as of March 31, 2017).
Maturity (months)	Loan maturity in months.
Interest rate (monthly)	Effective interest rate, which is the sum of the monthly interest rate and service fee.
Borrower characteristics:	
New	Indicator that equals 1 if a borrower has not taken up a loan from Quant Group before her current application, and 0 otherwise.
Sesame score	A credit score ranging from 350 to 950 generated by Sesame Credit based on five criteria: credit history, online transaction habits, personal information, ability to honor an agreement, and social-network affiliations.
Quant score	A credit score generated by Quant Group using a proprietary model that incorporates an individual's Sesame score, phone book information, and borrowing and repayment history at Quant Group.
Female	Indicator that equals 1 if a borrower is female, and 0 otherwise.
Age	The age of a borrower.
Junior college or above	Indicator that equals 1 if a borrower reports her education as master or above, college, or junior college (a three-year college), and 0 otherwise.
Below junior college	Indicator that equals 1 if a borrower reports her education as vocational secondary school, vocational high school, high school, middle school, or elementary school or below, and 0 otherwise.
Edu missing	Indicator that equals 1 if a borrower does not report her education level, and 0 otherwise.

Appendix B. Examples of loan contracts

To illustrate a typical loan contract underwritten by Quant Group, this appendix provides the key clauses of an agreement on a loan funded by a reporting lender and by a non-reporting lender.

Key clauses of an agreement on a loan funded by a reporting lender

Article 5. Liability for breach of agreement

5.7 If Party B (the borrower) fails to make any repayment for more than 10 days and the guarantor (if any) fails to assume the guarantee responsibility to repay the loan principal, interest, and other costs of the outstanding loan on behalf of Party B, or if Party B misses the due date more than three (including three) times, or if Party A (the lender) or Party C (the platform) finds that Party B evades, refuses to communicate or refuses to acknowledge the fact of arrears, intentionally transfers the funds in this Loan, if Party B's credit conditions deteriorate, etc., all the principal and interest of the loan under this Agreement will mature in advance, whereas:

(1) Party A has the right to announce that all the principal and interest of the loan under this Agreement are due in advance, and Party B shall pay off all outstanding loan principal, interest, penalty interest, and other costs incurred under this Agreement immediately;

(2) Both Party A and Party C have the right to file Party B's "late payment records," "malicious behaviors," or "negative standing" in the personal credit-reporting system, and have the right to share the aforementioned information with Party B's affiliates, business partners, credit-reporting agencies, etc. Party B gives its consent to Party A and Party C in exercising this right;

(3) Party C has the right to disclose relevant information about Party B's breach of agreement and other information related to Party B to institutions including, but not limited to, the public media, Party B's individual clients, Party B's client institutions, the public security units, prosecution service, the courts, and relevant debt-collection-service agencies. Party B agrees to this and does not hold any claim against Party C.

Article 10. Authorization of credit query

10.1 The Borrower (Party B) hereby irrevocably authorizes the Lender (Party A) and the platform (Party C) to collect the Borrower's personal information and credit history (including bill payment history and borrowing history), derogatory information, etc., and may also provide the information to the People's Bank of China's Financial Credit Information Foundational Database and other credit-reporting agencies established in accordance with the law. The Borrower hereby irrevocably authorizes the Lender and the platform to query, print, and save the Borrower's personal information and credit history (including bill payment history and borrowing history), derogatory information, etc., in accordance with the law and with the relevant national regulations via the People's Bank of China's Financial Credit Information Foundational Database, other legally established credit-reporting agencies, and the Ministry of Public Security's citizen information database, or to query, print, and save the Borrower's credit information via Lender-designated institutions in partnership with the Financial Credit Information Foundational Database of the People's Bank of China.

A key clause of an agreement on a loan funded by a non-reporting lender

7.6 If the borrower (Party B) fails to make any repayment for more than five calendar days and the guarantor (if applicable) fails to assume the guarantee responsibility to repay the loan principal, interest, and other costs outstanding on behalf of Party B, or if Party B fails to make any repayment for three consecutive installments (including three), or if Party B fails to make any repayment via the intermediary party's (Party C's) platform for more than five times (including five), or if other parties find Party B chooses to evade, refuses to communicate or refuses to acknowledge the fact of arrears, intentionally relocates the funds in this loan, the credit conditions of Party B deteriorate, or Party B does not use this loan in accordance with the agreed purpose, all of the principal and interest of the loan under this Agreement will mature in advance. In the meantime,

(1) Party B shall immediately settle all payments, including loan principal, interest, penalty interest, and all other expenses incurred under this Agreement;

(2) The platform (Party C) has the right to record Party B's "late payment records" or "malicious borrowing behaviors" in its personal information file, change Party B's credit rating, and report Party B's aforementioned records to the regulatory agency, including but not limited to the Financial Credit Information Foundational Database, credit reporting agencies, etc. Party B agrees with such arrangement;

(3) Party C has the right to disclose relevant information about Party B's breach of agreement and other information related to Party B to institutions including but not limited to the public media, Party B's individual clients, Party B's client institutions, the public security units, prosecution service, the courts, and relevant debt-collection-service agencies.

Party B agrees to this arrangement and does not hold any claim against Party C. Party C will notify the Lender (Party A) in writing to reassign the unrealizable portion of the creditor's rights mentioned above. Upon receiving the written notice from Party C, Party A shall have the right to collect from Party B directly, and Party C shall cooperate to provide Party A with the documents needed to realize the creditor's rights.