

Tit for Tat? The Consequence of Personal Information Misuse in Debt Collection

Li Liao Zhengwei Wang Congyi Zhou^{*}

This version: December 2019

Abstract

We examine consumers' behavioral response to the misuse of personal information in the special case that personal contact data is employed to collect consumer loans without consumer authorization. Without controlling for endogeneity, this collection practice seems to reduce the default rate by 35%. However, using the fact that some borrowers are not collected due to excessive workloads for the collectors to develop our identification strategy, we find that the collection practice actually increase the default rate by 51%. Cross-section results suggest that the misuse of personal data has elicited negative reciprocity; that is, borrowers retaliate by deliberately choosing to default. Furthermore, based on online consumption data, we did not find evidence supporting that the increased default rate is related to declined repayment ability.

Keywords: Privacy Concerns; Personal Information; Negative Reciprocity; Debt Collection

JEL: D14, D18, G41

* We thank Li An, Zhuo Chen, Raymond Fisman, Emma Li, Bibo Liu, Qiang Ren, Stephan Siegel, Jun Yang, Hong Zhang, Yi Zhou, Xiaodong Zhu and seminar participants at Tsinghua University, Peking University, Southeast University, 3rd Edinburgh-SUFE Shanghai Fintech Conference, 2019 China Finance Review International Conference for helpful comments and suggestions. All errors are our own.

Liao: Corresponding author, PBC School of Finance, Tsinghua University, liaol@pbcfs.tsinghua.edu.cn;

Wang: PBC School of Finance, Tsinghua University, wangzhw@pbcfs.tsinghua.edu.cn;

Zhou: PBC School of Finance, Tsinghua University, zhoucy@pbcfs.tsinghua.edu.cn.

1. Introduction

The study of privacy has been among the important topics of economic research for decades (Stigler, 1980; Posner, 1981). There is a rich and growing literature focusing on the value of personal information, consumer's privacy decision and its associated consequences. This area is receiving unprecedented attention as information technology rapidly evolves in the digital era (Acquisti, Taylor and Wagman, 2016).

As tremendous volume of personal data are continuously produced and accumulated, consumers are increasingly exposed to the risk that their personal information will be inappropriately used, and hence privacy is becoming a major concern. For instance, Facebook users were hit by several data breaches over the recent years¹. The misuse of personal information causes harm to consumers, however, how consumers react to this harm and the further outcomes to intentional or unintentional data providers remains largely unknown. There are empirical evidences showing that data breaches impose negative effect on firm performances and stock prices (Acquisti, Friedman and Telang, 2006; Martin, Borah and Palmatier, 2017), but little has been known about the consumer behavior at the individual level.

Several challenges hindered the study of consumers' behavioral response to privacy invasion. First, consumers are often uninformed about the way their personal data are used. Even with the data breach news, consumers are still unaware that whether their own personal data are improperly used. Hence consumers' attitude and behavior usually depend on their subjective beliefs, which cannot be observed. Second, it's hard to construct counterfactuals and identify the causality once personal information misuse actually happens.

We overcome these challenges by observing consumers' behavior in the special case that personal contacts data are employed to collect consumer loans while no authorization have been obtained to use the data for collection purpose. By utilizing the fact that some borrowers

¹ See: <https://www.cbsnews.com/news/millions-facebook-user-records-exposed-amazon-cloud-server/>;
<https://money.cnn.com/2018/03/19/technology/business/facebook-data-privacy-crisis/index.html>

in delinquent status are not collected due to excessive workloads to develop our identification strategy, we find that the private-information based collection leads to lower recovery rate, which is contradictory to the collection purpose. The default rate increases by 51%, causing huge loss to the lender and the market welfare.

We focus on the debt collection in the consumer credit market, where severe conflict exists between personal information sharing and protection. Technology innovations in the FinTech era help to alleviate information asymmetry in the financial market and yield positive value across industries (Chen, Wu, and Yang, 2019; Goldstein, Jiang and Karolyi, 2019). As with the debt collection business, Drozd and Serrano-Padial (2017) show that information-technology-based collection, which is associated with reduced costs and improved efficiency, plays an essential role in the expansion of risky lending to consumers. However, due to much lowered costs for information acquisition, online credit suppliers have the incentive to collect as much private information as possible to empower collection efficiency. Thus the debt collection of online consumer credit products provides us with a proper environment to identify the misuse of personal information and investigate the associated consequences.

Our study is rooted in the Chinese online consumer credit market wherein the last five years have witnessed an explosive growth. Before this time, due to China's institutional and cultural background, it was difficult for individuals to obtain consumer credit, and a large portion of the population was credit constrained. FinTech activated the market by providing easily accessible and rapidly processed borrowing products. Cash loans, which are high-cost, unsecured consumer loans similar to payday loans, are among the most popular products. There are thousands of online platforms providing cash loans, and over 30 million consumers now use these high-cost borrowing products. The cash loan industry is IT intensive, and all procedures, from loan applications to collections, are completed online. We focus on debt collection in the cash loan industry for three reasons. First, cash loan collections rely primarily on machines and are conducted using standardized procedures; they follow a typical IT-based

debt collection system with little human interference involved. Second, fierce competition in the cash loan industry has attracted large numbers of high-risk borrowers and has pushed collection companies to improve efficiency. With no clear regulations on personal information protection, major concerns exist with regard to privacy when collections are conducted based on the intensive use of personal information. Third, the rapid growth of the market has imposed a heavy workload on debt collection companies. This excessive working capacity has resulted in a quasi-random selection of delinquent borrowers subject to collection; this can be utilized to identify the casual effects of implementing debt collection. Therefore, the Chinese online cash loan industry provides a suitable setting for examining the impact of debt collection that misusing personal information on repayment behavior.

Our data comes from an online cash loan platform that holds a leading market share in China. We observe the borrowing and repayment records of a representative sample of borrowers on the platform from late 2014 to 2017. Borrowers must authorize the platform to collect their personal data in order to get an internal credit rating and a resulting credit line. In October 2015, the platform initiated a new collection policy that is based on personal contacts data extracted from borrowers' mobile address books. When a borrower with overdue loans is contacted for collection, his/her social network will also be notified of the delinquency. By taking this tactic, the platform intended to place reputational pressure on borrowers to reduce credit risk. However, when collecting this data, the platform claimed that the contacts data was collected for the purpose of credit evaluation, so its use for collection can be regarded as a typical case of personal information misuse. Hereafter, we refer to this collection practice as private-information-based collection. We explore how the misuse of private information from borrowers' social networks impacts debt collection results.

We utilize the platform's quasi-random collection decisions, resulting from an excessive workload, to identify the real effects of private-information-based collection on the recovery of overdue loans. On average, the default rate in borrowers who are contacted for collection is

35% lower than their uncollected counterparts. However, our method, mitigating endogeneity concerns, revealed that, actually, loan performance worsens if borrowers' social networks are contacted. Collections misusing personal data lead to a 51% increase in the borrower default rate. Thus, we find evidence of personal information misuse in the procedure of debt collection cause losses in market welfare.

We explore the possible mechanisms through which private-information-based collection leads to worse loan performance. Borrowers suffer from a loss of reputation when their social networks are notified of the overdue loans. The pressure and reputational loss brought by such undesirable collection practices could be so great that borrowers feel deeply harmed, causing them to respond in a negative reciprocal manner. Cross-sectional results are consistent with this behavioral explanation. The negative effects are stronger among borrowers with lower credit risk, who should be less likely to default but suffer more loss from such collection practices. The largest increase in default rate comes from borrowers with the best credit ratings. The negative effects are more significant among male borrowers than female borrowers, which is consistent with the fact that testosterone levels are responsible for engaging aggressive behaviors. To further support the mechanism of retaliation and deliberate default, we exclude the possible explanation of declined repaying ability. We observe the borrowers' online consumption record and find no evidence showing that the higher default rate of the collected borrowers is related to tighter liquidity constraints.

We do not come to any conclusions on the overall effect of private-information-based collection on loan performance since this effect is complex, and the results can be mixed. Although the effects on borrowers who have been in delinquency are identified to be negative, it is possible that this intense collection practice will become a reliable threat to all borrowers. In that case, borrowers will behave better and enter delinquency less. However, this indirect effect is difficult to assess, and we leave it for further study. In this paper, we limit the analysis

to borrowers who have already entered delinquency, and we focus on the direct effect of private information misuse when delinquency happens.

Our findings shed light on the importance of proper regulation in the debt collection industry, and more broadly on consumer data protection in the big-data era. In May 2018, the European Union enforced the General Data Protection Regulation (GDPR) to fundamentally reshape the way in which data is processed and managed across every sector. In terms of the debt collection procedure, the United States has already enacted the Fair Debt Collection Practices Act to supervise collection practices and protect consumers' legal rights. Moreover, lenders and collectors bear the social responsibility of self-regulation to avoid undesirable behaviors.

Our study adds to the literature on online privacy concerns. Gross and Acquisti (2005) evaluate the willingness to provide personal information in online social networks, and highlight that personal privacy is exposed to various potential attacks. To address consumer privacy concerns, the self-regulatory approach includes reminding consumers by sending privacy notices. However, Adjerid, Acquisti, Brandimarte, and Loewenstein (2013) find that these notices can be misleading and nudge consumers toward disclosing more private information. Consumer behaviors are found to deviate from their self-reported preferences regarding privacy in the presence of small incentives (Athey, Catalini, and Tucker, 2017). Using large transaction data on smartphone applications, Kummer and Schulte (2019) show that consumers will give up some privacy to benefit from cheaper and more convenient service. Our findings add to the literature by studying consumers' reactions when they become aware of privacy infringement.

Our study also adds to the literature on the impact of debt collection on borrower behavior and loan performance. In contrast to the rich body of literature on pre-loan risk evaluation, there has been little work addressing post-loan management (Alan and Loranth, 2013; Bertrand and Morse, 2011; Karlan and Zinman, 2008; Ramcharan, Verani, and Van den Heuvel, 2016).

Particularly, the impact of debt collection on borrower behavior and loan performance remains largely unexplored. Within the small literature on debt collection, our findings are consistent with Du, Li, Lu, and Lu (2019) to some extent. They show that the information content of reminder messages plays an important role in repayment behavior. Consumer loan performance can be improved by conveying positive expectations rather than negative consequences. Laudenbach, Pirschel, and Siegel (2018) also find that when borrowers are reminded of late loan repayments, personal communication through phone calls significantly affects loan performance. At the industry level, Fedaseyeu (2015) investigates debt collection regulation in the U.S. and shows that collection efficiency decreases under tight regulation. We show how personal information misuse in the procedure of debt collections and associated privacy concerns impact the recovery of overdue loans at the individual level.

Finally, our paper is also related to the study of reciprocal behavior, which fits broadly within the topic of social preferences. It is revealed that individuals behave in a reciprocal manner, either positively or negatively (Fehr and Gächter, 2000). Beginning with the study of the ultimatum bargaining game, there have been a sufficient number of studies to show that, in certain social interactions, especially actions that are intentionally unkind, negative reciprocity exists, and it usually leads to significant welfare loss (Reuben and Winden, 2008; Herold, 2012; Caliendo, Fossen, and Kritikos, 2012; Drouvelis and Grosskopf, 2016). The current literature on negative reciprocity primarily focuses on the labor market (Charness, 2004; Mitchell and Ambrose, 2007); in contrast, there has been much less work on the financial market. Our study provides empirical evidence of negative reciprocal interactions between lenders and borrowers in the consumer credit market.

The rest of the paper is organized as follows. In the next section we describe the institutional background of this research. In section 3, we describe the data. In section 4, we introduce the empirical design for casual identification. In section 5, we present and discuss the results, and finally, we conclude in section 6.

2. Institutional Background

2.1 Chinese Cash Loan Industry

Along with the development of the FinTech industry, the consumer credit market in China has experienced explosive growth since 2014. Due to China's cultural and institutional background, many individuals had no access to consumer credit until recent years. Only one third of China's population is covered by the People's Bank of China (PBOC) credit reporting system; the rest have no established personal credit history². Thus, it is difficult for them to receive consumer credit from banks. Online lending platforms have helped to alleviate credit constraints by providing easily accessible credit services, serving consumers that do not qualify for loans from traditional financial institutions.

The typical business model of these platforms is the provision of cash loans, which is a high-cost borrowing product similar to payday loans. Cash loans are small and uncollateralized, and they are often used for emergency consumption such as paying bills. The term of a cash loan varies from several days to several months, usually no longer than 12 months. To reduce operating costs, cash loan platforms do not have physical stores, but instead run all lending business online. They rely on information collected online to obtain the borrower's profile and make loan approval decisions. Compared with traditional borrowing procedures in banks, online platforms require much less documentation from borrowers.

We describe the general borrowing procedure on a cash loan platform and the process used to acquire consumer data, as illustrated in Figure 1. Authorization from borrowers is necessary for platforms to legally collect consumer information. When the mobile application (APP) that provides the lending service is downloaded and installed, it requires permission to

² According to the official report, in the year 2014, among 1.07 billion Chinese adults, 0.86 billion people are covered in the PBOC system, in which only 0.35 billion have lending records.
<http://www.pbccrc.org.cn/zxxz/zxzs/201508/f4e2403544c942cf99d3c71d3b559236/files/0e78bdbd53cf4ed39b25d886a16054c9.pdf>

read the information on the mobile device, which usually includes the mobile address book, messages, call records, and so on. If this permission is not given, the APP will not be installed. When using the APP, the borrower must register for an account to use the borrowing service. Creating an account requires a national ID number, debit card number, and cellphone number under the borrower's name for identity verification. The borrower must authorize the platform to collect personal information for credit evaluation and other business purposes. With verified identity information and authorization, the platform can inquire as to the borrower's PBOC credit report as well as online behavioral data collected by third-party information service providers. Therefore, the platform obtains access to large volume of multi-dimensional consumer data, including, but not limited to, historical borrowing records in financial institutions, criminal records, public penalty records, mobile phone bills, and information regarding online behaviors. After the borrowing account has been opened, the borrower is often encouraged to share additional information from personal social media accounts, online shopping, and payment accounts with the platform, which can greatly contribute to more accurate credit evaluations but are less likely to be collected through public channels. This authorization is not necessary for using the borrowing service, but it generally helps to improve the credit line, so many borrowers are willing to authorize the cash loan platform to directly collect data from their personal accounts. In this way, the platform acquires abundant consumer information. By employing credit scoring models to analyze the information, the platform quickly develops a snapshot of the borrower's credit risk and makes a decision as to his or her credit rating. The borrower will be approved for a credit line if his/her credit rating passes a specific threshold. The loan account has a similar function as a credit card in terms of withdrawing cash, but it cannot be used directly for consumption. Whenever the borrower withdraws any amount less than the credit line, a cash loan is issued. The money will be immediately deposited into the borrower's debit account, subject to the predetermined interest

rate and fees. This auto-processing procedure allow borrowers to access loans within several seconds.

[Figure 1 inserted about here]

Convenient access to cash loans has activated the huge potential demand for consumer credit in China. In a short period, large numbers of borrowers and lenders have flooded the cash loan market. Statistics show that, as of the end of 2017, there were more than 30 million borrowers using cash loan products. The outstanding loans are estimated to be worth more than 100 billion Yuan.³ Due to the rapid growth in the market, the business has become so competitive that subprime customers are often given loans, and many platforms have accumulated a large volume of loans in delinquency. Unlike peer-to-peer lending platforms, which are neutral intermediaries between borrowers and lenders, cash loan platforms act on behalf of lenders or are sometimes the lender themselves. To deal with poor loan performance, cash loan platforms put a great deal of effort into debt collection and attempt to improve collection efficiency by fully utilizing borrower information.

2.2 Private-information-based Collection Practice

With regard to collection costs, the cash loan platforms collect overdue loans through phone calls and short messages rather than face-to-face communication. The large volume of personal information collected plays an important role in improving collection power, thus enabling more targeted loan collections. Among the collection practices based on intensive borrower information, the one targeting borrowers' social connections has been widely adopted. With information from borrowers' mobile address books and call records, the platform is able to reach borrower's social connections. When a loan enters the collection procedure, in addition to calling the borrower himself/herself, a collector will also make calls to any contact in the

³ Data Source: <https://news.p2peye.com/article-505707-1.html>

borrower's address book. The collector will tell them that the borrower has a cash loan overdue and ask if they can help urge the borrower to repay.

This collection practice has aroused heated discussion on how private information is used. It infringes on the borrower's privacy by notifying others about the borrowing, and it also causes the borrower's social connections to be harassed. Although the borrowers have authorized the platform to access their mobile address books, the method and scope of how the data will be used is usually not clearly defined in the authorization clauses. According to the clauses from several large platforms, address book information is collected mainly for credit risk evaluation. As such, the collection practice of calling borrowers' social connections can be regarded as a misuse of private information.

However, before regulation forbidding this practice was enacted in December 2017, this collection tactic, heavily based on borrowers' private information, was widely adopted despite the fact that it was not quite morally accepted. The reason for this could be that, when a borrower's moral hazard cannot be observed, platforms believe that more intensive collection methods help to reduce moral hazard. For borrowers with high credit risks, distributing information about their failure to repay loans, which badly hurts their personal reputations, will place great pressure on borrowers and reduce their incentive to deliberately default. Moreover, notifying borrowers' contacts could provide potential sources for loan repayment.

We wonder if there are any side effects of the intensive use of private information. As information has become easier to collect, information asymmetry has been greatly alleviated, and selective debt collection has become more accurate. However, the more personal information used, the more likely the borrower's privacy will be infringed upon. How will borrowers respond to private-information-based debt collection? Does intensively using private information indeed help to recover overdue loans? The cash loan market in China provides suitable circumstances to conduct empirical research on consumers' reaction to the misuse of their personal information. In this study, we examine whether the intensive use of

private information helps to increase the efficiency of debt collection and how private-information-based collection practices impact the recovery of overdue loans.

3. Data

Our data come from an online cash loan platform with a leading market share in China. The platform targets younger people, who have not yet established a credit history strong enough to borrow from banks, and it provides them with easy access to uncollateralized consumer credit. The borrowing procedure on the platform follows the common practice in the industry, as described in the previous section. Once the credit account has been approved, the borrower initiates the loan by withdrawing any amount that does not surpass than his/her credit line, and the money is then transferred to his/her debit card. The term and interest rate of the loan are determined by the platform according to the borrower's credit grade. The term varies from one to twelve months, and the borrower is expected to pay equal installments of principal and interest each month. Reminder messages will be sent to borrowers around the due date until the loan is fully paid. If a monthly payment is more than four days late, the loan will enter a collections procedure.

The platform developed this collection strategy and delegated its execution to a specialized third-party collection company. Beginning in October 2015, the platform initiated the private-information-based collection policy of contacting borrowers' social connections as well as the borrowers themselves. At that time, the market was experiencing explosive growth, and the platform had a sharply increasing default rate, like many of its competitors. With no clear regulations for the emerging business model, more than one thousand cash loan platforms were established within a very short period of time, and many high-risk borrowers were allowed entry into the market. Are these private-information-based collection practices really effective in improving loan performance? Due to the large number overdue loans, not every borrower with overdue loans is sent to collections. We utilize this quasi-randomization to

examine the effect of this collection practice on loan recovery. To clarify our empirical strategy, the collection procedure is described in detail in the next section.

We conduct the empirical study using borrowing records of a representative sample consisting of 10,000 borrowers on the platform. The data record detailed borrowing and repaying behavior from November 2014 to July 2017. In addition to borrowers' profile and loan characteristics, the data also record the time when borrowers are contacted for collections. We select loans which were applied for between October 2015 and March 2017 to avoid survival bias. During this period, there were 3101 borrowers with at least one installment more than four days overdue. For borrowers with more than one loan in delinquency at the same time, it is hard to tell which loan is being collected upon, so we focus on the first overdue loan of each borrower. Thus, the sample consists of 3101 loans with at least one late installment payment that have entered collections procedures. Table 1 shows the summary statistics.

[Table 1 inserted about here]

Forty-three percent of loans with a payment more than four days past due will eventually go into default, as measured by a delinquency status of more than 60 days. Seventy-seven percent of these borrowers will receive collection calls, while the rest are never sent to collections. The average size of a loan in delinquency is 1,765 Yuan, and the average term is six months. The rate is a category variable ranging from 1 to 10, with 1 corresponding to the lowest interest rate offered by the platform and 10 corresponding to the highest. More than half of all loans miss the first installment due date and run into delinquency at very early stage. The platform evaluates borrowers' credit risks and classifies them into six credit grades based on its internal credit rating system. Borrowers with the lowest credit risk are marked as grade A, accounting for 17.6% of the sample, while borrowers with the highest credit risk are categorized as grade F, accounting for 10% of the sample. The distribution across credit grades is generally even, with relatively more borrowers in grades C and D, in accordance with the borrower population on the platform. Sixty-five percent of borrowers in our sample are new

customers to the platform. Most borrowers (80%) are male. Their average age is 26 years old. Forty-six percent of the borrowers live in big cities, defined by Tier 1 and Tier 2 cities in China. Eighty percent of the borrowers authorized the platform to check their personal account on Taobao, the largest online shopping marketplace in China. Borrowers' social networks can be observed through their mobile address books and call records. On average, each borrower is connected to 248 individuals, who might be the borrower's family and friends, or someone they are familiar with.

4. Empirical Design

4.1 Collection Procedure and Discontinuity

To isolate the impact of implementing debt collections, we utilize a quasi-natural experiment created during the collection procedure in which some borrowers are selected for collections, while some are not. We describe our empirical strategy by first illustrating how the platform and collection company cooperate to collect overdue loans.

The loan installments are paid monthly. If any installment is not paid on time, the borrower will receive a reminder message from the platform. The message contains information on the amount due, the due date, and penalty fees for late payment, and it will be sent repeatedly until the installment is fully paid. If the platform has not received payment by the end of third day after the due date, it will notify the collection team to call the borrower. To maximize the benefit of the collection cost, the platform evaluates the possibility of recovering loans and selects those with a higher probability of paying to call first. Every working day, the collection team receives a list of borrowers entering four-day delinquency; the list contains the borrowers' names and contacts in sequence, based on the estimated probability of repayment, as shown in Figure 2. Collectors will call borrowers on the list one by one, and they will also call borrowers' contacts in the address book. They prefer to follow the recommended order because the easier-

to-harder organization helps increase recovery performance and makes workers happier at the start of the workday. Moreover, collectors are well trained to closely follow suggested wording. Thus, the standardized collection practice prevents intervention caused by collectors' personal emotions.

[Figure 2 inserted about here]

Due to the excessive amount of loans to be collected, collectors are allocated many more collection tasks than within their working capacity. Thus, they usually are unable to finish calling all borrowers on the list by the end of the workday. They often work overtime but are still unable to complete all tasks. At the end of the workday, the borrowers listed after the last borrower called are left uncontacted. These borrowers will be not moved to the next working day because a new list will be generated, and collectors again must make calls in the sequence suggested by the platform. Figure 3 shows the distribution of time when collection happens within a day. Most calls are made between 9 a.m. and 5 p.m., regular working hours. A small portion are called before 9 a.m. or in the evening, indicating that collectors try to complete as many tasks as possible by working overtime.

[Figure 3 inserted about here]

In the data, 23% of borrowers are not contacted due to the limited working capacity of the collection team. It is clear that the borrowers called are quite different from the ones not contacted since loans that are easier to recover are more likely to be sent to collections. However, we notice that a discontinuity exists where collectors stop calling at the end of each working day, as pointed out in Figure 2. Since the borrowers with delinquent status are ranked by the estimated probability of recovering payment based on observable loan and borrower characteristics, the borrowers around the discontinuity should be very similar, and whether they end up being contacted or not is due to the collector's random decision to stop. Therefore, we can employ a regression discontinuity method to examine the effect of private-information-based collection using the borrowers' rankings in the area of the last call.

4.2 One-to-one Matching by Mahalanobis Distance

The challenge is that we can observe whether a borrower is being contacted, but we have no information on the recommended order. Thus, it is hard to tell where the discontinuity lies, and which borrowers are around it. Although we do not know the exact algorithm and variables used to estimate the probability of recovering loans and cannot replicate the original order, it is clear that the probability and associated order are strongly related to loan and borrower characteristics. Borrowers ranking close to one another on the list should be more similar in any observed dimension than those farther apart on the list. Consequently, we employ a one-to-one distance matching method to identify borrowers close to the discontinuity. Instead of the commonly used propensity score matching techniques, we use the Mahalanobis distance for matching because the application date is an important variable to be matched, and distance matching is more flexible in dealing with discontinuous date variables.

The distance between any two borrowers is measured by the Mahalanobis distance,

$$d_{ij}^2 = (X_i - X_j)^T \Sigma^{-1} (X_i - X_j) \quad (1)$$

where X_i and X_j are vectors containing multi-dimensional information on borrowers i and j , and Σ is the variance-covariance matrix of X_i and X_j . For the components of $X = (x_1, x_2, x_3, \dots, x_n)^T$, we input almost all the borrower information that can be observed in the dataset, including loan size, term, interest rate, application date, borrower age, gender, number of contacts, internal credit grade, new borrower or not, provide Taobao account information or not, and live in big cities or not.

For each collected borrower i in the sample, we calculate the distance from i to any borrower j who was not contacted for collection, and we find the closest pair i and j^* .

$$d_{ij^*}^2 = \min\{d_{ij}^2\}, \forall \text{ uncollected borrower } j \quad (2)$$

The distribution of shortest Mahalanobis distance $d_{ij^*}^2$ for each collected borrower i is summarized in Figure 4. It is left-skewed, with a long tail on the right. The average squared

distance from a collected borrower to the nearest uncollected borrower is six, and the median is five. A larger distance indicates a larger difference between the collected and uncollected pair. In order to pick up pairs around the discontinuity, we limit the distance to within a specified threshold so that the collected borrowers have a small enough Mahalanobis distance, and the corresponding uncollected counterparts are regarded to be in the random treatment group and control group, respectively. The threshold is set to the median distance, considering matching efficiency and sample size⁴. Thus, our experimental sample consists of 1,177 pairs of borrowers, a collected borrower along with its most similar counterpart in the uncollected group.

[Figure 4 inserted about here]

4.3 Is Mahalanobis Distance a Proper Proxy for Collection Sequence?

Before we proceed to the next section, we need to verify whether the Mahalanobis Distance properly captures the real collection sequence. The matching technique helps to identify samples around the discontinuity only if the distance measure is a valid proxy for the real collection sequence. We test the following hypothesis:

H₁: The Mahalanobis distance predicts the real collection sequence.

If the method employed by the platform to generate the recommended collection sequence is indeed largely based on the loan and borrower information that we used for the distance matching, and the collectors closely follow the suggested sequence, then the borrowers on the top of the list will have a larger distance from the uncollected group, who are listed on the bottom. We know that the collection list is ranked by the estimated probability of recovering loans, so there should be a positive relationship between the calculated Mahalanobis distance and estimated recovering rate. The observed loan performance is the overall effects of estimated loan recovery and the treatment effect imposed by collection, and the latter is the

⁴ In the section of robustness checks, we set the threshold to multiple levels, and all results are robust.

same for borrowers who are contacted for collection. Therefore, if H_1 is true, we expect a positive (negative) relationship between the calculated Mahalanobis distance and the observed recovering rate (default rate) among the group subject to collection.

We run a probit regression on the distance and loan performance of borrowers who are contacted for collection,

$$Prob(Default_i = 1 | Collected_i = 1, d_{ij*}^2, X_i) = \Phi(\beta d_{ij*}^2 + \gamma X_i) \quad (3)$$

where *Default* is 1 if a loan has at least one installment in delinquency for more than 60 days, and 0 otherwise. *X* contains a set of covariates. The results are presented in Table 2. The Mahalanobis distance d_{ij*}^2 is negatively related to the likelihood of the loans going into default, showing that the distance measure is consistent with the recovery probability estimated by the platform. For one-unit increase in Mahalanobis distance, the estimated default rate decreases by 1.3 percentage point when no covariate is controlled and 0.8 percentage point when we add loan-level and borrower-level controls. Thus, when the distance increases by a standard deviation (4.53), the default rate decreases by 3.6 percentage point, corresponding to 9.5% change in the average default rate of borrowers who have been contacted for collection. Consequently, borrowers listed on the top and being called earlier in a workday are indeed associate with better recovery rate than the borrowers who are called later. With this supporting evidence, we have shown that the Mahalanobis distance is a valid proxy for the real collection sequence.

[Table 2 inserted about here]

In this section, by employing one-to-one distance matching, we identify a quasi-random sample which is generated by the collectors' random choice to stop working. In the next section, we present the result of matching and further analysis on the post-match sample.

5. Results

5.1 Pre-match and Post-match Sample

Before conducting a distance match to select the subsample around the discontinuity, we first examine the relationship between collection and loan performance in the full sample. We run the probit regression

$$Prob(Default_i = 1|Collected_i, X_i, \varphi_i) = \Phi(\beta Collected_i + \gamma X_i + \varphi_i), \quad (4)$$

where *Default* is 1 if a loan has at least one installment in delinquency for more than 60 days, and 0 otherwise. *X* contains a set of covariates, and φ is a fixed effect for application time and credit rating.

Table 3 shows the result. Being contacted for collection is negatively related to going into default, indicating that loans called for collections are associated with better performance. The marginal effect is -0.21, which means the collection treatment is associated with a 21-percentage-point decrease in the default rate, when we do not control any co-factors. However, when the covariates of loan and borrower characteristics are included, the marginal effect drops to 0.02, which is not significant from 0, showing that the private-information-based collection treatment is not responsible for the improved loan performance. It should be noted that the linear correlation between the collection treatment and loan performance in the pre-match sample does not reveal any causal relationship due to the endogeneity concern. These results may be misleading for industry practitioners, who are usually not highly sophisticated in economics research; some may misinterpret the results of a linear correlation analysis as being an indicator of a causal relationship. Therefore, the large gap in the default rate between the borrowers who are contacted for collection and those who are not (21 percentage points compared with a default rate of 60% in the sample of borrowers who have overdue loans but are never contacted for collection) cannot be interpreted as evidence of the effectiveness of the collection practice.

[Table 3 inserted about here]

To identify the real effect of private-information-based collection on the recovery of overdue loans, we have to use a subsample, in which loans are randomly selected to be collected based on when the collector stops working. The Mahalanobis distance matching technique is employed to select this subsample; it consists of 1,177 pairs of contacted and uncontacted borrowers with an overdue loan. We compare the pre-match and post-match sample in Table 4. Panel A presents the results of the regressions on being contacted for collection and the set of loan and borrower characteristics. Column 1 confirms that collection is selective. Loans with smaller sizes and shorter terms are more likely to be contacted. Becoming delinquent in later installments indicates that past dues have been paid and the borrower does not have a severe moral hazard problem, so the loan will be more easily recovered. Repeat borrowers who are male, older, and share more information with the platform are more likely to be targeted in the collection procedure. Column 2 shows that, in the post-match sample, being contacted for collection is not related to the loan or borrower profile, except for time of delinquency and number of contacts in the mobile address book. However, the Wald test of model fitness shows that the model is not significant. The pseudo R-squared drops from 0.24 in the pre-match sample to 0.02 in the post-match sample, a level at which the result of being called for collection cannot be predicted by the observable loan or borrower characteristics. Panels B and C of Table 4 show the t-test results of the pre-match and post-match samples, respectively. The significant difference between the collected and uncollected groups disappears after the one-to-one match⁵. Thus, we obtain a subsample around the place where collectors stop working due to capacity issues. The shock of being contacted by a collector can be regarded as exogenous in the sample, and borrowers are randomly selected into treatment and control groups.

[Table 4 inserted about here]

⁵ The difference gets smaller as we use a smaller caliper to generate the post-match sample. When the caliper is set to less than the lower quartile of distances, observable differences between the collected and uncollected group completely disappear.

5.2 The Impact of Private-information-based Collection on Loan Performance

We compare the treatment and control groups in the post-match sample to identify the impact of private-information-based collection on the recovery of overdue loans, as presented in Table 5. The coefficient estimates of *collected* turn out to be significantly positive, which means keeping other variables constant, the fact that private contact information is used in the collections process leads to a higher probability of default. Even though the purpose of this practice is to impose pressure on delinquent borrowers and expand potential sources for loan recovery, the effect of collection based on personal private information is actually the opposite. Column 1 shows the coefficient estimate on *Collected* when no covariates are included, with the marginal effect of 0.11. When loan-level variables are included in Column 2, the estimated marginal effect of being contacted for collection on loan default rises to 0.19. Borrower-level covariates are further incorporated in Column 3, the estimate on *Collected* is still significantly positive, and the marginal effect is 0.17. For loans already in delinquency, this collection practice increases the default rate by 17 percentage points. This is a large magnitude, which accounts for about 50% of the default rate of borrowers with overdue loans that are not sent to collections (33%). Therefore, compared with the misleading statistic of a 21-percentage-point decrease in the default rate using the pre-match sample, our method, which mitigates endogeneity concerns, helps identify the real effect of a 17-percentage-point increase, which means, the effect of private-information-based collection is contrary to its intention. Personal information misuse in collections actually does harm to both borrowers and lenders. The estimates for the covariates are consistent with those in the pre-match sample. Loans with longer maturities, and those that become delinquent at an earlier stage, are associated with more potential moral hazard and are more likely to go into default.

[Table 5 inserted about here]

We check the robustness of the results to make sure the above findings are not driven by a specific sample or variable measurement. We first examine whether the measure of default

affects the regression results. Till now, we have defined default as any loan installment more than 60 days late, which is the platform's definition. Due to the fact that the terms of cash loans are usually very short and overdue loans are hard to recover if they were not repaid at the early stage of delinquency, we change the definition of default to 15, 30, and 45 days in delinquency. We re-run Probit model (4) for the post-match sample, and we find that the negative impact of private-information-based collection consistently holds, as shown in Panel A of Table 6.

In the baseline model, we use the strategy of distance matching with a caliper to construct a post-match sample close to the loans called when collectors are about to get off work. The ideal experimental sample should be sufficiently close to the discontinuity, but it is hard to tell what magnitude of Mahalanobis distance is close enough. We exclude half of the collected loans, and the analysis on this subsample has shown that the private-information-based collection practice places a negative effect on loan performance. It is possible that the caliper taking the value of the median distance is too large to procure an ideal sample, and the systematic difference between the treatment and control groups leads to our findings. To check robustness, we set the caliper to multiple levels, from the 5th to 60th percentile in the shortest distance from collected loans to uncollected ones. The generated post-match sample size varies accordingly, and we examine the effect of private-information-based collection for each corresponding sample. The estimation results using different post-match samples are summarized in Panel B of Table 6. The negative effect of private-information-based collection on loan recovery is robust to sample variation.

[Table 6 inserted about here]

5.3 Possible Mechanism: Negative Reciprocity

We propose a possible mechanism behind this counterintuitive fact; that is, the negative reciprocity elicited by the misuse of customer information. Essentially, borrowers feel deeply harmed by the platform and retaliate by refusing to make further repayments.

The collection tactic of notifying borrowers' social connections was put forward with the intention of increasing the costs of default and imposing pressure on borrowers through potential reputational loss. Indeed, reputation and social image are among the most important considerations in interpersonal communication (Andreoni and Douglas, 2009; Ariely, Bracha, and Meier, 2009). To avoid paying this high cost to their personal reputations, borrowers will be motivated to repay on time. However, a huge reputational loss is realized once a borrower's social network is informed of the late payment. The reputational loss caused by the misuse of private information could be so large, and the collection behavior so morally unacceptable, that it destroys the relationship between borrowers and the platform. That means, borrowers are angered when they find that their social networks have been contacted for collection, and there is a great reputational loss associated with this contact. This leads them to adopt a "tit for tat" strategy. We find anecdotal evidence supporting this psychological motivation. In the online forums of the cash loan platform, some borrowers post about their experiences of having their social networks contacted for collection. Many of them express disappointment and anger about the collection practice. They say that "if they were milder, I would like to repay as long as I can afford to, but now I won't."⁶

To formally test this mechanism, we examine whether the theory of negative reciprocity predicts the borrowers' reactions. Reciprocal behavior is exemplified by responding in a friendly and cooperative manner when individuals perceive kindness, but when treated with unkindness they will respond with more hostile actions. Güth, Schmittberger, and Schwarze (1982) first demonstrate the negative reciprocal behavior by conducting an ultimatum bargaining experiment. The experiment has been repeated in a wide range of countries, and negative reciprocal reactions have been consistently observed (Roth et al., 1991). In the game, responders do not behave in a self-interest maximizing manner; rather, they tend to reject low

⁶ Such opinion is commonly seen online, as the following webpages show.
<https://bbs.51credit.com/forum.php?mod=viewthread&tid=2860745>
<http://app.myzaker.com/news/article.php?pk=5c3862dd77ac64558744aba5>

offers since they regard them as unfair. Falk and Fischbacher (2006) present a formal theory of reciprocity and develop an individual decision model based on perceived kindness. They show that, in the ultimatum bargaining game, the responder's willingness to accept an offer decreases with the size of the offer. Especially, when a low offer is regarded as intentional, it will be rejected with a higher probability. Thus, the theory predicts the existence of a threshold. Once the perceived unfairness level passes the threshold (estimated to be an offer size of 0.2-0.3 in the ultimatum game), the probability of taking negative reciprocal reactions will jump to a high level and retaliatory behavior will be easily elicited. In our settings, the private-information-based collection caused reputational loss and other potential costs to the collected borrowers. It is clear that the size of the costs varies among different groups. The costs are larger for borrowers with higher credit grades since they are usually associated with better social capital, but the reputational loss makes the social capital significantly deteriorate. For example, the overdue status may send a negative signal, so borrowers may have difficulty obtaining further informal financing from family members and friends. Therefore, borrowers with higher credit grades will be hurt more, and higher levels of unfairness will be perceived by these borrowers. If the borrowers respond in a negative reciprocal manner, we should observe a negative relationship between the tendency to repay and the borrowers' credit risk. To test this, we examine the heterogeneous effects of collection on borrowers with different credit grades.

We introduce the interaction term *collected* multiplied by the *credit grade* indicator to see the heterogeneous effects of private-information-based collection on borrowers with different credit risk levels. The credit grade is rated at the time of loan origination, so it reflects past credit performance on the platform and will not be affected by later repayment. We find that borrowers with different credit grades respond differently to this type of collection. As shown in Table 7 (and Figure 5), the default rate of borrowers with better credit ratings sharply increases if their social networks are contacted by collectors. For borrowers with an A credit

rating, those with lowest risk based on the platform's risk evaluation system, the default rate of borrowers contacted for collection is 25 percentage points higher than those who are not. The marginal effects of private-information-based collection on borrowers with credit grades of B, C, and D are 0.23, 0.19, and 0.24, respectively, and all estimates are statistically significant at the 95% confidence level. For borrowers with high risk (with credit ratings of E or F), the effects of private-information-based collection on the default rate are much smaller. There is a negative estimate for borrowers with the highest risk, which means this type of collection can indeed impose a positive effect on loan recovery among high-risk borrowers, although the estimates are not statistically significant. Our findings suggest that, borrowers who suffer from excessive costs and perceive higher level of unfairness to are more likely to respond by deliberately defaulting, which is consistent with the prediction of negative reciprocity.

[Table 7 inserted about here]

[Figure 5 inserted about here]

The desire to punish unkind behaviors is found to be systematically linked to testosterone levels, which are thought to be important mediators of male willingness to engage in aggressive behavior (Burnham, 1999). If the increased default rate is driven by negative reciprocity, the propensity to taking retaliatory actions should be different among male and female borrowers. We further examine whether male and female borrowers respond differently to the private-information-based collection practice. The result is presented in Table 8. After controlling other confounding factors, the default rate of male borrowers significantly increases by 18.1 percentage points when their private contacts information is misused in the collection process. By comparison, the marginal effect on female borrowers is estimated to be 0.117, which is not significant at the 90% confidence level. The dispersed effects of collection on male and female borrowers are in accordance with the explanation that negative reciprocity is elicited by the improper use of private contacts information.

[Table 8 inserted about here]

[Figure 6 inserted about here]

The heterogeneous effects on different borrower groups indicates that the collection practice may cause a significant decline in the borrowers' willingness to repay. Thus, we find a loss in terms of the welfare of the cash loan market caused by the misuse of private information. Collected borrowers have the desire to punish hostile intentions from the platform, even though the action would bring further costs on themselves.

In the literature, there remains little disagreement about the facts indicating reciprocal behavior. However, most of the evidence is observed through laboratory experiments. Empirical findings on negative reciprocity mainly come from the labor market (Fehr and Gächter, 2000). As Anderson and Pearson (1999) noted, workplace incivility, which is defined as negative behaviors, such as impoliteness or rudeness, may have a spiraling effect between coworkers, and can eventually lead to intense aggressive behaviors. They showed that people tend to reciprocate when incivility or mistreatment is perceived, and this exchange of actions is more likely to happen when people perceive more intense forms of mistreatment. We find that borrowers in the consumer credit market also display this behavior pattern when they find their private information is misused.

5.4 Alternative Explanation: Declined Repayment Ability

The cross-section results support the hypothetical mechanism of negative reciprocity. The borrowers retaliatory response to the collection practice indicates that they deliberately refuse to further repay the loan. In this section, we provide further evidence for this mechanism by refuting alternative explanations.

If the negative effects of private-information-based collection on loan recovery are not derived through borrowers' willingness to repay, the channel should be associated with a decreased ability to repay. There is evidence indicating that both liquidity constraints as well as subjective willingness explain consumer credit defaults (d'Astous and Shore, 2017; Gross

and Souleles, 2002; Guiso, Sapienza, and Zingales, 2013; Keys and Wang, 2019). We examine whether the deteriorated loan performance that occurs once a loan is brought to collection is due to tightened liquidity constraints. Since the platform obtained authorization to access borrower’s online shopping accounts, and it updated purchasing information periodically, we can observe borrowers’ online consumption patterns and examine whether borrowers subject to collection experienced sharp declines in consumption. This would reflect the problem of liquidity constraint.

We employ the Difference-in-Difference (DID) strategy to identify the effect of private-information-based collection on online consumption. We use borrowers’ purchasing records on Taobao, the largest online shopping marketplace in China. Taobao is a comprehensive online shopping marketplace, comprised of a C2C platform taobao.com and a B2C platform tmall.com, where numerous sellers provide goods and services, covering almost everything needed in daily life. The trading volume on Taobao generally accounts for over 80% of all online retail sales in China⁷. Therefore, consumption on Taobao can be regarded as a representative indicator of online consumption.

A borrowers’ total amount of consumption on Taobao is aggregated on a monthly level. For each borrower in the post-match sample, we retain a six-month observation window of online consumption: the three months before the collection month ($t-3$, $t-2$, $t-1$), the month they are sent for collection (t_0), and the two months following (t_1 , t_2); t_0 to t_2 are defined as the period after collection. Since the final loan recovery result will be observed within sixty days of the due date, a six-month window is sufficiently long to examine the potential problem of liquidity constraints. We apply the Difference-in-Difference approach to the post-match sample to examine whether private-information-based collection leads to a sharp change in Taobao consumption.

$$Consumption_{i,t} = \alpha Collected_i + \beta After_t + \gamma Collected_i * After_t + \varepsilon_{i,t} \quad (5)$$

⁷ Please see Fan et al. (2018) for more details on the Chinese online retail industry and Taobao platforms.

The results are shown in Panel A of Table 9. The average monthly consumption on Taobao before entering delinquency and being sent for collection is 727 Yuan for the treatment group and 792 Yuan for the control group. After the collection shock, the monthly consumption for the two groups are 692 and 723, respectively. The third column shows that both groups experience slight consumption declines. The fourth column displays the DID estimate, showing that the difference in the change in Taobao consumption between the treatment and control groups is not statistically significant from 0.

The DID approach is valid only with the assumption of a parallel trend. To examine whether this assumption is satisfied, we conduct multiple diagnostic tests. First, we compare the monthly consumption growth of the two groups, as presented in Panel B of Table 9. In each month before the collection shock, there is no significant difference in terms of Taobao consumption growth between the treatment and control groups, so the parallel trend assumption is not violated. Moreover, we examine the dynamics of DID estimates, with monthly observation from t_{-3} to t_2 .

$$\begin{aligned}
Consumption_{i,t} = & \alpha Collected_i + \beta_{-2} Before_{2,t} + \beta_{-1} Before_{1,t} + \beta_0 After_{0,t} + \\
& \beta_1 After_{1,t} + \beta_2 After_{2,t} + \gamma_{-2} Collected_i * Before_{2,t} + \gamma_{-1} Collected_i * \\
& Before_{1,t} + \gamma_0 Collected_i * After_{0,t} + \gamma_1 Collected_i * After_{1,t} + \gamma_2 Collected_i * \\
& After_{2,t} + \varepsilon_{i,t}
\end{aligned} \tag{6}$$

We display the regression results in Panel C of Table 9 and the dynamic trend in Figure 7. The first column shows the standard DID estimates, with a dummy *After* indicating that the observation is within t_0 to t_2 . The second column shows the dynamics in each month. The coefficients on *Collect*Before₂* and *Collect*Before₁* are not significant, suggesting that the parallel trend assumption is not violated. None of the coefficients on *Collect*After*, *Collect*After₀*, *Collect*After₁*, or *Collect*After₂* are statistically significantly at the 99% confidence level. Thus, we did not observe a sharp decline in online consumption caused by the private-information-based collection.

[Table 9 inserted about here]

[Figure 7 inserted about here]

The online consumption is revealed to be very smooth before and after the collection event. The borrowers subject to collection did not experience a significant shock in online consumption compared with their uncollected counterparts. Since online consumption is usually for goods that are not basic survival necessities, the smooth consumption pattern online indicates that the borrowers subject to collection are not significantly liquidity constrained. Consequently, we exclude the explanation of declined repayment ability, and the underlying mechanism through which the private-information-based collection leads to worse loan recovery is the result of a negative reciprocal motivation. The borrowers who suffered from undesirable collection practices choose to respond with hostile actions and default deliberately.

Our findings suggest that borrowers do care about privacy and reputation, and they will seek revenge against the platform if these are damaged. Although information plays an important role in improving loan performance, privacy protection is challenged when personal information is collected and misused.

6. Conclusion and implications

As consumer data are continuously collected in the big-data and FinTech era, consumer privacy protection becomes increasingly challenging. Consumers are exposed to potential harm if the information is misused. We examine the impact of intensive use of personal information in the cash loan market in China, where personal data are collected and utilized to support online borrowing and there is no clear regulation for online cash loan platforms. With many subprime borrowers entering the market, the platforms adopted a special private-information-based collection practice in which borrowers' and their social networks are contacted by collectors.

The exogenous collection shock, which is imposed by collectors who have given up collecting some borrowers due to their oversized workloads, allow us to identify the effect of this style of collection on loan performance. Raw statistics show that the default rate of borrowers who are contacted for collection is 35% lower than the borrowers in delinquent status but never subject to collection. However, our method mitigating endogeneity concerns reveals that the special collection practice based on private information actually leads to worse recovery rates for overdue loans and pushed the default rate 51% higher. The negative effect of this type of collection is stronger in borrowers with less credit risk. The underlying mechanism of this is associated with negative reciprocity. Since private-information-based collection hurts borrowers by violating their privacy and causes a huge loss of personal reputation, the borrowers' trust is destroyed, and they retaliate by deliberately defaulting.

We must note that the overall effect of this private-information-based collection practice can be mixed. In this paper, we only focus on the borrowers who have already entered delinquency because they are directly exposed to collection and information misuse. However, the collection practice may lead to a reduction in moral hazard because, when faced with the threat of potential reputational cost, borrowers may behave more properly and become less likely to enter delinquent status. Moreover, the collection practice may mitigate the adverse selection and improve borrower quality on the platform at the early stage of user registry. Therefore, the overall effect of this collection practice on loan performance is complex and undetermined. In this paper, we focus the analysis of the direct effect of private-information-based collection on borrowers in delinquent status. Future research on personal information and debt collection would be very fruitful.

Our study adds to the empirical evidence on potential caveats in the rapid development of information-driven FinTech innovation. In the digital era, personal information can easily be used for business purposes. Our findings indicate that people do care about privacy, and the misuse of private information leads to market welfare losses. There is a boundary between

information and privacy, and information users should strictly follow relevant codes of conduct. Once the boundary is crossed, misuse of personal information will bring undesirable results. The policy implication is that, technological development and innovations in the financial market should be accompanied by proper regulations to ensure consumer wellbeing is protected.

References

- Adjerid, I., Acquisti, A., Brandimarte, L., Loewenstein, G., 2013. Sleights of privacy: framing, disclosures, and the limits of transparency. *Proceedings of the ninth symposium on usable privacy and security*.
- Alan, S., Loranth, G., 2013. Subprime consumer credit demand: evidence from a lender's pricing experiment. *The Review of Financial Studies* 26(9), 2353-2374.
- Andersson, L., Pearson, C., 1999. Tit for tat? The spiraling effect of incivility in the workplace. *Academy of Management Review* 24(3), 452-471.
- Andreoni, J., Douglas, B., 2009. Social image and the 50–50 norm: a theoretical and experimental analysis of audience effects. *Econometrica* 77(5), 1607-1636.
- Acquisti, A., Friedman, A., Telang, R., 2006. Is There a Cost to Privacy Breaches? An Event Study. *ICIS 2006 Proceedings*.
- Acquisti, A., Taylor, C., Wagman, L., 2016. The economics of privacy. *Journal of Economic Literature* 54(2), 442-92.
- Ariely, D., Bracha, A., Meier, S., 2009. Doing good or doing well? Image motivation and monetary incentives in behaving prosocially. *American Economic Review* 99(1), 544-555.
- Athey, S., Catalini, C., Tucker, C., 2017. The digital privacy paradox: small money, small costs, small talk. *NBER Working Paper*.
- Berg, T., Burg, V., Gombović, A., Puri, M., 2019. On the rise of FinTechs: credit scoring using digital footprints. *The Review of Financial Studies*, forthcoming.
- Bertrand, M., Morse, A., 2011. Information disclosure, cognitive biases, and payday borrowing. *The Journal of Finance* 66(6), 1865-1893.
- Burnham, Terence. 1999. Testosterone and Negotiations, mimeo, John F. Kennedy School of Government, Harvard University.
- Caliendo, M., Fossen, F., Kritikos, A., 2012. Trust, positive reciprocity, and negative reciprocity: do these traits impact entrepreneurial dynamics? *Journal of Economic Psychology* 33(2), 394-409.
- Charness, G., 2004. Attribution and reciprocity in an experimental labor market. *Journal of Labor Economics* 22(3), 665-688.
- Chen, M. A., Wu, Q., & Yang, B., 2019. How valuable is FinTech innovation? *The Review of Financial Studies*, 32(5), 2062-2106.
- d'Astous, P., Shore, S. H., 2017. Liquidity constraints and credit card delinquency: evidence from raising minimum payments. *Journal of Financial and Quantitative Analysis* 52(4), 1705-1730.

- Dobbie, W., Liberman, A., Paravisini, D., Pathania, V., 2018. Measuring bias in consumer lending. *NBER Working Paper*.
- Drouvelis, M., Grosskopf, B., 2016. The effects of induced emotions on pro-social behaviour. *Journal of Public Economics* 134, 1-8.
- Drozd, L., Serrano-Padial, R., 2017. Modeling the revolving revolution: the debt collection channel. *American Economic Review* 107(3), 897-930.
- Du, N., Li, L., Lu, T., Lu, X., 2019. Pro-social compliance in P2P lending: a natural field experiment. *Management Science*, forthcoming.
- Duarte, J., Siegel, S., Young, L., 2012. Trust and credit: the role of appearance in peer-to-peer lending. *The Review of Financial Studies* 25(8), 2455-2484.
- Falk, A., Fischbacher, U. 2006. A theory of reciprocity. *Games and Economic Behavior*, 54(2), 293-315.
- Fan, J., Tang, L., Zhu, W., Zou, B., 2018. The Alibaba effect: spatial consumption inequality and the welfare gains from e-commerce. *Journal of International Economics* 114, 203-220.
- Fedaseyev, V., 2015. Debt collection agencies and the supply of consumer credit. *FRB Working Paper*.
- Fehr, E., Gächter, S., 2000. Fairness and retaliation: the economics of reciprocity. *Journal of Economic Perspectives* 14(3), 159-181.
- Fuster, A., Goldsmith-Pinkham, P., Ramadorai, T., Walther, A., 2017. Predictably unequal? The effects of machine learning on credit markets. *CEPR Working Paper*.
- Goldstein, I., Jiang, W., Karolyi, G. A., 2019. To FinTech and beyond. *The Review of Financial Studies*, 32(5), 1647-1661.
- Gross, D. B., Souleles, N. S., 2002. An empirical analysis of personal bankruptcy and delinquency. *The Review of Financial Studies* 15(1), 319-347.
- Gross, R., Acquisti, A., 2005. Information revelation and privacy in online social networks. *Proceedings of the 2005 ACM workshop on privacy in the electronic society*.
- Guiso, L., Sapienza, P., Zingales, L., 2013. The determinants of attitudes toward strategic default on mortgages. *The Journal of Finance* 68(4), 1473-1515.
- Güth, W., Schmittberger, R., & Schwarze, B. 1982. An experimental analysis of ultimatum bargaining. *Journal of Economic Behavior & Organization*, 3(4), 367-388.
- Herold, F., 2012. Carrot or stick? the evolution of reciprocal preferences in a haystack model. *American Economic Review* 102(2), 914-940.
- Iyer, R., Khwaja, A., Luttmer, E., Shue, K., 2016. Screening peers softly: inferring the quality of small borrowers. *Management Science* 62(6), 1554-1577.

- Karlan, D. S., Zinman, J., 2008. Credit elasticities in less-developed economies: implications for microfinance. *American Economic Review* 98(3), 1040-68.
- Keys, B. J., & Wang, J., 2019. Minimum payments and debt paydown in consumer credit cards. *Journal of Financial Economics* 131(3), 528-548.
- Laudenbach, C., Pirschel, J., Siegel, S., 2018. Personal communication in a Fintech world: evidence from loan payments. *CESifo Working Paper*.
- Kummer, M., & Schulte, P., 2019. When private information settles the bill: money and privacy in Google's market for smartphone applications. *Management Science*.
- Martin, K. D., Borah, A., Palmatier, R. W., 2017. Data privacy: Effects on customer and firm performance. *Journal of Marketing* 81(1), 36-58.
- Mitchell, M., Ambrose, M., 2007. Abusive supervision and workplace deviance and the moderating effects of negative reciprocity beliefs. *Journal of Applied Psychology* 92(4), 1159-1168.
- Posner, R. A., 1981. The economics of privacy. *The American Economic Review* 71(2): 405-409.
- Ramcharan, R., Verani, S., Van den Heuvel, S. J., 2016. From Wall Street to main street: the impact of the financial crisis on consumer credit supply. *The Journal of Finance* 71(3), 1323-1356.
- Reuben, E., van Winden, F., 2008. Social ties and coordination on negative reciprocity: the role of affect. *Journal of Public Economics* 92(1), 34-53.
- Roth, A. E., Prasnikar, V., Okuno-Fujiwara, M., & Zamir, S., 1991. Bargaining and market behavior in Jerusalem, Ljubljana, Pittsburgh, and Tokyo: An experimental study. *The American Economic Review*, 1068-1095.
- Stigler, G. J., 1980. An introduction to privacy in economics and politics. *The Journal of Legal Studies* 9(4), 623-644.

Figure 1 Borrowing Procedure and Personal Information Acquisition Process

This figure shows the borrowing procedure as well as the process used to acquire consumer data. Authorization in the first two steps is compulsory in order to use the borrowing service, but it is voluntary in the third.

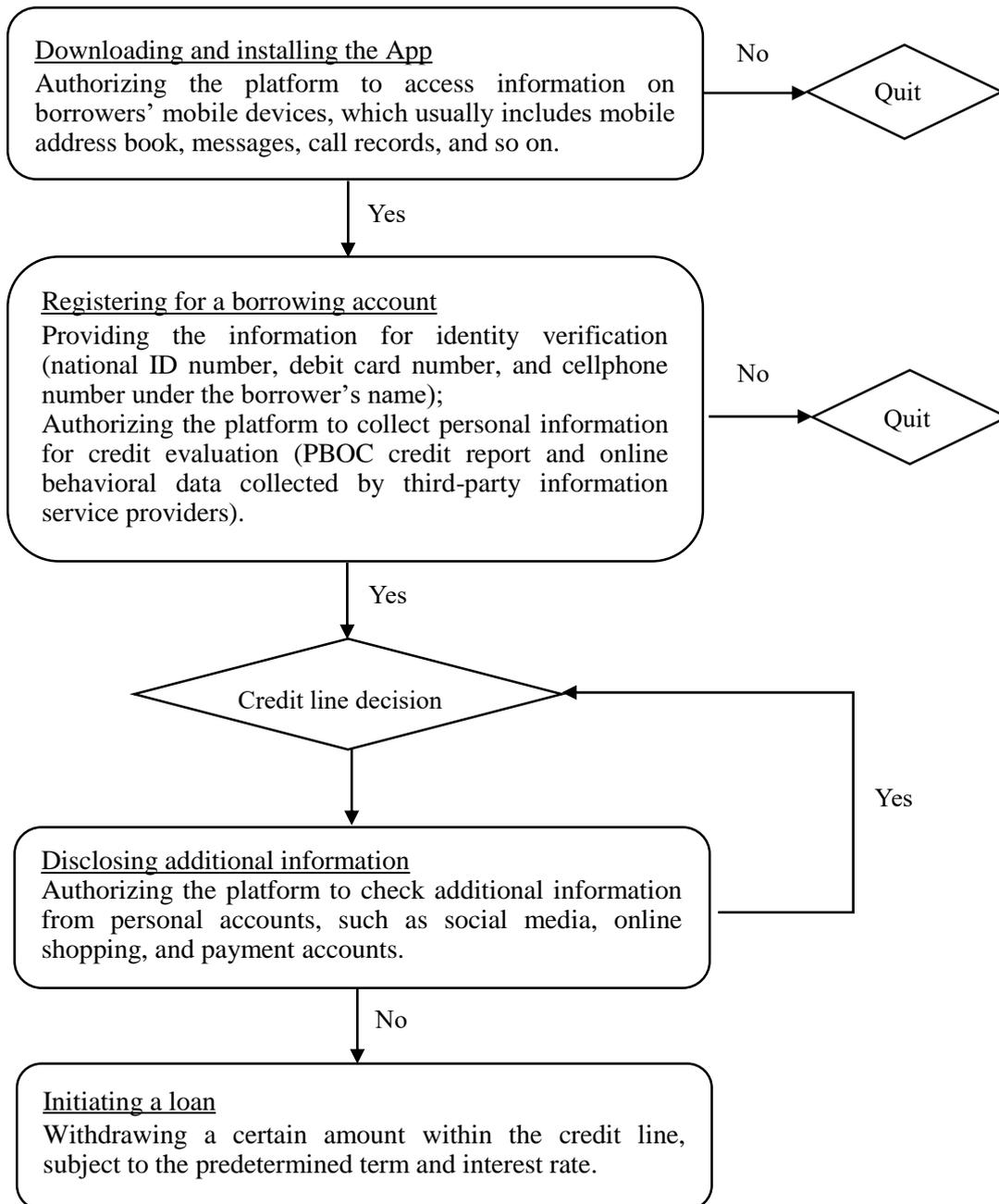


Figure 2 Loan Collection Procedure and Empirical Design

This figure shows the collection procedure and the discontinuity, which is utilized to develop the empirical strategy. The collection system uses the strategy of “easier tasks first.” The platform ranks overdue loans by the estimated probability of recovering payments, and collectors call ranked borrowers one by one. Some borrowers will not be contacted due to collectors’ excessive workloads.

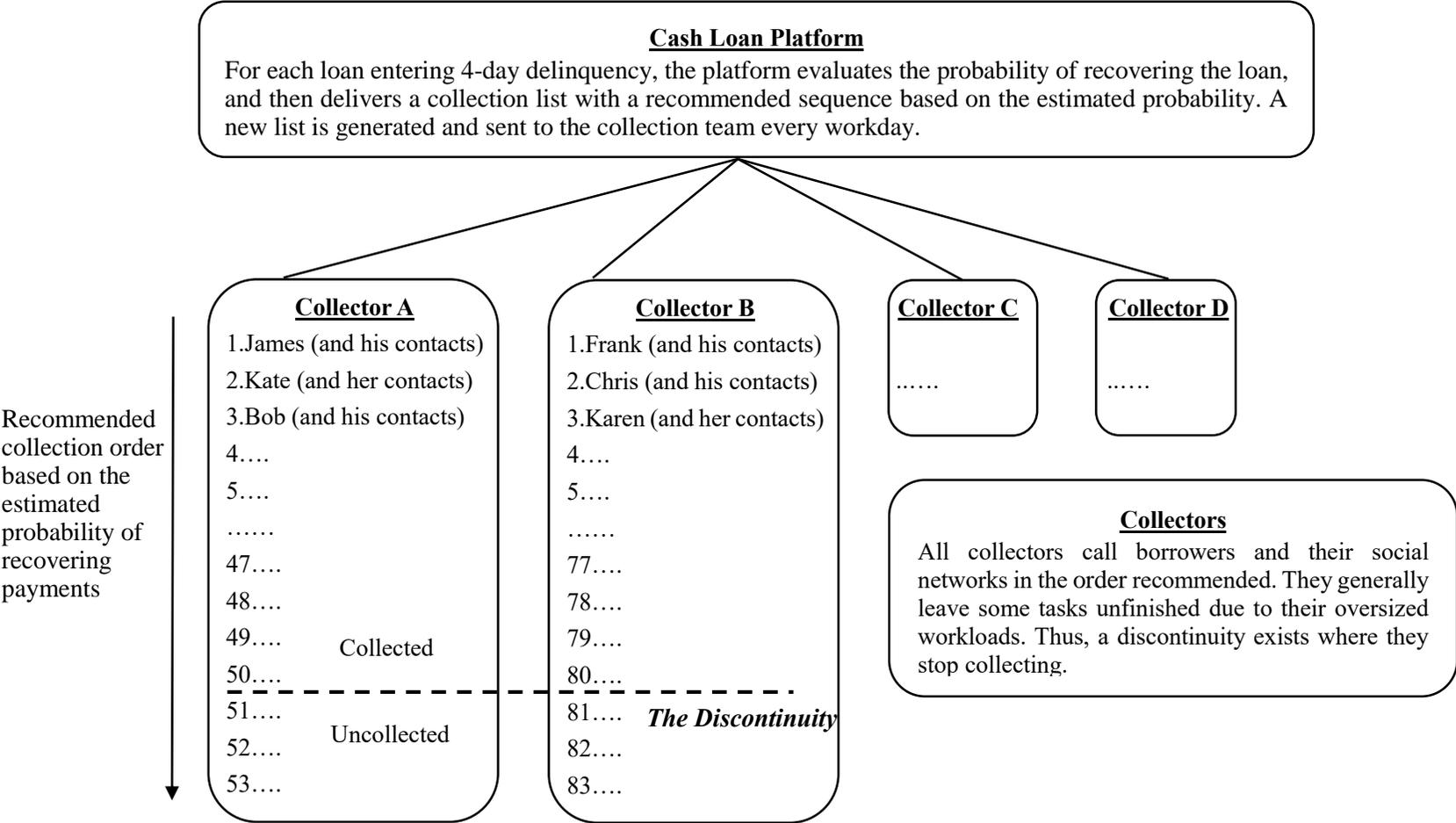


Figure 3 Distribution of Collection Times

This figure shows the distribution of time when collection calls are made. The horizontal axis indicates the time in a 24-hour system.

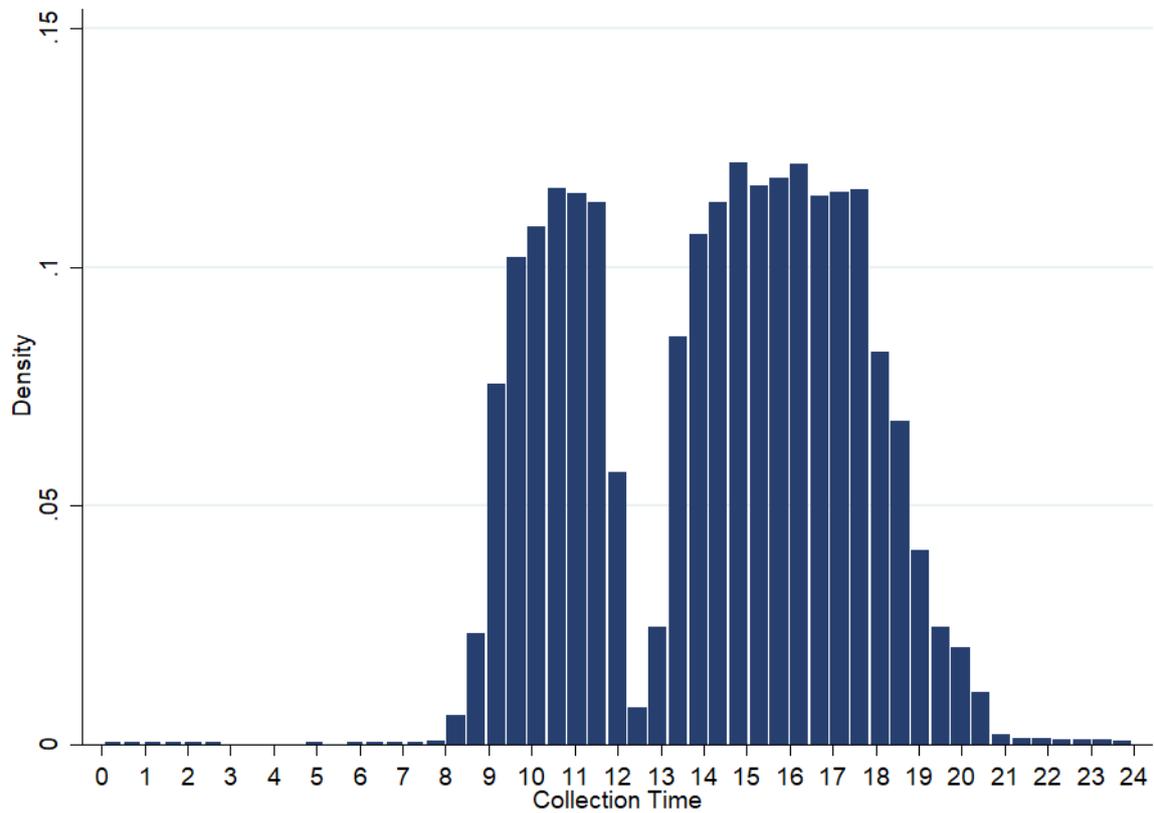


Figure 4 Distribution of Mahalanobis Distance

This figure shows the distribution of shortest Mahalanobis distance $d_{ij^*}^2$ from each collected borrower i to the nearest uncollected borrower j^* .

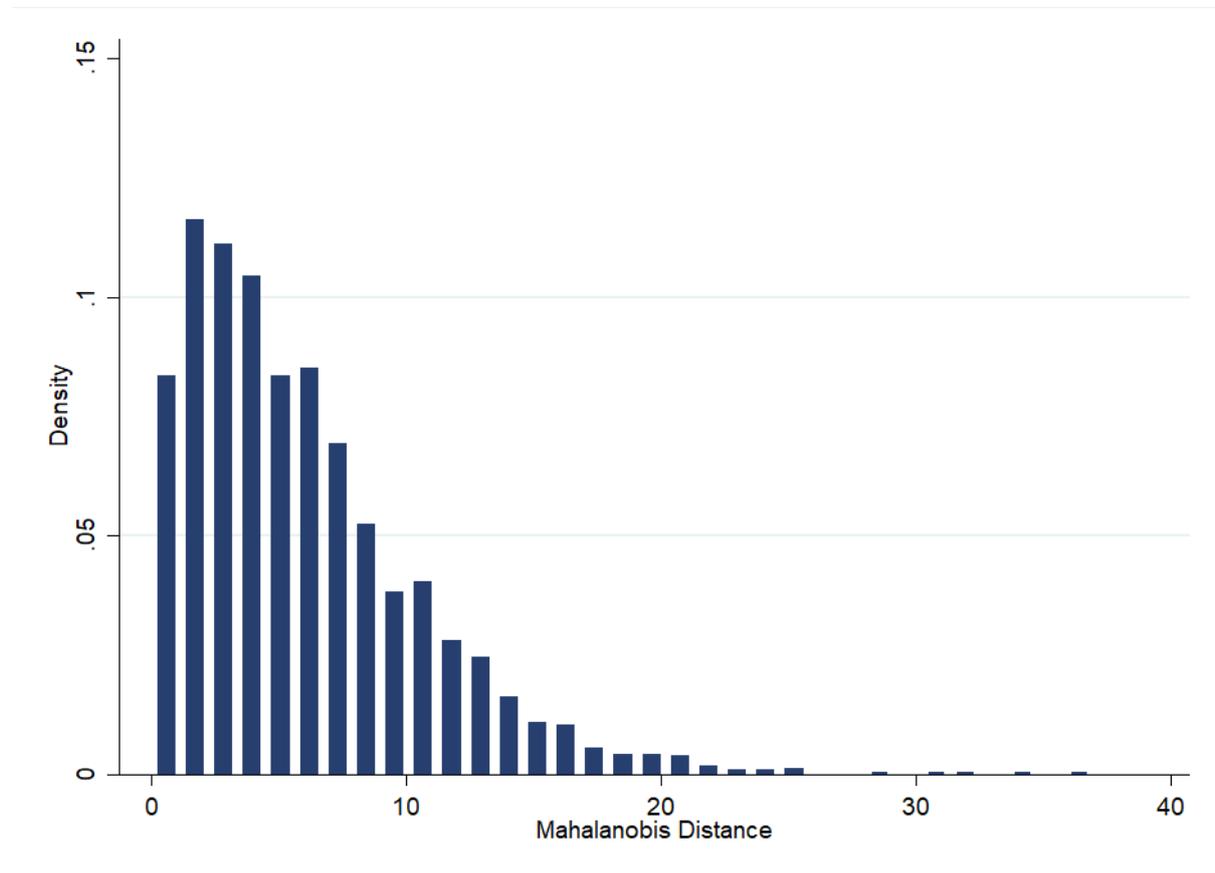


Figure 5 Collection, Credit Grades, and Repayment Behavior

This figure shows the heterogeneous marginal effect estimated from the probit model of *Default on Collect* for borrowers with different credit grades. The credit grades are assigned by the platform's internal risk evaluation system. Borrowers in grade A are evaluated as the lowest credit risk, while borrowers with the highest credit risk fall into grade F. The solid line represents the average marginal effects and the vertical dotted lines represents the upper and lower bound with a 95% confidence level. Both the loan-level and borrower-level covariates are included, and month fixed effects are controlled. The standard errors are clustered at the borrower level.

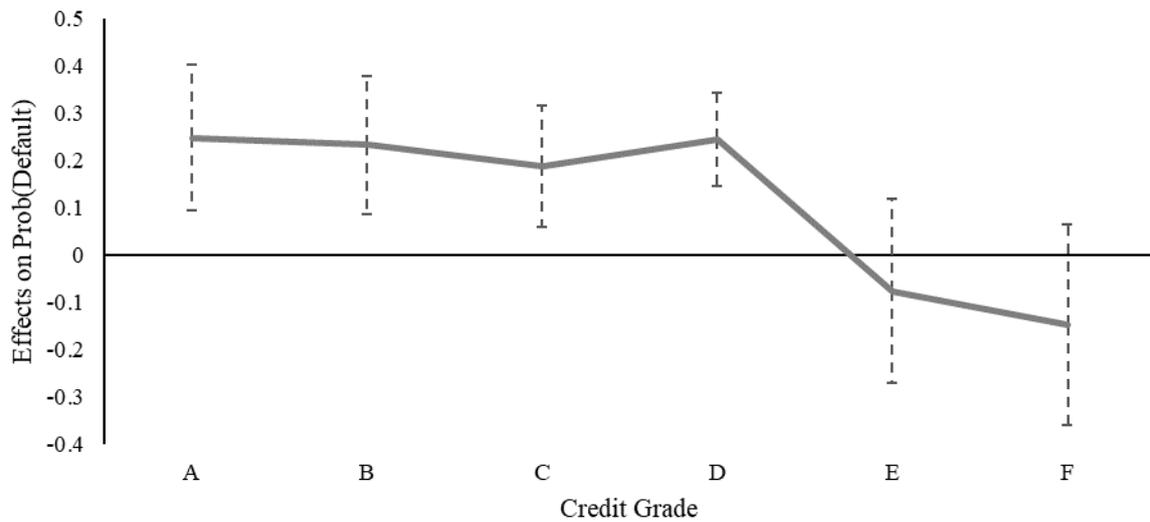


Figure 6 Collection, Gender, and Repayment Behavior

This figure shows the heterogeneous marginal effect estimated from the probit model of *Default* on *Collect* for male and female borrowers. The column represents the average marginal effects, and the vertical dotted lines represent the upper and lower bounds with a 95% confidence level. Both the loan-level and borrower-level covariates are included, and month fixed effects are controlled. The standard errors are clustered at the borrower level.

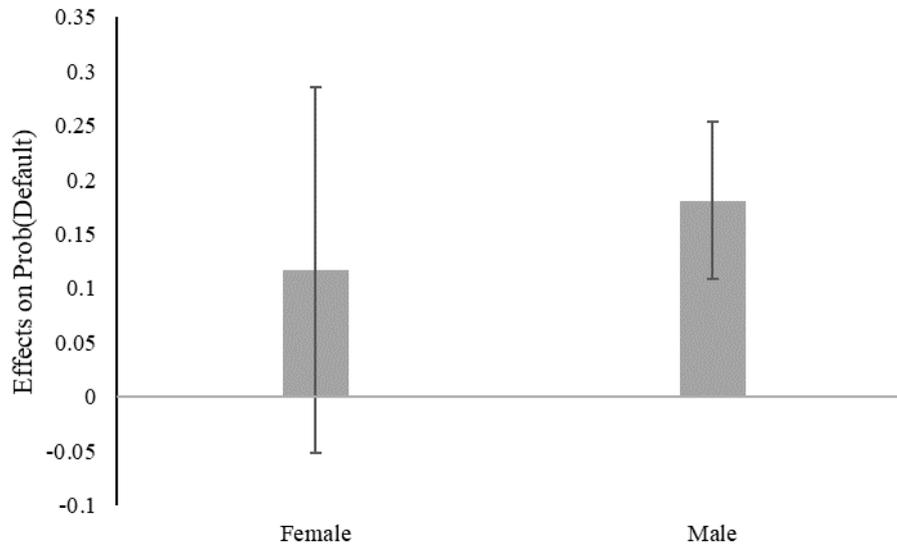


Figure 7 Difference-in-Difference Analysis for Online Consumption Dynamics

This figure shows the estimates of the Difference-in-Difference regression in each month. The dependent variable is the natural logarithm of the borrower's monthly consumption on Taobao. The treatment and control groups are collected and uncollected borrowers respectively in the post-match sample. The observation window starts from three months before the collection month to two months following. The collection months are denoted as $t(0)$. The solid line represents the estimated coefficients on the interaction terms, and the vertical dotted lines represents the upper and lower bound with a 95% confidence level. The horizontal axis represents the time relative to the month when borrowers are sent for collection.

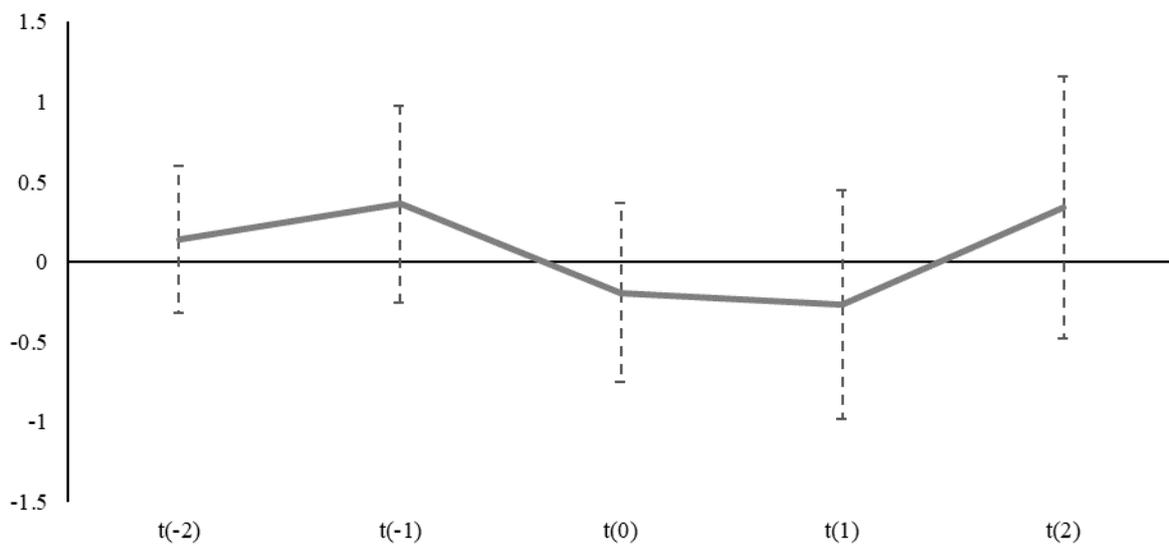


Table 1 Summary Statistics**Panel A Loan and Borrower Characteristics**

This table reports the summary statistics for the loan-level and borrower-level variables. *Default* equals 1 if any installment of a loan is late for over 60 days, otherwise it equals 0. *Collect* equals 1 if a loan is called for collection, otherwise it equals 0. *Loan size* is the loan size in Chinese Yuan. *Term* is the loan term in months. *Interest rate level* is the interest rate category from 1 to 10 defined by the platform, with the lowest interest rate being 1, while the highest is 10. *Overdue term* is the first overdue installment of a loan. *New borrower* equals 1 if the borrower has never borrowed from the platform before, otherwise it equals 0. *Male* equals 1 if the borrower is male, otherwise it equals 0. *Age* is the borrower's age at the time of loan application. *Big city* equals 1 if the borrower lives in more developed cities¹ in China, otherwise it equals 0. *Taobao account* is a dummy variable indicating whether the borrower authorizes the platform to check personal information from his/her Taobao account, which is the largest online shopping mall operated by Alibaba. *#Contacts* indicates the number of mobile phone contacts the borrower has.

	Obs.	Mean	SD	P1	P25	Median	P75	P99
<i>Default</i>	3098	0.43	0.50	0	0	0	1	1
<i>Collect</i>	3101	0.77	0.42	0	1	1	1	1
<i>Loan size</i>	3101	1765.25	1436.09	110	800	1400	2498	5888
<i>Term</i>	3101	6.43	4.09	1	3	6	12	12
<i>Interest rate level</i>	3095	6.56	2.72	1	4	7	9	10
<i>Overdue term</i>	3101	1.94	1.69	1	1	1	2	9
<i>New borrower</i>	3101	0.65	0.48	0	0	1	1	1
<i>Male</i>	3101	0.80	0.40	0	1	1	1	1
<i>Age</i>	3101	26.45	5.35	19	22	26	29	43
<i>Big city</i>	3101	0.46	0.50	0	0	0	1	1
<i>Taobao account</i>	3101	0.80	0.43	0	1	1	1	2
<i>#Contacts</i>	3101	248.15	265.71	0	94	187	326	1217

¹ Tier 1 and Tier 2 cities, defined by the China National Bureau of Statistics, include Beijing, Shanghai, Guangzhou, Shenzhen, Beihai, Changchun, Changsha, Chengdu, Chongqing, Dalian, Fuzhou, Guiyang, Haikou, Hangzhou, Harbin, Hefei, Huhhot, Jinan, Kunming, Lanzhou, Nanchang, Nanjing, Nanning, Ningbo, Qingdao, Sanya, Shenyang, Shijiazhuang, Suzhou, Taiyuan, Tianjin, Urumqi, Wenzhou, Wuhan, Wuxi, Xi'an, Xiamen, Xining, Yinchuan, and Zhengzhou.

Panel B Distribution of Credit Grades

This table reports the distribution of borrowers' credit grades in the sample. The credit grades are assigned by the platform's internal risk evaluation system. Borrowers in grade A are evaluated the lowest credit risk, while borrowers with the highest credit risk fall into grade F.

Credit Grade	A	B	C	D	E	F
Obs.	334	359	646	974	420	368
Percentage(%)	10.77	11.58	20.83	31.41	13.54	11.87

Table 2 Mahalanobis Distance and Loan Performance

This table examines whether mahalanobis distance is a proper proxy for collection sequence. We report the coefficient estimates from the probit model of *Default* on *Mahadis*, which is measured by the shortest Mahalanobis distance from each collected loan to the uncollected one in the sample. The covariates are not included in Column (1), loan-level covariates are included in Column (2), and loan-level and borrower-level covariates are included in Column (3). The standard errors are clustered at the borrower level, displayed in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: <i>Default</i>	(1)	(2)	(3)
<i>Mahadis</i>	-0.013*** (0.002)	-0.008*** (0.002)	-0.008*** (0.002)
<i>Loan size</i>		0.022* (0.013)	0.013 (0.015)
<i>Term</i>		0.020*** (0.004)	0.021*** (0.004)
<i>Overdue term</i>		-0.048*** (0.006)	-0.040*** (0.006)
<i>Interest rate level</i>		0.013** (0.006)	0.006 (0.005)
<i>Male</i>			0.029 (0.024)
<i>Age</i>			0.010*** (0.002)
<i>Big city</i>			-0.063*** (0.021)
<i>#Contacts</i>			0.014*** (0.005)
<i>Taobao account</i>			-0.141*** (0.027)
<i>New borrower</i>			0.081*** (0.024)
<i>Credit Grade: B</i>			0.126*** (0.035)
<i>Credit Grade: C</i>			0.134*** (0.032)
<i>Credit Grade: D</i>			0.184*** (0.031)
<i>Credit Grade: E</i>			0.124*** (0.038)
<i>Credit Grade: F</i>			-0.052 (0.041)
<i>Constant</i>	0.461*** (0.016)	0.175* (0.091)	-0.105 (0.121)
Observations	2,397	2,397	2,397
Adjusted R-squared	0.0145	0.0627	0.122
F-stat	39.18	34.22	26.61

Table 3 Effects of Collection in the Pre-match Sample

This table reports the coefficient estimates from the probit model of *Default* on *Collect* for the pre-match sample. The covariates are not included in Column (1), loan-level covariates are included in Column (2), and loan-level and borrower-level covariates are included in Column (3). Month fixed effects are controlled in Columns (2) and (3). The standard errors are clustered at the borrower level, displayed in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: <i>Default</i>	(1)	(2)	(3)
<i>Collect</i>	-0.561*** (0.055)	-0.098 (0.063)	0.058 (0.070)
<i>Loan size</i>		0.123*** (0.035)	0.168*** (0.045)
<i>Term</i>		0.067*** (0.012)	0.084*** (0.012)
<i>Overdue term</i>		-0.202*** (0.019)	-0.162*** (0.020)
<i>Interest rate level</i>		0.083*** (0.016)	0.044*** (0.016)
<i>Male</i>			0.093 (0.062)
<i>Age</i>			0.021*** (0.005)
<i>Big city</i>			-0.179*** (0.056)
<i>#Contacts</i>			0.053*** (0.015)
<i>Taobao account</i>			-0.682*** (0.080)
<i>New borrower</i>			0.204*** (0.068)
<i>Credit Grade: B</i>			0.444*** (0.112)
<i>Credit Grade: C</i>			0.604*** (0.100)
<i>Credit Grade: D</i>			0.755*** (0.100)
<i>Credit Grade: E</i>			0.757*** (0.118)
<i>Credit Grade: F</i>			0.578*** (0.120)
<i>Constant</i>	0.263*** (0.048)	-1.530*** (0.274)	-3.189*** (0.383)
Fixed effect: Month	No	Yes	Yes
Observations	3,098	3,090	3,090
Pseudo R-squared	0.0253	0.128	0.196

Table 4 Pre-match and Post-match Sample**Panel A Propensity Score Regression**

The table reports coefficient estimates from the probit model used to estimate propensity for borrowers in the treatment and control groups. The dependent variable is the indicator *Collect*. Column (1) reports the regression result for the pre-match sample, and Column (2) reports the diagnostic regression result for the post-match sample. The standard errors are clustered at the borrower level, displayed in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: <i>Collect</i>	(1)Pre-match	(2)Post-match
<i>Loan size</i>	-0.352*** (0.057)	-0.049 (0.096)
<i>Term</i>	-0.029** (0.012)	-0.011 (0.024)
<i>Overdue term</i>	0.250*** (0.043)	0.158** (0.063)
<i>Interest rate level</i>	0.052*** (0.017)	0.026 (0.031)
<i>Male</i>	0.134** (0.068)	-0.038 (0.140)
<i>Age</i>	0.014*** (0.005)	0.011 (0.011)
<i>Big city</i>	-0.101 (0.068)	0.015 (0.117)
<i>#Contacts</i>	0.026 (0.016)	0.094*** (0.028)
<i>Taobao account</i>	0.387*** (0.079)	-0.055 (0.202)
<i>New borrower</i>	-0.448*** (0.083)	0.060 (0.148)
<i>Credit Grade: B</i>	0.128 (0.133)	0.007 (0.216)
<i>Credit Grade: C</i>	0.001 (0.115)	-0.034 (0.198)
<i>Credit Grade: D</i>	0.196 (0.119)	-0.008 (0.204)
<i>Credit Grade: E</i>	-0.276** (0.137)	0.054 (0.239)
<i>Credit Grade: F</i>	-0.858*** (0.130)	0.024 (0.275)
<i>Constant</i>	2.318*** (0.458)	-0.667 (0.819)
Observations	3,095	2,354
Pseudo R-squared	0.237	0.0219
Wald Chi2	553.3	18.84
Prob>chi2	0	0.221

Panel B Treatment and Control Difference in the Pre-match Sample

This table reports the univariate comparisons between the treatment (collected borrowers) and control (uncollected borrowers) groups in the pre-match sample with regard to loan-level and borrower-level characteristics. The S.E. column displays heteroskedasticity-robust standard errors. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Collected	Uncollected	Difference		S.E.	T-stat
<i>Default</i>	0.38	0.60	-0.22	***	0.02	-10.57
<i>Loan size</i>	1520.44	2504.97	-984.53	***	51.97	-18.95
<i>Term</i>	6.01	7.97	-1.96	***	0.17	-11.37
<i>Overdue term</i>	2.14	1.26	0.88	***	0.07	12.33
<i>Interest rate level</i>	6.34	7.34	-0.99	***	0.12	-8.58
<i>Male</i>	0.81	0.74	0.07	***	0.02	4.17
<i>Age</i>	26.60	25.93	0.67	***	0.23	2.92
<i>Big city</i>	0.50	0.34	0.15	***	0.02	7.23
<i>#Contacts</i>	252.21	208.85	43.36	***	9.79	4.43
<i>Taobao account</i>	0.87	0.57	0.30	***	0.02	16.90
<i>Credit Grade</i>	3.42	4.26	-0.83	***	0.06	-13.77
<i>New borrower</i>	0.59	0.87	-0.28	***	0.02	-14.13
<i>Application Date</i>	2016/05/08	2016/04/28	10		6.94	1.43

Panel C Treatment and Control Difference in the Post-match Sample

This table reports the univariate comparisons between the treatment (collected borrowers) and control (uncollected borrowers) groups in the post-match sample with regard to loan-level and borrower-level characteristics. The S.E. column displays heteroskedasticity-robust standard errors. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Collected	Uncollected	Difference		S.E.	T-stat
<i>Default rate</i>	0.43	0.33	0.11	**	0.04	2.57
<i>Loan size</i>	1533.80	1532.41	1.39		97.77	0.01
<i>Term</i>	5.38	5.37	0.00		0.32	0.01
<i>Overdue term</i>	1.56	1.39	0.17	**	0.08	2.15
<i>Interest rate level</i>	5.90	5.79	0.11		0.22	0.50
<i>Male</i>	0.90	0.90	0.00		0.03	0.00
<i>Age</i>	25.79	25.37	0.42		0.38	1.11
<i>Big city</i>	0.56	0.56	0.00		0.04	0.00
<i>#Contacts</i>	252.81	239.47	13.34		17.54	0.76
<i>Taobao account</i>	0.92	0.92	0.00		0.03	0.00
<i>Credit Grade</i>	3.50	3.50	0.00		0.11	0.00
<i>New borrower</i>	0.66	0.66	0.00		0.04	0.00
<i>Application Date</i>	2016/07/03	2016/07/25	-22	*	11.86	-1.89

Table 5 Effect of Collection in the Post-match Sample

This table reports coefficient estimates from the probit model of *Default* on *Collect* for the post-match sample. The covariates are not included in Column (1), loan-level covariates are included in Column (2), and loan-level and borrower-level covariates are included in Column (3). Month fixed effects are controlled in Columns (2) and (3). The standard errors are clustered at the borrower level, displayed in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable: <i>Default</i>	(1)	(2)	(3)
<i>Collect</i>	0.280*** (0.105)	0.596*** (0.118)	0.590*** (0.109)
<i>Loan size</i>		0.111 (0.076)	0.103 (0.086)
<i>Term</i>		0.077*** (0.027)	0.084*** (0.026)
<i>Overdue term</i>		-0.336*** (0.056)	-0.258*** (0.056)
<i>Interest rate level</i>		0.046 (0.035)	0.000 (0.033)
<i>Male</i>			0.122 (0.156)
<i>Age</i>			0.009 (0.011)
<i>Big city</i>			-0.149 (0.107)
<i>#Contacts</i>			0.090*** (0.034)
<i>Taobao account</i>			-0.977*** (0.229)
<i>New borrower</i>			0.389*** (0.132)
<i>Credit Grade: B</i>			0.225 (0.215)
<i>Credit Grade: C</i>			0.580*** (0.195)
<i>Credit Grade: D</i>			0.582*** (0.191)
<i>Credit Grade: E</i>			0.556** (0.235)
<i>Credit Grade: F</i>			0.148 (0.294)
<i>Constant</i>	-0.453*** (0.098)	-1.641*** (0.607)	-2.121*** (0.752)
Fixed effect: Month	No	Yes	Yes
Observations	2,354	2,354	2,354
Pseudo R-squared	0.00906	0.127	0.190

Table 6 Robustness Checks**Panel A Regression Results with Different Measures of Loan Default**

This table reports the coefficient estimates from the probit model of *Default* on *Collect* for the post-match sample, with a different measurement of loan default. *Default15/30/45* equals 1 if any installment of a loan is late for more than 15/30/45 days, and 0 otherwise. Both the loan-level and borrower-level covariates are included, and month fixed effects are controlled. The standard errors are clustered at the borrower level, displayed in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
	<i>Default15</i>	<i>Default30</i>	<i>Default45</i>
<i>Collect</i>	0.399*** (0.123)	0.360*** (0.111)	0.320*** (0.109)
<i>Constant</i>	-2.933*** (0.920)	-2.480*** (0.788)	-1.879** (0.794)
Control variables	Yes	Yes	Yes
Observations	2,354	2,354	2,354
Pseudo R-squared	0.265	0.224	0.215

Panel B Regression Results for Different Post-match Samples

This table reports the robustness checks of the probit regressions of *Default* on *Collect* for different post-match samples. Each row presents the regression results for the post-match sample derived using a corresponding caliper. For example, the first row presents the result of the regression using the matched sample with the shortest 5% Mahalanobis distance. The first column reports the caliper and the second column reports the resulting sample size. The third column reports the estimated coefficients of *Collect*. The fourth column reports the Pseudo R-squared of the regression on the corresponding sample. Both the loan-level and borrower-level covariates are included, and month fixed effects are controlled. The standard errors are clustered at the borrower level, displayed in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

(1) Caliper Used in Distance Matching	(2) Post-match Sample Size	(3) Coefficient Estimates on <i>Collect</i>	(4) Pseudo R-squared of the Probit Model
5 th percentile	191	1.059*** (0.279)	0.283
10 th percentile	426	0.752*** (0.174)	0.207
20 th percentile	934	0.589*** (0.131)	0.229
30 th percentile	1410	0.585*** (0.116)	0.204
40 th percentile	1888	0.610*** (0.110)	0.190
50 th percentile	2354	0.590*** (0.109)	0.190
60 th percentile	2828	0.560*** (0.105)	0.185

Table 7 Collection, Credit Grades, and Repayment Behavior

This table reports the coefficient estimates from the probit model of *Default* on *Collect* for the post-match sample, with interaction terms for the indicators *Collect* and *Creditgrade*. The first column shows the coefficient estimates on the interaction terms. The second column shows the coefficient estimates of *Collect* for borrowers in each credit grade, with the Chi2 value of the test on the significance of the coefficients in parentheses. The third column shows the corresponding marginal effects. Both the loan-level and borrower-level covariates are included, and month fixed effects are controlled. The parentheses in columns (1) and (3) represent the standard errors clustered at the borrower level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent: <i>Default</i>	(1) Coefficients	(2) Joint Coefficients Test: <i>Collect</i> + <i>Collect</i> * <i>Credit grade_X=0</i>	(3) Marginal Effects
<i>Collect</i> (Baseline: <i>Credit grade_A</i>)	1.061** (0.455)	1.061** (5.440)	0.248*** (0.078)
<i>Collect</i> * <i>Credit grade_B</i>	-0.209 (0.557)	0.852*** (6.890)	0.232*** (0.075)
<i>Collect</i> * <i>Credit grade_C</i>	-0.473 (0.494)	0.588*** (7.020)	0.188*** (0.066)
<i>Collect</i> * <i>Credit grade_D</i>	-0.290 (0.484)	0.771*** (18.560)	0.245*** (0.051)
<i>Collect</i> * <i>Credit grade_E</i>	-1.300** (0.546)	-0.239 (0.590)	-0.076 (0.099)
<i>Collect</i> * <i>Credit grade_F</i>	-1.554*** (0.590)	-0.492 (1.78)	-0.148 (0.108)
Control variables	Yes		
Observations	2,354		
Pseudo R-squared	0.185		

Table 8 Collection, Gender, and Repayment Behavior

This table reports the coefficient estimates from the probit model of *Default* on *Collect* for the post-match sample, with the interaction terms for the indicators *Collect* and *Male*. The first column shows the coefficient estimates on the interaction terms. The second column shows the coefficient estimates of *Collect* for male and female borrowers, with the Chi2 value of the test on the significance of the coefficients in parentheses. The third column shows the corresponding marginal effects. Both the loan-level and borrower-level covariates are included, and month fixed effects are controlled. The parentheses in columns (1) and (3) represent the standard errors clustered at the borrower level. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent: <i>Default</i>	(1) Coefficients	(2) Joint Coefficients Test: <i>Collect</i> + <i>Collect</i> * <i>Male</i> = 0	(3) Marginal Effects
<i>Collect</i> (<i>Baseline: Female</i>)	0.388 (0.300)	0.388 (1.67)	0.117 (0.086)
<i>Collect</i> * <i>Male</i>	0.191 (0.329)	0.579*** (20.62)	0.181*** (0.037)
Control variables	Yes		
Observations	2,354		
Pseudo R-squared	0.170		

Table 9 Difference-in-Difference Analysis for Online Consumption**Panel A Online Consumption Level**

This table reports the DID result of borrowers' monthly online consumption (in Chinese Yuan) on Taobao in the treatment and control groups. The first column shows the average monthly consumption from three months before the collection to the collection month. The second column shows the average monthly consumption within two months following the collection month. The third column shows the difference between (1) - (2). The last column shows the difference between the treatment and control group in column (3). The heteroskedasticity-robust standard errors are displayed in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Before	(2) After	(3) After-Before	(4) Diff-in-Diff
Collected	727 (54)	692 (84)	-35 (102)	35 (164)
Uncollected	792 (45)	723 (45)	-70 (129)	

Panel B Parallel Trend

This table reports the parallel trend of borrowers' online consumption in the treatment and control groups. *Consumption Growth₃* (*Consumption Growth₂* or *Consumption Growth₁*) denotes the growth of borrower's online consumption on Taobao in three (two or one) months before the collection month compared with four (three or two) months before that. The heteroskedasticity-robust standard errors are displayed in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Collected	(2) Uncollected	(3) Difference
<i>Consumption Growth₃</i>	0.063 (0.080)	0.150 (0.086)	-0.087 (0.269)
<i>Consumption Growth₂</i>	-0.005 (0.085)	-0.181 (0.085)	0.176 (0.242)
<i>Consumption Growth₁</i>	-0.081 (0.098)	-0.224 (0.101)	0.143 (0.331)

Panel C Difference-in-Difference Regression Results

This table reports the results of the DID regression of monthly online consumption for the post-match sample. The dependent variable is the natural logarithm of the borrower's monthly consumption on Taobao. The treatment and control groups are collected and uncollected borrowers, respectively, in the post-match sample. The observation window starts from three months before collection to two months following. The collection months are denoted as t_0 . *After* is a dummy indicating that the observation is in t_0 to t_2 . *Before2* (*Before1*/*After0*/*After1*/*After2*) is a dummy indicating that the observation is in t_{-2} ($t_{-1}/t_0/t_1/t_2$). The standard errors are clustered at the borrower level, displayed in parentheses. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent: $\ln(\text{Consumption})$	(1)	(2)
<i>Collect</i>	0.129 (0.184)	-0.032 (0.241)
<i>After</i>	-0.124 (0.211)	
<i>Collect*After</i>	-0.220 (0.229)	
<i>Before2</i>		-0.175 (0.218)
<i>Before1</i>		-0.482 (0.300)
<i>After0</i>		-0.265 (0.260)
<i>After1</i>		-0.110 (0.343)
<i>After2</i>		-0.648 (0.395)
<i>Collect*Before2</i>		0.140 (0.233)
<i>Collect*Before1</i>		0.362 (0.313)
<i>Collect*After0</i>		-0.192 (0.285)
<i>Collect*After1</i>		-0.268 (0.366)
<i>Collect*After2</i>		0.337 (0.417)
<i>Constant</i>	5.046*** (0.174)	5.252*** (0.229)
Observations	7,567	7,567
R-squared	0.003	0.008