Angry Borrowers:

Negative Reciprocity in a Financial Market*

Li Liao, Tsinghua University
liaol@pbcsf.tsinghua.edu.cn

Zhengwei Wang, Tsinghua University
wangzhw@pbcsf.tsinghua.edu.cn

Hongjun Yan, DePaul University
hongjun.yan@depaul.edu

Jun Yang, Indiana University
jy4@indiana.edu

Congyi Zhou, Tsinghua University
zhoucy.16@pbcsf.tsinghua.edu.cn

This Draft: June 2021

* We thank Li An, Zhuo Chen, William Cong, Ha Diep-Nguyen, Raymond Fisman, Umit Gurun, Naveen Khanna, Emma Li, Bibo Liu, Qiang Ren, Stephan Siegel, Huan Tang, Hong Zhang, Yi Zhou, Xiaodong Zhu, and seminar participants at Baylor University, Hong Kong Polytechnic University, Indiana University, Michigan State University, University of Illinois in Chicago, Peking University, Southeast University, Tsinghua University, 5th International Conference on FinTech Development, 2019 China Finance Review International Conference, 2020 Georgetown Privacy Day conference, and 2020 GSU-RFS FinTech Conference for helpful comments and suggestions. Special thanks go to Julie Steiff and Estella Yan for their editorial help. All remaining errors are our own. Please address all correspondence to Hongjun Yan. The latest version of this paper is available at https://sites.google.com/site/hongjunyanhomepage/.

Electronic copy available at: https://ssrn.com/abstract=3415808

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Abstract

We examine the consequences of an intrusive debt-collection tactic that targets delinquent borrowers' social circles. Our identification strategy relies on the fact that some of the delinquent loans are not worked on due to collection agents' excessive workload. We show that this tactic backfires and increases the borrowers' default rate by 5.9 to 14.3 percentage points. Male borrowers and borrowers with better credit respond more strongly. Moreover, the effect is concentrated in the period when this collection practice was emerging and likely unexpected. These findings are consistent with the negative reciprocity interpretation: angered borrowers retaliate by defaulting on their loans.

Keywords: Behavioral Finance; Reciprocity; Privacy Infringement; Social Pressure

JEL: D14, D18, G41

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1 Introduction

How would you choose between \$20 and \$0? The answer seems obvious until we add context to the question. In the well-known ultimatum bargaining experiment that divides \$100 between two individuals, the Responder frequently rejects an offer below \$20 to penalize the Proposer for being unfair, which results in a \$0 payoff for both (Güth, Schmittberger, and Schwarze, 1982). The Responder's behavior is an example of negative reciprocity; that is, people often respond in kind to hostile actions, retaliating even at their own expense (Fehr and Gächter, 2000).[1]

Reciprocity is believed to play an important role in a variety of key areas in economics, from public goods and social norms (Hirshleifer and Rasmusen, 1989) to wage rigidity and labor market bargaining (Akerlof 1982). More recently, Hart and Moore (2008) argue that reciprocity provides a basis for flexible contracts. However, most evidence on reciprocity has been experimental or based on survey data.[2] Our paper attempts to provide the first direct evidence of negative reciprocity in a real financial market. We examine the consequences of an intrusive debt-collection tactic that targets delinquent borrowers' social circles. Our evidence suggests that affected borrowers negatively reciprocate the privacy infringement by deliberately defaulting on their loans: their default propensity increases by 5.9 to 14.3 percentage points, which correspond to 10% to 25% of the baseline default rates for delinquent loans.

Our data come from a leading cash-loan lender in China. Cash loans are small-dollar loans for personal consumption. At the end of 2017, the cash-loan market involved more than 600

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[1] Güth, Schmittberger, and Schwarze (1982) demonstrate this negative reciprocal behavior in an ultimatum bargaining experiment, and it has been observed consistently over time and across countries (Roth, Prasnikar, Okuno-Fujiwara, and Zamir, 1991). In the game, when subjects perceive their opponents as unfair, they tend to choose actions that penalize their opponents, even though these actions also hurt their own financial interests.

[2] The main progress on the empirical side of this literature has been the indirect evidence on fairness in labor markets. For example, more profitable firms tend to offer higher wages to their workers (Krueger and Summers, 1987; Blanchflower, Oswald, and Sanfey, 1996; and the references therein).

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lending platforms, 30 million borrowers, and $14 billion in outstanding balance.[3] Cash loans are typically extended to subprime borrowers, and they have high default rates. Debt collection is thus crucial for the industry's survival. However, as explained in Section 2.1, cash-loan lenders are handicapped in their collection abilities. Many lenders have thus attempted to collect debts by calling the borrowers' social contacts. Although this collection strategy may seem unusual, it is not confined to emerging economies.[4]

This debt-collection strategy has two effects on loan repayments. Ex ante, the concern of social sanction can be a powerful motivator of behavior (Bursztyn and Jensen, 2017). Prior literature shows that the threat of disclosing delinquency to a borrower's social circle invokes social pressure and reduces the borrower's default propensity (Brusa, Luo, and Fang, 2019; Diep-Nguyen and Dang, 2020). Ex post, such disclosure damages borrowers' social image. Some consider it unfair when lenders disclose personal information to their family and friends without obtaining their fully informed consent. The main hypothesis in our paper is that some borrowers may become enraged and choose to retaliate by deliberately defaulting on their loans, even though doing so is costly.[5] While the prior literature has offered insight into the ex-ante effect, to the best of our knowledge, our paper is the first to analyze the ex-post effect.

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[3] See https://news.p2peye.com/article-505707-1.html for detailed information.

[4] For example, The Washington Post reported on May 7, 2019 that debt collectors in the U.S. have also started monitoring delinquent borrowers' webpages on social media such as LinkedIn and Facebook. One debt collector even contacted a delinquent borrower's former boss and family members via social media. The Fair Debt Collection Practices Act of 1977 prohibits harassment in debt collection, but it does not address most forms of digital communication. See https://www.washingtonpost.com/business/2019/05/07/trump-administration-wants-allow-debt-collectors-call-times-week-text-email-much-they-want/?noredirect=on, last accessed on 5/27/2021.

[5] Defaulting is costly for at least three reasons. First, the default severs the borrower's tie to the platform and cuts off her future access to financing from that source. This is especially costly to financially constrained borrowers. Second, defaulters may be concerned about escalated harassment by debt collectors in the future. Third, repaying a debt is the right thing to do, and people tend to feel guilty if they do not do so (Benabou and Tirole, 2006; Guiso, Sapienza, and Zingales, 2013). The overall costs likely exceed the financial benefit of not repaying.

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The debt-collection procedure works as follows. During the first three days past the due date, the lender contacts borrowers via text messages and repeated phone calls, reminding them that their key social contacts will be notified if they do not repay immediately. These contacts are typically family members, friends, and colleagues with whom the borrowers frequently communicate via phone calls and text messages. The information is extracted from the borrowers' phone accounts.

Unpaid loans are marked as delinquent at the end of the third day past the due date. On the fourth day, collection agents make phone calls to the key social contacts of delinquent borrowers. For ease of exposition, we label a loan as *worked* if an agent reached any of the borrower's social contacts. A loan is *unworked* if the agent did not call or failed to reach any contact of the delinquent borrower.

To estimate the effect of the collection tactic, we rely on the fact that collection agents are routinely assigned tasks exceeding their capacities, and they manage to work on only 75% of delinquent loans. In allocating its collection efforts, the lender prioritizes borrowers who are more likely to repay. Each day, the lender generates a list of delinquent borrowers and the phone numbers of their key social contacts. These borrowers are ranked based on their repayment propensity as predicted by the lender's proprietary algorithm, with the borrower most likely to repay at the top of the list.[6] The lender then randomly divides the list among approximately 200 collection agents such that the overall predicted repayment propensity of each agent's list is comparable. Collection agents are instructed to start at the top of their lists and work their way down. They have no incentives to deviate from the prescribed order because they receive a fraction of the collected payments as compensation, conditional on reaching the delinquent

[6] Interviews with the management suggest that the lender prioritizes borrowers with a higher repayment propensity in its collection efforts. Our empirical evidence in Section 4 is consistent with this stated collection strategy. It is beyond the scope of this paper to evaluate whether this collection strategy is optimal from the lender's perspective.

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borrowers' social contacts as proved by phone records. Loans at the bottom of the list are often left unworked when the agent stops that day, and they are rarely revisited in the future.

Our strategy is to create a subsample consisting of comparable worked and unworked loans. For any agent on a given day, the loans worked on right before "stopping time" and those that barely missed the cutoff should be comparable. In this subsample, whether a loan is worked on or not depends on idiosyncratic factors that determine the agent's stopping time. However, there is one empirical challenge: the calls of all collection agents are pooled in our data. We know when a call was made, but not who made it. As these collection agents have flexible work hours, they may stop at different times of the day. Thus, we are unable to precisely identify the last few loans worked on by any individual agent.

To overcome this challenge, we use two approaches. The first is to construct a subsample that includes all unworked loans and the loans worked on after a certain time of day. We verify that the credit quality of worked borrowers deteriorates with the time of the collection calls and, towards the end of the day, becomes similar to that of unworked borrowers. This approach is simple and transparent, because the only discretion is the choice of the cutoff time. In our main analysis, we include all unworked loans and all loans worked on after 4 pm, which constitute a balanced sample. We find that the debt-collection tactic is associated with an increase of 5.9 percentage points in default propensity, after we control for loan and borrower characteristics. As we postpone the cutoff time, fewer worked loans are included in the subsample, but they become more similar to the unworked ones. The estimated effect of debt collection becomes stronger. For example, when we choose a cutoff time of 10 pm, the default rate of the worked loans is 14.3 percentage points higher than that of the unworked loans.

We obtained similar results using the Propensity Score Matching (PSM) approach. Specifically, we match each unworked loan with three worked loans based on their propensity to be worked on as predicted by observable borrower and loan characteristics. After we control for loan and borrower characteristics, the estimated treatment effect is 11.6 percentage points.

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To shed light on the economic mechanism, we conduct sub-period and cross-sectional analyses. The first analysis is based on the loan's origination month. The social-shaming debt-collection practice was introduced in late 2015, but it was hushed up until mid-2016 when the national media reported horrific cases involving student-borrowers' suicides.[7] These events caused widespread outrage, and the cash-loan business was banned from college campuses on August 24, 2016.

For most borrowers, the possibility that the lender would call their social contacts was unimaginable before the summer of 2016. Many borrowers were outraged by what they perceived as an unfair practice, even though they had authorized the disclosure of delinquency to third parties during the loan application process. As noted by Srivastava, Espinoza, and Fedorikhin (2009), anger triggered by a sense of unfair treatment contributes to retaliation in the ultimatum bargaining game. This implies that the negative reciprocity effect should be stronger in the first half of our sample (October 2015 to August 2016). Indeed, we find that the effect doubles in the first half of our sample and becomes insignificant in the second half.

We next examine the cross-sectional variation in the negative reciprocity effect. Since Knez and Camerer (1995), numerous experiments have shown in the context of the ultimatum bargaining game that negative reciprocity is stronger when the Responder has better outside options. In our context, retaliating against the lender may make the borrower feel good, but a defaulter will be banned from future financing at the platform. This penalty is less detrimental to borrowers who have better credit and more outside options, i.e., access to alternative financing sources. Thus, these borrowers should be better positioned to retaliate when their social circles are targeted. Our evidence is consistent with this insight: intrusive debt collection increases the default rate more for borrowers with better credit.

Moreover, we find that the debt-collection tactic substantially increases the default rate of male borrowers, while the effect is insignificant for female borrowers. This is consistent with

[7] See the report in The China Daily on June 16, 2016; Campus loans - Opinion - Chinadaily.com.cn.

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studies based on surveys and experiments, which suggest that men tend to display stronger negative reciprocal behavior than women (Eckel and Grossman, 2001; Burnham, 2007; Falk and Hermle, 2018).

An alternative interpretation of our results is that after the lender calls the borrowers' social contacts, the targeted borrowers have less left to lose and hence lower incentive to repay than untargeted borrowers. Ex ante, the threat of damaging borrowers' images in their social circles increases repayment propensity. Under this alternative hypothesis, lifting such a threat lowers the repayment propensity. That is, the collection calls negate the ex-ante effect, leading to a higher default rate among targeted borrowers and hence the appearance of retaliation. While this mechanism might have contributed to the higher default propensity of worked loans, it is unlikely to account for our overall results for the following two reasons.

First, prior literature suggests that the ex-ante effect should be stronger among women because they tend to value privacy more than men do (Goldfarb and Tucker, 2012; Prince and Wallsten, 2020; Tang, 2020). Hence, the alternative interpretation suggests that we should see a stronger appearance of retaliation among female borrowers. This is the opposite of our evidence on gender. Second, the rampant media coverage of aggressive debt collections in the summer of 2016 enhanced the salience of the damage to targeted borrowers' social images and strengthened the ex-ante effect. Thus, the alternative interpretation suggests that we should see a stronger appearance of retaliation in the second half of our sample, which goes against our evidence from the sub-period analysis.

We further examine an alternative interpretation based on the potential responses of the targeted borrowers' social contacts. After the debt-collection calls, a borrower's social contacts may become less willing to help the borrower with liquidity needs. This would tighten the borrower's liquidity constraints and exacerbate his ability to repay the loan. However, we do not find any evidence supporting this interpretation. Specifically, we obtain the delinquent borrowers' purchasing records on Taobao, the biggest online shopping website in the world, which accounts

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for over 80% of online retail sales in China. We detect a decrease in their online consumption around delinquency, but the intrusive collection tactic does not further reduce the consumption of the targeted borrowers.

1.1 Literature

Our research contributes to four strands of literature: reciprocity, privacy, social incentives in contract enforcement, and FinTech applications in consumer finance.

Prior research examining the role of reciprocity in key areas in economics is based primarily on experiments (Fehr and Gächter, 2000). Recent research shows that reward-based crowdfunding relies on positive reciprocity among the backers and creators of the projects (Boudreau, Jeppesen, Reichstein, and Rullani, 2018). To the best of our knowledge, our paper is the first to provide direct empirical evidence of negative reciprocity in a financial market. The phenomenon analyzed in our paper is consistent with the premise of Hart and Moore (2008), who argue that a party may “shade” on performance if he is “shortchanged” by the other party based on his understanding of contracting terms. In our context, the privacy infringement is the perceived shortchanging; in response, delinquent borrowers shade their performance by reducing their repayment efforts.

Our paper is related to the literature on privacy and consumer decisions (Athey, Catalini, and Tucker, 2017; Kummer and Schulte, 2019; Tang, 2020). Granting lenders access to their mobile phone accounts is one example of how “consumers’ ability to make informed decisions about their privacy is severely hindered because consumers are often in a position of imperfect or asymmetric information regarding when their data is collected, for what purpose, and with what consequence” (Acquisti, Taylor, and Wagman, 2016). Two findings in this literature are closely related to our research. First, individuals value their contacts and social media accounts more than they value other private information such as browsing history and location (Savage and Waldman, 2013; Tang, 2020). Second, women generally value privacy more than men do

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(Goldfarb and Tucker, 2012; Prince and Wallsten, 2020). Our paper adds to this literature by examining the consequences of privacy infringement in financial markets.

Our paper also adds to the growing literature on debt collection.[8] Studies on how lenders interact with debtors in collection are rare, mainly due to data limitations. Positive reminders and pleasant personal phone calls are shown to be effective in preventing default (Du, Li, Lu, and Lu, 2020; Laudenbach, Pirschel, and Siegel, 2018). In addition, the anticipation of social shaming significantly reduces delinquency and default (Brusa, Luo, and Fang, 2019; Dai, Han, Shi, and Zhang, 2020; Diep-Nguyen and Dang, 2020). Complementing these three papers on the ex-ante effect of social incentives on debt repayments, we focus on the ex-post effect of social shaming.[9]

Finally, our research contributes to the growing literature on the influence of FinTech on consumer finance (Carlin, Olafsson, and Pagel, 2020; D'Acunto, Prabhala, and Rossi, 2019). D'Acunto, Rossi, and Weber (2020) analyze the influence of information about peers' spending. Technology has greatly expanded the information lenders can use to evaluate the credit of loan applicants (Dobbie, Liberman, Paravisini, and Pathania, 2018; Fuster, Goldsmith-Pinkham, Ramadorai, and Walther, 2017). Non-credit score information is shown to be effective in alleviating the information asymmetry between borrowers and lenders (Berg, Burg, Gombović,

[8] Information technology has improved the efficiency of debt collection and helped expand consumer lending (Drozd and Serrano-Padial, 2017), while regulatory changes that restrict debt-collection activities lead to a decrease in access to credit and a deterioration of financial health (Fonseca, Strair, and Zafar, 2017). Regarding debtor outcomes, consumer bankruptcy protection is shown to increase annual earnings and decrease foreclosure and mortality (Dobbie and Song, 2015). In contrast, settlements of civil collection lawsuits increase financial distress relative to going to court, especially among less financially literate consumers (Cheng, Severino, and Townsend, 2021). Among debt-relief programs, delayed interest write-downs are more effective than immediate payment reductions (Dobbie and Song, 2020).

[9] Dai et al. (2020) also analyze delinquent borrowers' ex-post responses to collection phone calls to their social contacts. However, they focus on comparing the borrowers who provided their social contacts with those who did not.

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and Puri, 2020; Duarte, Siegel, and Young, 2012; Iyer, Khwaja, Luttmer, and Shue, 2016). Our paper highlights the potential large-scale misuse of personal information, which is important yet understudied in the FinTech literature.

The rest of the paper is organized as follows. In Section 2, we describe the institutional background and data for this study. In Section 3, we describe the empirical design. The main results and the mechanism are reported in Sections 4 and 5. Section 6 discusses alternative interpretations of our results, and Section 7 concludes.

2 Institutional Background and Data

2.1 The cash-loan industry in China

Most households in China had no access to consumer credit until recent years. The World Bank Group reported that among the 910 million individuals covered by the People's Bank of China's (PBC) credit reporting system in May–June 2017, only 430 million had a credit history. For the rest of the population, it is very difficult to obtain consumer credit from financial institutions.[10]

Starting in 2012, various online lending platforms have emerged to fill the void. One consumer credit product is the so-called "cash loan," which is a misnomer since no cash is involved and the entire business is conducted online. Cash loans are uncollateralized small-dollar loans for subprime borrowers' personal consumption. The term of a cash loan varies from 1 to 12 months. Cash-loan lenders rely on a variety of information sources for their credit assessments. Compared with financial institutions, cash-loan lenders require much less documentation from borrowers. With the development of the FinTech industry, the cash-loan market has experienced an explosive growth since 2014 and reached $14 billion in 2017.

[10] See The World Bank Report of December 2017. The People's Bank of China, the central bank in China, defines financial institutions as commercial banks and non-depository financial institutions such as financial trust and investment corporations, financial leasing companies, auto-financing companies, and loan companies.

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Figure 1 illustrates a typical application procedure for cash loans. It starts when the borrower installs the lender's mobile application (app) on his mobile phone. To install the app, the borrower must provide his mobile phone account information, via which the lender can identify the borrower's key contacts from text messages, phone call records, etc.

After the installation, the loan applicant creates an account to initiate his application via the app. The account creation requires a national ID number, a debit card number, and a cell phone number registered under the borrower's name for identity verification. The national ID number in China is similar to the Social Security Number in the U.S. The debit card is linked to the applicant's bank account and used to transfer funds. To proceed, the applicant must authorize the lender to collect personal information for "credit evaluation and other business purposes." With verified identity information and the borrower's authorization, the lender can access the borrower's criminal records, administrative sanction records, and mobile phone bills, as well as other information collected by third-party information service providers.

Using the gathered information, the lender generates an internal credit score for the applicant. The application is approved if the credit score surpasses a certain threshold. Upon approval, the applicant obtains a credit line with a predetermined interest rate, term, and fee. The borrower can simply draw down his credit line when needed. The withdrawal amount will be deposited to the borrower's bank account immediately. This auto-processing procedure allows the borrowers to access credit in just seconds.

Borrowers are expected to pay equal monthly installments for the principal and interest. The lender sends the borrower reminder messages before each due date. If the installment is not fully paid by the due date, borrowers will be texted repeatedly with information on the due date, amount due, and penalty charges. In line with common practice in the Chinese consumer-lending market, a loan is considered delinquent if an installment is not fully repaid three days after the due date and is considered in default if it is not fully paid 60 days after the due date.

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Cash-loan lenders are handicapped in their collection abilities. These loans are uncollateralized and small, so it is economically infeasible to collect via litigation. In addition, the public credit registry in China has only limited coverage of individuals; during our sample period, it gathered loan performance information exclusively from financial institutions.[11] Thus, high-tech lenders of cash-loans are unable to discipline borrowers by reporting loan defaults to the public credit registry.

As in many emerging economies, social capital plays a critical role when delinquency occurs in the close-knit Chinese society. Even the court system in China sometimes relies on social shaming to enforce debt payments. For example, the huge electronic screens in Shanghai railway stations displayed the names, photos, identification card numbers, registered addresses, and the amount of money owed (ranging from $297 to $437,117) for eight people and 10 companies that failed to repay their debts in defiance of court orders. The debtors' personal information appeared every 10 minutes from 9 am to 10 pm for seven days in July 2016.[12]

It is perhaps not surprising that cash-loan lenders resort to the shaming strategy to improve debt collection. Our lender is believed to be the first to adopt the controversial collection tactic that targets the social circles of delinquent borrowers in October 2015. Presumably, by exerting social pressure, lenders hope to reduce the moral hazard problem among borrowers, which occurs when borrowers are unwilling to repay even though they can. Our goal is to analyze the consequences of this intrusive collection strategy.

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[11] FinTech companies that participated in the consumer lending market are not financial institutions under China's regulatory framework. Cash loans were not typically financed by financial institutions. These ultimate lenders were required to report loan performance to the public credit registry. Our platform did not use funds from any financial institutions during our sample period. Reporting regulation changed after our sample period ended. In December 2020, the China Banking and Insurance Regulatory Commission and the PBC proposed rules to regulate small-dollar internet loans. Rule 16 recommends that small-dollar lenders report loan performance to the public credit registry under the PBC or the credit bureau approved by the PBC (namely, Baihang Credit).

[12] "Defaulters shamed at Shanghai railway stations," *Shanghai Daily*, July 6, 2016; see http://www.china.org.cn/china/2016-07/06/content_38820236.htm, last accessed on May 27, 2021.

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The ensuing anger suggests that this innovation was probably beyond the imagination of the borrowers, at least initially. The lender disclosed private information on the borrowers' loan delinquency to their social circles without explicit permission, infringing on borrowers' privacy. Although all borrowers authorized the lender to access their phone books and allowed the delinquency information to be shared with third parties, the actual identities of the third parties and the method of disclosure were not clearly defined when the borrower granted disclosure permission during the loan application process. This practice became more widespread in the industry over time and provoked a public outcry in mid-2016 after several tragic events grabbed national attention.

2.2 Data

Our data are from a leading cash-loan lender in China. This lender targets young borrowers whose credit records are too thin for them to obtain bank loans. The lender provides them with easy access to uncollateralized consumer credit. We obtained the records of a random sample of 7,308 borrowers from October 1, 2015 to March 31, 2017.[13] The data include detailed information on borrower and loan characteristics, as well as repayment and debt-collection records.

In our sample of 7,308 borrowers, 3,101 have at least one delinquent loan that entered the debt-collection stage.[14] For convenience, we refer to the sample of delinquent borrowers as the "original sample" for debt collection. We adopt this term to contrast it with its two subsamples, which we define as follows. The lender had resources to execute the new collection

[13] We originally obtained the records of a random sample of 10,000 borrowers from November 1, 2014 to July 3, 2017. The data before October 1, 2015 were excluded because the debt-collection strategy was not clearly defined during that period. Our sample stops on March 31, 2017 to ensure that the performance of all the loans is observable.

[14] When a borrower has multiple delinquent loans at the time of the collection call, we keep the loan whose due date plus four days is closest to the date of the collection call. Our results are very similar if we keep the first delinquent loan instead.

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strategy on some of the loans. We refer to the subsample where the collection strategy was implemented on the first day after a loan entered the debt-collection stage as the "worked sample" and the rest of the original sample as the "unworked sample."[15]

Table 1 reports the summary statistics of the original sample. As the first row shows, 75% of the loans were worked. Moreover, 43% of the loans defaulted. The average loan size is 1,751 RMB (approximately $250), and the average term is 6.4 months. The lender did not provide us with the interest rates the loans but did provide a categorical variable that ranges from 1 to 10, with 1 representing to the lowest interest rate and 10 the highest. Sixty-five percent of borrowers are new customers. The borrowers' average age is 26 years. About 80% of the borrowers are male. Forty-six percent of the borrowers live in big cities, which are defined as Tier 1 and Tier 2 cities in China.[16] On average, a borrower has 248 contacts in the address book of his mobile phone.

After the approval of the initial credit line, borrowers are encouraged to disclose additional information, such as information on their social media accounts and online shopping and payment accounts. The lender may increase the borrower's credit limit after observing favorable information. As Table 1 shows, 79% of the borrowers in our sample voluntarily provided the lender access to their online shopping account with Taobao.

Using all of the information above, the lender classifies borrowers into six credit rating categories (categories A through F) based on its proprietary algorithm. The credit rating distribution is reported in Panel B. The highest credit rating, A, accounts for 10.77% of the

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[15] In our sample, 97% of the collection phone calls occurred on the first day after a loan entered the debt-collection stage, which is the fourth day past the due date. On rare occasions, a collection agent may fail to work on the day she receives the list (e.g., due to health reasons or family emergencies). She will get back to the list when she resumes working. Our results remain similar if we define the worked sample as all loans on which this collection strategy was implemented.

[16] Four Tier 1 cities are Beijing, Shanghai, Guangzhou, and Shenzhen, each of which has a population over 10 million. There are 36 Tier 2 cities, most of which are provincial capitals. The average population of Tier 2 cities is around 8 million (China Statistical Yearbook; see www.stats.govn.cn/tjsj/ndsj/2019/indexeh.htm.)

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sample, while the lowest credit rating, F, accounts for 11.87%. The distribution across credit grades is generally even, with relatively more borrowers in the C and D ratings.

2.3 Debt-collection procedure

Our lender relies on social shaming for debt collection. The procedure works as follows. In the first three days past the due date, it contacts borrowers via text messages and repeated phone calls, reminding them that their key social contacts will be notified if they do not repay immediately. Unpaid loans are marked as delinquent at the end of the third day past the due date.

Each morning, the lender compiles a list of borrowers who have entered delinquency. Delinquent borrowers are ranked by their repayment propensity as predicted by the platform's proprietary algorithm; borrowers at the top of the list are most likely to repay. The phone numbers of the borrowers' key social contacts are also included in the list. The lender divides the list among approximately 200 in-house collection agents, who are trained to closely follow suggested scripts to minimize the influence of their emotions. Collection agents call to notify the borrower's key contacts about the delinquency and ask them to urge the borrower to repay.[17] Collection agents are instructed to start at the top of their lists and work their way down. They have no incentive to deviate from the prescribed order when calling, because their compensation depends on the repayments of the loans they have worked on, as supported by phone records.

Due to the excessive number of delinquent loans, agents are assigned more work than they have time to complete. At the end of each day, the loans at the bottom of the list are left untouched. These borrowers' social contacts are rarely called in the future because their loans are presumably less collectable than the delinquent loans that enter the collection pool the following day.

[17] These collection phone calls are typically very brief. For example, the agent reads the following script: "Do you know Mr. XYZ? He is delinquent on a loan from Platform ABC. Could you please urge him to repay immediately? Thank you!"

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Panel C of Table 1 describes the time of day when the collection phone calls occur. More than half of the collection calls were made between 9 and 11:59 am. Perhaps due to lunch breaks and the habit of taking a nap after lunch, only nine calls occurred between noon and 12:59 pm. Activities started picking up in the afternoon and continued until midnight. On any given day, an agent is free to determine her own schedule. The stopping time is determined primarily by her personal situation, which explains why the collection times are spread throughout the day. In general, more agents work in the morning than later in the day.

3 Empirical Design

Our goal is to analyze the treatment effect of the intrusive collection tactic on borrowers' repayment behavior. A direct comparison of the default rates between the worked and unworked loans would reflect a selection effect (in addition to the treatment effect) if the lender follows a systematic strategy in implementing its collection tactic. Indeed, the lender explicitly states that it prioritizes borrowers with higher predicted repayment propensity in its debt-collection efforts. Moreover, collection agents have a strong incentive to follow the order as their compensation is directly linked to the collected payments from the delinquent loans they worked on.

Panel D of Table 1 shows that the worked and unworked samples are systematically different. Worked loans are smaller and have a lower interest rate and a shorter term, and their borrowers have made more payments than the borrowers of unworked loans. In addition, borrowers of worked loans are more likely to be male and repeat borrowers, to live in a big city, and to disclose Taobao account information; they also have more social contacts and better credit than borrowers of unworked loans.

To shed further light on the lender's collection strategy, we examine the loan and borrower characteristics of the loans worked on during each hour of the day. In Panels A through C of Figure 2, we plot three key characteristics against $CallTime_i$, which is the hour of the day

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when borrower i's social contacts were called. For example, we use 10 to denote calls made from 10 to 10:59 am.[18] Group 99 represents unworked loans.

Panel A plots the average credit ratings of the borrowers worked on during each hour of the day. We convert credit ratings A through F into numerical values of 1 through 6, respectively. Hence, a higher numerical value represents a lower credit rating. Panel A shows that the average credit rating deteriorates during the late hours, especially after 8 pm.

The literature has shown that repeat borrowers are more likely to repay, given the value of the lending relationship (Liao, Martin, Wang, Wang, and Yang, 2020). Panel B plots the fraction of new borrowers against $CallTime_i$ and shows a clear upward trend towards the end of the day, especially after 4 pm.

If a borrower has made a larger fraction of loan payments, he has less incentive to default. Accordingly, Panel C shows a clear downward trend in the average number of payments normalized by the loan term, especially after 4 pm.

Panel D of Figure 2 plots the average default rates against $CallTime_i$. The clear upward trend suggests that the loans worked on during the late hours of the day have higher default intensity. We further examine this relationship using the following Probit regression for worked loans:

$$Prob(Default_i = 1) = \Phi(\alpha + \beta CallTime_i + \gamma X_i + \epsilon_i) \tag{1}$$

where $\mathrm{Default_i}$ is a dummy variable that is 1 if borrower i defaulted on his loan, and 0 otherwise; X_i denotes loan and borrower characteristics, including the loan size, term, number of payments, interest rate, application date, gender, age, the number of contacts in the address book of the borrower's mobile phone, and credit rating. The regression also includes dummy variables that indicate whether the borrower lives in a big city, whether the borrower voluntarily provided

[18] There are three exceptions: group 9 includes all calls made from 9 to 9:59 am and one made before 9 am, group 11 includes all calls made from 11 to 11:59 am and nine calls made from noon to 12:59 pm, and group 22 includes all calls made from 10 to 10:59 pm and four made after 11 pm.

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access to his Taobao account, and whether the borrower is a new customer. $\Phi(\cdot)$ is the CDF of a standard normal distribution. The regression results reported in Table 2 confirm the pattern shown in Panel D of Figure 2. In terms of economic magnitude, calling a borrower's social contacts one hour later corresponds to a 0.5% increase in the loan's default rate, after we control for loan and borrower characteristics.

The above results are consistent with the lender's stated collection strategy of prioritizing loans with a higher repayment propensity. Moreover, the lender appears to have the information necessary to predict the repayment propensity. Therefore, the selection effect would drive up the repayment rate of the worked loans. A direct comparison of the default rates of the worked and unworked loans would overstate the effectiveness of the collection strategy.

3.1 Identification strategy

To estimate the treatment effect of debt collection, we need to create a subsample in which borrowers were randomly chosen for debt collection. We take advantage of the fact that collection agents were regularly assigned more work than they could finish due to the excessive number of delinquent loans. Each day, they started calling from the top of the list and stopped at their preferred time, which was presumably determined by their personal situations. The loans at the bottom of their lists were left unworked. Thus, for any agent on a given day, the few loans worked on immediately before the stopping time closely resemble the loans that barely missed the cutoff point for collection. The agents would have worked on these loans if they had decided to continue a little longer.

Our identification strategy is to create a subsample of loans "around the stopping time." In this subsample, whether a loan is worked on or not depends primarily on idiosyncratic factors that determine the collection agents' stopping time each day. However, the empirical challenge is that we do not have access to the lender's recommended calling sequences, nor do we have

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the information to link the worked loans to the agents who made the phone calls. To overcome this, we take two approaches.

3.2 Approach 1: Analysis based on a cutoff time

Our first approach constructs a subsample that includes all the unworked loans and the loans worked on after a certain time of day. We use this empirical design because the lender's stated collection strategy is to prioritize borrowers with higher predicted repayment propensity, which we verified in Section 3.1. Hence, the loans that are worked on during the later hours of a day are on average closer to the stopping time.

Note that collection agents have flexible work hours. For example, one agent may work from 9 am to 5 pm, so the collection calls made from 4 to 4:59 pm are her last few calls. Another agent may work from 1 pm to 10 pm, so the calls made from 9 to 9:59 pm would be her last few. We do not have the information to attribute debt-collection calls to individual agents or to infer the stopping time for each agent, which prevents us from precisely identifying the loans worked on immediately before the stopping time. Instead, we simply use a specific time of the day as the cutoff point to generate the matched sample, because loans worked on towards the end of a day are more likely to be at the bottom of the list and better resemble the unworked loans.

To test the effect of intrusive collection on default propensity, we run the following Probit regression on the subsample:

$$Prob(Default_i = 1) = \Phi(\alpha + \beta Work_i + \gamma X_i + \epsilon_i) \tag{2}$$

where Default_i is an indicator for loan default; $Work_i$ is 1 if borrower i is worked on, and 0 otherwise; X_i includes all control variables; and $\Phi(\cdot)$ is the CDF of a standard normal distribution. The coefficient estimate of β measures the effect of collection on default propensity.

In the baseline regression, we choose 4 pm as the cutoff time to create the subsample. This construction provides a balanced sample of 713 unworked loans and 694 worked loans. We then vary the cutoff time to create alternative subsamples to further examine the treatment effect.

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A later cutoff time implies that the worked loans are more likely to be at the bottom of the list; hence, they are more comparable to the unworked loans. This leads to a more accurate estimate of the treatment effect. However, using a later cutoff time reduces the sample size and enlarges the estimation error.

3.3 Approach 2: Propensity Score Matching (PSM)

Approach 1 is simple and transparent. It leaves little room for subjective choices. However, as collection agents have flexible working hours, a fixed cutoff time would introduce noise to our estimation. Suppose we use 4 pm as the cutoff time. If an agent stops working at 3 pm, the worked loans at the bottom of his list would not be included in the treatment sample. Conversely, for an agent who starts calling at 4 pm and stops at 10 pm, all the loans she works on enter the treatment sample, even though those at the top of her list are not comparable to the unworked loans. Moreover, the matched sample of Approach 1 includes all unworked loans, and those at the very bottom of the list may have much lower repayment propensity and may not closely resemble the loans in the treated sample.

Fortunately, our data are granular enough to allow us to fine-tune the procedure using the PSM method. We first calculate each loan's propensity to be worked on based on observable borrower and loan characteristics. We match each unworked loan with worked ones that have the closest propensity. We then use the matched sample to estimate the treatment effect of debt collection. The estimated treatment effect is very similar to that based on the procedure discussed in Section 3.2. Hence, we will rely mainly on the first approach.

4 Main Results

This section estimates the effect of debt collection on borrowers' default propensity using the subsamples constructed based on various cutoff times. Section 4.1 presents the results of the main analysis, and Section 4.2 examines the economic mechanism.

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4.1 The treatment effect of debt collection—main analysis

To estimate the treatment effect of debt collection, we run the Probit regression specified in Equation (2) and report the results in Table 3. The coefficient of $Collect_i$ is positive and statistically significant at the 5% level. Economically, the coefficient estimate of 0.218 corresponds to an increase of 5.9 percentage points in default propensity. Given that the average default rate of unworked (delinquent) loans is 60%, this increase in default propensity corresponds to 10% of the sample mean. This finding suggests that although the controversial collection tactic was designed to pressure delinquent borrowers to repay their loans, the tactic appears to have backfired and *increased* borrowers' default propensity.

Our interpretation is that although the borrowers authorized the lender to disclose their delinquencies to third parties when they applied for the loan, they had probably never imagined that the lender would call their social contacts. Some of the targeted borrowers were angered by the intrusive collection tactic and reciprocated negatively, choosing to default even when they were able to repay. This is similar to the angry Responder's action triggered by unfair treatment in the ultimatum bargaining game (Srivastava, Espinoza, and Fedorikhin, 2009).

In the above analysis, the cutoff time for selecting worked loans to construct the subsample is 4 pm. For an agent who stops much later than 4 pm, the treatment sample includes the loans that she worked on well before her stopping time. These loans tend to have higher repayment rates than the loans worked on near the stopping time, as illustrated in Figure 2. Hence, the above estimates would overstate the repayment rate of the treatment group and *underestimate* the retaliation caused by debt collection. Adjusting the cutoff time to a later time of day narrows the "bandwidth," and the worked loans become more similar to the unworked ones. Hence, the selection bias diminishes, and the estimated treatment effect should be larger.

This is exactly what we find in Table 4. We construct the matched samples using 4 pm, 5 pm, 6 pm, 7 pm, 8 pm, 9 pm, and 10 pm as the cutoff time. The estimated treatment effect increases with the cutoff time in general. For example, if we include only loans worked on after

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10 pm, debt collection is linked to an increase of 14.3 percentage points in default propensity. Not surprisingly, Column 4 shows that the sample size decreases as the cutoff time moves to a later hour of the day. Accordingly, the standard error of the estimated treatment effect increases.

It is worth noting that our results do not necessarily imply that the intrusive collection tactic reduces the lender's overall profits, because our analysis focuses on the ex-post effect. Ex ante, the collection tactic could pressure borrowers and thereby reduce the delinquency rate in the first place. Had none of the delinquent borrowers' social contacts been called, the threat of damaging the borrowers' social image would be empty and the ex-ante effect would not exist. Our data do not permit us to estimate the ex-ante effect precisely.[19]

4.2 Economic Mechanism

The goal of the debt-collection tactic is to pressure delinquent borrowers to repay. The lender hopes that social norms may push the borrowers to make an extra effort.[20] However, this tactic may have backfired. It may have embarrassed and angered some borrowers so much that they retaliated by refusing to make further payments even if they had the means to do so. Anecdotally, online discussions echo this sentiment. Many borrowers expressed their anger about the collection tactic and claimed that they would not repay even if they could afford to.

This retaliatory response is consistent with the idea of *negative reciprocity* in the psychology literature. Fehr and Gächter (2000, p. 159) explain reciprocity as follows: "in response to friendly actions, people are frequently much nicer and much more cooperative than

[19] Anecdotal evidence suggests that aggressive debt collection may not be in the lenders' best interest. For example, JP Morgan Chase robo-signed court documents in an attempt to collect delinquent credit card debt in 2015. Chase paid $216 million in total in consumer refunds and penalties and was ordered to permanently stop all attempts to collect, enforce in court, or sell more than 528,000 consumers' accounts. Source: https://www.consumerfinance.gov/about-us/newsroom/cfpb-47-states-and-d-c-take-action-against-jpmorgan-chase-for-selling-bad-credit-card-debt-and-robo-signing-court-documents/ on July 8, 2015 by CFPB.

[20] Historically, China has had strong social norms about repaying one's debts. This belief is exemplified by an old saying: "A murderer must pay with his life just as a borrower must pay with his money."

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predicted by the self-interest model; conversely, in response to hostile actions they are frequently much more nasty and even brutal."

In the context of debt collection, targeted delinquent borrowers feel surprised and offended by the privacy intrusion. The sense of unfairness may push some borrowers to take retaliatory action by simply refusing to repay. In this section, we examine the variations of the treatment effect over time and in the cross-section to shed light on the economic mechanism.

4.2.1 Unfair treatment

Anger caused by a sense of unfair treatment contributes to retaliation in the ultimatum bargaining game (Srivastava, Espinoza, and Fedorikhin, 2009). In our context, the social-shaming tactic emerged in October 2015 and became widely known in mid-2016 when a number of high-profile incidents, including student-borrowers' suicides, were extensively covered in the media. This led to widespread outrage, and the cash-loan business was banned from college campuses on August 24, 2016. Hence, the intrusive debt-collection tactic was more surprising to borrowers in the first half of our sample (October 2015 to August 2016). Surprised by what they perceive as an unfair practice, borrowers are more likely grow angry about the collection calls. Thus, the negative reciprocity effect should be stronger in the first half of our sample, everything else equal.

We first compare the characteristics of loans and borrowers in the two subsamples. Panel A of Table 5 shows that loans have a lower interest rate, a shorter term, and a larger fraction of repayment in the second half than in the first half of the sample. Borrowers' credit quality is also better: they have more social contacts and are more likely to live in large cities, disclose Taobao account information, and be repeat borrowers. Not surprisingly, we find a lower default rate in the second half of our sample (0.45 vs. 0.39).

We then examine the effect of debt collection in the two sub-periods separately. Consistent with our hypothesis, the negative reciprocity effect is indeed stronger in the first half of our sample. Specifically, Column 1 of Panel B shows that this collection tactic is associated with a 10.6 percentage point increase in defaults for the first half of our sample, nearly double the effect

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of the main sample. In contrast, Column 2 shows that collection does not have a significant effect on loan default in the second half of our sample.[21] Therefore, we focus on the first half of our sample for subsequent analyses.

4.2.2 Gender difference

Numerous studies have examined the role of gender in negative reciprocal behavior. Using survey data across countries, Falk and Hermle (2018) show that women are more prosocial and less negatively reciprocal than men. Evidence in the context of the ultimatum bargaining game is also suggestive. Burnham (2007) finds that male players' negative reciprocal behavior is correlated with their testosterone level. This evidence leads us to expect stronger negative reciprocity in men than in women. In addition, Eckel and Grossman (2001) show that women are more likely than men to accept any given offer, which suggests that men display stronger negative reciprocal behavior. The above studies are based on survey or experimental data. We examine whether the same insight applies to a financial market.

We introduce an interaction term *Work*×*Male* into Probit regression (2) and use the following regression specification:

$$Prob(Default_i = 1) = \Phi(\alpha + \beta Work_i + \eta Work_i \times Male_i + \gamma X_i + \epsilon_i) \tag{3}$$

where $Male_i$ is a dummy variable that is 1 if borrower i is a male, and 0 otherwise; X_i includes all control variables (including $Male_i$).

As shown in Panel A of Table 6, the coefficient of *Work*×*Male* is positive and statistically significant at the 10% level. Combining the coefficient of *Work* and the interaction coefficient, we obtain the marginal effect of the debt collection on the default rate for female and male borrowers. Panel A of Figure 3 plots the implied marginal effect with its 95% confidence interval

[21] The relative magnitude of the debt-collection effect in the two sub-periods of our sample is driven by two forces. On one hand, borrowers in the latter period were less surprised by the collection calls and thus retaliated less. On the other hand, these borrowers have better credit (as reported in Panel A of Table 5) and may have access to alternative financing and thus retaliate more (to be reported in Section 4.2.3). Our empirical findings suggest that the former dominates.

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for each category. The marginal effect of collection on the default rate is 12.8% (s.e. = 3.1%) for male borrowers. That is, the debt collection has a significantly positive effect on the default rate of male borrowers. For female borrowers, the marginal effect is 3.4% (s.e. = 5%) and statistically insignificant. Hence, our evidence supports the hypothesis that male borrowers exhibit stronger negative reciprocity.

4.2.3 Outside options—credit quality

Knez and Camerer (1995) and several other experimental studies have shown that in ultimatum bargaining games, negative reciprocity is stronger when the responder has better outside options. In our context, borrowers with better credit have better outside options. They are more likely to have access to alternative financing sources and thus may be less concerned about severing their ties to a particular lender. When they consider the lender's harassment of their social circles an insult, borrowers with good credit are in a better position to retaliate. We use the credit ratings determined at the time of the borrowers' loan applications, which do not reflect the delinquency of the loan. Our hypothesis is that borrowers with higher credit ratings have stronger retaliatory responses to the intrusive debt collection.

There are six credit ratings, A through F. Using the A rating as the baseline case, we introduce the interaction terms between *Work* and the five credit rating dummies (for ratings B through F) into the regression; that is, we replace *Male* with *Rating B* through *Rating F* in the interaction terms of regression specification (3). The results are reported in Panel B of Table 6.

The coefficient of *Work* is 1.258 (s.e. = 0.386), which implies that the intrusive debt collection substantially increases the default probability of A-rated borrowers. Moreover, the interaction coefficients are all negative and display a generally decreasing pattern from rating B to rating F. Consistent with the hypothesis, the retaliatory response to the debt collection is weaker for borrowers with lower credit ratings.

Panel B of Figure 3 plots the implied marginal effect for each rating category with its 95% confidence interval. It clearly shows negative reciprocity for A- and B-rated borrowers. The

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debt-collection tactic increases their default rate by 33.1 and 35.0 percentage points, respectively. The reciprocity effect is weaker for D- and C-rated borrowers.

For F-rated borrowers, the collection tactic reduces the targeted borrowers' default rate by 27.8 percentage points. Collection calls can have two countervailing effects. On one hand, targeted borrowers may ramp up their repayment efforts when they are actually facing pressure from their social contacts. On the other hand, the intrusive collection tactic may trigger negative reciprocity. As noted earlier, the reciprocity effect is weaker for borrowers with bad credit. For F-rated borrowers, the social pressure effect dominates the negative reciprocity effect; hence the debt collection tactic reduces their default rate.

4.2.4 Outside options—Taobao account disclosure

Recall that during the loan application process, loan applicants are encouraged to disclose information about their online activities, with the stated purpose of better credit analysis. Around 80% of the borrowers voluntarily provided the lender with access to their online shopping account at Taobao, a comprehensive online marketplace that consists of the C2C platform taobao.com and the B2C platform tmall.com. A vast number of sellers provide goods and services on these two sites, which carry almost everything needed in daily life. Transactions on Taobao account for over 80% of all online retail sales in China.[22]

By disclosing their online shopping information and payment history, borrowers with higher repayment capacity wish to signal their good credit quality and receive better financing terms. Consistent with this view, the negative coefficient estimate for *Taobao* in Tables 2 and 3 suggests that Taobao disclosers are indeed less likely to default. Thus, they should have better outside options (i.e., greater financing capacity) than other borrowers. We hypothesize that Taobao disclosers can better afford to sever their ties with the lender and thus retaliate more in response to the intrusive debt-collection tactic.

[22] See Fan, Tang, Zhu, and Zou (2018) for more details on the Chinese online retail industry and Taobao platforms.

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We test this hypothesis by including an interaction term *Work×Taobao* (to replace *Work×Male*) in regression (3), where *Taobao* is an indicator that is 1 if the borrower provided access to his Taobao account, and 0 otherwise. Consistent with our hypothesis, the interaction coefficient is 1.444 (s.e. = 0.271) in Panel C of Table 6. That is, Taobao disclosers appear to respond more strongly to intrusive debt collection. The debt-collection tactic increases their default rates by 24.5 percentage points. For non-disclosers, the social pressure effect dominates the reciprocity effect, and collection calls actually reduce the default rate by 14.6 points. The implied marginal effects on the default rates are illustrated in Panel C of Figure 3.

5 PSM Analysis

In this section, we construct a matched sample using the PSM approach to account for selection bias and to estimate the local treatment effect. We focus on the first half of our sample period. The same conclusion holds for the whole-sample analysis.

The matching procedure is as follows. For each unworked loan, we select four worked loans (n=4) that have the closest propensity to be worked on, which is calculated based on loan and borrower characteristics.[23] In the matching process, we include all worked loans, regardless of the time when collection calls are made. We keep a matched worked loan only if its propensity score is sufficiently close to that of the unworked loan, using a caliper of 0.001 (the standard deviation of the difference in propensity scores is 0.01). Replacements of worked loans are allowed as matching proceeds. We can match 214 unworked loans with 432 unique worked loans. In an unreported Kolmogorov–Smirnov test, we find that the call-time distribution of the matched worked loans lies to the right of that of the original worked loan sample. Thus, our PSM procedure tends to select loans worked on later in the day.

[23] Our results are robust when we set n=3 or n=5 in the matching procedure.

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Panel A of Table 7 shows that in the matched sample, worked loans resemble unworked ones in all observable borrower and loan characteristics. Thus, whether a loan is worked on or not depends on idiosyncratic factors that determine the time when collection agents stop working. In the absence of treatment, loans in the matched sample would have similar default propensities. Hence, the difference in default propensity reflects the treatment effect, that is, the effect of the intrusive collection. The last row shows that worked loans are more likely to default by 17 percentage points. The difference in default propensity is statistically significant at the 1% level.

We further estimate the effect of the debt collection using a Probit regression for the matched sample, as specified in Equation (2). All observable loan and borrower characteristics are included in the regression. Panel B shows that the coefficient estimate for *Work* is positive and statistically significant at the 1% level. This suggests that the intrusive collection tactic increases the default rate by 11.6 points. Overall, the results of the PSM analysis confirm the conclusion of the baseline analysis: intrusive debt collection leads to more default.

6 Alternative Interpretations

In Sections 4 and 5, we show that debt collection leads to an increase in the default propensity of targeted borrowers, and we attribute this effect to negative reciprocity. In this section, we discuss two alternative interpretations of our empirical findings.

6.1 The ex-ante effect of debt collection

An alternative interpretation is that ex ante, debt collection increases the repayment propensity due to its potential damage to borrowers' social images. After the phone calls, targeted borrowers have less to lose and thus lower incentive to repay. That is, the collection calls negate the ex-ante effect, leading to an increase in default propensity and the appearance of retaliation. The stronger the ex-ante effect, the stronger the appearance of retaliation. While this mechanism

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might have contributed to the higher default propensity of targeted borrowers, it is unlikely to account for our overall results for the following two reasons.

First, this alternative interpretation is inconsistent with our cross-sectional results on gender. Prior literature suggests that the ex-ante effect should be stronger among women because they tend to value privacy more than men do (Goldfarb and Tucker, 2012; Prince and Wallsten, 2020; Tang, 2020). Hence, the alternative interpretation implies a higher default propensity among female borrowers after the collection calls. This is the opposite of our evidence that among targeted borrowers, only male borrowers are more likely to default (Panel A of Table 6).

Second, this alternative interpretation is inconsistent with the results of the sub-period analysis. In the first half of our sample, the intrusive debt-collection tactic was more of a surprise to borrowers. However, the rampant media coverage of aggressive debt collection in the summer of 2016 should have enhanced the salience of the damage to targeted borrowers' social images and hence strengthened the ex-ante effect.[24] Therefore, the alternative interpretation implies that the retaliation should also appear stronger in the later period. This goes against our findings reported in Table 5.

6.2 Reduced ability to borrow from social contacts

Another alternative interpretation of our findings is that the aggressive debt-collection tactic may have reduced targeted borrowers' ability to borrow from their social contacts, leading to a higher default rate. For example, people in the borrower's social circle may view the debt collection as a warning sign and become less willing to help the borrower with his short-term liquidity needs. This would tighten the borrower's liquidity constraints and reduce his ability to repay the loan.

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[24] In unreported analysis, we examine the repayment propensity in the first three days after the due date. During this period, delinquent borrowers received warnings that their social contacts would be notified if they did not repay by the end of the third day after the due date. The repayment rate during these three days can serve as a proxy for the ex-ante effect of the debt-collection threat. In a regression analysis, we control for borrower and loan characteristics and find that borrowers in the second half of our sample have a significantly higher repayment rate than borrowers in the first half of our sample.

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We investigate this interpretation by analyzing borrowers' consumption patterns. The lender gave us access to all borrowers' online shopping records at Taobao. Each borrower's consumption on Taobao is aggregated monthly. We then run the following panel regression on the first half of our sample using all unworked loans and the loans worked on after 4 pm:

$$\ln(Consumption_{i,t}+1) = \alpha + \sum_{k=-1}^{2} \beta_k Month_{it}^{k} + \sum_{k=0}^{2} \gamma_k \left(Work_i \times Month_{it}^{k}\right) + \varepsilon_{i,t} \quad (4)$$

where $\ln(Consumption_{i,t}+1)$ is the logarithm of 1 plus borrower i's online consumption in month t. $Work_i$ is a dummy variable that is 1 if borrower i's loan was worked on, and 0 otherwise. $Month_{it}^{k}$ (for k = -1, 0, 1, 2) are dummy variables that characterize the time relative to borrower i's delinquency. Specifically, $Month_{it}^{-1}$ is 1 if the current month (i.e., month t) is one month before borrower i becomes delinquent. The cases for k = 0 and 1 are defined similarly. $Month_{it}^{2}$ is 1 if the current month (month t) is two or more months after borrower i becomes delinquent.

As shown in Column 1 of Table 8, after we account for month fixed effects and borrower fixed effects, a borrower's online consumption is much lower in the delinquency month. The coefficient of $Month_{it}^{0}$ is -0.407 (s.e. = 0.109), suggesting that a borrower's online consumption in the delinquency month is 33% lower than his baseline-case consumption (i.e., the consumption level during the period of two or more months before his delinquency).[25] The coefficients of $Month_{it}^{-1}$, $Month_{it}^{1}$, and $Month_{it}^{2}$ are all insignificantly negative. These results suggest that those delinquent borrowers are likely to be experiencing financial difficulties in keeping up their pre-delinquency consumption level.

It is reassuring that our sample has enough statistical power to detect consumption changes. How does debt collection affect the consumption pattern? If intrusive debt collection reduces a targeted borrower's ability to repay, it should further reduce the targeted borrower's consumption in the delinquency month and the month immediately after. We do not detect such

[25] The consumption decrease is given by 1-exp(-0.407) = 33%.

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an effect. As Column 2 shows, none of the three interaction coefficients are statistically significant. That is, among delinquent borrowers, debt collection does not appear to have an incremental effect on the borrowers' consumption. This evidence does not support the alternative hypothesis that debt collection worsens the targeted borrowers' ability to get help from their social contacts and thus causes more default.

7 Conclusion

Reciprocity has long been considered important to understanding many key economic questions. However, measures of reciprocity have been elusive, which probably explains why most of the evidence has been based on experimental or survey data. Our paper provides the first direct evidence of negative reciprocity in a real financial market. Analyzing the consequences of an intrusive debt-collection tactic for consumer lending, we find that this controversial tactic increases the default rate of the targeted borrowers. Further evidence is consistent with the negative reciprocity interpretation, whereby delinquent borrowers retaliate by deliberately defaulting.

We focus on the cash-loan market in China because the detailed data make the measurement possible. What we uncover, however, is likely to be the tip of more widespread iceberg. For example, in recent years some U.S. lenders have started using social media such as LinkedIn and Facebook to reach delinquent borrowers' social contacts for debt-collection purposes.

There are reasons to expect reciprocity to play an important role in many other areas in finance, especially when household decisions are involved. One prominent example is the real estate markets: a foreclosure-related sale reduces the value of a house by an estimated 27% (Campbell, Giglio, and Pathak, 2011). Part of the value destruction may be due to previous owners vandalizing the foreclosed properties, even though they may face serious consequences. In this context, reciprocity is crucial for the valuation of real estate and mortgage-related assets;

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it may also be important to consider when formulating policy responses to mitigate the effects of a housing crisis. For example, reworking delinquent mortgages to avoid the negative reciprocity costs of foreclosure might benefit both homeowners and mortgage lenders.[26] Detailed analysis of these issues is likely to become feasible with the development of the FinTech industry and the associated accumulation of data.

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[26] For further discussion, see the op-ed "Mortgage Justice Is Blind" by John Geanakoplos and Susan Koniak, which appeared in *The New York Times* on October 30, 2008; see Opinion | Mortgage Justice Is Blind - The New York Times (nytimes.com).

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Appendix. Variable Definitions

Variable	Definition
Work	A dummy variable that equals 1 if a debt collector reached some key social contact(s) in the address book of the borrower's mobile phone on the 4th day of delinquency, and 0 otherwise.
Credit Rating	Credit rating assigned by the lender at the time of loan application, denoted as A (the highest credit quality) through F (the lowest). We assign the value of 1 to 6 to Grade A to F, respectively, in our regression analysis.
Default	A dummy variable that equals 1 if the borrower defaulted on his loan (i.e., the borrower did not repay by 60 days past the due date), and 0 otherwise.
Size	The loan size, denominated in RMB.
Term	The loan term, denominated in months.
InterestRate	A categorical variable representing the interest rate level, which is provided by the lender and ranges from 1 (lowest) to 10 (highest).
#Payments	The number of payments made before the loan becomes delinquent.
NewBorrower	A dummy variable that equals 1 if the borrower is a new customer, and 0 otherwise.
Male	A dummy variable that equals 1 if the borrower is a male, and 0 otherwise.
Age	The borrower's age at the time of loan application, denominated in years.
BigCity	A dummy variable that equals 1 if the borrower lives in a Tier 1 or Tier 2 city in China, and 0 otherwise. Tier 1 includes Beijing, Shanghai, Guangzhou, and Shenzhen. Tier 2 includes 36 cities, most of which are provincial capitals.
#Contacts	The number of contacts in the address book of a borrower's mobile phone.
Taobao	A dummy variable that equals 1 if the borrower voluntarily shares his *Taobao* account information with the lender, and 0 otherwise.

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Figure 1. Loan Application Procedure

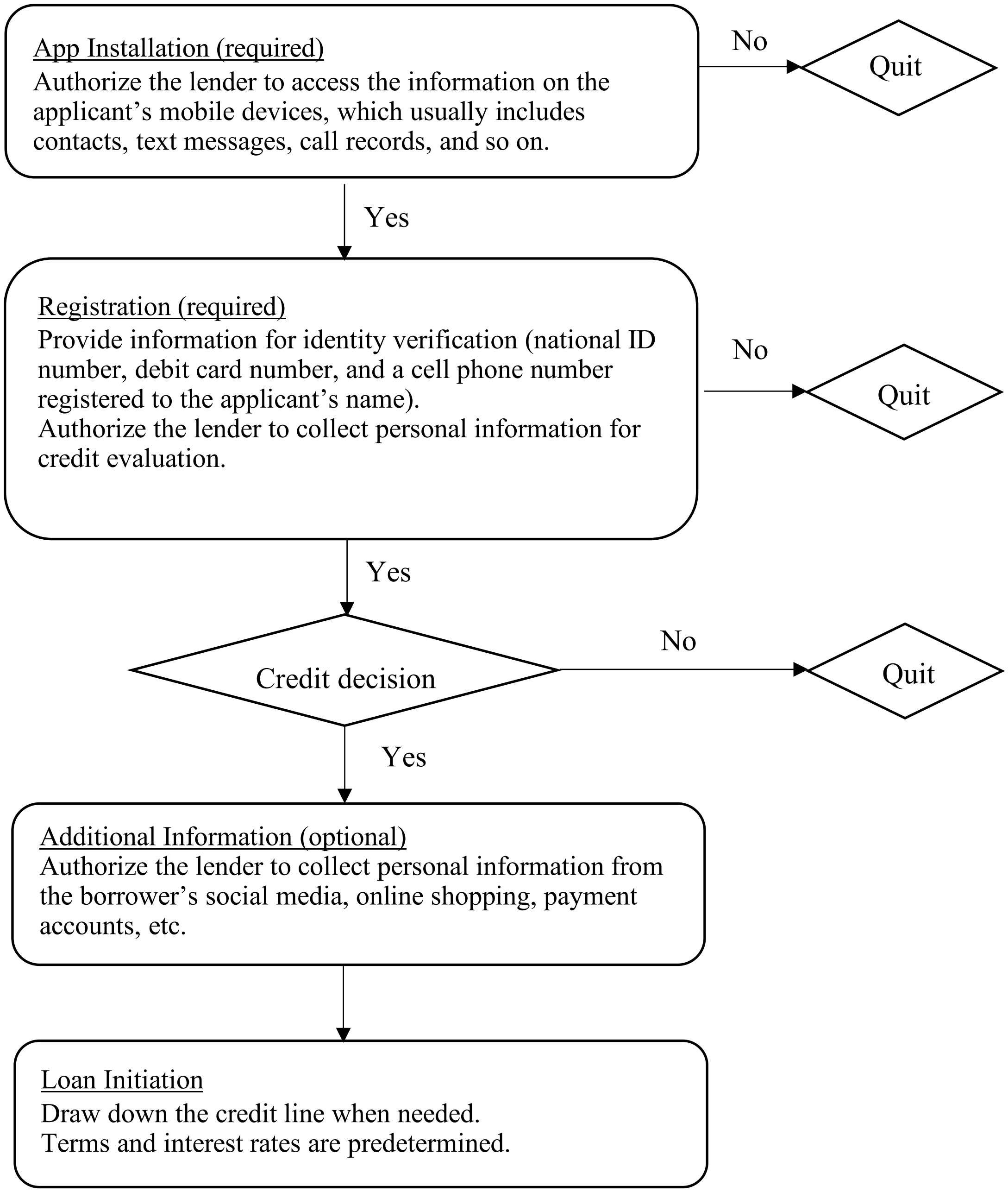

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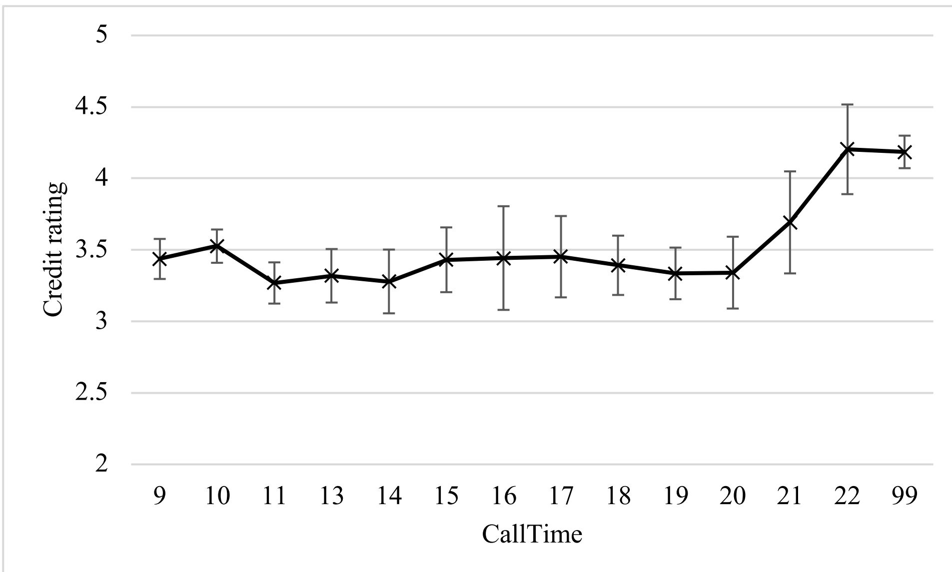
Figure 2. Loan and Borrower Characteristics by the Time of Calls

Panel A plots the average credit rating against the time of collection calls, *CallTime*. Credit ratings are converted into numbers with 1 representing Grade A (the highest rating) and 6 Grade F. Each group typically includes loans worked on during a one-hour interval. For example, group 10 includes all loans worked on from 10:00 am to 10:59 am. There are four exceptions: group 9 includes all loans worked on from 8:00 am to 9:59 am; group 11 includes all loans worked on from 11:00 am to 12:59 pm; group 22 includes all loans worked on after 10 pm. Group 99 represents all unworked loans. Panels B through D show *NewBorrower*, the ratio of *#Payments* to *Term*, and *Default*, respectively. All variables are defined in the Appendix.

Panel A. Credit rating



Panel B. New borrowers

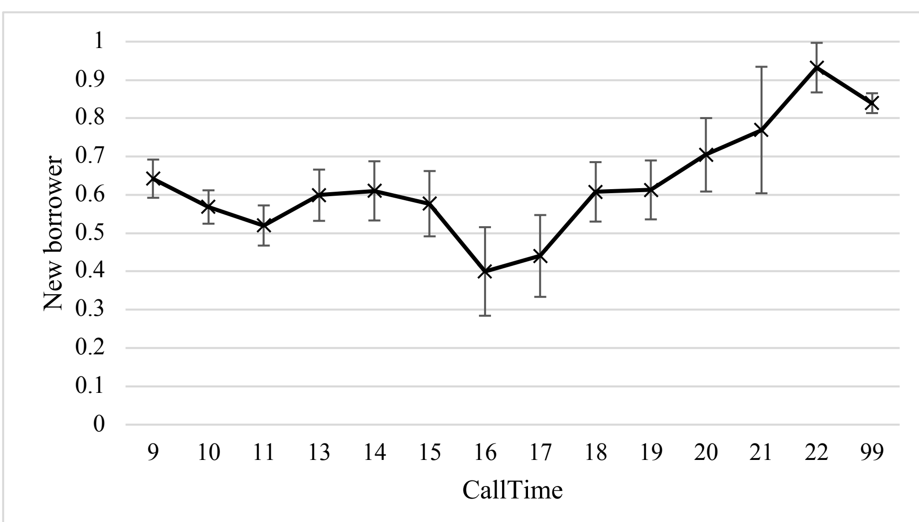


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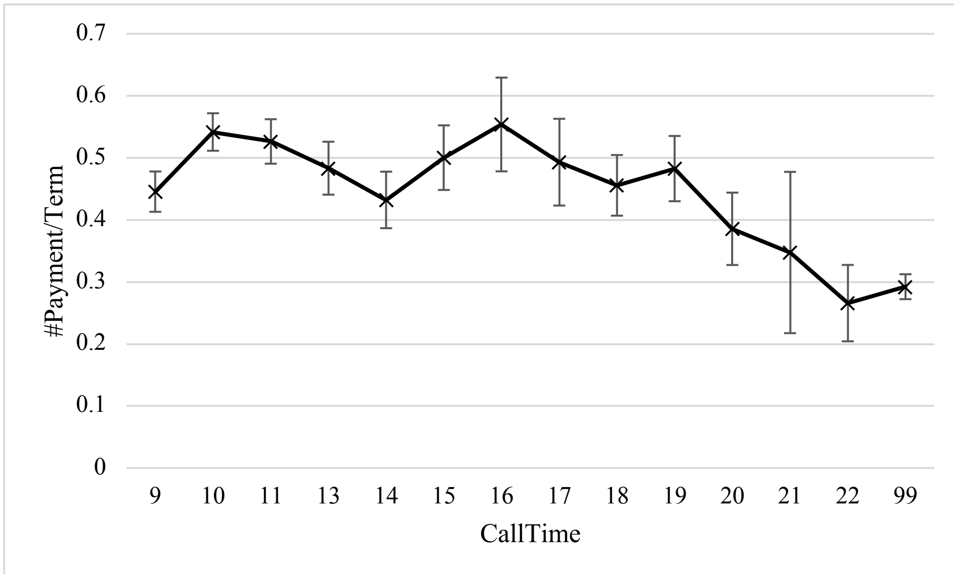
Figure 2. Loan and Borrower Characteristics by the Time of Calls, continued

Panel C. #Payment/Term



Panel D. Default

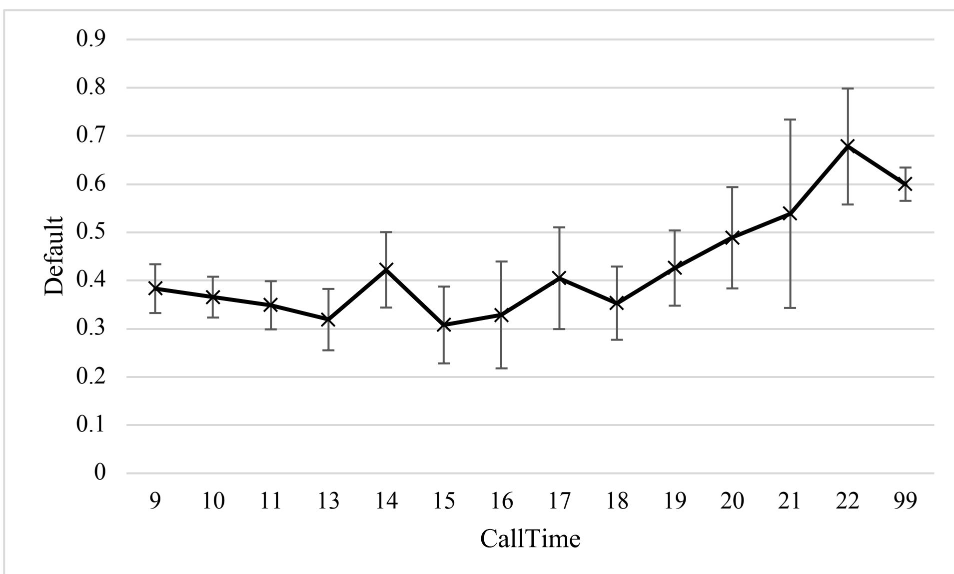


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Figure 3. Cross-Sectional Variations in the Effect of Debt Collection

This figure illustrates the estimated marginal effect of debt collection on the default probability for each group of borrowers. Panel A plots the debt-collection effect for male and female borrowers. It is based on the regression in Panel A of Table 6. Panel B plots the debt-collection effect for borrowers in the six credit rating groups. It is based on the regression in Panel B of Table 6. Panel C plots the debt-collection effect for the borrowers based on whether they provided their Taobao account information. It is based on the regression in Panel C of Table 6. Each grey bar represents the implied marginal effect of debt collection on the default probability for one group, and the vertical line represents its 95% confidence interval.

Panel A. Gender

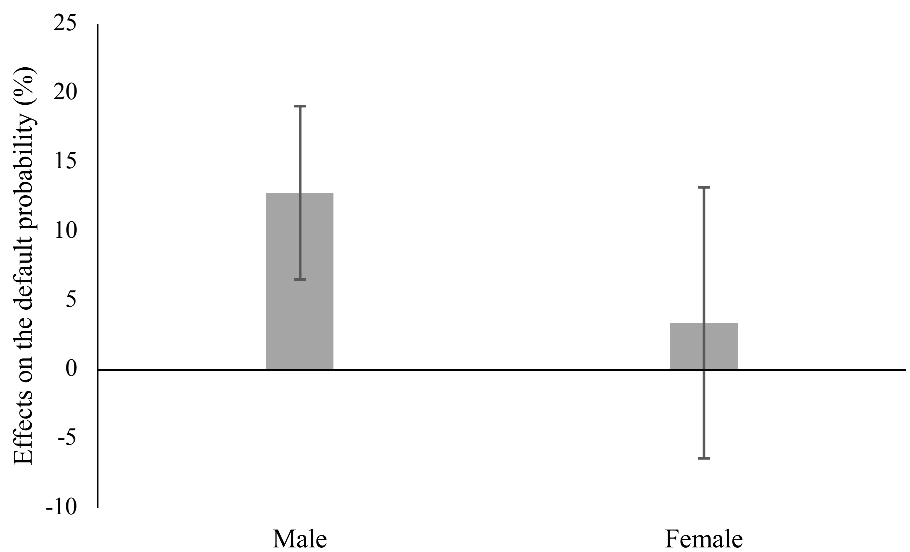

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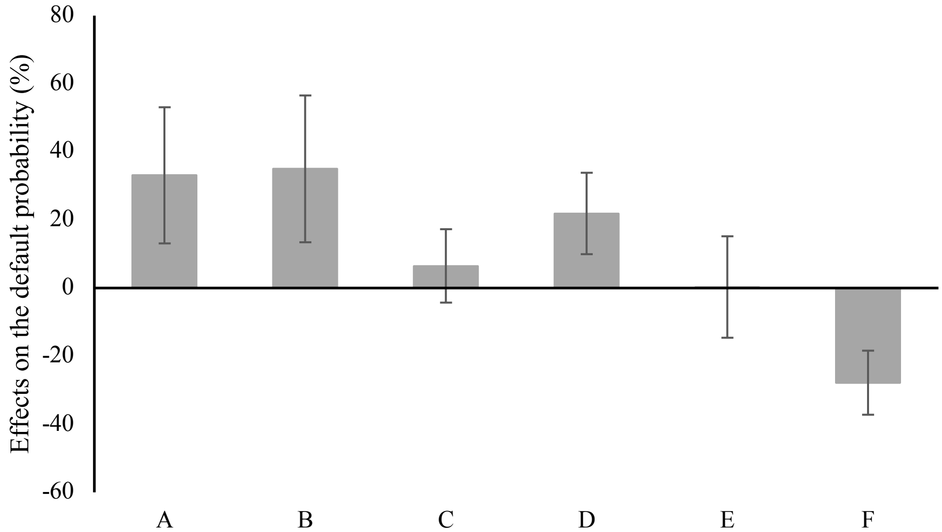
Figure 3. Cross-Sectional Variations in the Effect of Debt Collection, continued

Panel B. Credit rating



Panel C. Voluntary Taobao disclosure

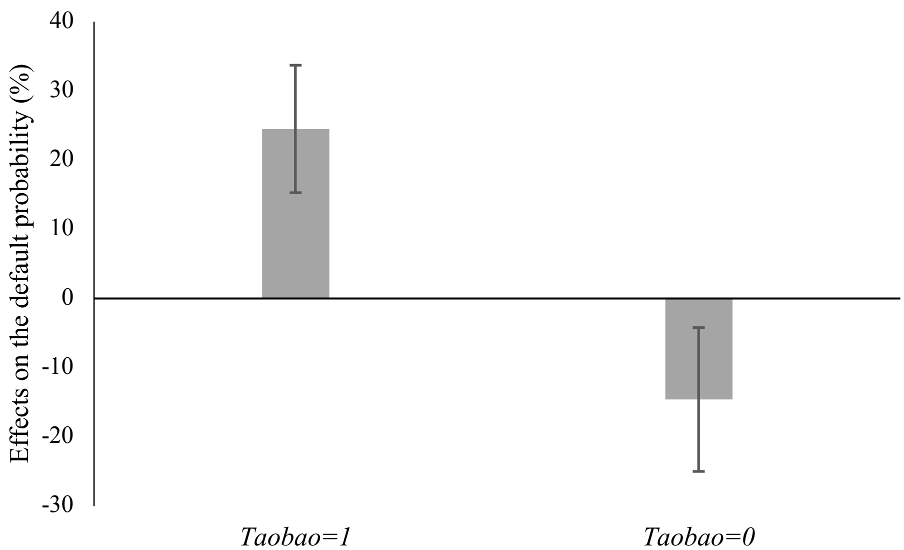


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Table 1. Summary Statistics

Panel A reports the summary statistics for the loan-level and borrower-level variables in the original sample for debt collections. Panel B reports the distribution of borrowers' credit ratings. Panel C reports the distribution of the hour of the day for debt-collection phone calls. Panel D contrasts the default rate as well as the loan and borrower characteristics of worked and unworked loans. All variables are defined in the Appendix.

Panel A. Distribution of loan and borrower characteristics

	Obs.	Mean	S.D.	*p*1	*p*25	Median	*p*75	*p*99
Work	3,101	0.75	0.43	0	1	1	1	1
Default	3,101	0.43	0.50	0	0	0	1	1
Size (RMB)	3,101	1,751	1,410	108	800	1,379	2,420	5,888
Term (Month)	3,101	6.40	4.10	1	3	6	12	12
#Payments	3,101	1.93	1.68	1	1	1	2	9
InterestRate	3,096	6.55	2.72	1	4	7	9	10
Male	3,101	0.80	0.40	0	1	1	1	1
Age (Year)	3,101	26.45	5.35	19	22	26	29	43
BigCity	3,101	0.46	0.50	0	0	0	1	1
#Contacts	3,101	248.15	265.71	0	94	187	326	1,217
Taobao	3,101	0.79	0.41	0	1	1	1	1
NewBorrower	3,101	0.65	0.48	0	0	1	1	1
CreditRating	3,101	3.61	1.45	1	3	4	5	6

Panel B. Distribution of credit ratings

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

Panel C. Distribution of debt-collection time of day

Hour	Obs.	Percentage	Cum. Percentage	Hour	Obs.	Percentage	Cum. Percentage
9	355	15.24%	15.24%	17	84	3.61%	79.35%
10	498	21.38%	36.63%	18	153	6.57%	85.92%
11	341	14.64%	51.27%	19	155	6.66%	92.57%
12	9	0.39%	51.65%	20	88	3.78%	96.35%
13	207	8.89%	60.54%	21	26	1.12%	97.47%
14	154	6.61%	67.15%	22	55	2.36%	99.83%
15	130	5.58%	72.74%	24	4	0.17%	100.00%
16	70	3.01%	75.74%				

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Table 1. Summary Statistics, continued

Panel D. Contrasting worked with unworked loans

Variable	Worked	Unworked	Difference	*t*-statistics
Default	0.38	0.60	-0.22***	-10.87
Size (RMB)	1,505.90	2,409.46	-903.56***	-17.99
Term (Month)	5.99	7.62	-1.63***	-9.67
#Payments	2.12	1.34	0.78***	11.33
InterestRate	6.35	7.16	-0.81***	-7.17
Male	0.82	0.74	0.08***	4.69
Age	26.59	26.02	0.57**	2.57
BigCity	0.50	0.36	0.14***	6.86
#Contacts	250.31	219.30	31.01***	3.28
Taobao	0.85	0.59	0.26***	16.16
NewBorrower	0.59	0.84	-0.25***	-12.90
CreditRating	3.42	4.19	-0.77***	-13.08

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Table 2. Default and Call Time

This table reports the results from Probit regression (1). It relates the default rate of worked loans to the time of the collection call. Column 1 reports the results without control variables, and Column 2 reports the results with loan and borrower characteristics. All variables are defined in the Appendix. Standard errors are displayed in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	*Default*	
	(1)	(2)
CallTime	0.021***	0.015**
	(0.007)	(0.007)
Size (RMB)		-0.012
		(0.048)
Term (Month)		0.083***
		(0.012)
#Payments		-0.153***
		(0.021)
Interest rate		-0.015
		(0.081)
Male		0.163**
		(0.073)
Age		0.026***
		(0.005)
BigCity		-0.162***
		(0.061)
#Contacts		0.028
		(0.018)
Taobao		-0.476***
		(0.095)
NewBorrower		0.330***
		(0.072)
RatingB		0.422***
		(0.117)
RatingC		0.437***
		(0.108)
RatingD		0.562***
		(0.106)
RatingE		0.397***
		(0.128)
RatingF		-0.332**
		(0.163)
Constant		-1.998***
		(0.395)
Month fixed effects	Yes	Yes
Observations	2,329	2,329
Pseudo R-squared	0.015	0.115

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Table 3. Main Regression: Default and Debt Collection

This table reports the results of Probit regression (2) for the sample including all unworked loans and loans worked on after 4 pm. The sample period is from October 2015 to March 2017. It relates the default rate to whether a loan is worked, *Work.* All variables are defined in the Appendix. Standard errors are displayed in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	*Default*
Work	0.218**
	(0.096)
Size(RMB)	0.372***
	(0.077)
Term(Month)	0.126***
	(0.020)
#Payments	-0.181***
	(0.037)
Interest rate	0.040
	(0.125)
Male	0.086
	(0.097)
Age	0.026***
	(0.008)
BigCity	-0.215**
	(0.092)
#Contacts	0.070***
	(0.025)
Taobao	-0.810***
	(0.145)
NewBorrower	-0.014
	(0.111)
RatingB	0.421**
	(0.189)
RatingC	0.776***
	(0.166)
RatingD	1.049***
	(0.171)
RatingE	1.161***
	(0.194)
RatingF	1.075***
	(0.205)
Constant	-4.699***
	(0.652)
Month fixed effects	Yes
Observations	1,407
Pseudo R-squared	0.305

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Table 4. Varying the Stopping Time of Collection Calls

This table reports the results from Probit regression (2) when the sample is constructed by using 4 pm, 5 pm, 6 pm, 7 pm, 8 pm, 9 pm, and 10 pm as the cutoff point. The sample period is from October 2015 to March 2017. Each regression relates the default rate to whether a loan is worked, *Work.* Column 1 reports the cutoff time, and Columns 2 through 4 report the corresponding coefficient estimates for *Work*, the estimated marginal effects, and the number of observations, respectively. Standard errors are displayed in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Cutoff time	Coefficient estimate for *Collect*	Marginal effect	*N*
(1)	(2)	(3)	(4)
16:00	0.218**	0.059**	1,407
	(0.096)	(0.026)	
17:00	0.225**	0.061**	1,337
	(0.098)	(0.026)	
18:00	0.221**	0.059**	1,253
	(0.101)	(0.027)	
19:00	0.410***	0.099***	1,100
	(0.117)	(0.028)	
20:00	0.528***	0.113***	945
	(0.148)	(0.031)	
21:00	0.654***	0.126***	857
	(0.200)	(0.038)	
22:00	0.770***	0.143***	826
	(0.243)	(0.044)	

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Table 5. Sub-Period Analysis

This table is based on the sample including all unworked loans and loans worked on after 4 pm. Panel A compares the default rate, as well as the loan and borrower characteristics of the first and second halves of our sample. Panel B reports the results of the Probit regression (2). The first half sample is from October 2015 to August 2016. The second half sample is from September 2016 to March 2017. All variables are defined in the Appendix. Standard errors are displayed in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Comparing the characteristics of the two sub-samples

Variable	First half	Second half	Difference	*t*-statistics
Default	0.45	0.39	0.06***	3.26
Size (RMB)	1,896.70	1,290.89	605.81***	12.12
Term (Month)	7.76	2.79	4.97***	35.79
#Payments	2.11	1.44	0.67***	10.10
InterestRate	7.22	4.77	2.46***	24.45
Male	0.79	0.82	-0.03**	-2.05
Age	26.52	26.25	0.27	1.23
BigCity	0.41	0.59	-0.18***	-9.05
#Contacts	195.43	367.68	-172.24***	-19.94
Taobao	0.72	0.98	-0.26***	-16.63
NewBorrower	0.72	0.49	0.23***	12.22
CreditRating	3.67	3.45	0.22***	3.72

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Table 5. Sub-Period Analysis, continued

Panel B. Regression analysis

Dependent variable:	*Default*	
	First half	Second half
	(1)	(2)
Work	0.460***	-0.039
	(0.127)	(0.158)
Size (RMB)	0.552***	-0.184
	(0.099)	(0.146)
Term (Month)	0.123***	0.126**
	(0.025)	(0.062)
#Payments	-0.160***	-0.163**
	(0.043)	(0.076)
Interest rate	-0.050	-0.003
	(0.205)	(0.168)
Male	0.010	0.298*
	(0.120)	(0.179)
Age	0.025***	0.038***
	(0.009)	(0.014)
BigCity	-0.178	-0.304**
	(0.123)	(0.144)
#Contacts	0.081***	-0.004
	(0.029)	(0.056)
Taobao	-0.792***	-0.268
	(0.159)	(0.412)
NewBorrower	-0.085	0.169
	(0.151)	(0.171)
RatingB	0.512**	0.117
	(0.226)	(0.395)
RatingC	0.872***	0.651*
	(0.197)	(0.357)
RatingD	1.028***	0.923***
	(0.205)	(0.355)
RatingE	1.190***	0.832**
	(0.239)	(0.376)
RatingF	1.533***	-0.785
	(0.242)	(0.524)
Constant	-6.190***	-0.827
	(0.837)	(1.158)
Month fixed effects	Yes	Yes
Observations	987	420
Pseudo R-squared	0.398	0.154

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Table 6. Cross-Sectional Variations in Response to Debt Collection

This table reports the results of regressions based on the sample including all unworked loans and loans worked on after 4 pm during the first half of our sample period: from October 2015 to August 2016. The regression in Panel A reports the results of Probit regression (3) and the implied marginal effects of collection on male and female borrowers. Panels B and C are similar. In Panel B, the Probit regression includes the interaction terms between *Work* and the five credit rating dummies. *RatingB* is 1 if the borrower has a credit rating of *B*, and 0 otherwise. The other four rating dummies are defined similarly. In Panel C, the Probit regression includes the interaction term between *Work* and *Taobao*. All variables are defined in the Appendix. Standard errors are displayed in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Gender

	Coefficient estimate		Marginal effect
Dependent var.: *Default*	(1)		(2)
Work	0.150	*Female*	0.034
	(0.219)		(0.050)
Work×Male	0.403*	*Male*	0.128***
	(0.232)		(0.031)
Male	-0.246		
	(0.158)		
Month fixed effects	Yes		
Control	Yes		
Observations	987		
Pseudo R-squared	0.400		

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Table 6. Cross-Sectional Variations in Response to Debt Collection, continued

Panel B. Credit rating

	Coefficient estimate		Marginal effect
Dependent var.: *Default*	(1)		(2)
Work	1.258***	*RatingA*	0.331***
	(0.386)		(0.102)
Work×RatingB	-0.055	*RatingB*	0.350***
	(0.519)		(0.110)
Work×RatingC	-1.015**	*RatingC*	0.065
	(0.427)		(0.055)
Work×RatingD	-0.481	*RatingD*	0.219***
	(0.434)		(0.061)
Work×RatingE	-1.246***	*RatingE*	0.003
	(0.477)		(0.076)
Work×RatingF	-2.659***	*RatingF*	-0.278***
	(0.516)		(0.048)
RatingB	0.445		
	(0.452)		
RatingC	1.509***		
	(0.352)		
RatingD	1.233***		
	(0.373)		
RatingE	1.917***		
	(0.412)		
RatingF	2.835***		
	(0.412)		
Control	Yes		
Month fixed effects	Yes		
Observations	987		
Pseudo R-squared	0.425		

Panel C. Taobao disclosure

	Coefficient estimate		Marginal effect
Dependent var.: *Default*	(1)		(2)
Work	-0.638***	*Taobao=0*	-0.146***
	(0.238)		(0.053)
Work×Taobao	1.444***	*Taobao=1*	0.245***
	(0.271)		(0.047)
Taobao	-1.761***		
	(0.238)		
Control	Yes		
Month fixed effects	Yes		
Observations	987		
Pseudo R-squared	0.419		

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Table 7. PSM analysis

This table reports the results of the PSM analysis. Panel A reports the covariate balance after matching. Panel B reports the Probit regression results using the matched sample. We match each unworked loan with four worked loans that have the closest propensity to default. We use a caliper of 0.001 and allow replacements in the matching process. The sample period is the first half of our sample: from October 2015 to August 2016. All variables are defined in the Appendix. The last column reports the *t*-statistics for the differences based on heteroskedasticity-adjusted standard errors. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Covariate balance of the matched sample

Variable	Worked	Unworked	Difference	*t*-statistics
Size (RMB)	2,491.96	2,273.96	218.00	1.58
Term (Month)	8.64	8.58	0.06	0.15
#Payments	1.72	1.66	0.06	0.36
InterestRate	7.43	7.30	0.13	0.48
Male	0.80	0.74	0.06	1.43
Age	26.70	26.56	0.14	0.25
BigCity	0.37	0.42	-0.05	-0.98
#Contacts	180.40	182.93	-2.53	-0.12
Taobao	0.64	0.68	-0.04	-0.90
CreditRating	3.58	3.53	0.05	0.31
NewBorrower	0.79	0.81	-0.03	-0.65
Default	0.56	0.39	0.17***	3.39

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Table 7. PSM analysis, continued

Panel B. Regression analysis using the matched sample

Dependent variable:	*Default*
Work	0.557***
	(0.134)
Size (RMB)	0.592***
	(0.115)
Term (Month)	0.110***
	(0.027)
#Payments	-0.196***
	(0.046)
Interest rate	0.278
	(0.218)
Male	0.292**
	(0.146)
Age	0.008
	(0.010)
BigCity	-0.023
	(0.136)
#Contacts	0.056*
	(0.032)
Taobao	-0.788***
	(0.177)
NewBorrower	-0.044
	(0.179)
RatingB	0.150
	(0.244)
RatingC	0.707***
	(0.201)
RatingD	0.764***
	(0.211)
RatingE	1.285***
	(0.281)
RatingF	1.024***
	(0.257)
Constant	-6.276***
	(0.955)
Month fixed effects	Yes
Observations	646
Pseudo R-squared	0.302

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Table 8. Online Consumption around Delinquency

This table reports the results of panel regressions based on the sample including all unworked loans and loans worked on after 4 pm during the first half of our sample period: from October 2015 to August 2016. The dependent variable is Ln($Consumption_{it}$+1), where $Consumption_{it}$ is the consumption (in RMB) by borrower i on Taobao during month t; $Month_{it}^{0}$ is a dummy variable, which is 1 if borrower i became delinquent in month t, and 0 otherwise. For k=-1, 1, $Month_{it}^{k} = Month_{it+k}^{0}$. Similarly, $Month_{it}^{2}$ is 1 if borrower i became delinquent two or more months before month t. The standard errors are displayed in parentheses and are double clustered by month and borrower. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	Ln ($Consumption_{it}$+1)	
	(1)	(2)
$Month_{it}^{-1}$	-0.101	-0.101
	(0.099)	(0.100)
$Month_{it}^{0}$	-0.407***	-0.441***
	(0.109)	(0.148)
$Month_{it}^{1}$	-0.252	-0.141
	(0.149)	(0.238)
$Month_{it}^{2}$	-0.146	-0.216
	(0.121)	(0.318)
$Work_i \times Month_{it}^{0}$		0.056
		(0.155)
$Work_i \times Month_{it}^{1}$		-0.181
		(0.285)
$Work_i \times Month_{it}^{2}$		0.115
		(0.378)
Constant	5.216***	5.216***
	(0.012)	(0.011)
Month fixed effects	Yes	Yes
Borrower fixed effects	Yes	Yes
Observations	6,684	6,684
R-squared	0.401	0.401

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