What If Borrowers Were Informed About Credit Reporting? Two Randomized Field Experiments*

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What If Borrowers Were Informed about Credit Reporting?

Two Randomized Field Experiments

Abstract

Using two randomized field experiments, we examine how warning individual retail borrowers that their loan performance will be reported to a public credit registry before and after the loan take-up affects their borrowing behavior. We show that credit warnings reduce default rates by 3.7–7 percentage points and increase loan take-up rates by 4.1 percentage points, which suggests that credit warnings benefit both lenders and borrowers. The main drivers appear to be borrowers' anticipation of a reduction in lenders' informational rents and improved repayment incentives. Moreover, the reduction in default rates is comparable for borrowers who receive the credit warning before and after the loan take-up. As credit warnings received before but not after a loan take-up can affect the borrower pool, and thus the overall credit risk of the pool, the results suggest that credit warnings have little net effect on the pool's credit risk due to selection.

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

JEL: G10, G21, G23

1. Introduction

The credit-reporting industry has witnessed rapid growth worldwide. In 2005, only 67% of all economies had a private credit bureau (PCB) or a public credit registry (PCR). In 2019, that figure climbed to 88%. For East Asia & Pacific, this fraction was 47% in 2005 and 72% in 2019 (see *Doing Business 2020*).[1] Given the fast expansion of credit-reporting practices in these economies, it is important to study whether and how credit reporting affects the decisions of lenders and borrowers.

Information asymmetry and the resulting adverse selection and moral hazard impede efficient credit allocation (Dell'Ariccia and Marquez 2004; Djankov, McLiesh, and Shleifer 2007). Theories suggest that sharing loan performance information among lenders (e.g., credit reporting) helps to address these imperfections and fosters credit expansion. Information sharing can improve lender screening by reducing information asymmetry between borrowers and lenders (Pagano and Jappelli 1993). It can also increase borrowers' repayment efforts by narrowing incumbent lenders' informational advantage and reducing their rents (Padilla and Pagano 1997), and by restricting defaulted borrowers' access to future credit (Padilla and Pagano 2000).

In this study, we examine borrowers' response to credit reporting by conducting a pair of randomized field experiments in the Chinese consumer credit market in early April 2017. The Chinese market has at least three institutional features that make it an ideal setting to examine this question. First, China's outstanding short-term consumer loans issued by commercial banks increased by 115% from 2015 to 2020,[2] giving rise to an urgency to address market frictions. Second, in 2017, China's PCR (i.e., the Credit Reference Center at the People's Bank of China)

[1] https://documents1.worldbank.org/curated/en/688761571934946384/pdf/Doing-Business-2020-Comparing-Business-Regulation-in-190-Economies.pdf.
[2] See http://www.pbc.gov.cn/eportal/fileDir/defaultCurSite/resource/cms/2017/06/2017061416350093101.htm and http://www.pbc.gov.cn/eportal/fileDir/defaultCurSite/resource/cms/2021/01/2021011818005922737.htm.

had limited coverage (approximately 40% of the adult population),[3] and China had no PCB because lending platforms did not trust each other enough to share their customers' credit information due to the fierce competition in consumer lending. Third, due to the weak judicial system, lenders have limited legal recourse to enforce loan repayment. These three features underscore the possibility that credit information sharing among lenders can mitigate adverse selection and moral hazard issues. Specifically, we examine how messages informing borrowers that their loan performance will be reported to PCR (hereafter "credit warnings") affect their loan take-up and repayment decisions. 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 how borrowers respond to credit warnings.

We conducted the experiments at Quant Group, a large online lending platform in China. The platform assigns institutional lenders to individual borrowers and makes small uncollateralized consumer loans. According to the credit-reporting policy of the People's Bank of China (PBC) in 2017, there are two types of institutional lenders: reporting lenders (e.g., financial institutions regulated by PBC) and non-reporting lenders (e.g., unregulated Fintech companies). Reporting lenders have played a dominant role in the formal credit market (e.g., credit cards, home mortgages, and car loans) and must report loan repayments and defaults to PCR, while such reporting is neither required of nor available to non-reporting lenders. Half of Quant Group's lenders are reporting lenders, and the other half are not. In addition, the language Quant Group uses in the loan contract to describe the reporting policy is very similar for loans funded by non-reporting lenders and those

[3] The goals of the Credit Reference Center at the People's Bank of China are (1) to establish, operate, maintain, and manage the National Centralized Commercial and Consumer Credit Reporting System; (2) to collect the credit information of both individual consumers and enterprises from banks and other lending institutions, and to provide credit-reporting services according to the relevant laws and regulations; and (3) to manage the establishment of a unified credit-reporting platform for the financial industry: http://www.pbccrc.org.cn/crc/zyzz/index_list_list.shtml.

funded by reporting lenders (see Articles 7.6(2) and 10.1 in Appendix B for details). Thus, borrowers at Quant, especially first-time borrowers, might not know whether their loan performance will be reported to PCR. 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 funded by a single *reporting lender*, assuming that the average first-time borrower is unaware of the underlying credit-reporting policy.

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 PCR. These borrowers are classified as *treated*, while the rest are classified 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, borrowers who received credit warnings may perceive that if they repay the loan, they will have a positive record at PCR. A positive record will reduce the information asymmetry with other lenders (both formal and informal), which helps borrowers gain access to future credit (both formal and informal) and cuts the incumbent lender's informational rents (Padilla and Pagano 1997). This impact is called the *informational-rents effect*. Second, upon receiving credit warnings, borrowers understand that if they default on the loan, the increased likelihood that the default will be reported to PCR could jeopardize their future access to the credit market (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*. Both effects predict a lower default rate for borrowers receiving credit warnings. We show that the default rate, defined based on the industry standard of two months overdue, is 7 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 11.4%, the credit-warning effect on default rates is economically large. The evidence supports our conjecture that credit warnings improve 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 and altered their loan-approval message to include a credit warning stating that their loan repayment or default would be reported to PCR. 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 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 who received credit warnings (*treated*) and those who did not (*control*). We find that the loan take-up rate is 4.1 percentage points higher for the treatment group than for the control group. This magnitude is economically meaningful, given that 25.9% of borrowers who did not receive credit warnings did not take out a loan. These results suggest that on average, the informational-rents effect dominates the disciplinary effect of credit warnings on 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 method that classifies new borrowers with high, medium and low expected informational rents (discussed in detail in section 5).[4] 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 the lender's informational 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. Doing so allows us to evaluate not only whether lenders benefit from sending credit warnings before borrowers take out a loan, but also which timing is better – before or after the loan take-up – by comparing the credit-warning effects on default rates between the two experiments. We find that the default rate is 3.7 percentage points lower for the treatment group than for the control group, which suggests that on the net, credit warnings before loan take-up reduce the default rates. We further show that the credit-warning effect on default is similar across the two experiments. This result suggests that sending credit warnings before loan take-up benefits lenders more because it improves the extensive margin of lending without sacrificing the profit margin.

Although the lending platform used in our field experiments is from China, the institutional features of the consumer credit market, especially those pertaining to limited coverage of credit reporting and constrained credit access, are similar in many developing countries such as Argentina and Mexico.[5] Therefore, our findings have direct implications for the banking regulators of those economies who wish to improve consumer's credit access and consumption without

[4] As lenders have private information about repeat borrowers, gleaned from their repayment history, we use repeat borrowers to estimate lenders' informational rents. We sort repeat borrowers into high-, medium-, and low-rents groups. We identify their observable characteristics that are associated with informational rents. We then match each new borrower with a repeat borrower by these characteristics and assign the new borrower the group of the matched repeat borrower.

[5] For relevant papers, see Powell, Mylenko, Miller, and Majnoni (2004); Luoto, McIntosh, and Wydick (2007); Brown, Jappelli, and Pagano (2009); Peria and Singh (2014); Liberman (2016); Liberman, Neilson, Opazo, and Zimmerman (2018); and World Bank Group (2019).

injecting additional risk. Equally important, our study can inform policy makers in developed economies that credit reporting reduces borrowers' moral hazard, which is hard to disentangle from other economic mechanisms due to universal credit reporting.

While our paper complements prior empirical literature (e.g., Jappelli and Pagano 2002), three distinctions are key in defining our contributions. First, to the best of our knowledge, our study is the first to provide evidence on borrowers' responses to lender information sharing. Extant research using a natural experiment brought about by the staggered entry of lenders into a private credit bureau (e.g., Doblas-Madrid and Minetti 2013; Sutherland 2018) cannot distinguish borrowers' responses from those of lenders (Balakrishnan and Ertan 2021). For example, Sutherland (2018, page 128) explicitly acknowledges that "my tests do not require borrowers to even be aware of PayNet's existence…." Nevertheless, this distinction is critical because it has policy implications. For instance, if the decline in default rate documented in Doblas-Madrid and Minetti (2013) is due to lenders' response to the increased lending competition, which steers lenders to shed risky borrowers and switch to safer borrowers, policymakers might consider softening the competition while maintaining the benefits of improved information precision associated with information sharing (Brown and Zehnder 2007). On the other hand, if the default reduction is due to borrowers' response to lenders' improved ability to discipline borrowers, policy makers should promote information sharing.

Second, our method can decompose the overall effects of credit reporting into the effect on the composition of the pool of borrowers and the effect of mitigating the moral-hazard problem of a given borrower. This distinction also has important policy implications. For example, loan guarantees work effectively when hidden information (adverse selection) is the main source of informational asymmetries. This is because lenders are made whole if a borrower defaults, which in turn improves lenders' willingness to lend ex ante. By contrast, when hidden action (moral hazard) is the main problem, it is more useful to improve garnishment or dynamic contracting schemes (Karlen and Zinman 2009). We highlight the importance of establishing a PCR and informing borrowers about credit reporting in order to mitigate borrowers' moral hazard.[6]

Third, there is a broad interest in Fintech companies due to their growing importance (Berg, Fuster, and Puri 2021). The literature falls into three broad categories. First, it focuses on screening techniques and finds that technology such as machine learning has greatly expanded the information that Fintech lenders can use to evaluate the credit quality of loan applicants (Dobbie, Liberman, Paravisini, and Pathania 2021; Fuster, Goldsmith-Pinkham, Ramadorai, and Walther 2022).[7] Second, the literature focuses on information production and suggests that Fintech lenders rely on investors (e.g., wisdom of the crowd; Zhang and Liu 2012) to produce information (Vallée and Zeng 2019). Third, the literature compares the clientele of Fintech lenders and the clientele of banks and identifies the types of borrowers that Fintech lenders acquire (see Tang 2019; Cornaggia, Wolfe, and Yoo 2019; De Roure, Pelizzon, and Thakor 2022). Our paper extends the literature by highlighting that Fintech lending can provide a means for underbanked borrowers to establish a track record at PCR and then graduate to the formal credit market.

2. Institutional background on consumer credit markets in China

[6] Karlen and Zinman (2009) (hereafter KZ) examine how interest rate intervention affects borrowers' repayment decisions in a natural field experiment. Our paper differs from KZ in four key aspects. First, KZ do not examine borrowers' take-up decisions. Doing so allows us to differentiate whether lenders' hold-up incentive (e.g., informational rents) or borrowers' moral hazard drives the effect of credit warnings on borrowers' take-up decisions. Second, our pair of experiments enables us to disentangle selection from moral hazard. We find support for the moral hazard effect but not for the adverse or advantageous selection effect. Third, our intervention involves (informing borrowers about) credit reporting, which differs from KZ's intervention in interest rates. Our findings have regulatory implications for whether to establish public credit registries in developing countries, whereas KZ's findings have implications for interest rate regulation. Finally, we can easily scale up our intervention at very low incremental costs. We simply append credit warnings to the text messages routinely sent to borrowers. In contrast, KZ reduce the interest rates of current or future loans, which presumably affects lenders' profit margin.

[7] Relatedly, non-credit score information such as digital footprint (Berg, Burg, Gombović, and Puri 2020), social network (Iyer, Khwaja, Luttmer, and Shue 2016; Lin, Prabhala, and Viswanathan 2013) and borrowers' trustworthiness (Duarte, Siegel, and Young 2012) is shown to be effective in alleviating the information asymmetry between borrowers and lenders.

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 (including 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, and are termed formal credit markets. Since 2005, Chinese regulators have required financial institutions to report repayment/default information on both business and consumer loans to PCR, the Credit Reference Center at the People's Bank of China. Formal credit reports containing loan-performance information are provided at no cost to all financial institutions, but they are not shared with Fintech companies.[8] The number of reporting financial institutions has increased over time (from 23 in 2005 to 1,811 in 2014). PCR's coverage of individual borrowers was, however, very limited at the time of our experiments – approximately 40% of the adult population.[9]

With recent advances in technology, and in the absence of regulation, Fintech lending via 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

[8] A formal credit report contains information on an individual's formal credit history, such as 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. While on-time repayment stays on the record for two years, a default that is fully repaid stays on the record for five years.

[9] In 2016, the Chinese adult population was 1.041 billion according to World Bank data (source: the 2016 World Bank Doing Business Survey). The number of individuals with credit histories at PCR was 430 million (sources: Credit Information System Bureau of PBC, China Credit Report (2019), China Financial Publishing House, China, 2020, p. 13). The coverage ratio of the Chinese adult population (with credit histories at PCR) at the time of our experiment was 430/1,041 = 41.3%.

Chinese authorities to consider imposing stricter regulations and establishing a nationwide credit-reporting system.[10]

Given PCR's limited coverage of individuals, the inability of Fintech companies to access PCR data, the non-existence of any PCB officially approved by the central bank, 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, which was rolled out in 2015 by Sesame Credit, under Ant Financial of the Alibaba Group. Sesame Credit covered much more of the Chinese adult population than PCR. It generates Sesame scores based on individuals' transactions at Alibaba and its affiliates,[11] assigning users a score ranging from 350 to 950. Legitimate companies can obtain an individual's Sesame score with a nominal fee of 0.4 yuan per inquiry if the individual authorizes the access. They have been widely used in both retail business decisions (e.g., waivers on car rental deposits) and informal credit markets. Thus, in this study we consider Sesame scores a measure of an individual's observable credit quality.

Sesame scores have two limitations. First, unlike its US counterparts Equifax and Experian, Sesame Credit *does not* incorporate loan-performance information at other lending platforms such as Quant Group, because most lenders are concerned about the potential increase in competition with other informal lenders due to information sharing (Yang and Yu, *WSJ*, June 23, 2021).[12] Second, when banks allocate credit, they ignore informal credit scores including Sesame scores and rely solely on credit reports from PCR. Because formal credit markets still play a dominant

[10] The new regulation requiring Fintech lenders to share credit information with PCR was not passed until September 2019. At the time of our study, no Fintech lenders reported credit information to PCR.
[11] The transactions include payment and credit information via Alipay (i.e., the Alipay platform handled payment transactions and originated loans), information on payments via Alipay to credit cards issued by other financial institutions, and online transactions at Taobao and Tmall.
[12] Source: https://www.wsj.com/articles/jack-mas-ant-in-talks-to-share-data-trove-with-state-firms-11624442902.

role in the consumer credit supply (e.g., only banks can issue credit cards and originate mortgages),[13] establishing credit files at PCR is crucial for many individuals who have good credit quality and want to gain access to formal credit.

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 company 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 in China may serve as an intermediary between lenders and borrowers without bearing borrowers' credit risk; alternatively, it may choose to assume the credit risk. Quant Group, like 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. To mitigate its risk exposure, Quant Group developed a rigorous screening model and imposed hefty monthly service fees on top of the interest charged by lenders.

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 PCR and thus affect borrowers' credit reports. However, there is no such reporting requirement or mechanism

[13] "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.

for non-reporting lenders. At the time of our experiments, there were six reporting lenders and six non-reporting lenders to fund the loans offered by Quant Group.

Typical Quant Group applicants are males in their late 20s who are employed, have decent incomes – 4,000 yuan/month (approximately $600) on average – and are heavy smartphone users. They have fair credit scores (the average Sesame score is 602) and high education levels (three-year college degree, on average). They often use loans to pay down other debt or to fund their 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, which suggests 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 a larger loan, often with a lower interest rate. Approximately 90% of first-time borrowers who repaid their loans return to the platform. A typical repeat borrower borrows 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 her age, gender, and social security, which can be verified by her residence ID card.[14] The borrower also needs to provide information on income, education, whether she has a credit card, and whether she is a homeowner; this information is largely unverifiable. Quant Group approves or rejects the application based on the borrower's characteristics described in the application, along with the borrower's Sesame score purchased

[14] 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.

from Ant Financial and its own assessment of the borrower's creditworthiness, the Quant score. Quant scores are generated using a proprietary model that incorporates individuals' Sesame scores, phone book information, and borrowing and repayment histories at Quant Group. Quant Group updates the scores based on loan performance regardless of whether the ultimate lender is reporting or non-reporting. As noted above, because Quant Group does not share the data with other lending platforms, the Quant scores of repeat borrowers may incorporate private credit information, which we validate in our empirical test. We use these scores to capture the lender's private information and develop a method to identify new borrowers who expect to be charged with informational rents when they return to the same lender for another loan in the future. We then examine the argument that credit reporting improves these borrowers' repayment efforts by lowering the expected informational rents of the incumbent lender.

If the application is approved, a lender is assigned 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 experimental design is that lender information is buried in a seven-page loan contract, which makes 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, the loan contract for a non-reporting lender uses similar language: "loan performance will 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 PCR or any other agency. Appendix B provides two 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 due date. However, the borrower does not save on interest for early loan repayments. This lack of financial incentives may explain why most borrowers (68.1%) repay a loan immediately before the due date (i.e., in the window [-3,0] days relative to the due date).

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 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, the credit quality of new borrowers is still dispersed, and their default rates are much higher than those of repeat borrowers (approximately 10% vs. 4%). Importantly, the subjects of the two experiments do not overlap.

Our experiments rely critically on our assumption that the treatment group borrowers and the control group borrowers differ in their awareness of credit reporting. In other words, we assume that the credit-warning message sent to borrowers in the treatment group increases their awareness of the lender's credit reporting. If their awareness of credit reporting before they receive the message is comparable to that of the borrowers in the control group, we can attribute the difference in the take-up rate and default rates between the two groups to the increased awareness due to credit warnings. Phone interviews that Quant Group conducted in October 2017 provide anecdotal evidence supporting this assumption.[15]

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

[15] The Quant Group randomly interviewed 221 new borrowers *who had received the credit warning* in the second experiment by phone. Of these borrowers, 43 completed the interview. Three findings of the interview are relevant: (1) Nearly all participants knew that loan default affects their credit scores. (2) Borrowers reported learning about the lender's credit reporting for the loan from the following sources: credit warnings from Quant Group, Baidu Forum, family and friends, the Quant app, Quant's customer service, credit reports at PCR, and loan agreements. Of these sources, credit warnings ranked the highest. (3) A significant fraction of the credit-warning recipients acknowledged that the credit-warning message affected their take-up (19.2%) and repayment (25.6%) decisions. This evidence supports our assumption that the credit warning substantially improves new borrowers' awareness of credit reporting.

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 (the 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.

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 applicants who had been 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 stratified randomization algorithm. 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 control groups.

In implementing the experiments, Quant Group treated a smaller fraction of borrowers who had larger loan amounts because it was concerned that credit warnings could adversely affect the loan take-up rates of these economically important borrowers. More specifically, Quant Group sent the credit-warning message to 24% of borrowers (222) with a loan of 2,000 yuan (the small-loan group) and to 20% of borrowers (110) with a loan of 4,000 or 6,000 yuan (the large-loan group) in Experiment 1. Similarly, it sent the credit-warning message to 49% of borrowers (817) with a loan of 2,000 yuan and to 40% of borrowers (372) with a loan of 4,000 or 6,000 yuan in Experiment 2. If borrowers with a larger loan are systematically different from those with a smaller loan, and these differences are correlated with both credit warnings (by experimental design) and the outcome variables (e.g., take-up likelihood), such differences could drive our findings. To address this concern, we reduce the representation of treated borrowers in the small-loan group by randomly excluding 32 borrowers from this group. As result, the fraction of treated borrowers in the small-loan group decreases to 20%, which is comparable to the fraction in the large-loan group that received the treatment. We label these subsamples the *trimmed subsamples* and use them for the subsequent analyses.

Field experiment studies typically conduct a power analysis to assess the adequacy of the sample size (Floyd and List 2016; Tomy and Wittenberg-Moerman 2021). To calculate the sample size, we use the following formula based on List, Sadoff, and Wagner (2011):

$$n_0^* = n_1^* = n^* = \left(t_{\frac{\alpha}{2}}\sqrt{2\overline{p}(1-\overline{p})} + t_\beta\sqrt{p_0(1-p_0)+p_1(1-p_1)}\right)^2 \delta^{-2}$$

where $\overline{p} = (p_0 + p_1)/2$. Note that δ is the difference between the mean treatment effect and control, α is the probability of committing a type I error in a two-sided test, and β is the probability of committing a type II error. Our calculations below assume that the probability of type I error is 10% and the probability of type II error is 80%.

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 full sample for the first experiment. In Panel A, we compare borrowers who received credit warnings (CW=1) with those who did not (CW=0). The default rate is 5.1% for the treatment group and 11.4% for the control group. The difference of 6.3% between the two groups is statistically significant at the 1% level. This evidence suggests that the credit-warning message reduces default likelihood. While most loan and borrower characteristics are balanced across the two groups, there is one notable difference between the two groups: the fraction of female borrowers is greater for the credit-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). We report the summary statistics of the trimmed subsample in Panel B. As expected, the absolute difference in loan size between the treatment and control groups falls from 105.8 (Panel A) to 3.6. Importantly, we continue to find that the credit-warning message significantly reduces default likelihood (by 6.1 percentage points).

Likewise, in Panels C and D, we report the summary statistics of the full sample and the trimmed subsample for the second experiment, respectively. Panel C shows a take-up rate of 76.1% for the treatment group and 74.1% for the control group.[16] The difference is statistically insignificant, as indicated in columns (5) and (6). In addition, the default rate is 7.7% for the treatment group and 11.6% for the control group, and the difference is statistically significant at the 1% level. Regarding loan characteristics, loans in the treatment group are smaller (2,920 vs.

[16] 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.

3,202) and have higher interest rates (6.9% vs. 6.8%). Borrower characteristics are in general balanced across the two groups with two exceptions: Sesame score (651 vs. 648) and the fraction of credit card holders (10.1% vs. 8.1%) are higher for credit-warning recipients than for non-credit-warning recipients.

Panel D, which is based on the trimmed subsample, shows similar results to those in Panel C. Notably, the difference in loan take-up rates between the treatment and control groups increases from 2% to 3% and becomes marginally significant. To mitigate the possibility that loan size and correlated omitted loan and borrower characteristics drive our findings, in our subsequent empirical analyses, we use the trimmed subsamples of both experiments and control for loan and borrower characteristics.

[Insert Table 1]

4.2 Credit warnings and loan defaults

In this section, we examine the effect of credit reporting on repayment incentives. We argue that credit warnings increase borrowers' perceived likelihood of credit reporting. In response, credit-warning recipients will exert greater effort to repay their loans because of the disciplinary effect and the informational-rents effect. Therefore, we predict that credit-warning recipients will have a lower loan default rate than non-warning recipients. The first experiment provides a clean setting to test this hypothesis because borrowers receive credit warnings after taking out a loan, and thus the selection channel is shut down.

Table 2 reports the results of the univariate and multiple regression analyses based on a logit model, which allows a non-linear relationship between the dependent and independent variables. We report the marginal effects of the credit-warning message and other independent variables. Column (1) of Panel A shows that in the first experiment, the default rate for borrowers receiving a credit warning is 7.5 percentage points lower than that for borrowers not receiving the warning. Column (2) shows a negative and statistically significant coefficient on CW, implying that the credit-warning message reduces borrower default likelihood by 7 percentage points.[17] The credit-warning effect is economically substantial, given the control group's default rate of 11.4% (this corresponds to a 61.4% reduction in default rates). These results are robust to using alternative models such as OLS.[18] Regarding control variables, we find that the default likelihood is negatively correlated with Quant score, Sesame score, and junior college or above, which suggests that borrowers with better credit quality are less likely to default. Taken together, the findings suggest that credit warnings improve borrowers' incentives to repay their loans.

Recall that in the second experiment, the borrowers received credit warnings before they took out a loan. Thus, credit warnings can affect defaults through two channels: the incentive effect (which includes both disciplinary and informational-rents effects) and the selection effect. The incentive effect reduces default rates as discussed above. The selection effect can also alter the composition of the borrower pool, potentially increasing or decreasing the credit risk of the average borrower. The net effect depends on the relative importance of the two.

Columns (3) and (4) of Panel A report the results for the second experiment. As in the first experiment, the credit-warning message significantly reduces the default likelihood (by 3.7 percentage points; see column (4)) after we control for loan and borrower characteristics. This

[17] Relatively small R-squared values are not uncommon in studies on lending outcomes. For example, in examining the effect of moral incentive on credit card delinquency, Bursztyn, Fiorin, Gottlieb, and Kanz (2019) conduct a field experiment and obtain R-squared values of 0.2–0.8% without controls and an R-squared value of 5.7% with exhaustive control variables (Tables 2–4). Similarly, in examining the effect of self-efficacy on delinquency, Kuhnen and Melzer (2018) use survey data and report R-squared values of 1% for regressions without control variables and R-squared values of 3–5% for regressions with extensive controls (Table 3). These R-squared values are very similar to ours, even though the sample sizes of Bursztyn et al. (2019) and Kuhnen and Melzer (2018) are much larger.

[18] With an OLS model, we can use the method of Sterck (2019) to estimate the importance of CW relative to other independent variables. We find that CW is responsible for 22.2% of the ceteris paribus deviations in default, which ranks second only to Sesame score (22.4%).

effect is economically large, representing 32.8% of the 11.6% unconditional default rate. Of the control variables, Quant score, Sesame score, and junior college or above are negatively associated with default likelihood.

To further mitigate potential correlated omitted variable concerns, we use the Mahalanobis distance matching (MDM) method to match each borrower in the treatment group with a borrower in the control group (1:1) within each loan size group (i.e., 2,000, 4,000, and 6,000 yuan). The matches are based on Quant score, Sesame score, interest rate, credit card, female, age, junior college or above, and education missing. The results (untabulated) indicate that the treatment and control groups are comparable in all loan and borrower characteristics. We report the results for the first experiment in Panel B and those for the second experiment in Panel C. The credit-warning message reduces default likelihood by 5.7 percentage points for the first experiment and 4.8 percentage points for the second experiment, both of which are statistically significant at the 1% level. Overall, Table 2 provides evidence that the credit-warning message reduces the default likelihood.

[Insert Table 2]

4.3 Credit warnings and loan take-up

Section 4.2 presents evidence that the credit-warning message received before a borrower takes out a loan reduces the likelihood of default. As discussed above, this result can come from the repayment-incentive effect and the borrower-selection effect. In this section, we use Experiment 2 to test the selection effect explicitly by examining how credit warnings (received *before* taking out a loan) affect borrowers' take-up decision.

As we discussed earlier, credit warnings can have two opposing effects on the loan take-up decision. The informational-rents effect predicts a higher take-up rate because borrowers who are subject to the informational rents with the incumbent lender (e.g., a hold-up problem) expect to gain future access to the formal credit market by repaying a loan funded by a reporting lender. On the other hand, the disciplinary effect predicts a lower take-up rate because the expected costs of default are high, which discourages borrowers from taking out a loan. As a borrower's awareness of credit reporting increases, the change in her utility of taking out a loan depends on the sum of these effects. Ultimately, how credit warnings affect borrowers' loan take-up decisions is an empirical question.

Borrowers who received credit warnings and took out a loan may have higher or lower credit quality than those who took out a loan without receiving credit warnings, depending on the credit quality of the marginal borrowers. The effect of credit warnings on the overall credit quality of the borrower pool depends on the relative change in the expected utility of risky and safe borrowers. If safe borrowers are more likely to take out a loan than risky borrowers, credit warnings will improve the average credit quality of the borrower pool. Conversely, if the increase in take-up is more pronounced for risky borrowers than for safe borrowers, we expect credit warnings to tilt the borrower pool towards riskier borrowers.

To examine the effect of credit warnings on borrowers' selection, we first compare the borrower and loan characteristics of borrowers who took out a loan with those of borrowers who did not, and then we compare how these characteristics differ between the treatment and control groups. We report the results in Panel A of Table 3. In general, borrowers who took out a loan have lower credit quality based on observables (e.g., lower Sesame scores and a lower education level). However, across treatment and control groups, we do not find significant differences in any other observable dimension. The lack of differences in observable characteristics (column (7)) might be due to three factors: (1) The informational-rents effect and the disciplinary effect offset each other. (2) Our measures of observable credit risk are noisy, as evidenced by the low R-squared in Panel A of Table 2. The low explanatory power is not unique to China. Focusing on the mortgage market in the US, Rajan, Seru and Vig (2015) show in their Table 7 that the pseudo R-squared for the default model of regressing default on FICO score along with other loan characteristics is only 7.05%, which is comparable to our 5–6%. (3) Ex ante, Quant Group had limited ability to resolve information asymmetry using observables, as evidenced by its high credit rationing – it denied 90% of loan applications from new borrowers.

We do not find that warning recipients differ from non-warning recipients in observables, but do credit warnings affect loan take-up decisions? We address this question by analyzing the effect of credit warnings on loan take-up likelihood and report the marginal effects of the independent variables of a logit model in Panel B of Table 3. The univariate analysis in column (1) shows that take-up likelihood is 3 percentage points higher for the credit-warning recipients, implying that the credit-warning message increases take-up likelihood. The multiple regression analysis in column (2) shows an even stronger effect: the loan take-up rate is 4.1 percentage points higher for warning recipients than for non-warning recipients. This effect is statistically significant at the 5% level. It is also economically meaningful, given that 25.9% of non-warning recipients turned down an approved loan. Our evidence suggests that the repayment-incentive effect of information sharing dominates the disciplinary effect, resulting in a net increase in loan take-up rates.

With respect to control variables, Quant score has a significant and positive association with take-up decision. Holding a borrower's observable credit information constant, we find that the higher the Quant group's internal credit assessment, the more likely the borrower takes out the loan. Combined with the negative association between Quant score and default probability (reported in Table 2), the evidence suggests that Quant score contains credit-relevant information incremental to Sesame score and other observables and affects borrowers' loan take-up decision. In addition, Sesame score, credit card, junior college or above, and education missing are negatively associated with take-up likelihood, which suggests that borrowers with better credit profiles are likely to have more outside options for financing.[19]

[Insert Table 3]

To check the adequacy of the sample size for our analyses, we use the method of List, Sadoff, and Wagner (2011), and the results confirm that the sample size is sufficient.[20] Our evidence suggests that credit warnings increase the likelihood of taking out a loan. This result raises a question: who are the borrowers affected by credit warnings? Do credit warnings increase or decrease the credit risk of the overall borrower pool? Given that lenders can send credit warnings either before or after loan take-up, which timing benefits the lenders more? We seek to answer these questions by comparing the effect of credit warnings on default likelihood across the two experiments. Recall that the effect of credit warnings in the first experiment comes from the improved repayment incentive alone, whereas their effect in the second experiment is the net effect of borrower selection and repayment incentive. Consequently, the comparison across the two experiments allows us to identify the selection effect.[21]

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[19] Our interpretation of the negative coefficient on Edu missing is that when borrowers do not fill out the education information that is critical for evaluating their creditworthiness, their action might indicate that they are not in great need of the credit; otherwise, they might do everything possible (i.e., fill out all information requested) to gain the loan approval. The results of an untabulated analysis provide some support for this interpretation. Holding all observable characteristics constant (i.e., Sesame score, gender, age, etc.), we find that borrowers with education information missing are given a lower interest rate, although this variable is *not* significantly related with default (see Table 6 Panel A column (1)).

[20] For the default analysis of E1, the default rate is 11.4% for CW=0 and 5.1% for CW=1, and the treatment effect in the regression is 0.070. The minimum sample size required is 382. Our sample size of 1,464 appears to be adequate. For the default analysis of E2, the default rate is 11.6% for CW=0 and 7.5% for CW=1, and the treatment effect in the regression is 0.038. The minimum sample size required is 1,482. For the take-up analysis of E2, the take-up rate is 74.1% for CW=0 and 77.1% for CW=1, and the treatment effect in the regression is 0.044. The minimum sample size required is 2,330. Our sample size of 2,631 for E2 appears to be adequate for both the take-up and default tests.

[21] The underlying assumption of this argument 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 use the trimmed samples and 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

In Panel A of Table 2, we conduct a Chow test on the differential effects of credit warnings on default likelihood across the two experiments, and we find that the differential effect is statistically insignificant. The difference in the marginal effect of credit warnings between E1 and E2 becomes even smaller (-0.057 vs. -0.048) when we use the samples based on the MDM procedure, as shown in Panels B and C of Table 2. This result suggests that the average credit quality of borrowers who took out a loan is comparable across borrowers who received credit warnings and those who did not. In other words, the marginal borrowers who are affected by credit warnings approximate the credit quality of the average borrower, which implies that credit warnings do not exacerbate or alleviate borrowers' adverse selection. This is also consistent with the results in Table 3, Panel A. However, it is possible that borrowers using online platforms differ from the population of borrowers, which is outside the scope of our study. Overall, our evidence suggests that the lender benefits more from sending credit warnings before take-up because doing so improves both the extensive margin of loan take-up and the borrowers' repayment incentive.

We interpret the effect of credit warnings on loan take-up and repayment decisions as the impact of sharing credit information with PCR. However, one may wonder whether these results are driven by information sharing with PCB or with other lenders in general, because the predicted effect of information sharing on default is similar across PCR and PCB (Jappelli and Pagano 2002, 2005). This alternative interpretation is unlikely to work because of the institutional setting. Recall that in 2017, China did not have any PCB. One can argue that Sesame Credit plays a similar role as a PCB. However, Sesame Credit did not incorporate the loan performance of Fintech lenders (e.g., Quant Group) into Sesame scores, possibly due to Fintech's competition concerns. That is,

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whether to take out the loan. Untabulated tests show that borrower characteristics are comparable across the two groups in all dimensions but *Credit card*: the fraction of credit card holders is 11.1% for the first experiment and 7.6% for the second experiment. Loans in the first experiment are slightly smaller and have a shorter term than those in the second experiment (all loans in the first experiment have a 3-month term, whereas a fraction of loans in the second experiment have a 6-month term).

individual lending platforms did not trust each other enough to share their customers' credit information, even though doing so would potentially benefit all.

To provide evidence to support the argument above, we examine if the effect of credit warnings on *loan take-up* depends on whether a borrower has a credit card. The logic is as follows: If warning recipients interpret credit warnings as information sharing with PCR, our results should hold primarily for non-credit card holders. Because credit card holders already have a credit profile at PCR, credit warnings are unlikely to generate additional incentives to establish a track record at PCR. On the other hand, if warning recipients interpret credit warnings as information sharing with PCB or other lenders, we expect credit card holders and non-credit card holders to respond to credit warnings similarly, ceteris paribus.

To test the above cross-sectional prediction, we partition the sample of the second experiment into credit card holders and non-credit card holders. We show in Table 4 that credit card holders did not respond to credit warnings (columns (1) and (2)), whereas non-credit card holders responded positively to credit warnings (columns (3) and (4)). We caution that having a credit card may be correlated with unobservable borrower credit quality that is not captured by the observable controls in our regression models and results in borrowers' muted response to credit warnings. Nevertheless, the evidence is consistent with the explanation that credit warnings worked via PCR as opposed to other channels.

[Insert Table 4]

4.4 A validation test of our assumption

We focus on new borrowers in both 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 have a minimal effect on their take-up and default decisions. To validate this assumption, we repeat the two experiments on repeat borrowers, randomly selecting 1,340 and 2,069 borrowers for Experiment 1 and Experiment 2, respectively. To maintain covariate balance, we follow the same procedure we used for new borrowers to obtain two trimmed subsamples for repeat borrowers.[22]

In Table 5, we report the summary statistics on loan and borrower characteristics for Experiment 1 in Panel A (the whole sample) and Panel B (the trimmed subsample) and for Experiment 2 in Panels C and D. In the discussion below, we use the trimmed subsample and focus on borrowers who did not receive credit warnings. Comparing Panel A of Table 5 with Panel A of Table 1, we find significant differences between repeat and new borrowers for Experiment 1. For example, among non-credit-warning recipients (column (3)), repeat borrowers have higher Quant scores (705 vs. 650) and Sesame scores (657 vs. 644) than new borrowers. They are slightly more likely to be female (27% vs. 19.9%) and are similarly educated (43.1% vs. 43.6% have junior college or above). Repeat borrowers are less likely to default (3.9% for repeat borrowers vs. 11.4% 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 (4,509 yuan vs. 3,064 yuan) and have lower interest rates (5.2% 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 5 and Panel C of Table 1. For the control group (column (3)), repeat borrowers are more likely to take out a loan (86.1% for repeat borrowers vs. 74.1% for new borrowers) and are less likely to default (3.5% vs. 11.6%).

[22] In an experiment similar to those done on new borrowers, Quant Group staff also sent the credit-warning text to a smaller fraction of repeat large-loan borrowers. This procedure results in the imbalance of loan size between the treatment and control groups.

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 using the trimmed subsamples. 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, many new borrowers gain novel information from credit warnings, which affects their take-up and default decisions. However, we acknowledge that the differential responses of repeat and new borrowers might be driven by unobservable differences that are not captured by the control variables in the regression model. Therefore, readers should use caution when interpreting this finding.

[Insert Table 5]

4.5 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, resulting in the credit-warning effect. This alternative explanation is unlikely 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, the 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.

5. Exploring the mechanisms

5.1 Lenders' informational rents

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. Repaying a loan on time establishes a positive record at PCR and enhances a borrower's formal credit profile. Such enhancement likely enables borrowers with fair credit quality but poor informal credit profiles (i.e., a low Sesame score and a lower education level) to access the formal credit market with lower interest rates, which in turn reduces the incumbent lender's informational rents.

Lenders' informational rents are clear in theory: when the incumbent lender possesses private information about a borrower's credit quality (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. Anecdotal evidence suggests that many online lending platforms engage in discriminatory pricing against repeat borrowers. Platforms are less likely to reduce interest rates and more likely to increase interest rates for borrowers who frequently take out loans than for those who borrow occasionally. This is the case even though the platforms raise the credit limit for both groups, which indicates that they consider the credit quality of both groups to have improved.[23, 24]

For informational rents to exist, there are at least two necessary conditions. One is that the observable credit quality is not high, which ensures that the borrowers have fewer outside options. The other is that the observable credit quality information is a noisy predictor of default, in which case private information will generate informational rents. In an untabulated test, we partition the new borrowers' sample into quintiles (Group 1 – low to Group 5 – high) based on Quant score. We find that the model's predictive power is much lower for the medium group (Group 3), which has an average Sesame score of 640. This result provides empirical support for the two necessary conditions for informational rents: Borrowers with a medium-level Sesame score are more likely to be exploited by lenders.

Identifying the presence of informational rents is challenging in practice, because researchers do not observe the incumbent lender's private information. Fortunately, we can observe the borrowers' credit scores assigned by the lender (Quant scores), which presumably reflect both *public* and *private* information. If Quant Group possesses favorable private information about borrowers, that is, if Quant scores have a *positive* deviation from observable credit quality, Quant Group is likely to be able to exploit these borrowers by charging informational rents. Thus, we expect to find higher loan prices (interest rates) than loan costs (default rates) among these borrowers.

To test whether lenders possess private information – a necessary condition for lenders to exploit informational rents – we regress the default likelihood on Quant score, Sesame score, and

[23] For more information, see https://zhuanlan.zhihu.com/p/337729612.

[24] To shed further light on whether Quant Group extracts informational rents from repeat borrowers, we had a conversation with the lending platform about its dynamic pricing strategy. We were told that Quant Group slowly lowers its interest rates for repeat borrowers; for example, it lowers the interest rates by 16%, on average, after observing that three to five loans are repaid fully, even though the default rate falls relatively sharply (i.e., by 28%).

other publicly observable borrower characteristics separately for repeat and first-time borrowers from Experiment 2. Table 6, 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 credit-risk information over and above that contained in the Quant score.[25]

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 evidence suggests that Quant Group relies largely on public information in assessing the credit risk of new borrowers due to lack of private information (e.g., borrowers' repayment history). Moreover, a 100-point increase in Quant score results in a decline of 0.072 in default rates, which accounts for 0.38% of the standard deviation of repeat borrowers' default (=0.072/0.19). This number is much lower for new borrowers (0.21%=0.064/0.298). Thus, Quant score has a higher power for predicting default among repeat borrowers. In sum, our results validate the assumption that Quant Group has private information on repeat borrowers. Moreover, it incorporates both *public* information (e.g., Sesame score) and *private* information (not reflected in Sesame score) into Quant score as it learns more about borrowers' credit quality through repeated lending relationships.

Next, we test the presence of informational rents. The Quant Group likely extracts informational rents from repeat borrowers but not from new borrowers because it learns about

[25] The insignificant loading on *Sesame score* among repeat borrowers could also be due to stale information in that score since lenders acquire it for new borrowers and typically do not update it when new borrowers come back to take out another loan. The tendency not to update reflects the tradeoff between the cost and benefit of obtaining the updated Sesame score. We thank the referee for pointing out this possibility.

borrowers' credit quality via repeated lending relationships. This is indeed what we find. Panel D of Table 1 and Panel D of Table 5 show that the average interest rate for new (repeat) borrowers is 6.8% (5.1%) per month, and their default rate over three months is 11.6% (3.2%). Thus, the average rate of return for new borrowers is 6.4% (=11.6% *(-1)+(1-11.6%)*0.068*3). Likewise, the average rate of return for repeat borrowers is 11.6% (=3.2%*(-1)+(1-3.2%)*0.051*3), which is much higher than that for new borrowers. The evidence of a higher profit earned from repeat borrowers than from new borrowers is consistent with the prediction of intertemporal subsidy between new and repeat borrowers based on the informational-rents argument by Petersen and Rajan (1994, p. 6); that is, "if the information generated in the relationship is private to the lender and not transferable by the borrower to others, the relationship reduces the interest rate *by less than the true decline in cost*."

Our next step is to identify new borrowers who expect to be exploited by the lender in the future when they become repeat borrowers. The informational-rents argument predicts that these borrowers can benefit from credit reporting, because information sharing reduces the incumbent lenders' informational rents, easing the borrowers' future access to the credit market. Assuming that the expected informational rents for new borrowers are comparable to those for repeat borrowers who have similar observable credit quality, we can apply the classification of the informational rents of repeat borrowers to those of comparable new borrowers using the MDM procedure.

Specifically, we consider interest rate, Sesame score, gender, age, and education level as observable credit quality. Using repeat borrowers, we regress Quant score on these six observable credit quality measures and obtain the residual, *e*, as shown in equation (1):

$$Quant\ score = a_1 + b_1 * Interest\ rate + b_2 * Sesame\ score + b_3 * Female + b_4 * Age\ + \\ b_5 *\ Junior\ college\ or\ above\ + b_6 * Edu\ missing +\ e. \tag{1}$$

The regression residual, *e*, captures Quant's private information that is unrelated to observable borrower credit risk. The higher the residual, the greater the deviation of Quant score from observable credit quality, and thus the more favorable the private information and likely the higher the informational rents.

To test our prediction, we partition the repeat borrowers into terciles based on the residual. Table 6, Panel B reports the results comparing Quant score, default, interest rate, Sesame score, and other borrower characteristics across the three groups. Quant score is significantly higher and the default rate is significantly lower for borrowers in the high (informational-rents) group than for those in the low group. However, the interest rate is comparable across the two groups. This evidence highlights that Quant Group's ex-ante assessment of borrowers' credit risk (i.e., Quant score) is, on average, consistent with their actual rate of default. It also shows that Quant Group charged borrowers in the high-informational-rents group disproportionately high interest rates relative to their default risk. Unsurprisingly, borrowers in the high-informational-rents group and borrowers in other groups have similar observable credit quality such as Sesame score and education levels. In sum, the evidence presented in Panel B supports our prediction that borrowers with higher regression residuals from Equation (1) are more likely to be subject to higher informational rents.

Next, we match each new borrower with a repeat borrower using the MDM method. Among observable borrower characteristics, only Sesame score and education levels are significantly correlated with default rates, as shown in column (2) of Table 6, Panel A. For this reason, we match each new borrower with a repeat borrower based on these two variables to be parsimonious, and we apply the residual of the matched repeat borrower obtained from the first step to the new borrower. We then partition the new borrower sample into high, medium, and low groups using new borrowers' residuals and conduct the take-up analysis across the three subsamples. We adopt the repeat borrowers' residual cutoff for new borrowers to ensure that the expected likelihood of being exploited by the lender is comparable across new and repeat borrowers. We run a regression of the take-up decision on CW and control variables, as shown in Equation (2):

$$Take-up = a_1 + b_0 * CW + b_1 * Quant\ score + b_2 * Sesame\ score + b_3 * Credit\ card + b_4 * Female + b_5 * Age + b_6 * Junior\ college\ or\ above + b_7 * Edu\ missing + \varepsilon. \quad (2)$$

The results are reported in Table 7. Notably, the coefficient on CW, b_o, is positive across the three groups, but it is statistically significant only for the high-informational-rents group (as column (3) shows). Although the difference in this coefficient is statistically insignificant across the low and high groups, its magnitude is economically large (5.9% vs. 2.5%). Our 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 (24%) for non-credit-warning recipients in the high-informational-rents group, a reduction of 5.9% is economically large. The finding suggests that reporting to PCR reduces lenders' informational rents. Overall, our findings support the argument that the desire to reduce lenders' informational rents for future loans is the underlying mechanism for the higher loan take-up rates among credit-warning recipients.

[Insert Table 7]

5.2 Additional cross-sectional analyses of borrower and loan characteristics

To shed further light on the mechanism for our findings, we explore whether the effects of credit warnings on loan take-up and default decisions vary with borrower characteristics. We consider three dimensions broadly gauging credit-risk profile: the Sesame score and Quant score, gender (female dummy), age, and education (junior college or above, and education missing). Regarding loan characteristics, we consider the interest rate. We then partition the sample based on these six characteristics one at a time for the loan take-up and default analyses. In untabulated results, we find that for any given borrower or loan characteristic, the credit-warning effect is statistically significant for one subgroup but not the other, and the difference between the two subgroups is generally statistically indistinguishable from zero. These results suggest that the credit warning effect does not vary significantly across borrower and loan characteristics.

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 PCR. 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 7 percentage points, which accounts for approximately 61.4% 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 4.1 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, we employ a novel method to identify new borrowers who expect the incumbent lender to charge informational rents when they become a repeat borrower in the future. We show that the effect of credit warnings on take-up is more pronounced for new borrowers who are subject to greater informational-rents exploitation.

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 (which decline by 3.7 percentage points) when borrowers receive the credit warning before versus after loan take-up. This finding suggests that sending credit warnings before loan take-up benefits lenders more because it improves the extensive margin of lending without sacrificing the profit margin. An interesting question is whether credit warnings affect borrowers' selection if they receive the message before submitting 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 cleanly estimate the effect of credit reporting on borrowers' responses. Our findings reveal that lenders' information reporting has significant benefits for borrowers: It allows underbanked consumers to establish or improve their formal credit files. It also improves the lenders' profits, at least in the short run. Overall, our findings provide insight into the implications of establishing PCRs for 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

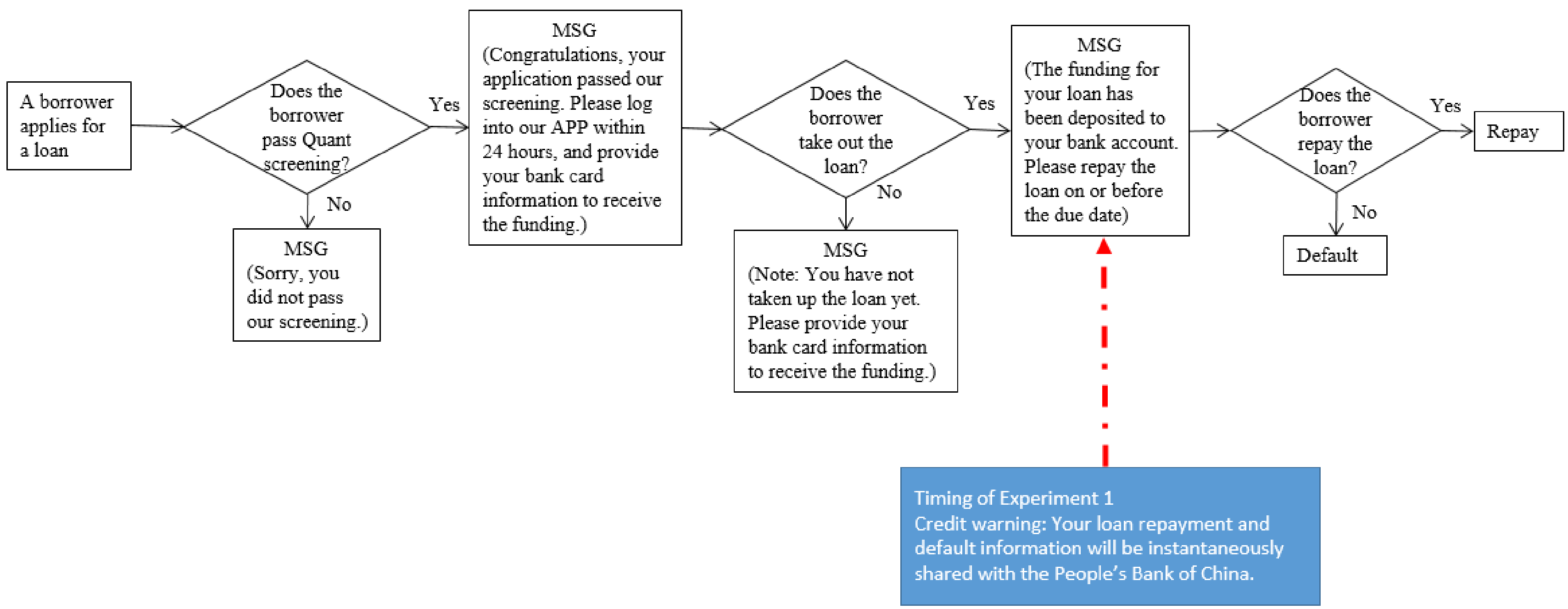

Figure 1. (Continued)
Panel B. Experiment 2

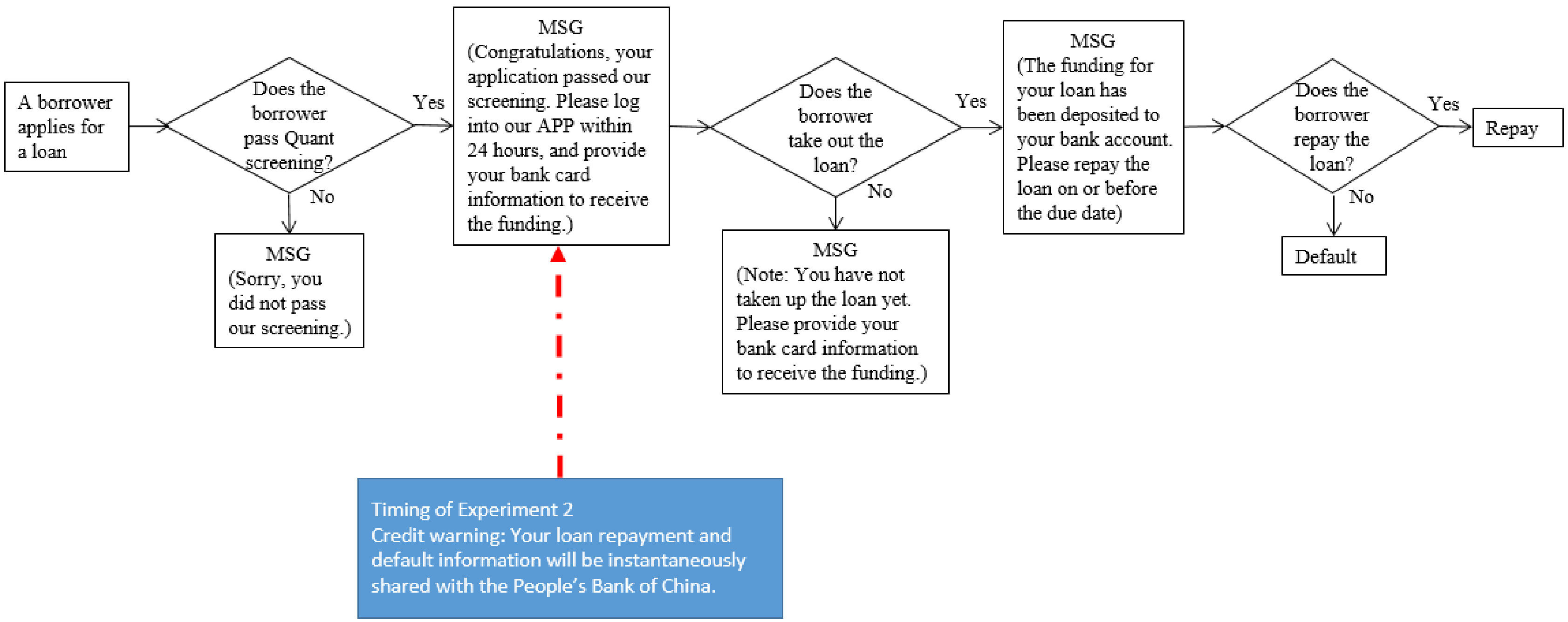

Figure 2. Sample description for the two field experiments

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 (Whole sample)

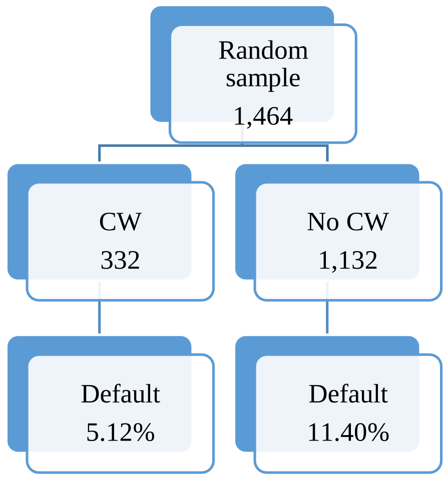

Figure B. Description of Experiment 2 (Whole sample)

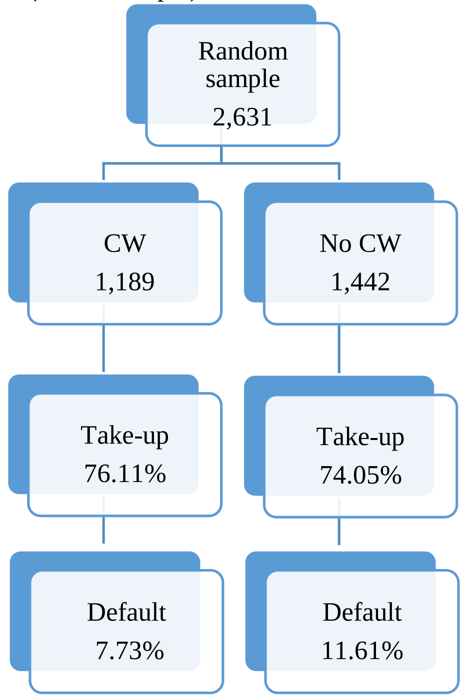

Table 1: Summary statistics

This table compares the outcome variables as well as loan and borrower characteristics between borrowers who received a credit warning and borrowers who did not. Panel A presents the results based on the whole sample of E1, while Panel B presents results for the trimmed subsample of E1. Panel C is for the whole sample of E2, and Panel D is for the trimmed subsample of E2. Variable definitions are included in Appendix A.

Panel A. Whole sample of E1

	CW = 1 (*N*=332)		CW = 0 (*N*=1,132)		Balance test	
	Mean	St. Dev.	Mean	St. Dev.	Diff	*t*-statistics
Variable:	(1)	(2)	(3)	(4)	(5) = (1)-(3)	(6)
Default	0.051	0.221	0.114	0.318	-0.063***	-3.366
Amount (yuan)	2,957.830	1,478.350	3,063.600	1,520.690	-105.773	1.121
Maturity (months)	3.000	0.000	3.000	0.000	0.000	-
Interest rate (monthly)	0.068	0.008	0.068	0.008	0.000	-0.48
Quant score	650.988	31.238	650.315	28.743	0.673	-0.367
Sesame score	646.907	37.401	643.724	35.518	3.183	-1.418
Credit card	0.123	0.329	0.111	0.315	0.012	-0.614
Female	0.256	0.437	0.199	0.399	0.057**	-2.248
Age	29.593	6.566	29.898	6.301	-0.305	0.768
Junior college or above	0.416	0.494	0.436	0.496	-0.02	0.642
Edu missing	0.105	0.308	0.111	0.315	-0.006	0.301

Panel B. Trimmed subsample of E1

	CW = 1 (*N*=300)		CW = 0 (*N*=1,132)		Balance test	
	Mean	St. Dev.	Mean	St. Dev.	Diff	*t*-statistics
Variable:	(1)	(2)	(3)	(4)	(5) = (1)-(3)	(6)
Default	0.053	0.225	0.114	0.318	-0.061***	-3.103
Amount (yuan)	3,060.000	1,520.121	3,063.604	1,520.686	-3.604	0.037
Maturity (months)	3.000	0.000	3.000	0.000	0	-
Interest rate (monthly)	0.068	0.008	0.068	0.008	0	0.231
Quant score	652.413	31.781	650.315	28.743	2.098	-1.099
Sesame score	647.407	37.585	643.724	35.518	3.683	-1.577
Credit card	0.113	0.318	0.111	0.315	0.002	-0.099
Female	0.253	0.436	0.199	0.399	0.054**	-2.064
Age	29.740	6.657	29.898	6.301	-0.158	0.383
Junior college or above	0.423	0.495	0.436	0.496	-0.013	0.378
Edu missing	0.097	0.296	0.111	0.315	-0.014	0.725

Panel C. Whole sample of E2

	CW = 1 (*N*=1,189)		CW = 0 (*N*=1,442)		Balance test	
	Mean	St. Dev.	Mean	St. Dev.	Diff	*t*-statistics
Variable:	(1)	(2)	(3)	(4)	(5) = (1)-(3)	(6)
Take-up	0.761	0.427	0.741	0.438	0.020	1.209
Default	0.077	0.267	0.116	0.321	-0.039***	-2.886
Amount (yuan)	2,920.101	1,474.077	3,202.497	1,601.281	-282.396***	4.666
Maturity (months)	3.023	0.260	3.015	0.209	0.008	-0.891
Interest rate (monthly)	0.069	0.007	0.068	0.008	0.001***	-3.431
Quant score	650.098	30.458	651.087	32.497	-0.989	0.8
Sesame score	650.941	38.045	647.723	37.090	3.218**	-2.190
Credit card	0.101	0.301	0.081	0.273	0.02*	-1.765
Female	0.230	0.421	0.221	0.415	0.009	-0.555
Age	29.876	6.203	29.929	6.462	-0.053	0.216
Junior college or above	0.427	0.495	0.433	0.496	-0.006	0.283
Edu missing	0.144	0.351	0.139	0.346	0.005	-0.324

Panel D. Trimmed subsample of E2

	CW = 1 (*N*=929)		CW = 0 (*N*=1,442)		Balance test	
	Mean	St. Dev.	Mean	St. Dev.	Diff	*t*-statistics
Variable:	(1)	(2)	(3)	(4)	(5) = (1)-(3)	(6)
Take-up	0.771	0.421	0.741	0.438	0.030*	1.657
Default	0.075	0.264	0.116	0.321	-0.041***	-2.815
Amount (yuan)	3,177.610	1,574.204	3,202.497	1,601.281	-24.887	0.372
Maturity (months)	3.029	0.294	3.015	0.209	0.014	-1.403
Interest rate (monthly)	0.068	0.008	0.068	0.008	0	-0.682
Quant score	653.530	31.454	651.087	32.497	2.443*	-1.809
Sesame score	653.184	38.088	647.723	37.090	5.461***	-3.463
Credit card	0.096	0.294	0.081	0.273	0.015	-1.237
Female	0.235	0.424	0.221	0.415	0.014	-0.803
Age	30.014	6.307	29.929	6.462	0.085	-0.315
Junior college or above	0.431	0.495	0.433	0.496	-0.002	0.104
Edu missing	0.149	0.356	0.139	0.346	0.01	-0.622

Table 2: Credit warnings and loan defaults

This table reports the effect of credit warnings on loan defaults. Panel A reports the results of default analysis for E1 (Columns 1 and 2) and E2 (Columns 3 and 4). We use the trimmed subsample that matches the treatment fraction across loan size groups. We use a logit model and report the marginal effects of independent variables. Panel B reports the covariance balance using MDM and the difference in default between credit-warning recipients and non-credit-warning recipients. 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. Variable definitions are included in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. Default for E1 and E2

Dependent variable:	Default			
	E1		E2	
	(1)	(2)	(3)	(4)
CW	-0.075***	-0.070***	-0.043***	-0.037**
	(-2.985)	(-2.873)	(-2.771)	(-2.453)
Quant score/100		-0.096**		-0.098***
		(-2.425)		(-2.961)
Sesame score/100		-0.083***		-0.065**
		(-2.777)		(-2.531)
Credit card		-0.017		-0.046
		(-0.624)		(-1.471)
Female		-0.035		-0.008
		(-1.570)		(-0.464)
Age		0.001		0.001
		(1.168)		(1.162)
Education dummies				
(Base group: Below junior college)				
Junior college or above		-0.029*		-0.038**
		(-1.657)		(-2.359)
Edu missing		-0.004		-0.001
		(-0.158)		(-0.064)
Observations	1,432	1,432	1,784	1,784
Pseudo R^2	0.012	0.059	0.007	0.052

Chow Test of CW diff: (1) vs. (3): chi2 = 1.17 Prob > chi2 = 0.2790
(2) vs. (4): chi2 = 1.31 Prob > chi2 = 0.2524

Panel B. MDM for E1, matching is done 1:1 within each loan size group

	Treated	Control	Diff	*t*-statistics
	(1)	(2)	(3) = (1)-(2)	(4)
Outcome variables:				
Default	0.053	0.110	-0.057	-2.353**
Control variables:				
Quant score	652.414	651.637	0.777	0.287
Sesame score	647.407	646.700	0.707	0.217
Interest rate (monthly)	0.068	0.068	0.000	0.000
Credit card	0.113	0.113	0.000	0.000
Female	0.253	0.250	0.003	0.087
Age	29.740	29.380	0.360	0.653
Junior college or above	0.424	0.427	-0.003	-0.076
Edu missing	0.096	0.093	0.003	0.132
Other variables				
Amount (yuan)	3,060.00	3,060.00	0.000	-

Panel C. MDM for E2, matching is done 1:1 within each loan size group

	Treated	Control	Diff	*t*-statistics
	(1)	(2)	(3) = (1)-(2)	(4)
Outcome variables:				
Default	0.075	0.123	-0.048	-2.429**
Control variables:				
Quant score	653.529	652.851	0.678	0.403
Sesame score	653.184	651.837	1.347	0.652
Interest rate (monthly)	0.068	0.068	0.000	0.000
Credit card	0.096	0.096	0.000	0.000
Female	0.235	0.234	0.001	0.045
Age	30.014	29.644	0.370	1.092
Junior college or above	0.431	0.431	0.000	0.000
Edu missing	0.148	0.147	0.001	0.054
Other variables				
Amount (yuan)	3,177.61	3,177.61	0.000	-

Table 3: Credit warnings and loan take-up

This table reports the effect of credit warnings on loan take-up using the trimmed subsample. Panel A reports the comparison of borrower characteristics between those who took up a loan and those who did not, and the comparison of the difference between borrowers who received credit warnings (CW = 1) and those who did not (CW = 0). Panel B uses a logit model and reports the marginal effects of independent variables. z-statistics are in parentheses. Variable definitions are included in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. Univariate comparison of borrower and loan characteristics

	CW = 1			CW = 0			Mean Diff
	Take-up =1	Take-up = 0	Mean Diff	Take-up = 1	Take-up = 0	Mean Diff	
Variable:	(1)	(2)	(3) = (1)-(2)	(4)	(5)	(6) = (4)-(5)	(7) = (3)-(6)
	(*N*=716)	(*N*=213)		(*N*=1,068)	(*N*=374)		
Quant score	654.369	650.709	3.660	652.043	648.358	3.685*	-0.025
Sesame score	649.528	665.474	-15.946***	643.785	658.968	-15.183***	-0.763
Interest	0.068	0.068	0.000	0.068	0.068	0.000	-0.000
Credit card	0.087	0.127	-0.040*	0.076	0.096	-0.020	-0.020
Female	0.230	0.249	-0.019	0.219	0.225	-0.006	-0.013
Age	30.158	29.531	0.627	30.081	29.497	0.584	-0.044
Junior college or above	0.409	0.502	-0.093**	0.416	0.481	-0.065**	-0.028
Edu missing	0.145	0.160	-0.015	0.127	0.174	-0.047**	0.032

Panel B: Logit regression reporting marginal effects

Dependent variable:	Take-up	
	(1)	(2)
CW	0.030*	0.041**
	(1.658)	(2.297)
Quant score/100		0.209***
		(6.971)
Sesame score/100		-0.259***
		(-10.620)
Credit card		-0.050*
		(-1.724)
Female		0.007
		(0.352)
Age		0.001
		(0.632)
Education dummies		
(Base group: Below junior college)		
Junior college or above		-0.052***
		(-2.708)
Edu missing		-0.089***
		(-3.451)
Observations	2,371	2,371
Pseudo R^2	0.001	0.054

Table 4: Credit warnings and take-up, contrasting credit card holders with non-credit card holders

This table reports the take-up decision for E2. We contrast the effect of credit warnings on credit card holders with that on non-credit card holders. We use the trimmed subsample that balances the treatment fraction across loan size groups. The logit regression model reports the marginal effects of the independent variables. z-statistics are in parentheses. Variable definitions are included in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Dependent variable:	Take-up			
	Credit card holders		Non-credit card holders	
	(1)	(2)	(3)	(4)
CW	0.004	-0.012	0.034*	0.043**
	(0.067)	(-0.184)	(1.784)	(2.353)
Quant score/100		0.394***		0.202***
		(2.899)		(6.655)
Sesame score/100		-0.100		-0.268***
		(-1.019)		(-10.706)
Female		0.215**		-0.009
		(2.496)		(-0.415)
Age		-0.005		0.002
		(-0.992)		(1.043)
Education dummies				
(Base group: Below junior college)				
Junior college or above		-0.049		-0.056***
		(-0.735)		(-2.784)
Edu missing				-0.092***
				(-3.582)
Observations	206	206	2,165	2,165
Pseudo R^2	0.000	0.059	0.001	0.060

Chow Test of CW diff: (1) vs. (3): chi2= 0.26 Prob > chi2 = 0.6085
(2) vs. (4): chi2= 0.86 Prob > chi2 = 0.3541

Table 5: Placebo tests using repeat borrowers

This table compares the outcome variables as well as loan and borrower characteristics between repeat borrowers who received a credit warning and repeat borrowers who did not. Panel A presents the results based on the whole sample of E1, while Panel B presents the results for the trimmed subsample of E1. Panel C is for the whole sample of E2, and Panel D is for the trimmed subsample of E2. Variable definitions are included in Appendix A.

Panel A. Whole sample of E1

	CW = 1 (*N*=377)		CW = 0 (*N*=963)		Balance test	
Variable:	Mean (1)	St. Dev. (2)	Mean (3)	St. Dev. (4)	Diff (5)	*t*-statistics (6)
Default	0.027	0.161	0.039	0.195	-0.012	-1.145
Amount (yuan)	4,312.997	1,694.065	4,508.827	1,609.055	-195.830	-1.973**
Maturity (months)	3.000	0.000	3.000	0.000	0.000	-
Interest rate (monthly)	0.054	0.014	0.052	0.013	0.002	1.617
Quant score	703.350	30.431	704.684	31.453	-1.334	-0.705
Sesame score	659.382	37.138	656.892	36.508	2.490	1.117
Credit card	0.005	0.073	0.002	0.046	0.003	0.974
Female	0.284	0.451	0.270	0.444	0.014	0.510
Age	29.775	6.230	29.895	6.175	-0.120	-0.321
Junior college or above	0.414	0.493	0.431	0.495	-0.017	-0.571
Edu missing	0.247	0.432	0.235	0.424	0.012	0.464

Panel B. Trimmed subsample of E1

	CW = 1 (*N*=346)		CW = 0 (*N*=963)		Balance test	
Variable:	Mean (1)	St. Dev. (2)	Mean (3)	St. Dev. (4)	Diff (5)	*t*-statistics (6)
Default	0.039	0.195	0.027	0.161	0.012	1.145
Amount (yuan)	4,520.231	1,613.672	4,508.827	1,609.055	11.404	0.113
Maturity (months)	3.000	0.000	3.000	0.000	0.000	-
Interest rate (monthly)	0.053	0.013	0.052	0.013	0.001	0.057
Quant score	704.618	30.228	704.684	31.453	-0.066	-0.034
Sesame score	660.434	36.364	656.892	36.508	3.542	1.549
Credit card	0.006	0.076	0.002	0.046	0.004	1.070
Female	0.280	0.450	0.270	0.444	0.010	0.371
Age	29.746	6.212	29.895	6.175	-0.149	-0.386
Junior college or above	0.419	0.494	0.431	0.495	-0.012	-0.382
Edu missing	0.254	0.436	0.235	0.424	0.019	0.734

Panel C. Whole sample of E2

Variable:	CW = 1 (*N*=1,003) Mean (1)	St. Dev. (2)	CW = 0 (*N*=1,066) Mean (3)	St. Dev. (4)	Balance test Diff (5)	*t*-statistics (6)
Take-up	0.860	0.347	0.861	0.346	-0.001	-0.049
Default	0.041	0.197	0.035	0.184	0.006	0.631
Amount (yuan)	4,602.193	1,602.230	4,592.871	1,644.826	9.322	0.13
Maturity (months)	3.350	0.963	3.355	0.969	-0.005	-0.109
Interest rate (monthly)	0.052	0.014	0.051	0.014	0.001	0.261
Quant score	701.898	32.450	704.602	30.531	-2.704*	-1.953
Sesame score	658.518	36.337	659.926	36.929	-1.408	-0.873
Credit card	0.002	0.045	0.004	0.061	-0.002	-0.743
Female	0.250	0.433	0.226	0.418	0.024	1.291
Age	28.860	5.716	29.566	5.976	-0.706***	-2.740
Junior college or above	0.461	0.499	0.478	0.500	-0.017	-0.811
Edu missing	0.233	0.423	0.229	0.420	0.004	0.238

Panel D. Trimmed subsample of E2

Variable:	CW = 1 (*N*=1,003) Mean (1)	St. Dev. (2)	CW = 0 (*N*=1,041) Mean (3)	St. Dev. (4)	Balance test Diff (5)	*t*-statistics (6)
Take-up	0.860	0.347	0.861	0.346	-0.001	0.019
Default	0.041	0.197	0.032	0.177	0.009	0.917
Amount (yuan)	4,602.193	1,602.230	4,655.139	1,614.000	-52.946	-0.744
Maturity (months)	3.350	0.963	3.363	0.979	-0.013	-0.306
Interest rate (monthly)	0.052	0.014	0.051	0.014	0.001	0.732
Quant score	701.898	32.450	704.903	30.395	-3.005**	-2.161
Sesame score	658.518	36.337	660.262	36.959	-1.744	-1.075
Credit card	0.002	0.045	0.003	0.054	-0.001	-0.406
Female	0.250	0.433	0.224	0.417	0.026	1.405
Age	28.860	5.716	29.567	5.998	-0.707***	-2.724
Junior college or above	0.461	0.499	0.478	0.500	-0.017	-0.804
Edu missing	0.233	0.423	0.230	0.421	0.003	0.199

Panel E. Credit warnings, loan defaults and take-up

Dependent variable:	Default (E1)		Default (E2)		Take-up (E2)	
	(1)	(2)	(3)	(4)	(5)	(6)
CW	-0.015	-0.015	0.008	0.007	-0.0003	-0.002
	(-1.133)	(-1.110)	(0.911)	(0.779)	(-0.019)	(-0.100)
Quant score/100		-0.039**		-0.059***		-0.002
		(-2.221)		(-3.917)		(-0.081)
Sesame score/100		0.006		-0.009		-0.055**
		(0.374)		(-0.674)		(-2.425)
Female		-0.027*		-0.017		-0.005
		(-1.804)		(-1.418)		(-0.274)
Age		0.001*		0.001*		-0.000
		(1.726)		(1.700)		(-0.178)
Education dummies (Base group: Below junior college)						
Junior college or above		-0.014		-0.006		-0.039*
		(-1.126)		(-0.578)		(-1.955)
Edu missing		0.001		0.011		-0.065***
		(0.103)		(0.942)		(-3.008)
Observations	1,309	1,305	1,759	1,754	2,044	2,039
Pseudo R^2	0.004	0.037	0.002	0.054	0.000	0.011

Table 6: Analysis of informational rents

Panel A reports the results of default analysis for repeat and new borrowers, showing that for repeat borrowers, Quant score but not Sesame score is statistically significant. We follow a two-step procedure. In the first step, we regress Quant score on Sesame score along with other variables such as gender, age, education, etc. and obtain the residual. The higher the residual, the higher the informational rents. In the second step, we use the MDM to match the repeat borrowers with new borrowers (1:1) based on their Sesame score and education level, and we apply the residuals of repeat borrowers obtained from step 1 to new borrowers. We then partition the sample into high, medium, and low groups based on new borrowers' residuals and then conduct a take-up analysis across the three subsamples. In Panel B, we contrast borrower and loan characteristics across the three informational-rent groups. We report the marginal effects of independent variables. z-statistics are in parentheses. Variable definitions are included in Appendix A. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A: Default analyses contrasting repeat and new borrowers

Dependent variable:	Default	
	Repeat borrowers (1)	New borrowers (2)
Quant score/100	-0.072***	-0.064**
	(-4.709)	(-2.389)
Sesame score/100	-0.005	-0.066***
	(-0.403)	(-3.023)
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: 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 (*t-statistics*)		
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	L vs. M	M vs. H	L vs. H
Variable:	(1)	(2)	(3)	(4)	(5)	(6)	(7)=(1)-(3)	(8)=(3)-(5)	(9)=(1)-(5)
Quant score	670.517	24.327	707.729	16.727	731.581	14.547	-33.102***	-28.264***	-56.579***
Default	0.065	0.246	0.026	0.160	0.022	0.147	3.201***	0.472	3.596***
Interest rate	0.052	0.013	0.051	0.014	0.052	0.014	2.593***	-1.601	0.978
Sesame score	660.071	39.234	657.232	37.483	660.429	32.886	1.374	-1.684*	-0.184
Female	0.241	0.428	0.222	0.416	0.251	0.434	0.845	-1.267	-0.422
Age	29.299	6.161	29.168	5.702	29.204	5.714	0.409	-0.118	0.296
Junior college or above	0.469	0.499	0.454	0.498	0.487	0.5	0.565	-1.24	-0.675
Below junior college	0.312	0.464	0.274	0.446	0.312	0.463	1.556	-1.538	0.018
Edu missing	0.219	0.414	0.272	0.446	0.201	0.401	-2.301**	3.111***	0.806

Table 7. Subsample analysis of take-up based on low, medium, and high informational rents

This table reports loan take-up results across the low-, medium-, and high-informational-rents groups. The informational-rents partition is detailed in Table 6. 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 marginal effects of independent variables of a logit model. z-statistics are reported in parentheses. 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
	(1)	(2)	(3)
CW	0.025	0.018	0.059**
	(0.866)	(0.618)	(2.184)
Quant score/100	0.260***	0.162***	0.198***
	(5.069)	(3.072)	(4.268)
Sesame score/100	-0.295***	-0.233***	-0.244***
	(-7.596)	(-5.218)	(-6.386)
Credit card	-0.035	-0.134***	-0.025
	(-0.699)	(-2.906)	(-0.565)
Female	0.028	0.013	0.000
	(0.779)	(0.374)	(0.003)
Age	-0.001	0.000	0.002
	(-0.374)	(0.158)	(0.725)
Junior college or above	-0.061*	-0.048	-0.065**
	(-1.929)	(-1.395)	(-2.200)
Edu missing	-0.156***	-0.081**	-0.001
	(-3.454)	(-2.019)	(-0.017)
Observations	907	818	906
Pseudo R^2	0.065	0.045	0.065

Chow Test of CW diff: Low vs. High: chi2= 1.08 Prob > chi2 = 0.2980
Low vs. Medium: chi2= 0.02 Prob > chi2 = 0.8997
High vs. Medium: chi2= 1.25 Prob > chi2 = 0.2636

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 (i.e., is more than two months overdue), and 0 otherwise.
Lenders' informational rents	We calculate lenders' informational rents in two steps. In the first step, we use repeat borrowers and regress the Quant score on the Sesame score, along with other variables such as female, age, and education dummies and obtain the residual. The higher the residual, the higher the informational rents. In the second step, we use the Mahalanobis distance matching (MDM) method to match a new borrower with a repeat borrower (1:1) based on their Sesame score and education level, and we apply the residuals of repeat borrowers obtained from the first step to the new borrower. We then partition the new borrower sample into high-, medium-, and low-informational-rents groups based on new borrowers' residuals, which are termed the informational rents.
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., PCR), 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 did not take 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.