Digital Footprints as Collateral for Debt Collection

Lili Dai, Jianlei Han, Jing Shi, and Bohui Zhang[☆]

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☆ Lili Dai is from UNSW Business School, UNSW Sydney, Sydney, Australia; Jianlei Han and Jing Shi are from Macquarie Business School, Macquarie University, Sydney, Australia; Bohui Zhang is from the School of Management and Economics and Shenzhen Finance Institute, The Chinese University of Hong Kong, Shenzhen (CUHK-Shenzhen), Longxiang Boulevard, Longgang District, Shenzhen, China, 518172. Authors' contact information: Lili Dai, lili.dai@unsw.edu.au; Jianlei Han, jianlei.han@mq.edu.au; Jing Shi, jing.shi@mq.edu.au; Bohui Zhang, bohuizhang@cuhk.edu.cn. We are grateful for the valuable comments from Yi-Chun Chen, Junshan Duan, Yan Guo, Guangzhong Li, Yongxiang Wang, Susan Thorp, Xiaoneng Zhu, Tom Smith, and the conference and seminar participants at Guangdong University of Finance and Economics, La Trobe University, Lanzhou University, Macquarie University, Shanghai Jiao Tong University, Tianjin University, Xi'an Jiao Tong University, the 2020 Summer Research Workshop of China Journal of Accounting Research, and the 2020 Academic Forum of Young and Middle-aged Committee of Guangdong Economic Society.

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Abstract

We examine the role of borrowers' digital footprints in debt collection. Using a large sample of personal loans from a fintech lender in China, we find that the information acquired by the lender through borrowers' digital footprints can increase the repayment likelihood on delinquent loans by 18.5%. The effect can be explained by two channels: bonding borrowers' obligations with their social networks and locating borrowers' physical locations. Moreover, the lender is more likely to approve loan applications from borrowers with digital footprints, even though these borrowers may occasionally have a higher likelihood of delinquency. The use of digital footprints can remain legitimate under stringent privacy protection regulations and fair debt collection practices. Our findings suggest that digital footprints, as a new type of collateral, can ultimately enhance financial inclusion by facilitating the lender's collection of delinquent loans.

JEL classification: D14, G14, G23, G51

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1. Introduction

Delinquency is a pervasive issue in consumer credit markets worldwide. According to the 2020 report of the Consumer Financial Protection Bureau (CFPB), outstanding credit card debt reached $927 billion in 2019 in the U.S., and 8.4% was more than 90 days in arrears. Similarly, in the same year, Chinese credit card holders accumulated a comparable amount of $13 billion overdue for more than six months. This enduring problem of loan delinquency indicates there is a need for new tools to help creditors obtain repayments. The wide use of smartphones and internet services generates information about the online activities of users, such as their contacts, the mobile applications they use, and the websites they frequent. We refer to such information as digital footprints and propose the use of debtors' digital footprints as a novel channel to facilitate creditors' debt collection.

Creditors' efforts in the loan process mainly involve loan approval and debt collection. Recent research suggests that digital footprints are useful in evaluating borrowers' creditworthiness and thereby can assist creditors' loan approval decisions (Jiang et al. 2019; Agarwal et al. 2020; Berg et al. 2020).[1] Different from these studies, we consider the role of digital footprints in debt enforcement when loans are either delinquent or in default. In particular, we argue that the information acquired by lenders through borrowers' digital footprints can be used as collateral to recover the delinquent debt.

Pledged collateral has long been regarded as a commitment device to enforce debt repayment (e.g., Jimenez, Salas, and Saurina 2006; Benmelech and Bergman 2009; Rampini and Viswanathan 2010, 2013; DeMarzo 2019). However, as featured with unsecured loan contracting without any collateral, consumer credit often lacks such a guarantee. Especially in fast and small consumer credit contracts like those in marketplace lending, borrowers typically do not provide collateral assets. Thus, lenders need to look for other commitment technologies to secure debt claims (Thakor 2020). In such scenarios, we view borrowers' digital footprints as a new form of collateral – *digital collateral*.

Digital collateral could be effective in debt collection for at least two reasons. First, by using the information contained in borrowers' digital footprints, lenders can identify who borrowers contact via mobile phones, email, or instant messaging applications, and thus might be able to discover their social networks. When a loan is delinquent, the lender can contact the

[1] Digital footprints are the traceable digital activities, actions, communications, and contributions that people leave on the Internet or through mobile devices when they access and register websites and mobile applications. Other studies on debt markets have examined the general role of technology-based lenders in mortgage lending markets (Fuster et al. 2019), the online shadow banks (Buchak et al. 2018), and the peer-to-peer (P2P) lending platforms (Tang 2019; Vallée and Zeng 2019; Du et al. 2020).

borrower's family members and friends to collect further information about the borrower. As long as the lender's conduct is not abusive and deceptive, such contact is usually allowed by the U.S. Fair Debt Collection Practices Act. However, in countries with weak debtor protection, the lender sometimes shares the borrower's debt delinquency information with her key contacts and asks them to urge the borrower to repay. Either possibility might threaten the borrower's trustworthiness among her social network, and more generally, her social capital. If the borrower's social capital is at risk, the borrower might be incentivized to repay the debt (e.g., Karlan et al. 2009; Lee and Person 2016; Diep-Nguyen and Dang 2020).[2] Therefore, digital footprints as collateral could be used to bond borrowers' social capital with debt claims. We consider this view as the *social capital channel* through which digital collateral can facilitate debt collection.

Second, lenders may obtain borrowers' address information such as postal addresses for online shopping from their digital footprints. Such information would enable lenders to identify borrowers' physical locations. In case of delinquency, by knowing the borrower's address, lenders can employ local legal institutions to go after her income and assets without resorting to violence (Djankov, McLiesh, and Shleifer 2007; Djankov et al. 2008). For example, lenders can exercise liens to seize goods from a borrower's dwellings or other addresses.[3] Moreover, if the delinquent borrower knows that the lender has her address, additional pressure may be imposed on the borrower due to a reduced psychological distance and a heightened threatening stimulus (McGraw et al. 2012; Williams, Stein, and Galguera 2014; Boothby et al. 2016). Therefore, when a delinquent borrower receives a phone call from the debt collector mentioning her address information, she could believe the lender would come and go after her assets for debt enforcement, and may also face more pressure caused by the shortened psychological distance with the lender. Both possibilities can motivate the borrower to make loan repayments. We regard this conjecture as the *physical location channel* underlying the digital collateral effect on debt collection.

We also acknowledge that the effect of digital footprints as collateral on debt collection could be marginal. First, the information in digital footprints may simply reflect borrowers'

[2] Karlan et al. (2009) develops a theory by adopting sociologists' concept of social capital, which "constitutes a particular kind of resource available to an actor" (Coleman 1988), and "refers to features of social organization such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit" (Putnam 1995). Using the data on informal lending from Peru, Karlan et al. (2009) empirically documents the importance of using individuals' social capital to facilitate personal borrowings.

[3] Here, we refer the judgment liens to involuntary or non-consensual liens arise via statute or operation of the common law. When creditors seek legal actions for loan delinquency, liens can be imposed on borrowers' properties and chattels.

characteristics, such as age, income, and gender, which may render digital footprints less incremental information in facilitating debt collection. Second, the data from borrowers' digital activities could be noisy, leading to low information quality, which could make debt enforcement mechanisms less effective. Third, fintech lenders may complement banks and mainly serve low credit quality borrowers, who often have a high delinquency likelihood and are insensitive to debt collection tactics. Taken together, whether digital footprints can help in debt collection is an open empirical question.

We examine our conjectures using data on personal loan contracts from a leading fintech company in China. The fintech company only asks a borrower to provide her mobile number and national identity number. With such information, the lender can obtain other information about the borrower from third-party data providers, such as her credit score, the balance of her online payment accounts, and the historical record of past loan applications. The lender then computes the internal credit score and evaluates the borrower's creditworthiness.

More importantly, this fintech creditor can also obtain a borrower's digital footprints from data providers, including her frequent mobile contacts and delivery addresses provided when shopping online. When the loan is delinquent, the fintech lender will make phone calls to both the borrower and her key contacts.[4] According to our conjecture of digital collateral, the borrower's digital footprints would allow the lender to enforce debt collection by reaching the borrower's social network and/or locating her physical address. We expect borrowers with digital collateral to be more likely to repay their loans upon receiving the lender's phone calls.

Our empirical analyses start with a sample of 41,711 delinquent personal loan contracts over the period from July 2017 to November 2019. To examine the effect of digital collateral on the repayment of delinquent loans, we employ a difference-in-differences (DID) approach. Specifically, we first perform the propensity score matching (PSM) strategy by matching borrowers with digital collateral (the treatment group) to those without collateral (the control group). This step provides us with two samples. One sample consists of 14,768 delinquent borrowers having frequent mobile contacts in their social networks, together with the same number of borrowers with no frequent contact information. Another sample includes 9,994 delinquent borrowers with online shopping delivery addresses and the matched ones without

[4] Prior to the due date, the fintech lender sends reminder messages to borrowers via mobile phones (Cadena and Schoar 2012; Karlan, Morten, and Zinman 2015; Medina 2018; Bursztyn et al. 2019; Du et al. 2020). Three months after a delinquency, if the borrowers still fail to make repayments, the lender will hand over the cases to debt collection agencies for further debt enforcement (Fedaseyeu and Hunt 2018; Fedaseyeu 2020).

the address information.[5]

Second, in a timeline after delinquency, the lender will make five rounds of phone calls to these delinquent borrowers in the following quarter: the fourth day after the repayment due date (hereafter, Day 4), followed by another four dates (i.e., Day 16, Day 31, Day 61, and Day 91). If repayment does not occur within the chasing period, after Day 93, the delinquent loans will be turned over to external debt collection agencies.[6] We examine the likelihood of repayment in several six-day windows surrounding the dates when delinquent borrowers receive phone calls from the lender. This enables us to compare the changes in the likelihood of repayment after collection calls between the treatment and control groups.

Consistent with our conjectures on the social capital and physical location channels, we find that after receiving the lender's chasing calls, borrowers with digital collateral are more likely to repay their delinquent loans than those with no digital collateral. The effect is economically significant. For instance, in the first round of phone calls on Day 4, a delinquent borrower with frequent mobile contact (physical address) information has a 1.8% (1.8%) higher daily likelihood of loan repayment than those without such information from Days 4 to 6, compared to that from Days 1 to 3. The economic magnitude accounts for an increase of 16.6% (18.5%) relative to the sample mean of the daily repayment likelihood in the six-day window around Day 4. The results remain qualitatively similar for the second round of chasing calls on Day 16.

Next, we conduct two placebo tests to validate our baseline findings. First, we repeat the DID tests using a placebo sample period for the six-day window centered on the repayment due date (i.e., Day zero), during which the lender makes no phone call but sends repayment reminders through mobile messages in three days before the due of repayment. We find no significant difference in the loan repayment likelihood between borrowers backed by digital collateral and those with no collateral during the pre-event payment period. Second, to ensure that our baseline findings are not simply driven by chance, we conduct a simulation by artificially constructing pseudo borrowers with digital collateral. We randomly assign half of our sample borrowers as the pseudo borrowers with digital collateral to the new treatment groups and the remaining half of them to the pseudo control groups. We generate the

[5] Frequent mobile contacts are defined as a borrower's mobile contacts who have made phone calls to the borrower for more than *ten* times, with each conversation longer than 20 seconds. For the online shopping delivery addresses, we exclude non-residential addresses, such as the delivery addresses of convenience stores in the local residential communities that provide the services of dropping and picking up the delivered shopping packages.

[6] See Figure 2 regarding the timeline. The fintech lender will send reminding messages from Days -3 to 0 (delinquency date), and then make chasing calls on Day 4, Day 16, Day 31, Day 61 and Day 91. After Day 93, the delinquent loans will be handed over to external debt collection agencies.

randomized pseudo samples 1,000 times and then reconduct the DID analyses in these pseudo samples. We find that the mean and median values of the pseudo coefficients are statistically insignificant and much smaller in magnitude than those in our main tests, thus mitigating the by-chance concern.

Moreover, we perform several additional tests concerning the amount of digital collateral, the sequence of chasing calls, and the separation of the two types of digital footprints. We first decompose the metrics of digital collateral based on the median numbers of borrowers' frequent contacts and addresses. The results show that there is a marginal decline in the coefficients on collateral proxies for borrowers with a large amount of collateral compared to those with a small amount of collateral. This is likely because multiple pieces of digital footprints may distract debt collectors' efforts to borrowers' less important personal information, reducing the effectiveness of using digital collateral. Second, we compare the effect of digital collateral in the first two rounds of chasing calls with that in the next three rounds (i.e., Day 31, Day 61, and Day 91). We find that the effect of these further chasing calls on debt collection remains significant, but the magnitude of such an effect is significantly reduced. These results indicate that the borrowers, who continue to be delinquent after the first two chasing calls, are less concerned about their social capital and physical locations, suggesting the declining value of their digital footprints as collateral in sequence. Third, we examine whether our baseline findings are driven by one type of digital footprints rather than both (i.e., key contacts and physical locations). We conduct a subsample test to separate the effects of the two types of digital footprints and find that both types of digital footprints play significant roles in facilitating the debt collection process.

To provide further evidence on the *social capital* and *physical location channels*, we perform cross-sectional analyses to investigate whether the digital collateral effect on debt collection is more pronounced for subgroups of borrowers who are more subject to these two economic mechanisms. When borrowers are from hometowns where people have more social spending and attend more veneration events honoring ancestors, they are typically concerned about their social capital (Yang 1994; Lakos 2010). Thus, they are more likely influenced by the digital collateral with frequent contacts. For the borrowers living further away from the lender's headquarters and in areas with stronger law enforcement, the availability of their physical locations to the lender may incentivize them to make repayments because of the potential judicial enforcement (Djankov, McLiesh, and Shleifer 2007; Djankov et al. 2008) and additional psychological pressure (Williams, Stein, and Galguera 2014; Boothby et al. 2016). The results of these cross-sectional analyses are consistent with the two economic channels, corroborating our main findings.

To provide a complete picture of the role of borrowers' digital footprints in the loan process, we examine how digital footprints affect the repayment amount, delinquency likelihood, and loan approval. First, we study the impact of digital collateral on the magnitude of debt recovery after delinquency. Among the 41,711 delinquent loans, we find that the amount of debt repayment scaled by total debt outstanding is positively associated with the availability of borrowers' digital collateral. Furthermore, we focus on the dummy of debt recovery, indicating whether the repayment amount is equal to or more than total debt outstanding caused by the penalty of delinquency. We observe that the likelihood of debt recovery also increases with the availability of digital collateral. These results provide further confirmation on the role of digital footprints as collateral in debt collection.

Second, we examine whether the likelihood of loan delinquency is associated with the presence of borrowers' digital footprints. One possible concern on our headline findings is that the existence of frequent mobile contacts and physical addresses might proxy for borrowers' creditworthiness rather than collateral. For example, the availability of digital footprints could imply a low likelihood of delinquency. To test this possibility, we investigate our sample of 97,783 approved loan contracts, consisting of both delinquent and non-delinquent loans. We find that the incidence of delinquency is positively associated with the presence of borrowers' frequent contact information, while other conventional proxies for creditworthiness are negatively associated with the loan delinquency rate, consistent with prior studies. This finding helps to alleviate the concern that digital footprints are merely a measure of borrowers' credit quality.

Third, we investigate the impact of digital collateral on the fintech lender's loan approval decisions based on a sample of 236,967 loan applications, including unapproved contracts. Intuitively, we find that the lender is more likely to approve the loan for a borrower with digital collateral available, after controlling for credit quality proxies, such as the borrower's online credit score, payment account balance, and historical record of past loan applications. This finding suggests that digital collateral has an incremental effect on top of the information regarding the borrower's credit quality. That is, the lender does take the borrower's digital footprint information into account when evaluating the loan application, partly because the lender would be able to collect repayment effectively from the borrower in the case of delinquency.

Finally, we provide further discussions about the practical implications of our study in terms of the data privacy concerns, the fair debt collection practices, and the fintech impacts on financial inclusion. First, even under public awareness and policy debate about how to protect individuals' right to data privacy, the use of digital collateral can be maintained as legitimate if the collection and use of personal data are in accordance with a country's laws and regulations. Second, the debt collection tactic based on borrowers' digital collateral can be feasible not only in countries with weak debtor protections but also in those with strict laws and regulations against abusive debt collection practices, such as the U.S. Third, according to the 2014 report by World Bank, only seven percent of adults in developing countries have credit cards. Thus, our study offers a novel approach based on digital techniques to promote financial inclusion and especially help borrowers with no physical collateral available.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes the institutional background, variable construction, and summary statistics of the variables used in our study. Sections 4 presents the main results for the association between digital footprints and debt collection. Section 5 reports the additional tests of economic mechanisms and other outcome variables of the loan process, and Section 6 provides further discussions. Section 7 concludes the paper.

2. Related literature

We contribute to four strands of literature. First, previous literature examines the risk relevance of digital footprints for borrowers' credit assessment, complementing the credit bureau scores in debt markets (Agarwal et al. 2020; Berg et al. 2020). Jiang et al. (2019) show that big data credit scores (e.g., borrower's record of previous loan applications) can have an incremental predictive power for loan delinquency likelihood. In a similar vein, other novel characteristics of borrowers can be factored into the lending process, including, for example, borrowers' appearances (Duarte, Siegel, and Young 2012), online friendships (Lin, Prabhala, and Viswanathan 2013), peer lenders' creditworthiness (Iyer et al. 2016), and employment and income verification (Chan et al. 2020). Different from these studies, we consider the particular role of digital footprints in debt enforcement. We find that the information in digital footprints can be used as collateral to facilitate debt collection.

Second, more broadly, our study adds to the research on the impacts of big data analytics in capital markets in terms of reducing macro uncertainty (Mukherjee, Panayotov, and Shon 2020), improving informational efficiency (Zhu 2019; Grennan and Michaely 2020), disciplining corporate managers (Zhu 2019), increasing information asymmetry between sophisticated investors and individual investors (Katona et al. 2020), and predicting firm performance and stock returns (Froot et al. 2017; Huang 2018; Green et al. 2019; Agarwal, Qian, and Zou 2020). As one type of big data, our findings highlight that the usage of digital footprints can effectively increase the repayment likelihood on delinquent loans.

Third, we contribute to the literature on debt collateral and collection. Prior theoretical studies suggest the roles of collateral in mitigating financial frictions (Johnson and Stulz 1985; Aghion and Bolton 1992; Hart and Moore 1994, 1998), and in incentivizing repayments in debt markets (Kiyotaki and Moore 1997; Rampini and Viswanathan 2010, 2013). Empirically, Benmelech and Bergman (2009) has documented that debt collateral can lower the credit spread, and Schiantarelli, Stacchini, and Strahan (2020) finds that debt collateral backed by assets can mitigate the likelihood of delinquency. The literature on debt collection documents the determinants of the recovery of delinquent loans, including information technology development (Drozd and Serrano-Padial 2017), debt collection agencies (Fedaseyeu and Hunt 2018; Fedaseyeu 2020), and lenders' communications with borrowers via phone calls and reminder messages (Laudenbach, Pirschel, and Siegel 2018; Bursztyn et al. 2019; Du et al. 2020; Liao et al. 2020). Our study complements these studies by documenting that digital collateral backed by borrowers' social and physical capital is effective in enforcing debt repayments.

Fourth, our paper provides fresh insight on an emerging stream of literature examining the relation between fintech and traditional lenders. Prior studies have shown that fintech lenders can act as substitutes for banks (Tang 2019) and provide services in lending markets exited by traditional lenders (Erel and Liebersohn 2020). For example, the extant research suggests that fintech lenders tend to supply credit when banks face stringent regulatory constraints (Buchak et al. 2018; De Roure, Pelizzon, and Thakor 2019), when new credit regulations are introduced to limit borrowers' access to traditional lenders (Braggion, Manconi, and Zhu 2020), and when banks tighten credit standards (Allen, Shan, and Shen 2020). Moreover, fintech lenders typically process loan applications faster and adjust supply more elastically than traditional lenders (Fuster et al. 2019), and rely on investors' information production, different from the conventional banking paradigm (Vallee and Zeng 2019). In this paper, we document another key distinction of fintech lenders from the debt collection perspective, deviating from the traditional banking model.

3. Institutional background, variable definitions, and descriptive statistics

In this section, we describe the institutional background of our research setting and present the definitions and summary statistics of the variables used in our main analyses.

3.1. Institutional background

We obtain the data of personal loan contracts from a leading fintech company in China with the lending business starting from 2017. To allow the potential borrowers to submit their loan applications, the company set up application terminals in retail stores across most major cities in China, with staffs assisting loan applicants in the application process. Figure 1 illustrates the process of the loan application, approval, repayment, and collection.

[Insert Figure 1 Here]

An applicant can apply for a loan at the fintech company's terminal, which is a tablet with a touchscreen display designed for the submission of loan applications. The applicant will fill in the information in her national identity card as well as her mobile number in the loan application.[7] Subsequently, the lender can use the applicant's mobile number and national identity number to obtain the applicant's personal data from third-party data providers. The third-party information covers the applicant's mobile phone call logs from mobile carriers, delivery addresses for online shopping, credit score from Tencent (the largest social media company in China), Alipay account balance from Alibaba (the largest e-commerce company in China), and historical record of loan applications from other online lending companies.[8] With the information from the loan applicant's digital footprints and national identity card (e.g., age and gender), the fintech lender will determine whether the loan application should be approved. Then, the lender will inform the applicant with the decision of either loan approval or rejection, normally within ten minutes.

If the loan application is approved, the borrower will obtain money from the fintech lender and either use it to purchase goods or keep the cash for future use. In the next six or twelve months, subject to loan maturity, the borrower needs to pay the monthly principal and interest back to the lender. When a borrower fails to make a monthly repayment before the due date, the fintech lender will execute a standardized debt collection process against the delinquent borrower. Figure 2 illustrates the timeline of the company's debt collecting process.

As shown in the timeline, in a four-day window [-3, 0] up to the repayment due date (Day zero), the lender starts to send mobile messages as reminders to borrowers. If a borrower still does not make the repayment, on Day 4 the lender will call the borrower and tell her that debt delinquency may negatively impact her nationwide credit score, which is widely shared and

[7] The lender's staff can verify the mobile number and national identity number through a nationwide verification system after an applicant presents her physical national identity card to the staff.

[8] The applicant's digital footprints can be directly sourced from online and mobile service providers or extracted by the data providers using crawler technologies from internet websites.

used by financial institutions and public services in China. In general, it would be hard for a person with a low credit score to obtain future mortgage loans and even travel on high-speed trains and airlines.

[Insert Figure 2 Here]

The lender will also make phone calls to the borrower's frequent mobile contacts if such information can be obtained from her digital footprints. In addition, if the lender can obtain the borrower's physical location from her digital footprints, the borrower will be informed that failure to repay the debt could result in a visit by a debt collector at her physical location and probably the case will also be reported to the borrower's neighborhood committee.[9] Further, the lender will warn the borrower with penalties enforced by the police and a potential lawsuit in court. Especially, when a borrower's address information is available, the lender will inform the borrower about the possible enforcement actions in phone calls, such as releasing a legal notice to the borrower's physical location through personal service.

After Day 4, when the borrower still fails to make the loan repayment, the lender will call the borrower and her frequent contacts if available again on Day 16, Day 31, Day 61, and Day 91, if needed. Finally, following the last chasing call after Day 93, the fintech lender will hand over the delinquent loan to a third-party debt collection agency, who will make further efforts on loan collection.

3.2. Variable construction

3.2.1. Loan repayment and collection variables

Our sample starts with 236,967 personal loan applications from July 2017, when the fintech company started the lending business, to November 2019. Among these loan applications, 97,783 applications have been approved. Figure 3 presents the geographical distribution of the loan application density, (i.e., the number of applications per million of the population across the provinces in China).[10] As indicated in the figure, the sample of applications is widely spread over across the country and well represents the population in China.

[Insert Figure 3 Here]

Within the 97,783 approved loans, 41,711 borrowers experience loan delinquency. Our

[9] In China, a neighborhood committee administers the dwellers living in the residential community. Reporting to the committee may enable the spread of a borrower's loan delinquency news, thereby damaging the borrower's social capital in the residential community.

[10] The geographical distribution is estimated based on borrowers' hometown cities indicated in their national identity cards.

main analyses focus on first-time delinquency for these borrowers. To measure the outcome of loan repayment on a daily basis, we construct an indicator variable, $Paid_{t}$, equal to one if a borrower makes the repayment on Day t, and zero otherwise, with Day zero referred to the due date. We define $Chasing_{Day\ t}$ as an indicator variable equal to one for days in a three-day window [t, t+2] after the lender calls delinquent borrowers and zero otherwise for the DID analyses. Day t refers to Day 4, Day 16, Day 31, Day 61, and Day 91. To better identify the loan repayment triggered by chasing calls, we restrict the sample by only including borrowers who remain delinquent until Day t-3 for a chasing call on Day t. For example, we study the borrowers who remain delinquent on Day 1 (Day 13) in the analyses for chasing calls on Day 4 (Day 16).

In additional analyses, we further construct the loan outcome variables as follows. $Repayment_{Ratio}$ is defined as the ratio of the repayment amount to total debt outstanding. $Repayment_{Complete}$ is an indicator variable for loan recovery if the repayment amount is equal to the total debt outstanding, or more than the outstanding amount caused by the penalty of delinquency. *Delinquency* is an indicator variable that equals one if a loan is delinquent, and *Approval* is an indicator variable that equals one if a loan application is approved.

3.2.2. Digital collateral variables

We construct two measures of digital collateral in our main analyses. First, we define *Contact* as the indicator variable if a borrower's frequent mobile contacts can be obtained from her digital footprints. We apply the following filters to identify frequent contacts: 1) a frequent contact number should not be a phone number for commercial services; 2) a frequent contact should have made more than ten phone calls with the borrower; and 3) each phone call to be counted toward a frequent contact should last for more than 20 seconds.

Second, we construct the digital collateral metric, *Address*, as an indicator variable for whether a borrower's physical address can be obtained from her digital footprints. Specially, the fintech lender acquires the address data from the borrower's online shopping transactions in Taobao, the largest Chinese online shopping site operated by Alibaba. We filter out the addresses that do not appear to be the borrower's residential or office address, or those that are not helpful in identifying the borrower's location. First, we exclude the addresses with keywords in relation to convenience stores that provide the services for customers to pick up delivered packages. Second, we further exclude the addresses with no street or unit number.

In further analyses, we construct several additional digital collateral proxies in the following ways. We first construct two pseudo digital collateral measures, $Contact_{Pseudo}$ and

Address $_{Pseudo}$, by randomly assigning sample borrowers to treatment groups as if they have digital collateral. Moreover, to consider the amount of digital collateral, we count the number of the borrower's frequent mobile contacts, *Contact* $_{Number}$, and the number of the borrower's physical addresses, *Address* $_{Number}$. When a borrower has no digital collateral, we code *Contact* $_{Number}$ and *Address* $_{Number}$ as zero. We also decompose *Contact* $_{Number}$ (*Address* $_{Number}$) by the median value of the contact number (address number) in our sample, i.e., greater versus smaller than or equal to seven (one) for the contact number (address number), into *Contact* $_{1 \leqslant Number \leqslant 7}$ and *Contact* $_{Number>7}$ (*Address* $_{Number=1}$ and *Address* $_{Number>1}$). For example, *Contact* $_{1 \leqslant Number \leqslant 7}$ indicates whether a borrower has at least one and at most seven frequent contacts.

3.2.3. Control variables

We have three sets of control variables in our regression analyses. First, we include loan characteristics in the model. Du et al. (2020) finds that the loan size is negatively associated with the loan payoff likelihood and the repayment rate. We control the amount of loan principal in thousands of Chinese Yuan (*Amount*), which is converted to the logarithm value in regressions. We expect delinquent borrowers to be less likely to make repayments when they have higher debt levels. We also control for the interest rate of loan on an annual basis (*Rate*), as Iyer et al. (2016) has documented that the interest rates of loans are correlated with borrowers' credit scores, both predicting loan performance in terms of default and repayment.

Second, we control for the borrower's personal characteristics, including the age of the borrower in years (*Age*), which is converted to the logarithm value in regression analyses, and the indicator variable for the female borrower (*Gender*). Duarte, Siegel, and Young (2012) documents that lenders take borrowers' demographics, such as age and gender, into consideration, and charge low rates for old and female borrowers. Lusardi and Mitchell (2014) documents the gender differences in financial literacy around the world, which could lead to different repayment behaviors between female and male borrowers in our analyses.

Third, we control for the borrower's creditworthiness metrics (Iyer et al. 2016; Berg et al. 2020), such as the credit risk score provided by Tencent, with a high value suggesting a high-risk profile (*Score*), the balance of a borrower's Alipay account from Alibaba in Chinese Yuan (*Wealth*), and the number of a borrower's loan applications rejected by other online lending platforms (*History*). These credit quality proxies are converted to logarithm values in our regressions. We expect borrowers with higher credit scores to be more likely to make loan repayments.

3.3. Descriptive statistics

Table 1 presents the summary statistics of the main variables used in our analyses. We find that the average likelihood of loan delinquency, *Delinquency*, is 42.7% in a sample of 97,783 loans (41,711/97,783), and that of loan approval is 41.3% in a sample of 236,967 loan application (97,783/236,967). For 41,711 delinquent borrowers, 61.9% of them make repayments ($Paid_{[1,6]}$ = 61.9) within a six-day window [1, 6] after the first round of chasing calls. The average likelihood increases to 75.2% and 84.7% in an 18-day window [1, 18] and a 93-day window [1, 93], respectively.

The average ratio of repayment to total debt outstanding, $Repayment_{Ratio}$, is 1.07, and the average recovery likelihood, $Repayment_{Complete}$, is 73.8%, which is lower than the repayment likelihood in the window [1, 93]. This suggests that not all the repayments fully recover the outstanding loan amount. Indeed, in untabulated statistics, we find that among all the delinquent loans, 73.8% of borrowers make payments equal to or above the outstanding loan amount, accounting for 123.6% of the amount outstanding,[11] while 12.0% of borrowers make underpayments equal to 29.0% of the outstanding loan amount. The remaining 14.2% of borrowers make no payments.

Turning to the digital collateral metrics, 65.1% of delinquent borrowers have the information of frequent mobile contacts (*Contact* = 1), and the counterpart group includes 34.9% of borrowers with no contact that makes more than ten phone calls (*Contact* = 0), lending to a fairly large variation in the sample. For a typical borrower, the mean value of $Contact_{Number}$ is 7.49, and the median and upper quartile values are 3.00 and 9.00, respectively, suggesting a right-tailed skewness distribution. With regard to the physical address, the lender can find this information from digital footprints for 76.5% of delinquent borrowers (*Address* = 1). The mean and median values of $Address_{Number}$ are 1.06 and 1.00, respectively.

The average principal amount of personal loans in our sample is 3,966 Chinese Yuan, which is equivalent to about 567 U.S. dollars. This amount can be economically significant to an average borrower in China, considering the comment by the Premier of China, Keqiang Li, at the close of China's Two Sessions Congressional Meeting on May 28, 2020. That is, "600 million people have monthly incomes of just 1,000 Yuan" (around 143 U.S dollars), who are likely to borrow cash to complement their low incomes through fast and small lending contracts,

[11] There is a likelihood of overpayment because the fintech lender charges delay-repayment penalties on delinquent borrowers.

typically with no collateral. The annual nominal interest rate is 29.5%, substantially higher than the prime loan rate at 4.3% between 2017 and 2019, but lower than the cut-off rate for the usurious loan equal to 36.0% as per statute in China.[12]

The average age of borrowers in our sample is 27.1, with the top quartile equal to 31 and the bottom quartile equal to 21, representing a group of young borrowers who are generally familiar with the use of online services, and likely to leave their digital footprints through the use of electronic devices. Only about 18.2% of delinquent borrowers are female. Compared to the untabulated 19.2% of females in the full sample, this suggests that male borrowers are more likely to experience loan delinquency. On average, a typical borrower has the credit score at Tencent equal to 56.8, and personal wealth in the Alipay's account amounting to 4.22 Chinese Yuan, who has been rejected by other online lending platforms 0.12 times.

[Insert Table 1 Here]

4. Main results

We employ a difference-in-differences approach by matching borrowers with digital collateral (treatment group) to those with no collateral (control group). We conduct the tests based on the two matched samples: one for borrowers with or without the frequent contact information, and the other for borrowers with or without the physical address information.

4.1. Matched samples

We use the propensity score matching strategy to construct our matched samples on a one-to-one basis without replacement. The PSM approach accounts for both loan characteristics (*Amount* and *Rate*) and borrower characteristics (*Age*, *Gender*, *Score*, *Wealth*, and *History*), which may influence the debt collection process. Given that there are more delinquent borrowers with digital collateral than those with no collateral (e.g., the mean of *Contact* = 65.1%), it is likely that a borrower in the treatment group would have no match in the control group when the distance of her propensity score to any control borrower is not the least

[12] There are two cut-off rates for the usurious loans in China, 24% and 36%. For example, when a borrower enters a loan contract with an annual interest rate equal to 30%, the interest proportion below 24% needs to be paid by the borrower, but the proportion between 24% and 30% will not be protected by the law. However, if the borrower has paid the interest between 24% and 30%, she cannot require the lender to return the interest payment. In another example, if a borrower enters a loan contract with an annual interest rate equal to 40% and has paid the interest, she has a right to ask the lender to return the interest proportion between 36% and 40%, and this request will be supported by the court.

compared to all other treatment borrowers.[13]

This approach provides us with two matched samples. One sample consists of 14,768 delinquent borrowers having frequent mobile contacts in their social networks as the treatment group, together with the same number of borrowers with no frequent contact information as the control group. Another sample includes 9,994 delinquent borrowers with delivery addresses for online shopping as the treatment group and those without the address information as the control group.

Table 2 presents the results of a comparison of loan and borrower characteristics between the treatment and control groups. In Panel A, we focus on a treatment group of 14,768 borrowers with frequent contact information and find no statistical difference in loan and borrower characteristics between the two groups. This finding validates that our PSM process is well executed.

In Panel B, we find similar results for a treatment group of 9,994 borrowers with physical addresses, except that the borrowers in the treatment group encounter higher interest rates (*Rate*) and have lower balances in their online payment accounts (*Wealth*) than the borrowers in the control group. Although the significant differences in *Rate* and *Wealth* between the two groups may suggest some imperfection of our matching process, the direction of such differences is actually biased against our main analyses. That is, we conjecture that the borrowers with digital collateral in the treatment group are more likely to make loan repayments, while the higher interest rates and lower wealth balances, on the contrary, may make it more difficult for borrowers to repay the outstanding loans.

[Insert Table 2 Here]

4.2. Univariate analyses

We conduct the univariate analyses in Table 3 along the timeline of loan delinquency. In Panel A, we find that the likelihood of repayment is 11.7% in a three-day window [1, 3] after the delinquency for the treatment borrowers with frequent mobile contacts (*Contact*=1) in a sample of 44,304 borrower-day observations for 14,768 delinquent borrowers. The likelihood is 11.8% for the control borrowers with no frequent contact information (*Contact*=0). It is noteworthy that the pre-event difference between the two groups is insignificant.

[13] We find similar results when we perform the PSM strategy on a one-to-one basis *with* replacement, resulting in matched samples in which each treatment borrower can be matched to a borrower in the control group, while a control borrower can be re-used matching to multiple borrowers in the treatment group.

After the fintech lender makes chasing calls on Day 4, the borrowers in the treatment group have a significantly higher repayment likelihood (9.5%) in the window [4, 6] than the borrowers in the control group (7.8%). This is because the lender tells the treatment borrowers and their frequent contacts that debt delinquency may cause a negative impact on borrowers' nationwide credit scores, but only warns the control borrowers themselves given the unavailability of frequent contacts. The difference in the likelihood between the two groups is equal to 1.7% and statistically significant at the one percent level. Economically, moving from the control group to the treatment group, there will be a 21.5% (1.7%/7.8%) increase in the repayment rate in the post-call period.

[Insert Table 3 Here]

Our findings are similar around the second wave of chasing calls on Day 16 for 4,412 borrowers who remain delinquent on Day 13.[14] Specifically, the lender will warn the borrowers in the treatment group (*Contact*=1) and their frequent contacts again, as opposed to the control group in which only borrowers will be called. The results again show that in a three-day window [13, 15] prior to the phone call, there is no significant difference in the repayment likelihood between the treatment and control groups. However, in the post-call window [16,18], borrowers in the treatment group have a significantly higher repayment rate (3.7%) than those in the control group (2.5%), with the difference equal to 1.2% and significant at the one percent level. This finding is also economically significant. Compared to the control group, there is a 46.0% (1.2%/2.5%) increase in the repayment rate for the treatment group.

The DID results suggest that the differences between the pre- and post-windows are also significant for the two groups of borrowers. For example, we find that although in the post-window [4, 6] there are reductions in the repayment rates for both groups, the decrease in the repayment likelihood is lower for the borrowers with the frequent contact information (−2.2%, *Contact*=1) than the borrowers without such information (−4.0%, *Contact*=0). The difference in differences is 1.8% and significant at the one percent level (t-statistic=6.21). We find similar results for the second wave of chasing calls on Day 16 (*DID*=1.0%, and t-statistic=3.72).

Moreover, these results also hold in Panel B for 9,994 borrowers in the treatment group with physical addresses for the first round of chasing calls on Day 4. The difference in the repayment rate between borrowers with physical addresses (*Address*=1) and those with no

[14] We focus on the first and second phone calls on Day 4 and Day 16 in our main analyses because, after the first two calls, a majority of delinquent borrowers in the treatment group have made the repayments (69.6% and 66.8% for those with contact and address information, respectively). In additional tests, we find results hold for subsequent calls.

address (*Address*=0) is only -0.2% and insignificant in the pre-call window [1, 3], while this difference is 1.6% in the post-call window [4, 6] and significantly positive at the one percent level. The difference in the pre-post difference between the two groups is 1.8%, significant at the one percent level (t-statistic=5.38). This is because the lender will tell the treatment borrowers that the lender's staffs would come to their places for debt collection, report the delinquency to their neighborhood committees, and possibly take further legal action to enforce loan repayments at the borrowers' physical address. It is also likely that these borrowers will face more pressure due to reduced psychological distance and heightened threatening stimulus, with their addresses known by the lender. However, the lender will only warn the borrowers in the control group of the potential damages to their credit scores. In addition, we examine the second wave of chasing calls, when the lender will call the borrowers in the treatment group (*Address*=1) with physical addresses again on Day 16. We find similar results for 3,459 borrowers who remain delinquent until Day 13 (*DID*=0.9%, and t-statistic=3.20).

Lastly, we illustrate these prepayment likelihood patterns in Figures 4 and 5. The figures show that there are larger increases in repayments over periods after the fintech lender makes the chasing calls to the borrowers backed by digital collateral than those with no digital collateral.

[Insert Figures 4 and 5 Here]

4.3. Main findings

In this subsection, we examine the effect of digital collateral on debt collection using the multivariate regression analysis. We specify our main DID analysis within a six-day window [s-3, s+2] in the following linear probability model, with Day s indicating the date for the lender to make chasing calls:

$$\begin{aligned} Paid_t = \alpha &+ \beta_{CD\times DC}\, Chasing\ Day_s \times Digital\ Collateral\ Proxy \\ &+ \beta_{CD\times Control}\, Chasing\ Day_s \times Control\ Variables + \beta_{FE}\, Fixed\ Effects + \varepsilon, \end{aligned} \tag{1}$$

where $Paid_t$ indicates if the repayment is made by a borrower on Day t, and $Chasing\ Day_s$ is equal to one if Day t is in the three-day window [s, s+2], and zero if Day t is in the window [s-3, s-1].[15] *Digital Collateral Proxy* denotes the metrics of digital collateral constructed based on digital footprints, i.e., *Contact* and *Address*, constructed for each borrower. We interact

[15] We employ the linear probability model throughout the paper for the analyses using indicators as dependent variables, to accommodate the inclusion of fixed effects (Berg et al. 2020).

Chasing Day $_s$ with the *Digital Collateral Proxy* to capture the DID effect of *Digital Collateral* between the pre- and post-chasing call periods. We expect the coefficient of the interaction term to be significantly positive when digital collateral facilitates debt collection.

Control Variables denotes a vector of control variables of loan and borrower characteristics, as described in Subsection 2.2, which are interacted with *Chasing Day* $_s$ to account for the effects of chasing calls that may moderate the impact of control variables on the repayment likelihood. We also include *Fixed Effects*, the borrower and day fixed effects, to control for cross-sectional and time series omitted factors and cluster standard errors at the borrower level.[16]

We perform the DID tests based on Equation (1) for the first two rounds of chasing calls. Around the first chasing call on Day 4, for the 14,768 borrowers with in the treatment group with frequent mobile contacts, the matched sample in the DID analyses consists of 177,216 borrower-day observations for both the treatment and control groups in the six-day window (14,768×2×6). For the 9,994 treatment borrowers with the information of physical addresses, the matched sample includes 119,928 borrower-day observations (9,994×2×6). Similarly, we examine the second round of chasing calls on Day 16 for the remaining 4,412 and 3,459 borrowers in the treatment group with contact and address information who have not made repayments until Day 13. The two samples for the second chasing call tests consist of 52,944 (4,412×2×6) and 41,508 borrower-day observations (3,459×2×6), respectively.

The results in Table 4 suggest that digital collateral is useful for the fintech lender in the debt collection process. For example, in Model 1, we find that delinquent borrowers with frequent contact information have a significantly larger increase in the repayment likelihood, from the pre-call window [1, 3] to the post-call window [4, 6], than those with no frequent contact information. The coefficient on *Chasing* $_{Day\ 4}$×*Contact* is 1.76, and significant at the one percent level, which accounts for an increase of 16.6% relative to the average daily repayment likelihood in the window [1, 6]. We find similar results when we examine *Address*. For example, in Model 2, the coefficient on *Chasing* $_{Day\ 4}$×*Address* is 1.79 and significant at the one percent level (*t*-statistic=5.00), accounting for an increase of 18.5% relative to the sample mean of daily repayment likelihood.

Regarding the control variables, in Model 1, we find that chasing calls have a significantly

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[16] In this DID specification, we do not control for the main effect of *Chasing Day s*, because this effect has been absorbed by the day fixed effects. We also do not control for the main effects of the control variables, because the interaction terms have absorbed them. We find similar results when we drop the interaction terms and only control for the main effects of the control variables.

positive impact on relatively old borrowers (coefficient on $Chasing_{Day\ 4}\times Age$=5.71 and t-statistic=10.21) and borrowers with high credit risk profiles (coefficient on $Chasing_{Day\ 4}\times Score$=3.35 and t-statistic=6.50). This suggests that older and riskier borrowers are more concerned about the possible detrimental impact on their credit scores if they do not make loan repayments. In contrast, chasing calls have a significant and negative reciprocal effect on loan repayment for loans with large amounts (coefficient on $Chasing_{Day\ 4}\times Amount$=-1.92 and t-statistic=-4.62) and for loans with high interest rates (coefficient on $Chasing_{Day\ 4}\times Rate$=-12.74 and t-statistic=-6.98), and also for female borrowers who could be more annoyed by chasing calls and thereby may be less motivated to repay the delinquent loans (coefficient on $Chasing_{Day\ 4}\times Gender$=-2.29 and t-statistic=-5.72).

Further evidence shows that the inferences hold when we investigate the effect of digital collateral for the second chasing call on Day 16. For instance, in Models 3 and 4, the coefficients on $Chasing_{Day\ 16}\times Contact$ and $Chasing_{Day\ 16}\times Address$ are 1.03 and 0.90 and both significant at the one percent level (t-statistics=3.67 and 3.04). However, these coefficients are smaller in magnitude than those in Models 1 and 2 with z-statistics of differences in coefficients equal to 1.76 and 1.93, respectively. Intuitively, this finding suggests that borrowers who remain delinquent after the first round of chasing calls are less responsive to further calls, because they are less concerned about the potential loss of their social capital and/or about being chased by debt collectors through their physical locations.

Taken together, the results in Table 4 provide support for the use of digital collateral in debt collection.

[Insert Table 4 Here]

4.4. Placebo tests

One potential concern regarding our main findings is that the DID analysis results are either explained by a time trend effect around the chasing calls, which coincides with the presence of digital collateral, or driven largely by chance. In this subsection, we employ two placebo tests to alleviate this concern.

First, we re-run the DID analysis for a six-day window [-2, 3] by considering Day 1 as the placebo date for chasing calls. If our previously documented results for chasing calls made on Day 4 are driven by a time trend effect, we should observe a similar effect for digital collateral in this placebo test. That is, borrowers with the information about frequent contacts or physical addresses would have an increase in repayment likelihood from window [-2, 0] to window [1, 3] compared to those without such information.

The results are reported in Panel A of Table 5. We find that the coefficient on *Chasing Day* $_1$×*Contact* is -0.074 and insignificant (*t*-statistics=-0.40) in Model 1. This suggests that before receiving chasing calls, delinquent borrowers with key contact information in digital footprints are indifferent from those without this information in terms of loan repayment. We find similar results in Model 2 for borrowers in the treatment group with physical address information (coefficient on *Chasing Day* $_1$×*Address*=-0.266 and *t*-statistic =-1.22). Therefore, we find supportive evidence mitigating the concern about a time trend effect around the chasing calls for the change in repayment likelihood from the window [-2, 0] to window [1, 3].

[Insert Table 5 Here]

Second, following the approach of Leary and Roberts (2014), we conduct simulations by running placebo tests based on pseudo borrowers with digital collateral. Specifically, we begin with the matched samples of delinquent borrowers based on Day 4, consisting of 177,216 (119,928) borrower-day observations for borrowers in the treatment group with key contact (physical location) information. Next, we randomly assign half of the sample borrowers as the pseudo borrowers with digital collateral and define the new indicator variables equal to one for these pseudo treatment borrowers, $Contact_{pseudo}$ ($Address_{pseudo}$). We assign the remaining borrowers to the pseudo control groups with $Contact_{pseudo}$ ($Address_{pseudo}$) denoted by zero.

We generate 1,000 randomly assigned samples for pseudo borrowers and then repeat the DID analyses based on the chasing calls made on Day 4. Panel B of Table 5 presents the means and distribution percentiles of the coefficients on $Chasing_{Day\ 4}$×$Contact_{Pseudo}$ and $Chasing_{Day\ 4}$×$Address_{Pseudo}$ based on the 1,000 reiterations of the regression. If our baseline findings are largely driven by chance, we may find the coefficients on digital collateral in our main results close to the mean and median values of coefficients in these placebo tests.

In contrast, we find that the mean and median values of the $Chasing_{Day\ 4}$×$Contact_{Pseudo}$ ($Chasing_{Day\ 4}$×$Address_{Pseudo}$) coefficients are 0.004 and -0.005 (-0.017 and -0.011) and insignificant with *t*-statistics of 0.013 and -0.017 (-0.048 and -0.030), respectively. These statistics are much smaller than the coefficients on $Chasing_{Day\ 4}$×*Contact* and $Chasing_{Day\ 4}$×*Address* reported in Table 4 (1.759 and 1.794), implying that our main findings are not driven by chance.

Collectively, the findings in this subsection suggest that neither the time trend effect nor the by-chance explanation can be the main force driving our baseline findings, and therefore strengthen the inferences associated with the digital collateral effect in our main analyses.

4.5. Additional tests

In this subsection, we perform the additional tests concerning the amount of digital collateral, the sequence of chasing calls, and the separation of the two types of digital footprints.

4.5.1. Amount of digital collateral

First, we investigate whether the variation in the amount of digital information impacts debt collection. On the one hand, more relevant information from digital footprints may allow the lender to reach a larger group of a borrower's frequent contacts, and to discover her physical addresses more completely. On the other hand, given the lender's time and resource constraints faced the lender's staffs, a large amount of digital information may lead to information overload, limited attention, and inferior outcomes (e.g., Abdel-Khalik 1973; Hirshleifer and Teoh 2003; Campbell, Loumioti, and Wittenberg-Moerman 2019). Therefore, we expect that although a greater amount of digital information effectively facilitates debt enforcement, such effectiveness per se may decline with the information amount.

In Models 1 and 2 of Table 6, we employ the numbers of a borrower's frequent contacts and physical addresses (i.e., $Contact_{Number}$ and $Address_{Number}$) as the main independent variables of interest, and re-conduct our DID analyses for the first round of chasing calls around Day 4. Consistent with our main results, we find that both $Contact_{Number}$ and $Address_{Number}$ have positive impacts on the likelihood of loan repayment through chasing calls. The coefficients on $Chasing_{Day\ 4} \times Contact_{Number}$ and $Chasing_{Day\ 4} \times Address_{Number}$ are 0.51 and 1.84, respectively, and both are significant at the one percent level (t-statistics=3.93 and 4.43). These findings indicate an average positive effect of the digital footprint amount on loan repayment.

Also, as discussed in Section 2, we decompose $Contact_{Number}$ and $Address_{Number}$ into subcomponents, i.e., $Contact_{1 \leqslant Number \leqslant 7}$, $Contact_{Number>7}$, $Address_{Number=1}$, and $Address_{Number>1}$, based on the sample medians to examine the potential information overload effect (Abdel-Khalik 1973; Campbell, Loumioti, and Wittenberg-Moerman 2019). In Model 3, we find that the coefficients on $Chasing_{Day\ 4} \times Contact_{1 \leqslant Number \leqslant 7}$ and $Chasing_{Day\ 4} \times Contact_{Number>7}$ are 2.13 and 1.31 and both are significant at the one percent level (t-statistics=5.96 and 3.30). The difference between the two coefficients is significant at the ten percent level (z-statistic=1.83).

One possible explanation is that for a borrower with many frequent contacts, the lender's staff facing time and resource constraints may resort to simplified information processing and heuristics, and thus overlook or underweight relevant information (Hirshleifer and Teoh 2003). For example, the staffs may choose some contacts to make chasing calls rather than reaching out all contacts. However, for such a borrower with lots of contacts, these selected contacts may be less critical, compared to those for a borrower with a small number of key contacts.

In Model 4, we find a larger coefficient on $Chasing_{Day\ 4} \times Address_{Number=1}$ (coefficient=1.85, t-statistic=4.74) relative to the coefficient on $Chasing_{Day\ 4} \times Address_{Number>1}$ (coefficient=1.65, t-statistic=2.89), although the difference between the coefficients is statistically insignificant.

In sum, these results suggest that on average the likelihood of loan repayment increases with the amount of digital collateral, although the increase may not be linear. When there are a large number of digital footprints, the lender may spend more time identifying the key information, which could reduce the effectiveness of the digital collateral.

[Insert Table 6 Here]

4.5.2. Sequence of chasing calls

We focus on the first two chasing calls made on Day 4 and Day 16 in the main analyses. In this subsection, we first investigate the overall effect of digital collateral on the repayment rate along the whole collection timeline before the lender hands over delinquent loans to external collection agencies. After that, we conduct the analyses to compare the effect of digital collateral in the first two rounds of chasing calls (Day 4 and Day 16) with the effect in the next three rounds of chasing calls (Day 31, Day 61, and Day 91), as illustrated in Figure 2.

We start by performing the DID tests using the five six-day windows for all chasing calls. We construct an indicator variable, $Chasing_{All}$, equal to one for days in windows [4, 6], [16, 18], [31, 33], [61, 63], and [91, 93], and zero otherwise. The number of borrowers in the treatment group with frequent contact information who remain delinquent in the three days before each chasing call (i.e., on Day 1, Day 13, Day 28, Day 58, and Day 88), is 14,768, 4,412, 3,346, 2,638, and 2,388 for calls on Day 4, Day 16, Day 31, Day 61, and Day 91, respectively. Therefore, the sample testing the frequent contact information for all chasing calls includes 330,624 borrower-day observations.[17] For borrowers in the treatment group with physical location information, the sample consists of 241,812 observations, because the number of treatment borrowers varies across the five calling days and is equal to 9,994, 3,459, 2,696, 2,102, and 1,900, respectively.[18]

[17] The sample for treatment borrowers with contact information consists of (14,768+4,412+3,346+2,638 +2,388)×2×6 = 330,624 borrower-day observations.

[18] Accordingly, the sample size is equal to (9,994 +3,459 +2,696 +2,102 +1,900) ×2×6 =241,812.

Table 7 presents the results. In Models 1 and 2, we find that digital collateral has an overall effect on facilitating the debt collection process in all the five windows. For example, in Model 1, we find that in general, the borrowers with frequent contact information are more likely to repay debt after chasing calls than those with no contact information. The coefficient on $Chasing_{All} \times Contact$ is 1.17, significant at the one percent level (t-statistic = 6.68).

Next, we decompose $Chasing_{All}$ into $Chasing_{Day\ 4,16}$ and $Chasing_{Day\ 31,61,91}$ to differentiate the first two rounds of chasing calls from the last three chasing calls. The psychology literature suggests that repeated notifications may result in a boredom effect, making people feel irritated, bothered, or bored (Bornstein 1989; Bornstein, Kale, and Cornell 1990). Accordingly, we expect the effect of $Chasing_{Day\ 31,61,91}$ to be smaller than that of $Chasing_{Day\ 4,16}$. In Models 3 and 4, we find positive and significant coefficients on both interaction terms. For instance, in Model 3, the coefficients on $Chasing_{Day\ 4,16} \times Contact$ and $Chasing_{Day\ 31,61,91} \times Contact$ are 1.40 and 0.63, respectively, significant at the one percent level (t-statistics=6.46 and 4.89). Consistent with our expectation, the differences in these coefficients are statistically significant (z-statistics of difference=3.11 and 2.04) in Models 3 and 4.

These findings suggest that although chasing calls using digital information in the last three rounds are still effective in enforcing debt collection, the magnitude of the effect declines, consistent with our results in Table 4 for a comparison between chasing calls on Day 4 and Day 16. A potential explanation is that delinquent borrowers, who have been warned but fail to make repayments after the first two calls, are less concerned about their digital collateral (Bornstein 1989; Bornstein, Kale, and Cornell 1990). As a result, these remaining delinquent borrowers are less responsive to further calls.

[Insert Table 7 Here]

4.5.3. Separation of the two types of digital footprints

In the main analyses, we treat the two types of digital footprints separately. However, for some delinquent borrowers, the lender can obtain both the frequent contact and physical address information from the third-party data providers. Therefore, it is plausible that our main findings are driven mainly by one type of digital footprint. To address this concern, we conduct additional tests to differentiate the effects of the two types of digital footprints.

Specifically, we start with 14,768 borrowers in the treatment group with key contact information in the matched sample based on *Contact*. We then focus on those with only frequent contact information, which provides us with a subsample of 2,914 borrowers. The matched sample includes 34,968 borrower-day observations (2,914×2×6). We define $Contact_{Only}$ as an indicator variable equal to one if a borrower has at least one frequent contact but has no information about online shopping delivery address, and zero otherwise. In Model 1 of Table 8, we re-run the DID analyses with these *contact-only* borrowers. We find that the coefficient on $Chasing_{Day\ 4} \times Contact_{Only}$ remains positive and significant (coefficient=2.57 and *t*-statistic=3.63).

In Model 2, we follow a similar sample selection approach to construct a subsample of 3,024 *address-only* borrowers from the matched sample with 9,994 borrowers in the treatment group based on *Address*. We obtain a matched sample with 36,288 borrower-day observations (3,024×2×6). We define $Address_{Only}$ in a similar manner as an indicator variable equal to one if a borrower has at least one online shopping delivery address but has no information about frequent contact. We find that the coefficient on $Chasing_{Day\ 4} \times Address_{Only}$ is also positive and significant (coefficient on $Chasing_{Day\ 4} \times Address_{Number}$=1.40 and *t*-statistic=2.19).

In Model 3, we investigate a sample with 15,334 borrowers in the treatment group who have both frequent contact and physical address information. To construct this sample, we first obtain 11,854 borrowers with both types of digital information from the *Contact*-based matched sample, and then complement it with 3,480 borrowers from the *Address*-based sample but not included in the *Contact*-based sample. The sample in Model 3 includes 184,008 borrower-day observations (15,334×2×6). We construct $Collateral_{Both}$ as an indicator variable equal to one if a borrower has at least one frequent contact and at least one online shopping delivery address, and zero otherwise. The coefficient on $Chasing_{Day\ 4} \times Collateral_{Both}$ is 1.44 and significant (*t*-statistic=4.42).

Finally, in Model 4, we include $Chasing_{Day\ 4} \times Contact_{Only}$, $Chasing_{Day\ 4} \times Address_{Only}$, and $Chasing_{Day\ 4} \times Collateral_{Both}$ in the same model based on an aggregated sample. The sample includes 255,264 borrower-day observations used in Models 1 to 3 (34,968+36,288+184,008). We find positive and significant coefficients for all the interaction terms for $Contact_{Only}$, $Address_{Only}$, and $Collateral_{Both}$ (coefficients=1.93, 2.37, and 1.39, and *t*-statistics=4.04, 5.26, and 4.27, respectively).

These findings collectively suggest that both types of digital footprints play significant roles in facilitating debt collection, and thus mitigate the potential concern regarding the contamination effect between the *social capital channel* and *physical location channel*.

[Insert Table 8 Here]

5. Additional tests

In this section, we first perform cross-sectional tests for the economic channels of social capital and physical location. Then, we conduct the analyses for other outcome variables along the loan process, including the repayment amount, the likelihood of loan delinquency, and the decision of loan approval.

5.1. Cross-sectional analyses of social capital channel

We conjecture that the digital collateral effect on debt collection operates through the *social capital* and *physical location channel*s. In this subsection, we conduct the cross-sectional analyses to validate the economic mechanism in relation to borrower's social capital.

We employ the 2017 China Household Finance Survey (CHFS) data to test the *social capital channel*. Since 2011, this survey has been conducted biannually by the Survey and Research Center for China Household Finance (Clark, Yi, and Huang 2019; Lugauer, Ni, and Yin 2019). The 2017 survey questions in relation to social capital were designed to ask participants about their social behavior in 2016, one year prior to our sample period from July 2017 to November 2019.[19] We construct two social capital metrics, $Social_{Spending}$ and $Veneration_{Ancestor}$, based on the 2017 CHFS data.

First, we estimate $Social_{Spending}$ as the average amount of annual social spending by a household scaled by the average annual household income at the province-year level. This is because gift-giving is considered to be an important mechanism of social exchange in China to establish and maintain personal social networks (Hwang 1987; Yang 1994). Social spending by a household is measured as the value of cash and non-cash gifts given to and received from family members and friends, for festivals like Lunar New Year and personal social events, such as a birthday.

Second, we construct $Veneration_{Ancestor}$ to be the average percentage of households attending veneration events of honoring ancestors at the province-year level. Ancestor veneration and worship can stress social unity and are associated with familism, the basis of Chinese religious conception (Lakos 2010). In Chinese society, the family is deemed the most important social group of an individual (Hwang 1987).

We match the province information in the CHFS data to the address information indicated in a borrower's national identity card. We choose to use the address information in the national

[19] For example, one relevant question in the 2017 survey is: "In the last year (2016), what is the value of cash and non-cash gifts that you receive from family members and friends for festivals like Lunar New Year and Mid-Autumn Festival?"

identity card, not the delivery address information in digital collateral, for three reasons. First, the social capital effect that we examine operates through a borrower's social network, which connects to her family members and friends mostly built in her hometown, as reflected in the national identity card. Second, the culture and social norm in a borrower's hometown help form her social awareness and therefore shape her behavior, potentially influencing her future decision making in the lending process. Third, our results in this analysis on the *social capital channel* would be less subject to the *physical location channel* because we perform the tests in a large sample, rather than in a restricted sample that requires the existence of borrowers' physical locations in digital footprints.

We then split our matched sample for *Contact* by the sample medians of $Social_{Spending}$ and $Veneration_{Ancestor}$ and re-run our regression analysis as in Model 1 of Table 4.[20] We expect the digital collateral effect based on key contact information to be more pronounced for borrowers from hometowns with higher $Social_{Spending}$ and more frequent $Veneration_{Ancestor}$. This is because borrowers from hometowns, where people are more incentivized to maintain social networks and believe in familism (Yang 1994; Lakos 2010), and can be more concerned about the potential impairment on their social capital and thus are more likely to make repayments when the lender communicates with their frequent contacts.

The results are reported in Panel A of Table 9. Consistent with our prior, we find that the coefficients on $Chasing_{Day\ 4} \times Contact$ are larger in the subsamples characterized as high $Social_{Spending}$ and $Veneration_{Ancestor}$ (in Models 1 and 3, coefficients=2.41 and 2.37 and *t*-statistics=5.78 and 5.97, respectively), compared to borrowers from provinces with the low values of $Social_{Spending}$ and $Veneration_{Ancestor}$ (in Models 2 and 4, coefficients=1.16 and 1.51 and *t*-statistics=2.66 and 2.26). The differences are statistically significant for both $Social_{Spending}$ and $Veneration_{Ancestor}$ (*z*-statistics of differences=2.07 and 2.14).[21]

Taken together, these results are consistent with our conjecture on the *social capital channel*. That is, when the potential loss of a borrower's social capital is more substantial, the borrower would be more motivated to repay the loan (Karlan et al. 2009). The results are also generally aligned with the literature on corporate decisions and outcomes, which documents a positive role of social capital regarding, for example, debt contracting (Hasan, Hoi, and Zhang 2017), management compensation (Hoi, Wu, and Zhang 2019), and corporate innovation

[20] We split the sample based on the values of $Social_{Spending}$ and $Veneration_{Ancestor}$ for the treatment borrowers, and the borrowers in control group are assigned to subsamples aligned with their matched treatment borrowers.
[21] The sum of the subsamples can be slightly smaller than that in our main analysis, because not all of the provinces in our main sample are surveyed in the CHFS data.

(Gupta, Raman, and Shang 2020).

[Insert Table 9 Here]

5.2. Cross-sectional analyses of physical location channel

In this subsection, we perform the cross-sectional analyses to validate the *physical location channel*, based on two metrics related to borrowers' physical addresses identified in digital footprints.

We first estimate the geographical distance between the city of a borrower's physical location, as indicated in her digital footprints, and Shanghai, where the fintech lending company is headquartered. The majority of the fintech lender's staffs are employed in the head office of Shanghai, taking responsibility for the company's main business activities such as the implementation of the debt collection process. We denote this distance as $Distance_{FinTech}$. For a borrower with multiple physical locations, the most frequently used online shopping delivery address will be chosen to estimate the distance. When there are multiple addresses deemed the most frequent, the most recently used address will be selected.

The extant lending literature suggests that greater geographical distance can make it more difficult for lenders to renegotiate with borrowers and recover funds (Mian 2006). Also, lenders tend to reduce lending to long-distance borrowers during the financial crisis (De Haas and Van Horen 2013), and demand collateral and grant loans of short maturity (Beck, Ioannidou, and Schäfer 2018). Therefore, we expect that it would be more likely for the lender to recover delinquent loan when a borrower is geographically closer. Furthermore, a close-by borrower may psychologically face more threatening pressure from the lender (McGraw et al. 2012). This leads to a weaker digital collateral effect through the *physical location channel*, because a nearby borrower can be concerned about being chased by the lender, regardless of whether her physical location is mentioned or not in the chasing calls. In contrast, for a remote borrower, having identified physical address will substantially increase her concern about being physically located by the debt collector and induce pressure due to the reduced psychological distance between the lender and borrower and the heightened threatening stimulus (Williams, Stein, and Galguera 2014; Boothby et al. 2016).

Next, we again exploit the CHFS data to construct a confidence measure of law enforcement. The relevant question asked in the 2017 CHFS survey is: "Could you please give your satisfaction rating for the enforcement by the local police office and local court system?" We adopt the average satisfaction rating by households at the province-year level, *Litigation*

$_{Confidence}$, and match it to a borrower's physical location in digital footprints. The rating varies between one and five, with a higher value indicating more satisfaction. In alignment with the *physical location channel*, we expect the digital collateral effect to be stronger when the local police and court systems are perceived as more satisfactory in terms of law enforcement (Djankov et al. 2008). This is because delinquent borrowers believe that the lender will use the information of their physical location to pursue judicial enforcements, leading to judgment liens on the borrowers' assets.

The results are presented in Panel B of Table 9. Consistent with the *physical location channel*, we find a stronger digital collateral effect for borrowers in subsamples with long $Distance_{FinTech}$ and high $Litigation_{Confidence}$ (in Models 1 and 3, coefficients=2.56 and 2.55 and t-statistics=5.41 and 5.16, respectively) than their counterparties (in Models 2 and 4, coefficients=0.88 and 1.19 and t-statistics=1.71 and 2.43). The differences are statistically significant, with z-statistics of 2.39 and 1.97 for $Distance_{FinTech}$ and $Litigation_{Confidence}$, respectively.

Overall, these findings corroborate our main results in Table 4 and provide further support for the *physical location channel*. We document the scenarios under which delinquent borrowers will face pressure and are incentivized to make loan repayments.

5.3. Repayment amount for delinquent loans

To this end, we mainly focus on the probability of repayment for delinquent loans. In this subsection, we will investigate the impact of digital collateral on the amount of debt recovery. This analysis can provide important payoff implications for the lender (Karlan and Zinman 2010). When a delinquent borrower makes the loan repayment, she may underpay the overdue amount because of a shortfall of cash or make payments over the original amount for the overdue penalty. Therefore, from the lender's perspective, the expected payoff for an average delinquent loan is a function of the likelihood of repayment, and the perceived amount of contingent repayment.

We construct two measures for debt recovery, $Repayment_{Ratio}$, and $Repayment_{Complete}$. The former is the ratio of the amount of repayment for the delinquent loan divided by the payment amount due, and the latter is the indicator variable equal to one if a borrower makes the repayment equal to or greater than the delinquent amount. The analyses are performed in the following model for a sample of 41,711 delinquent borrowers:

$$Repayment_{Ratio} \,/\, Repayment_{Complete} = \alpha + \beta_{DC}\, Digital\ Collateral\ Proxy$$

$$+ \beta_{Control}\ Control\ Variables + \beta_{FE}\ Fixed\ Effects + \varepsilon, \qquad (2)$$

where *Digital Collateral Proxy* and *Control Variables* denote the metrics of digital collateral and control variables, which have been adopted in Equation (1). *Fixed Effects* denote the province and year fixed effects to control for the cross-sectional variations across geographic areas and the time series variations. The standard errors are clustered at the province level. We expect to find results consistent with the analyses of the repayment likelihood, i.e., a significant and positive coefficient on *Digital Collateral Proxy*, suggesting that the amount of debt recovery also increases with the availability of digital collateral.

Table 10 presents the results for the tests on the amount of debt recovery. In Models 1 and 2, we find that the coefficients on *Contact* and *Address* are 2.37 and 6.12 for $Repayment_{Ratio}$ and significant at the one percent level (t-statistics=5.50 and 7.19). Regarding our control variables, we find the intuitive results confirming that borrowers with higher risk profiles make the lower amounts of repayments, and borrowers with larger balances in online payment accounts pay off more outstanding debts. For example, in Model 1, the coefficients on *Score* and *Wealth* are -9.81 and 1.01 and significant at the one percent level (t-statistics=-12.00 and 10.25), respectively.

Furthermore, we focus on the completion of repayment, $Repayment_{Complete}$, in Models 3 and 4. The results show that borrowers with frequent contact information and physical address information are more likely to fully pay off the overdue amounts. The coefficients on *Contact* and *Address* are 1.22 and 5.21, respectively, both significant at one percent level (t-statistics=3.49 and 9.67).

These results suggest that the magnitude of debt recovery increases with the availability of borrowers' social network and physical location information in digital footprints.

[Insert Table 10 Here]

5.4. Loan delinquency likelihood

Another possible concern regarding our main findings is that digital collateral measures could also reflect borrowers' creditworthiness (Iyer et al. 2016). We have largely alleviated such concern by performing DID analyses and controlling for borrowers' characteristics, including the metrics of credit quality, such as *Score*, *Wealth*, and *History*.

Nevertheless, in this subsection, we intend to further mitigate this concern by examining the association between digital collateral and the likelihood of loan delinquency. The test will be performed in the model below with a sample including 97,783 loan contracts for both delinquent and non-delinquent borrowers:

$$Delinquency = \alpha + \beta_{DC}\, Digital\ Collateral\ Proxy + \beta_{Control}\, Control\ Variables \\ + \beta_{FE}\, Fixed\ Effects + \varepsilon, \tag{3}$$

where *Delinquency* is an indicator variable equal to one if a borrower fails to make a loan payment by the due date at least once during the loan term. The control variables and fixed effects are the same as specified in Equation (2).

If the availability of digital collateral metrics mainly reflects borrowers' high credit quality, we would expect a significantly negative association between *Delinquency* and *Digital Collateral Proxy*. However, the results in Table 11 indicate that the incidence of loan delinquency is even positively associated with the presence of borrowers' frequent contact information. That is, in Model 1, we find that the coefficient on *Contact* is 3.85 and significant at the one percent level (*t*-statistic=15.73). Economically, this coefficient accounts for 8.98% of the average likelihood of the loan delinquency in our sample. We do not find a significant coefficient on *Address* in Model 2 (coefficient=-0.848, and *t*-statistic=-1.65). These findings suggest that our digital footprint proxies cannot be interpreted as borrowers' credit quality measures with respect to their delinquency probability.

Regarding our control variables, we find that older and female borrowers are less likely to be delinquent as older people typically have built up a long-term credit record, and female borrowers may be less aggressive in making borrowing decisions (e.g., the coefficient on *Age*=-8.99 and *t*-statistic=-7.15, and the coefficient on *Gender*=-4.10 and *t*-statistic=-6.89 in Model 1), consistent with prior studies (Duarte, Siegel, and Young 2012; Du et al. 2020). For other conventional creditworthiness measures, we find that they are negatively associated with the loan delinquency rate. For instance, the coefficients on *Score* are significantly positive across all the models, aligned with the notion that risky borrowers tend to engage in loan delinquency (e.g., coefficient=11.41, and *t*-statistic=16.79 in Model 1). Borrowers with less wealth and more rejections in previous loan applications are also more likely to experience loan delinquency. For example, in Model 1, the coefficient on *Wealth* is -1.86 (*t*-statistic=-27.36), while that on *History* is 3.20 (*t*-statistic=5.15).

Overall, the findings in this subsection mitigate the concern that the digital footprint information mainly reflects the credit quality of borrowers rather than capturing the effect of digital collateral.

[Insert Table 11 Here]

5.5. Loan approval decision

We finally examine the effect of digital collateral on the loan approval decisions made by the fintech lender. Fuster et al. (2019) finds that fintech lenders tend to process loan applications faster without having higher default rates than traditional lenders. Agarwal et al. (2020) shows that digital footprints, such as the number of mobile applications and the use of the iOS mobile operating system, have predictive power for a fintech lender's loan approval decision in India. Following the literature, we conduct the analyses in a sample of 236,967 loan applications in the following model:

$$\begin{aligned} Approval = \alpha + \beta_{DC}\, &Digital\ Collateral\ Proxy + \beta_{Control}\, Control\ Variables \\ &+ \beta_{FE}\, Fixed\ Effects + \varepsilon, \end{aligned} \tag{4}$$

where *Approval* is an indicator variable equal to one if a borrower's loan application is approved by the fintech lender, and zero otherwise. We include the same control variables and the province and year fixed effects as in Equation (2).

In Table 12, we present the evidence indicating that the fintech lender is more likely to approve the loan application from a borrower with digital collateral. We find that the coefficients on *Contact* and *Address* are 0.97 and 4.67, respectively, and are significant at the one percent level (t-statistics=3.17 and 14.42).[22] Concerning the economic magnitude, these results imply that borrowers with frequent mobile contacts (physical address information) have an increased loan application approval likelihood of 2.21% (11.27%) higher than those with no digital collateral, compared to the sample mean.

Moreover, regarding the control variables, we also find that a borrower with a higher risk profile (*Score*), less wealth in online balance (*Wealth*), and more rejections from other lending platforms (*History*), is less likely to be approved by the fintech lender for her loan application. For example, the coefficients on *Score*, *Wealth*, and *History* are -35.25, 3.22, and -9.26 in Model 1, respectively, and all significant at one percent level.

In sum, the results show that the lender does consider borrowers' digital collateral during the loan application process. This is possibly due to the fact documented in our main findings that digital collateral can be used in debt collection when borrowers fail to make repayment on time in the future due date.

[Insert Table 12 Here]

[22] Different from our analyses, Agarwal et al. (2020) does not investigate the digital footprints containing the information of borrowers' physical addresses and finds insignificant results for the number of contacts.

6. Further discussion

In this section, we present further discussions about the practical implications of our study in terms of the data privacy concerns, the fair debt collection practices, and the fintech impacts on financial inclusion.

6.1. Data privacy

Recent information technology development has made substantial progress in collecting, transferring, and using the personal information in digital footprints, leading to public awareness and policy debate about how to protect individuals' right to data privacy.

For example, the California Right to Know Act Bill of 2013, which would have given consumers the right to know how their personal information is used, did not pass after facing a forceful opposition campaign from technology companies in Silicon Valley (Harmon 2013). In 2018, the California Consumer Privacy Act was passed by the state legislature. This Act provides the California residents with the rights to understand and control the use of their personal data effectively from January 2020 (Hautala 2020). Similarly, in 2016, the European Union passed the General Data Protection Regulation on data privacy protection, which became effective in May 2018.

Prior economic studies have documented that economic agents can take individuals' information privacy concerns into consideration (e.g., Abowd and Schmutte 2019; Ali and Bénabou 2020). In the fintech literature, Tang (2020) quantifies the monetary value of loan applicants' personal data. Liao et al. (2020) shows that when a lender makes phone calls to a delinquent borrower's contacts, there will be an increased likelihood of ultimate default because such a collection tactic can infringe on the borrower's privacy, leading to a negative reciprocity effect.[23]

Practically, to maintain legitimacy for the use of digital collateral, the fintech lender in our study has reached detailed legally binding agreements with the loan applicants in relation to information privacy. These legal agreements comply with China's laws and regulations and are also aligned with the drafted China Personal Information Protection Law (Blackmore and Yang 2020). For instance, when submitting the loan application, in corresponding legal

[23] One difference between our paper and Liao et al. (2020) is that their lender has limited resources to make phone calls. Thus, the lender strategically chooses some of the borrowers to apply the debt collection tactic on selective dates. In contrast, the lender in our paper applies one collection strategy consistently to all delinquent borrowers by making chasing phone calls on several given days after delinquency, exogenous to loans and borrowers' characteristics.

documents, an applicant authorizes the lender with the rights of collecting and assessing her personal information in digital footprints from the third-party data providers, along with credit score information provided by other financial institutions. The applicant also agrees that the lender has the right to use such information to chase the loan repayment in case of delinquency. A successful borrower in our study thus faces a tradeoff between the disclosure of privacy and the access to cash in marketplace lending (Acquisti, John, and Loewenstein 2013).

To provide further supportive evidence, we conduct additional tests in the Internet Appendix (IA). We focus on subsamples with the loan repayment due dates after the adoption of the China Internet Personal Information Security and Protection Guidelines. The guidelines were issued by the China Ministry of Public Security and became effective on April 10, 2019, as a measure to protect personal information privacy while the Personal Information Protection Law was being drafted. In Table IA1, we find that the effect of digital collateral on debt collection remains the same after the regulations are strengthened to protect individuals' right to data privacy.

Taken together, it is likely that the use of digital collateral can be maintained as legitimate, as long as the collection and use of personal data are in accordance with laws and regulations, even in the markets with strong data privacy rules.

6.2. Fair debt collection practices

Another concern for the use of digital collateral is the legitimacy of debt collection practices (Fedaseyeu 2020). People may cast doubts on whether the Chinese lender's practices of making phone calls to borrowers' contacts can be generalized to the personal lending markets in other countries.

For example, in the U.S., the Fair Debt Collection Practices Act (FDCPA) was passed by the Congress in 1977 to "eliminate abusive debt collection practices by debt collectors." The debt collection efforts, such as phone calls, letters, and emails, must comply with various laws and regulations, including FDCPA. In 2019, there were approximately 75,200 debt collection complaints received by the Consumer Financial Protection Bureau (CFPB 2020). Among those, some complaints were associated with communication tactics (12 percent), threatening to take negative or legal action (12 percent), and threatening to share information improperly (3 percent).

Under the FDCPA, when borrowers owe debts, U.S. debt collectors cannot disclose the information to third parties, such as borrowers' contacts and employers.[24] However, they can reach borrowers' contacts and ask questions about these borrowers' location information (e.g., address and phone number), usually no more than once (Hunt 2007). They may contact the third parties again if they believe that they were given false information previously. The collectors can even disclose their employers' names if the contacted parties specifically request such information (e.g., asking questions like "who do you work for?"). Moreover, the debt collectors may threaten to take legal actions that they intend to do so, but they are not allowed to threaten borrowers with illegal actions or actions that they do not intend to take (Hunt 2007; CFPB 2020).

Using the above communication strategies, debt collectors may expect that reaching borrowers' contacts would make borrowers pay off the debts to "prevent further embarrassment" (Irby 2020). Also, threatening to take intended legal actions (e.g., placing liens on borrowers' homes) can in some instances effectively facilitate debt collection.

In the Internet Appendix, we further conduct the analyses in the subsamples of 20 provinces in China that had implemented the province-level rules to regulate fintech lenders' abusive behavior by April 2018.[25] We incorporate the province regulation information into our baseline sample using borrowers' hometown information in their national identity cards.[26] We consider borrowers in these subsamples to be better protected against the lender's potential aggressive debt collection practices, because provincial governments are more concerned about the practices in the fintech lending markets, acting promptly to implement corresponding regulations. In Table IA2, we find that the effect of digital collateral on debt collection remains unchanged in provinces with strong fintech lending regulations.

In summary, the debt collection tactics based on borrowers' digital collateral may apply not only to the markets with weak debtor protections but also to those with strong laws and regulations against abusive debt collection practices.

6.3. Fintech and financial inclusion

Our study provides important policy implications for the roles of fintech development in

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[24] Our discussion in this subsection mainly refers to the debt collection practices by lenders. For studies on third-party debt collectors, see Fedaseyeu and Hunt (2018) and Fedaseyeu (2020).

[25] The information about the province-level regulation implementation was collated in a survey as reported by online media outlets such as the Sina Corporation. See, for example, the Sina's coverage in Mandarin on April 8, 2018: https://cj.sina.com.cn/articles/view/6298435788/1776a80cc019006p67 (accessed September 9, 2020).

[26] We use borrowers' hometown information in the matching process because a lawsuit against a delinquent borrower will be judged in the borrower's hometown, and the physical address in digital footprints is not available to all the borrowers.

enhancing financial inclusion. According to the World Bank's 2014 Global Financial Development Report, more than 2.5 billion adults (about half of the world's adult population) have no bank account, and many of them would "benefit from financial services but cannot access them due to market failures" (World Bank 2014). The lack of access to financial services caused by market imperfection can lead to poverty and inequality (Banerjee and Newman 1993; Galor and Zeira 1993; Aghion and Bolton 1997).

In credit markets, individuals in low-income countries have limited access to borrow from formal sources. According to the World Bank's 2014 Report, only seven percent of adults in developing economies have credit cards; however, they have essential reasons for borrowing (e.g., the most common reason for the outstanding loan is due to emergencies or health issues). One possible way to expand financial inclusion is to adopt new technologies and novel business models that can "lower the cost and inconvenience of accessing financial services" (World Bank 2014).

The extant fintech research has shown that advances in financial technologies can help enhance financial inclusion, one of the key promises of fintech for overall welfare (Goldstein, Jiang, and Karolyi 2019). For instance, Berg et al. (2019) and Agarwal et al. (2020) find that digital footprints complement credit bureau information and are associated with the likelihood of loan approvals and defaults. Moreover, fintech lenders fill the credit gap in areas where traditional banks face more regulatory constraints (Buchak et al. 2018) and when banks tighten credit standards (Allen, Shan, and Shen 2020). These findings suggest that fintech lending can boost financial inclusion, especially in countries where traditional banks provide limited financial services.

We document a new perspective on the role of fintech in enhancing financial inclusion. The World Bank's 2014 Report underscores that financial inclusion needs to be promoted properly and responsibly, and that the credit overextension can lead to defaults and exacerbate financial instability (World Bank 2014). This is evidenced by the U.S. subprime mortgage crisis in the 2000s, and India's microfinance crisis in 2010.[27] Traditional financial institutions rely on physical collateral to overcome default risk in the retail debt markets. Given information asymmetry between the lender and borrowers, collateral in general allows for hedging against borrowers' potential moral hazardous behavior.[28] Our study provides an alternative mechanism

[27] See studies on microfinance, for example, Pitt and Khandker (1998) and Kaboski and Townsend (2011).

[28] When a borrower becomes delinquent, the financial institution will be protected by collateral. The assets used as collateral will be seized and sold to recover debt claims. Thus, individuals without adequate collateral may find it difficult to secure a loan from conventional financial institutions, resulting in the inefficiency of resource

to address moral hazards, typically for individuals with no physical collateral in low financial inclusion economies. That is, when loans are unsecured by physical assets, fintech advancement allows lenders to target borrowers' personal information in their digital footprints as collateral and adopt a debt collection tactic based on digital collateral in case of debt delinquency.

Our analyses in Table 12 have shown supportive evidence that digital collateral can expand financial inclusion by increasing the likelihood of loan approval. This is because loan applicants may have low personal wealth and limited access to traditional lenders, partly indicated by the average balance of their Alipay's accounts equal to 4.30 Chinese Yuan. In Table IA3 of the Internet Appendix, we re-conduct the loan approval analysis in subsamples of applicants with low creditworthiness. Specifically, we focus on the loan applicants with credit risk scores (*Score*) higher than the sample median. The results remain qualitatively similar to those in Table 12, providing further evidence for the digital collateral's role in enhancing financial inclusion.

7. Conclusion

In this paper, we find that the information contained in borrowers' digital footprints can be used by lenders as collateral for debt collection when borrowers fail to make loan repayments. The role of digital collateral in debt collection operates through two potential channels: the possible damages to borrowers' social capitals and the accessibility to their physical locations. Our findings add to the fintech literature by documenting that technological innovations can create value for innovators and adopters in the financial markets. We also complement the debt literature by showing that digital footprints, used as one type of non-physical collateral, can facilitate the collection of delinquent loans.

allocation and low financial inclusion (Gine, Goldberg, and Yang 2012; Lin, Prabhala, and Viswanathan 2013; Hildebrand, Puri, and Rocholl 2017).

Appendix Variable Definitions

Variable	Definition
$Paid_t$	An indicator variable equal to one if a borrower makes the repayment on the Day *t*, and zero otherwise.
$Paid_{[i, j]}$	Cumulative repayment likelihood from Day *i* to Day *j* in *percentage*.
$Chasing_{Day\ t}$	An indicator variable equal to one for days in a three-day window [*t*, *t+2*], and zero otherwise.
$Chasing_{All}$	An indicator variable equal to one for days in windows [4, 6], [16, 18], [31, 33], [61, 63], and [91, 93], and zero otherwise.
$Chasing_{Day\ 4,16}$	An indicator variable equal to one for days in windows [4, 6], and [16, 18], and zero otherwise.
$Chasing_{Day\ 31,61,91}$	An indicator variable equal to one for days in windows [31, 33], [61, 63], and [91, 93], and zero otherwise.
$Repayment_{Ratio}$	Ratio of the amount of repayment for the delinquent loan by Day 93 divided by the amount required to be paid by the due date.
$Repayment_{Complete}$	An indicator variable equal to one if a borrower makes repayment equal to / more than delinquent amount by Day 93, and zero otherwise.
Delinquency	An indicator variable equal to one if a borrower fails to make a loan payment by the due date at least once during loan term, and zero otherwise.
Approval	An indicator variable equal to one if a borrower's local application is approved by the fintech lender, and zero otherwise.
Contact	An indicator variable equal to one if a borrower has at least one contact who has more than *ten* calls with borrower, and zero otherwise.
Address	An indicator variable equal to one if a borrower has at least one online shopping delivery address, and zero otherwise.
$Contact_{Number}$	Number of contacts who have more than *ten* calls with a borrower. Logarithm value is taken in regression analysis.
$Address_{Number}$	Number of a borrower's online shopping delivery addresses. Logarithm value is taken in regression analysis.
$Contact_{Pseudo}$	An indicator variable equal to one for a pseudo borrower assigned to a treatment group based on *Contact*, and zero otherwise.
$Address_{Pseudo}$	An indicator variable equal to one for a pseudo borrower assigned to a treatment group based on *Address*, and zero otherwise.
$Contact_{1 \leq Number \leq 7}$	An indicator variable equal to one if a borrower has at least one and at most seven contacts who have more than *ten* calls with borrower, and zero otherwise.
$Contact_{Number>7}$	An indicator variable equal to one if a borrower has more than seven contacts with more than *ten* calls with borrower, and zero otherwise.
$Address_{Number=1}$	An indicator variable equal to one if a borrower has one online shopping delivery address, and zero otherwise.
$Address_{Number>1}$	An indicator variable equal to one if a borrower has more than one online shopping delivery addresses, and zero otherwise.

Appendix (Continued)

Variable	Definition
$Contact_{Only}$	An indicator variable equal to one if a borrower has at least one contact who has more than *ten* calls with borrower, but has no information about online shopping delivery address, and zero otherwise.
$Address_{Only}$	An indicator variable equal to one if a borrower has at least one online shopping delivery address, but has no information about contact who has more than *ten* calls with borrower, and zero otherwise.
$Collateral_{Both}$	An indicator variable equal to one if a borrower has at least one contact who has more than *ten* calls with borrower and at least one online shopping delivery address, and zero otherwise.
Amount	Amount of loan principal in *thousands* of Chinese Yuan. Logarithm value is taken in regression analysis.
Rate	Interest rate of loan on annual basis.
Age	Age of a borrower in years. Logarithm value is taken in regression analysis.
Gender	An indicator variable equal to one if a borrower is female, and zero otherwise.
Score	Credit risk score provided by Tencent, with high value suggesting high risk profile. Logarithm value is taken in regression analysis.
Wealth	Balance of a borrower's Alipay account from Alibaba in Chinese Yuan. Logarithm value is taken in regression analysis.
History	Number of loan applications of a borrower rejected by other online lending platforms. Logarithm value is taken in regression analysis.
$Social_{Spending}$	Average amount of annual social spending by household scaled by the average annual household income at province-year level. Social spending by household is the cash and non-cash gifts given to and received from family members and friends for festivals like Lunar New Year, and personal social events such as birthday and so on.
$Veneration_{Ancestor}$	Average percentage of households attending the veneration events of honoring ancestors at province-year level.
$Distance_{FinTech}$	Geographical distance between the city of borrower's physical location and Shanghai, where the fintech lending company is headquartered. For a borrower with multiple physical locations, the most frequently used delivery address will be chosen to estimate the distance. When there are multiple addresses deemed as the most frequent ones, the most recently used address will be selected.
$Litigation_{Confidence}$	The average satisfaction rating by household at province-year level. The rating varies between 1 and 5. Higher value of the rating indicates more satisfaction.

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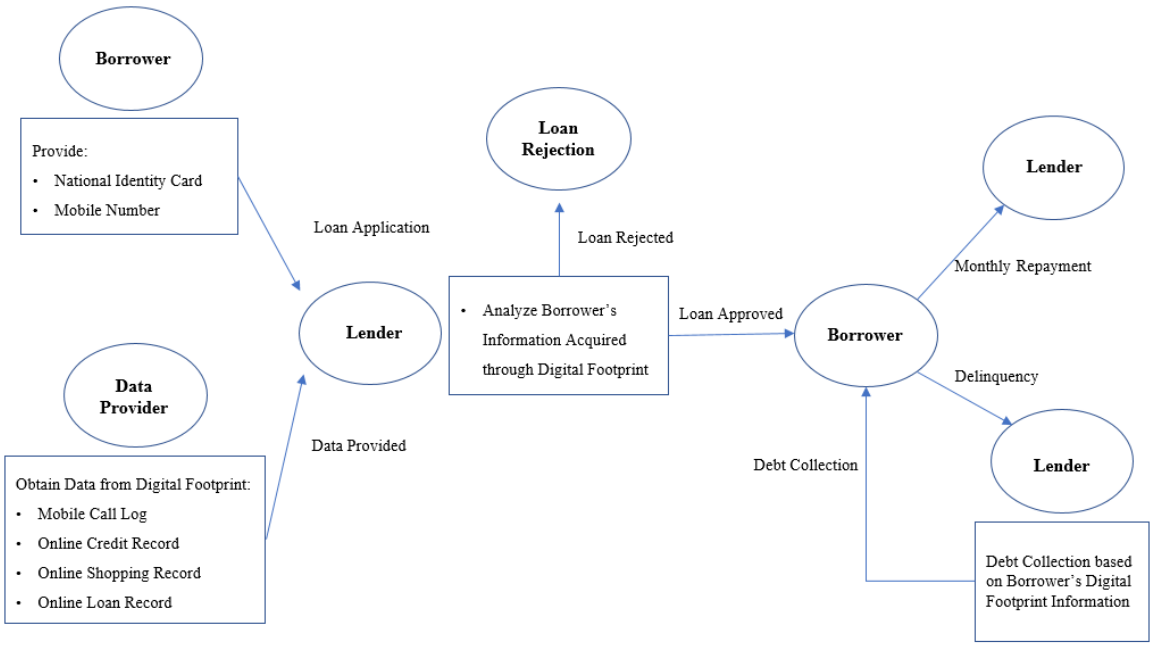
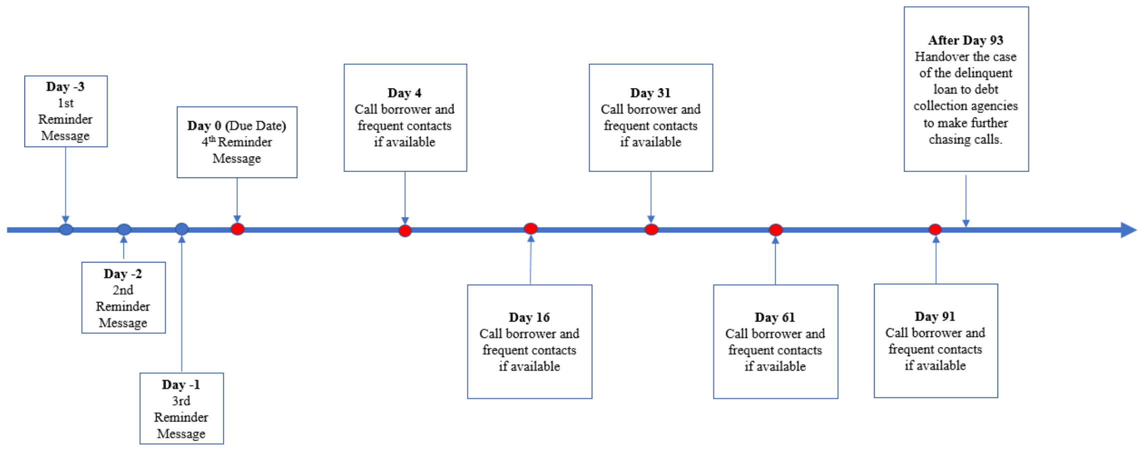
Figure 1 The Process of Loan Application, Approval, Repayment, and Collection



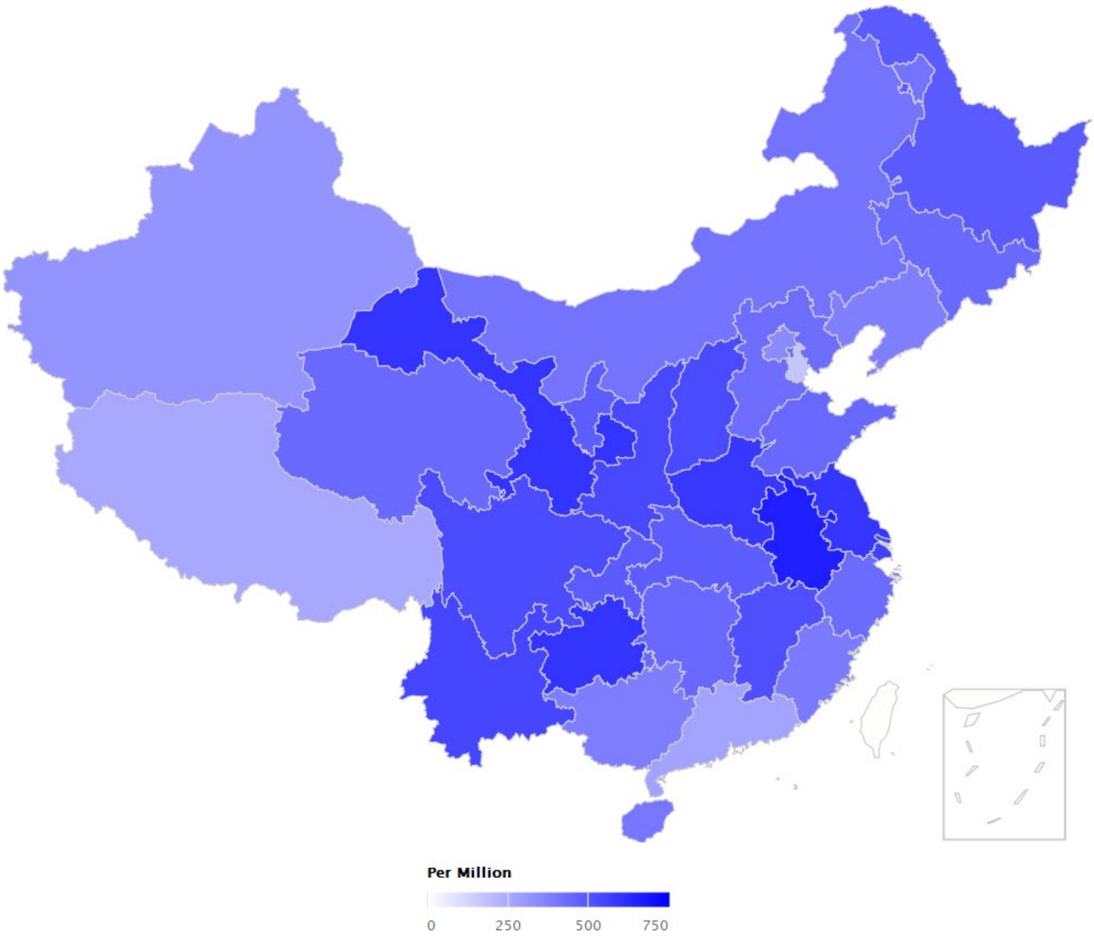
This figure illustrates the process of loan application, approval, repayment, and collection executed by the fintech lender. The sample analyzed in this paper includes 236,967 loan applications submitted to the fintech lender from July 2017 to November 2019, among which 97,783 loan applications have been approved and 41,711 approved loans experience borrower's delinquency.

Figure 2 Timeline of Debt Collection



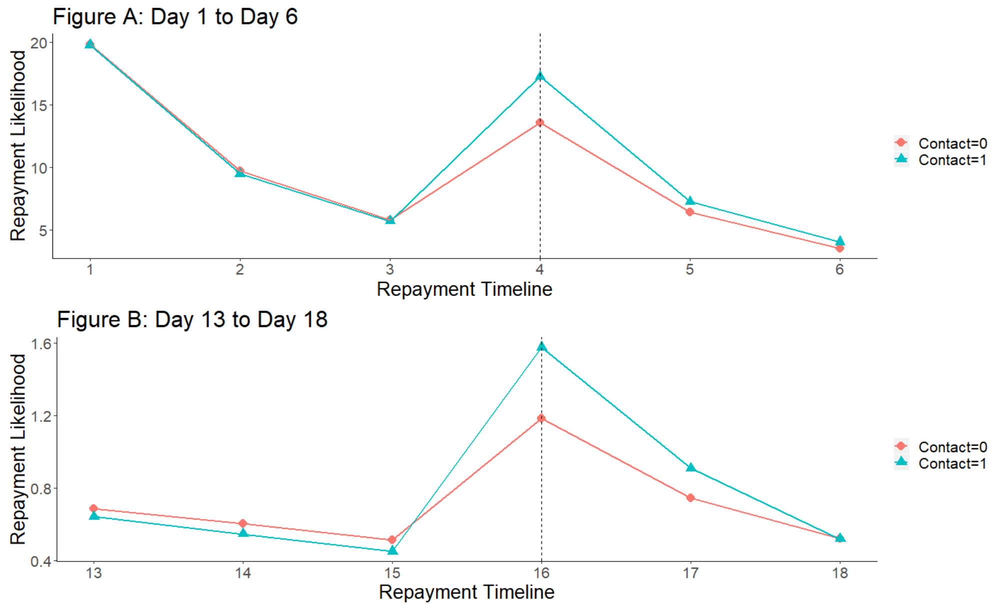
This figure presents the timeline of debt collection executed by the fintech lender. Day zero is the due date of the loan payment. The sample analyzed in this paper includes 97,783 approved loans from July 2017 to November 2019, among which 41,711 loans experience borrower's delinquency and enter the debt collection process.

Figure 3 Geographical Distribution of Loan Application



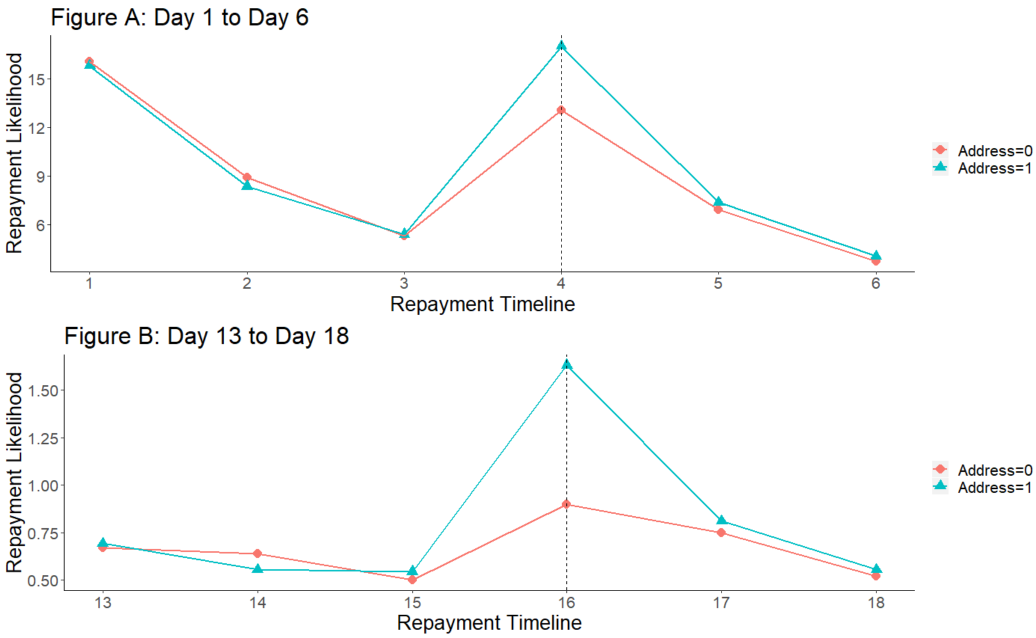
This figure shows the geographical distribution of the loan applications submitted to the fintech lender. The color depth denotes the application density regarding the number of applications per million population in a province of China. The sample analyzed in this paper includes 236,967 loan applications submitted between July 2017 and November 2019, among which 97,783 applications have been approved.

Figure 4 Daily Repayment Likelihood around Chasing Calls based on Frequent Contact



This figure shows the daily likelihood of loan repayment around the first two rounds of chasing calls for the delinquent payment in Day 4 and Day 16. The due date is Day zero. The repayment likelihoods of both the treatment group and control group are presented after the propensity score matching, which is conducted based on the existence of borrower's frequent contact information. The full sample of delinquent borrowers in the analyses includes 41,711 delinquent loans.

Figure 5 Daily Repayment Likelihood around Chasing Calls based on Delivery Address



This figure shows the daily likelihood of loan repayment around the first two rounds of chasing calls for the delinquent payment in Day 4 and Day 16. The due date is in Day zero. The repayment likelihoods of both the treatment group and control group are presented after the propensity score matching, which is conducted based on the existence of borrower's online shopping delivery address information. The full sample of delinquent borrowers in the analyses includes 41,711 delinquent loans.

Table 1 Summary Statistics

Variable	OBS	Mean	STD	25%	Median	75%
$Paid_{[1,6]}$	41,711	61.933	48.566	0	100	100
$Paid_{[1,18]}$	41,711	75.247	43.158	100	100	100
$Paid_{[1,93]}$	41,711	84.667	36.031	100	100	100
$Repayment_{Ratio}$	41,711	1.071	0.541	0.928	1.292	1.392
$Repayment_{Complete}$	41,711	0.738	0.440	0	1	1
Contact	41,711	0.651	0.476	0	1	1
$Contact_{Number}$	41,711	7.494	14.500	0	3	9
Address	41,711	0.765	0.423	0	1	1
$Address_{Number}$	41,711	1.06	0.808	0	1	1
Amount	41,711	3.966	1.297	3.000	3.980	4.780
Rate	41,711	0.295	0.083	0.205	0.357	0.359
Age	41,711	27.105	7.884	21	25	31
Gender	41,711	0.182	0.386	0	0	0
Score	41,711	56.761	15.261	48.000	60.200	66.750
Wealth	41,711	4.221	32.071	0.000	0.900	27.200
History	41,711	0.118	0.582	0	0	0
Delinquency	97,783	0.427	0.495	0	0	1
Approval	236,967	0.413	0.493	0	0	1

This table presents the summary statistics of the variables for the number of observations (*OBS*), mean (*Mean*), standard deviation (*STD*), the 25th (*25%*), median (*Median*), and 75th percentiles (*75%*) of the distributions of the variables. The samples of delinquent loans, approved loans, and loan applications consist of 41,711, 97,783, and 236,967 observations from July 2017 to November 2019, respectively. All variables are defined in the Appendix.

Table 2 Treatment and Control Groups under Propensity Score Matching

Panel A: Propensity Score Matching based on *Contact*

	Contact = 1 Mean	*Contact* = 0 Mean	Difference	*t*-statistic
$Paid_{[1,6]}$	63.591	58.830	4.761	8.421***
$Paid_{[1,18]}$	77.594	71.777	5.817	11.538***
$Paid_{[1,93]}$	86.301	81.827	4.474	10.313***
Amount	3.714	3.710	0.004	0.475
Rate	0.294	0.293	0.001	0.152
Age	27.611	27.679	-0.068	−0.858
Gender	0.175	0.174	0.001	0.068
Score	56.036	56.205	-0.169	−0.085
Wealth	6.080	6.203	-0.123	−0.982
History	0.046	0.045	0.001	0.947
Observations of borrowers	*14,768*	*14,768*		

Panel B: Propensity Score Matching based on *Address*

	Address = 1 Mean	*Address* = 0 Mean	Difference	*t*-statistic
$Paid_{[1,6]}$	58.065	54.072	3.993	5.708***
$Paid_{[1,18]}$	72.297	67.681	4.616	7.149***
$Paid_{[1,93]}$	83.711	78.907	4.804	8.645***
Amount	3.565	3.601	-0.036	−1.562
Rate	0.313	0.308	0.005	1.787*
Age	31.083	30.487	0.596	1.222
Gender	0.171	0.170	0.001	0.131
Score	58.323	58.382	-0.059	−0.329
Wealth	1.804	2.056	-0.252	−6.386***
History	0.052	0.060	-0.008	−1.387
Observations of borrowers	*9,994*	*9,994*		

This table presents the comparison of the characteristics between the treatment and control groups after the propensity score matching. In Panel A, the treatment (control) group includes delinquent borrowers who have at least one frequent mobile contact (no frequent mobile contact) in digital footprints. In Panel B, the treatment (control) group includes delinquent borrowers who have at least one online shopping delivery address (no delivery address) in digital footprints. The samples of the treatment and control groups both consist of 14,768 (9,994) delinquent loans from July 2017 to November 2019 in Panel A (Panel B). ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix.

Table 3 Univariate Analyses of Repayment Likelihood

Panel A: Univariate Analyses based on *Contact*				
	Contact = 1	*Contact* = 0		
$Paid_t$	Mean	Mean	Difference	*t*-statistic
Day 1 to Day 3	11.683	11.780	−0.097	-0.449
Day 4 to Day 6	9.514	7.830	1.684	8.926***
Δ [4,6] - [1,3]	−2.169	−3.950	**1.781**	**6.212*** **
Observations of borrowers	*14,768*	*14,768*		
Day 13 to Day 15	2.023	1.874	0.149	0.869
Day 16 to Day 18	3.681	2.520	1.161	5.387***
Δ [16,18] - [13,15]	1.658	0.646	**1.012**	**3.722*** **
Observations of borrowers	*4,412*	*4,412*		
Panel B: Univariate Analyses based on *Address*				
	Address = 1	*Address* = 0		
$Paid_t$	Mean	Mean	Difference	*t*-statistic
Day 1 to Day 3	9.867	10.102	−0.235	-0.965
Day 4 to Day 6	9.488	7.921	1.567	6.828***
Δ [4,6] - [1,3]	−0.379	−2.181	**1.802**	**5.378*** **
Observations of borrowers	*9,994*	*9,994*		
Day 13 to Day 15	1.834	1.663	0.171	0.936
Day 16 to Day 18	3.070	1.994	1.070	4.905***
Δ [16,18] - [13,15]	1.230	0.331	**0.899**	**3.196*** **
Observations of borrowers	*3,459*	*3,459*		

The table presents the univariate analyses of the daily loan repayment likelihood between the treatment group and control group after the propensity score matching. $Paid_t$ is an indicator variable equal to one if a borrower makes the repayment on the Day *t*, and zero otherwise. Day zero is the due date of loan repayment. In Panel A, the treatment (control) group includes delinquent borrowers who have at least one frequent mobile contact (no frequent mobile contact) in digital footprints. In Panel B, the treatment (control) group includes delinquent borrowers who have at least one online shopping delivery address (no delivery address) in digital footprints. Around Day 4 (Day 16), the samples of treatment and control groups both consist of 14,768 and 9,994 (4,412 and 3,459) delinquent loans from July 2017 to November 2019 in Panel A and Panel B, respectively. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix.

Table 4 Repayment Likelihood around the First Two Rounds of Chasing Calls

Dependent Variable	$Paid_t$			
	T=4		T=16	
	(1)	(2)	(3)	(4)
Chasing $_{Day\ T}$×*Contact*	**1.759*****		**1.033*****	
	(5.805)		**(3.666)**	
Chasing $_{Day\ T}$×*Address*		**1.794*****		**0.898*****
		(5.002)		**(3.037)**
Chasing $_{Day\ T}$×*Amount*	−1.919***	−1.539***	0.529	0.600*
	(−4.618)	(−3.432)	(0.359)	(1.695)
Chasing $_{Day\ T}$×*Rate*	−12.740***	−17.158***	−2.485	−3.527**
	(−6.976)	(−8.254)	(−1.477)	(−2.010)
Chasing $_{Day\ T}$×*Age*	5.710***	5.142***	−1.137*	−0.252
	(10.211)	(8.407)	(−2.410)	(−0.524)
Chasing $_{Day\ T}$×*Gender*	−2.289***	−1.243***	−0.031	−0.354
	(−5.722)	(−2.587)	(−0.079)	(−0.854)
Chasing $_{Day\ T}$×*Score*	3.349***	3.210***	-0.329	-0.027
	(6.497)	(4.751)	(-0.558)	(-0.038)
Chasing $_{Day\ T}$×*Wealth*	−0.327***	−0.158	0.089	−0.041
	(−5.119)	(−1.223)	(1.434)	(−0.342)
Chasing $_{Day\ T}$×*History*	−0.553	−0.743	0.566	0.072
	(−0.745)	(−0.928)	(0.832)	(0.099)
Borrower Fixed Effect	Yes	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes	Yes
Observations	177,216	119,928	52,944	41,508
R^2_{ADJ}	10.9%	10.8%	1.8%	1.8%

This table presents the difference-in-differences analyses of the daily loan repayment likelihood based on the lender's first two rounds of chasing calls made on Day 4 and Day 16. The analyses are performed at the delinquent-borrower-day level. The dependent variable, $Paid_t$, is an indicator variable equal to one if a borrower makes the repayment on the Day t, and zero otherwise. Day zero is the due date of loan repayment. In Models 1 and 2, the tests are conducted in window [1, 6], where Day 4 is the date that the lender makes the first round of chasing calls for delinquent loans. In Models 3 and 4, the tests are conducted in window [13, 18], where Day 16 is the date that the lender makes the second round of chasing calls for delinquent loans. *Chasing* $_{Day\ T}$ is an indicator variable equal to one for days in window [T, T+2], and zero for window [T-3, T-1]. The dependent variable, $Paid_t$, is regressed on *Chasing*, *Chasing* × *Digital Collateral Proxy* (i.e., *Contact* or *Address*), controlling for the interactions between the *Chasing* dummies and other characteristics of loan and borrower, as well as the borrower and day fixed effects. In Models 1 and 2 (Models 3 and 4), the matched samples based on *Contact* and *Address* consist of 177,216 and 119,928 (52,944 and 41,508) borrower-day observations from July 2017 to November 2019, respectively. The t-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and borrower-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix.

Table 5 Placebo Tests Based on Pseudo Calls and Pseudo Borrowers

Panel A: Pseudo Chasing Call Dates		
Dependent Variable	*Paid* $_t$	
	(1)	(2)
Chasing $_{Day\ 1}$×*Contact*	**−0.074**	
	(−0.400)	
Chasing $_{Day\ 1}$×*Address*		**−0.266**
		(−1.220)
Chasing $_{Day\ 1}$×*Amount*	1.074***	0.956***
	(4.219)	(3.507)
Chasing $_{Day\ 1}$×*Rate*	5.977***	10.981***
	(5.281)	(8.508)
Chasing $_{Day\ 1}$×*Age*	−4.664***	−3.804***
	(−13.662)	(−10.232)
Chasing $_{Day\ 1}$×*Gender*	1.566***	1.048***
	(6.312)	(3.559)
Chasing $_{Day\ 1}$×*Score*	−4.144***	−4.014***
	(−13.515)	(−9.839)
Chasing $_{Day\ 1}$×*Wealth*	0.419***	0.305***
	(10.831)	(3.934)
Chasing $_{Day\ 1}$×*History*	0.795*	1.367***
	(1.791)	(2.902)
Borrower Fixed Effect	Yes	Yes
Day Fixed Effect	Yes	Yes
Observations	177,216	119,928
R^2_{ADJ}	5.6%	4.2%

Table 5 (Continued)

Panel B: Pseudo Borrowers with Digital Collateral

	Actual Estimate	Mean	5%	25%	Median	75%	95%
$Chasing_{Day\ 4} \times Contact_{Pseudo}$	**1.759*** **	**0.004**	-0.525*	-0.210	**-0.005**	0.225	0.519*
	(5.805)	**(0.013)**	(-1.732)	(-0.692)	**(-0.017)**	(0.740)	(1.710)
$Chasing_{Day\ 4} \times Address_{Pseudo}$	**1.794*** **	**-0.017**	-0.605*	-0.268	**-0.011**	0.231	0.597*
	(5.002)	**(-0.048)**	(-1.690)	(-0.749)	**(-0.030)**	(0.646)	(1.667)

This table presents the placebo tests based on the pseudo calls and pseudo borrowers. Panel A reports the tests of the daily loan repayment likelihood in a six-day window [-2, 3] with no chasing call. $Chasing_{Day\ 1}$ is an indicator variable equal to one for days in window [1, 3], and zero for window [-2, 0]. $Paid_t$ is regressed on *Chasing*, *Chasing* × *Digital Collateral Proxy* (i.e., *Contact* or *Address*), controlling for the interactions between the *Chasing* dummies and other characteristics of loan and borrower, as well as the borrower and day fixed effects. The matched samples based on *Contact* (*Address*) consist of 177,216 (119,928) borrower-day observations from July 2017 to November 2019. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and borrower-level clustering. Panel B reports the tests of the daily loan repayment likelihood in a six-day window [1, 6] for pseudo borrowers with digital collateral. Day zero is the due date of loan repayment. $Chasing_{Day\ 4}$ is an indicator variable equal to one for days in window [4, 6], and zero for window [1, 3]. $Paid_t$ is regressed on *Chasing*, *Chasing* × *Pseudo Digital Collateral Proxy* (i.e., $Contact_{Pseudo}$ or $Address_{Pseudo}$), controlling for the interactions between the *Chasing* dummies and other characteristics of loan and borrower, as well as the borrower and day fixed effects. The samples based on $Contact_{Pseudo}$ and $Address_{Pseudo}$ consist of 177,216 and 119,928 borrower-day observations from July 2017 to November 2019, in which half of the borrowers are randomly assigned to be pseudo borrowers with digital collateral, regardless whether they indeed have or not have digital collateral. The regression analysis has been conducted in 1,000 randomly generated samples with pseudo borrowers. The mean values and the 5, 25, 50, 75, and 95 percentiles of the coefficients on $Chasing_{Day\ 4} \times Contact_{Pseudo}$ and $Chasing_{Day\ 4} \times Address_{Pseudo}$ are reported for the 1,000 samples, together with their *t*-statistics shown in parentheses. The actual estimates are also reported. In both panels, the analyses are performed on the delinquent-borrower-day level. The dependent variable, $Paid_t$, is an indicator variable equal to one if a borrower makes the repayment on the Day *t*, and zero otherwise. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix.

Table 6 Contact and Address Numbers

Dependent Variable	*Paid* $_t$			
	(1)	(2)	(3)	(4)
$Chasing_{Day\ 4} \times Contact_{Number}$	**0.514*****			
	(3.931)			
$Chasing_{Day\ 4} \times Address_{Number}$		**1.843*****		
		(4.425)		
$Chasing_{Day\ 4} \times Contact_{1 \leq Number \leq 7}$			**2.134*****	
			(5.961)	
$Chasing_{Day\ 4} \times Contact_{Number>7}$			**1.312*****	
			(3.302)	
$Chasing_{Day\ 4} \times Address_{Number=1}$				**1.846*****
				(4.737)
$Chasing_{Day\ 4} \times Address_{Number>1}$				**1.652*****
				(2.891)
$Chasing_{Day\ 4} \times Amount$	−1.941***	−1.537***	−1.941***	−1.537***
	(−4.668)	(−3.429)	(−4.668)	(−3.429)
$Chasing_{Day\ 4} \times Rate$	−12.903***	−17.230***	−12.903***	−17.230***
	(−7.063)	(−8.287)	(−7.063)	(−8.287)
$Chasing_{Day\ 4} \times Age$	5.495***	5.236***	5.495***	5.236***
	(9.784)	(8.545)	(9.784)	(8.545)
$Chasing_{Day\ 4} \times Gender$	−2.253***	−1.251***	−2.253***	−1.251***
	(−5.628)	(−2.602)	(−5.628)	(−2.602)
$Chasing_{Day\ 4} \times Score$	3.366***	3.230***	3.366***	3.230***
	(6.525)	(4.781)	(6.525)	(4.781)
$Chasing_{Day\ 4} \times Wealth$	−0.326***	−0.157	−0.326***	−0.157
	(−5.093)	(−1.215)	(−5.093)	(−1.215)
$Chasing_{Day\ 4} \times History$	−0.631	−0.735	−0.631	−0.735
	(−0.850)	(−0.916)	(−0.850)	(−0.916)
Borrower Fixed Effect	Yes	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes	Yes
Observations	177,216	119,928	177,216	119,928
R^2_{ADJ}	10.9%	10.8%	10.9%	10.8%

This table presents the analyses based on the amount of digital information. The analyses are performed at the delinquent-borrower-day level. The dependent variable, $Paid_t$, is an indicator variable equal to one if a borrower makes the repayment on the Day t, and zero otherwise. Day Zero is the due date of loan repayment. Day 4 is the date that the lender makes the first round of chasing calls for delinquent loans. $Chasing_{Day\ 4}$ is an indicator variable equal to one for days in window [4, 6], and zero for window [1, 3]. In Models 1 and 2, the dependent variables are the number of borrowers' frequent contacts and physical addresses, $Contact_{Number}$ and $Address_{Number}$, respectively. In Models 3 and 4, we construct four indicator variables equal to one for borrowers with contact number between one and seven ($Contact_{1 \leq Number \leq 7}$), and greater than seven ($Contact_{Number>7}$), and for borrowers with address number equal to one ($Address_{Number=1}$), and greater than one ($Address_{Number>1}$), and otherwise zero. The matched samples based on *Contact* (*Address*) consist of 177,216 (119,928) borrower-day observations from July 2017 to November 2019. The t-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and borrower-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix.

Table 7 Sequential Chasing Calls

Dependent Variable	*Paid* $_t$			
	All Chasing Calls		Early versus Later Calls	
	(1)	(2)	(3)	(4)
$Chasing_{All} \times Contact$	**1.170*****			
	(6.683)			
$Chasing_{All} \times Address$		**1.188*****		
		(6.151)		
$Chasing_{Day\ 4,16} \times Contact$			**1.401*****	
			(6.461)	
$Chasing_{Day\ 31,61,91} \times Contact$			**0.631*****	
			(4.893)	
$Chasing_{Day\ 4,16} \times Address$				**1.376*****
				(5.643)
$Chasing_{Day\ 31,61,91} \times Address$				**0.804*****
				(5.417)
$Chasing_{All} \times Amount$	−1.054***	−0.801**	−1.049***	−0.798***
	(−4.484)	(−3.371)	(−4.465)	(−3.357)
$Chasing_{All} \times Rate$	−6.745***	−8.850***	−6.725***	−8.827***
	(−6.431)	(−7.848)	(−6.415)	(−7.832)
$Chasing_{All} \times Age$	2.571***	2.475***	2.578***	2.447***
	(8.583)	(7.821)	(8.610)	(7.830)
$Chasing_{All} \times Gender$	−1.349***	-0.699***	−1.349***	−0.695***
	(−5.707)	(−2.644)	(−5.717)	(−2.630)
$Chasing_{All} \times Score$	2.148***	2.046***	2.141***	2.040***
	(6.207)	(4.725)	(6.186)	(4.713)
$Chasing_{All} \times Wealth$	-0.166***	-0.057	-0.165***	-0.057
	(-4.248)	(-0.786)	(-4.242)	(-0.773)
$Chasing_{All} \times History$	-0.157	-0.400	-0.163	-0.401
	(-0.361)	(0.866)	(-0.373)	(-0.869)
Borrower Fixed Effect	Yes	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes	Yes
Observations	330,624	241,812	330,624	241,812
R^2_{ADJ}	5.0%	5.4%	5.0%	5.4%

This table presents the analyses of the daily loan repayment likelihood based on all the chasing calls made on Day 4, Day 16, Day 31, Day 61, and Day 91. The analyses are performed on the delinquent-borrower-day level. The dependent variable, *Paid* $_t$, is an indicator variable equal to one if a borrower makes the repayment on the Day *t*, and zero otherwise. Day Zero is the due date of loan repayment. The tests are conducted in five six-day windows [1, 6], [13, 18], [28, 33], [58, 63], and [88, 93] after the due date. In Models 1 and 2, $Chasing_{All}$ is an indicator variable equal to one for days in windows [4, 6], [16, 18], [31, 33], [61, 63], and [91, 93], and zero otherwise. In Models 3 and 4, $Chasing_{Day\ 4,16}$ is an indicator variable equal to one for days in windows [4, 6] and [16, 18], and zero otherwise, while $Chasing_{Day\ 31,61,91}$ is an indicator variable equal to one for days in windows [31, 33], [61, 63], and [91, 93], and zero otherwise. *Paid* $_t$ is regressed on *Chasing*, *Chasing* × *Digital Collateral Proxy* (i.e., *Contact* or *Address*), controlling for the interactions between the *Chasing* dummies and other characteristics of loan and borrower, as well as the borrower and day fixed effects. The matched samples based on *Contact* (*Address*) consist of 330,624 (241,812) borrower-day observations from July 2017 to November 2019. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and borrower-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix.

Table 8 Borrowers with Both or Either Contact and/or Address Information

Dependent Variable	*Paid $_t$*			
	Non-Overlapping		Overlapping	Full Sample
	(1)	(2)	(3)	(4)
Chasing $_{Day\ 4}$×Contact $_{Only}$	**2.567*** **			**1.933*** **
	(3.625)			**(4.040)**
Chasing $_{Day\ 4}$×Address $_{Only}$		**1.397** **		**2.371*** **
		(2.186)		**(5.261)**
Chasing $_{Day\ 4}$×Collateral $_{Both}$			**1.437*** **	**1.390*** **
			(4.416)	**(4.273)**
Chasing $_{Day\ 4}$×Amount	-1.537*	−1.416***	-1.749***	-1.632***
	(−1.843)	(−1.708)	(-3.923)	(-3.826)
Chasing $_{Day\ 4}$×Rate	−19.441***	−19.945***	-11.942***	-15.162***
	(−5.216)	(−5.322)	(-6.068)	(-7.961)
Chasing $_{Day\ 4}$×Age	4.992***	3.739***	5.702***	5.499***
	(4.436)	(3.244)	(9.352)	(9.535)
Chasing $_{Day\ 4}$×Gender	−1.918**	−1.614***	-2.172***	-2.105***
	(−2.416)	(−1.868)	(-5.053)	(-5.008)
Chasing $_{Day\ 4}$×Score	2.953**	2.752**	3.173***	3.420***
	(2.490)	(2.353)	(5.776)	(6.355)
Chasing $_{Day\ 4}$ ×Wealth	-0.213	0.043	-0.318***	-0.256***
	(-1.283)	(0.191)	(-4.639)	(-3.732)
Chasing $_{Day\ 4}$×History	-0.075	-0.383	-0.184	-0.499
	(-0.037)	(-0.233)	(0.247)	(-0.693)
Borrower Fixed Effect	Yes	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes	Yes
Observations	34,968	36,288	184,008	255,264
R^2_{ADJ}	6.1%	6.2%	6.5%	6.8%

This table presents the analyses of the daily loan repayment likelihood for subsamples with no overlapping on *Contact* and *Address* or fully sample, based on all the chasing call made on Day 4. The analyses are performed on the delinquent-borrower-day level. The dependent variable, *Paid $_t$*, is an indicator variable equal to one if a borrower makes the repayment on the Day *t*, and zero otherwise. Day Zero is the due date of loan repayment. The tests are conducted in the full window [1, 6] after the due date. In Model 1 (Model 2), the matched sample includes borrowers in treatment group with only the information of *Contact $_{Number}$* (*Address $_{Number}$*). In Model 3, the matched sample includes borrowers in treatment group with the information of both *Contact $_{Number}$* and *Address $_{Number}$*. Model 4 uses a matched sample including borrowers in treatment group having at least one type of digital collateral. *Chasing $_{Day\ 4}$* is an indicator variable equal to one for days in windows [4, 6], and zero otherwise. *Paid $_t$* is regressed on *Chasing*, *Chasing × Digital Collateral Proxy* (i.e., *Contact*, *Address*, or *Collateral*), controlling for the interactions between the *Chasing* dummies and other characteristics of loan and borrower, as well as the borrower and day fixed effects. In Models 1 and 2, the matched samples consist of 34,968 and 36,288 borrower-day observations from July 2017 to November 2019, respectively. In Model 4 (Model 3), the sample consists of 255,264 (184,008) observations. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and borrower-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix.

Table 9 Economic Channels

Panel A: Economic Channel of Social Capital				
Dependent Variable	*Paid* $_t$			
	Social $_{Spending}$		*Veneration* $_{Ancestor}$	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Chasing $_{Day\ 4}$×*Contact*	**2.414*****	**1.162*****	**2.367*****	**1.508****
	(5.775)	**(2.655)**	**(5.967)**	**(2.262)**
Difference	***1.252*****		***0.859*****	
	(2.069)		***(2.135)***	
Chasing $_{Day\ 4}$×*Amount*	-1.537*	−1.416***	-2.087***	-1.444***
	(−1.843)	(−1.708)	(-3.538)	(-2.674)
Chasing $_{Day\ 4}$×*Rate*	−19.441***	−19.945***	-9.125***	-18.231***
	(−5.216)	(−5.322)	(-3.380)	(-7.253)
Chasing $_{Day\ 4}$×*Age*	4.992***	3.739***	5.236***	5.334***
	(4.436)	(3.244)	(6.410)	(6.829)
Chasing $_{Day\ 4}$×*Gender*	−1.918**	−1.614***	-1.712***	-1.484***
	(−2.416)	(−1.868)	(-2.977)	(-2.596)
Chasing $_{Day\ 4}$×*Score*	2.953**	2.752**	3.150***	3.144***
	(2.490)	(2.353)	(4.145)	(3.973)
Chasing $_{Day\ 4}$×*Wealth*	-0.213	0.043	-0.363***	-0.057
	(-1.283)	(0.191)	(-3.406)	(-0.362)
Chasing $_{Day\ 4}$×*History*	-0.075	-0.383	0.283	-0.481
	(-0.037)	(-0.233)	(0.306)	(-0.514)
Borrower Fixed Effect	Yes	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes	Yes
Observations	91,764	83,568	101,832	73,482
R^2_{ADJ}	6.8%	6.8%	6.8%	6.8%

Table 9 (Continued)

Panel B: Economic Channel of Physical Location				
Dependent Variable	*Paid $_t$*			
	Distance $_{FinTech}$		*Litigation $_{Confidence}$*	
	Long	Short	High	Low
	(1)	(2)	(3)	(4)
Chasing $_{Day\ 4}$×Address	**2.557*****	**0.881***	**2.551*****	**1.189****
	(5.413)	**(1.707)**	**(5.156)**	**(2.429)**
Difference	***1.676*****		***1.362*****	
	(2.394)		***(1.965)***	
Chasing $_{Day\ 4}$×Amount	-1.369**	−1.679***	-1.334**	-1.555**
	(−2.177)	(−2.674)	(-2.077)	(-2.525)
Chasing $_{Day\ 4}$×Rate	−16.819***	−16.982***	-18.477***	-16.856***
	(−5.993)	(−5.583)	(-6.269)	(-5.917)
Chasing $_{Day\ 4}$×Age	5.658***	4.300***	3.177***	6.589***
	(6.942)	(4.969)	(3.430)	(8.107)
Chasing $_{Day\ 4}$×Gender	−0.910	−1.535**	-1.746***	-0.675
	(−1.442)	(−2.268)	(-2.700)	(-1.022)
Chasing $_{Day\ 4}$×Score	2.971***	3.421***	2.241***	4.249***
	(3.576)	(3.596)	(2.589)	(4.681)
Chasing $_{Day\ 4}$×Wealth	-0.017	-0.317*	0.040	-0.341**
	(-0.107)	(-1.772)	(0.237)	(-1.999)
Chasing $_{Day\ 4}$×History	-0.447	-1.181	-1.179	-0.150
	(-0.488)	(-1.078)	(-1.92)	(-0.150)
Borrower Fixed Effect	Yes	Yes	Yes	Yes
Day Fixed Effect	Yes	Yes	Yes	Yes
Observations	65,124	54,804	60,456	59,184
R^2_{ADJ}	6.8%	6.5%	6.7%	6.5%

This table presents the cross-analyses for the economic channels of social capital and physical location. The analyses are performed on the delinquent-borrower-day level. The dependent variable, *Paid $_t$*, is an indicator variable equal to one if a borrower makes the repayment on the Day *t*, and zero otherwise. Day Zero is the due date of loan repayment. The tests are conducted in the full window [1, 6] after the due date. Day 4 is the date that the lender makes the first round of chasing calls for delinquent loans. *Chasing $_{Day\ 4}$* is an indicator variable equal to one for days in windows [4, 6], and zero otherwise. *Paid $_t$* is regressed on *Chasing*, *Chasing × Digital Collateral Proxy* (i.e., *Contact* or *Address*), controlling for the interactions between the *Chasing* dummies and other characteristics of loan and borrower, as well as the borrower and day fixed effects. In Panel A, the subsample analyses are performed for the social capital channel based on *Contact*, and the sample is split by *Social $_{Spending}$* and *Veneration $_{Ancestor}$*. In Panel B, the subsample analyses are performed for the physical channel based on *Address*, and the sample is split by *Distance $_{FinTech}$* and *Litigation $_{Confidence}$*. The sample period spans from July 2017 to November 2019 and sample size varies across subsamples. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and borrower-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. The differences in coefficients on *Chasing × Digital Collateral Proxy* are presented below the coefficients, with corresponding *z*-statistics reported in parentheses. All the variables are defined in the Appendix.

Table 10 Repayment Amount for Delinquent Loans

Dependent Variable	*Repayment* $_{Ratio}$		*Repayment* $_{Complete}$	
	(1)	(2)	(3)	(4)
Contact	**2.367*** **		**1.223*** **	
	(5.498)		**(3.487)**	
Address		**6.117*** **		**5.208*** **
		(7.192)		**(9.672)**
Amount	−7.523***	−7.711***	−5.964***	−6.133***
	(−10.709)	(−10.829)	(−11.357)	(−11.276)
Rate	11.524***	11.085***	−11.760***	−12.261***
	(3.061)	(2.860)	(−3.430)	(−3.538)
Age	−23.668***	−21.800***	−16.669***	−15.135***
	(−11.834)	(−11.206)	(−11.379)	(−10.272)
Gender	4.683***	4.522***	5.188***	5.044***
	(6.581)	(6.478)	(9.722)	(9.775)
Score	−9.806***	−9.338***	−8.765***	−8.342***
	(−12.002)	(−12.063)	(−11.386)	(−11.361)
Wealth	1.005***	0.780***	1.038***	0.843***
	(10.248)	(8.880)	(14.487)	(11.315)
History	0.880	0.781	−0.009	−0.200
	(0.967)	(0.880)	(−0.012)	(−0.268)
Province Fixed Effect	Yes	Yes	Yes	Yes
Year Quarter Fixed Effect	Yes	Yes	Yes	Yes
Observations	41,711	41,711	41,711	41,711
R^2_{ADJ}	3.8%	3.9%	2.9%	3.1%

This table presents the analyses of the repayment amount for the delinquent loan. The analyses are performed on the loan level. In Models 1 and 2, the dependent variable, *Repayment* $_{Ratio}$, is the ratio for the amount of repayment for the delinquent loan divided by the amount required to be paid by the due date. In Models 3 and 4, the dependent variable, *Repayment* $_{Complete}$, is an indicator variable equal to one if a borrower makes the repayment for the amount equal to or greater than the delinquent amount, and zero otherwise. *Repayment* $_{Ratio}$ and *Repayment* $_{Complete}$ are regressed on the *Digital Collateral Proxy* (i.e., *Contact*, or *Address* $_{Number}$), controlling for other characteristics of loan and borrower, as well as the province and year fixed effects. The sample of delinquent loans consists of 41,711 observations from July 2017 to November 2019. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and province-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix.

Table 11 Loan Delinquency Likelihood

Dependent Variable	*Delinquency*	
	(1)	(2)
Contact	**3.851***** **(15.732)**	
Address		**−0.848** **(−1.652)**
Amount	5.089*** (7.788)	5.124*** (7.853)
Rate	13.355*** (6.377)	13.959*** (6.862)
Age	−8.993*** (−7.152)	−8.918*** (−6.688)
Gender	−4.097*** (−6.892)	−4.042*** (−6.902)
Score	11.412*** (16.788)	11.223*** (17.010)
Wealth	−1.857*** (−27.360)	−1.807*** (−28.662)
History	3.195*** (5.152)	3.683*** (6.218)
Province Fixed Effect	Yes	Yes
Year Quarter Fixed Effect	Yes	Yes
Observations	97,783	97,783
R^2_{ADJ}	6.1%	6.0%

This table presents the analyses of the loan delinquency likelihood. The analyses are performed on the loan level. The dependent variable, *Delinquency*, is an indicator variable equal to one if a borrower fails to make the monthly loan payment by the due date for at least one time during the loan term, and zero otherwise. *Delinquency* is regressed on the *Digital Collateral Proxy* (i.e., *Contact*, or *Address* $_{Number}$), controlling for other characteristics of loan and borrower, as well as the province and year fixed effects. The sample of loans consists of 97,783 observations from July 2017 to November 2019. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and province-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix.

Table 12 Loan Approval

Dependent Variable	*Approval*	
	(1)	(2)
Contact	**0.974***** **(3.167)**	
Address		**4.666***** **(14.423)**
Amount	−14.994*** (−20.758)	−15.119*** (−20.931)
Rate	107.984*** (18.402)	107.514*** (18.538)
Age	−7.820*** (−7.952)	−6.317*** (−6.291)
Gender	12.066*** (27.097)	11.950*** (27.367)
Score	−35.251*** (−95.932)	−34.888*** (−97.897)
Wealth	3.222*** (83.566)	3.014*** (82.717)
History	−9.259*** (−13.538)	−9.482*** (−14.469)
Province Fixed Effect	Yes	Yes
Year Quarter Fixed Effect	Yes	Yes
Observations	236,967	236,967
R^2_{ADJ}	13.2%	13.3%

This table presents the analyses of the loan approval likelihood. The analyses are performed at the loan application level. The dependent variable, *Approval*, is an indicator variable equal to one if a borrower's local application is approved by the fintech lender, and zero otherwise. *Approval* is regressed on the *Digital Collateral Proxy* (i.e., *Contact*, or $Address_{Number}$), controlling for other characteristics of loan and borrower, as well as the province and year fixed effects. The sample of loan applications consists of 236,967 observations from July 2017 to November 2019. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and province-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix.

Internet Appendix (IA)

“Digital Footprints as Collateral for Debt Collection”

This online appendix provides additional tables for the paper, “Digital Footprints as Collateral for Debt Collection.” We summarize the content as follows:

Table IA 1: Additional tests for the regulation on data privacy and protection

Table IA 2: Additional tests for the regulation in fintech lending market

Table IA 3: Additional tests for the role of digital collateral in financial inclusion

Table IA1 Tests for Data Privacy and Protection

Dependent Variable	*Paid* $_t$	
	(1)	(2)
Chasing $_{Day\ 4}$×*Contact*	**1.078*** **	
	(2.659)	
Chasing $_{Day\ 4}$×*Address*		**1.059*** **
		(3.111)
Chasing $_{Day\ 4}$×*Amount*	-2.044***	-1.591**
	(-3.382)	(-2.215)
Chasing $_{Day\ 4}$×*Rate*	2.842	1.362
	(1.022)	(0.377)
Chasing $_{Day\ 4}$×*Age*	6.213***	6.772***
	(8.332)	(7.917)
Chasing $_{Day\ 4}$×*Gender*	-1.642***	-0.328
	(-3.008)	(-0.455)
Chasing $_{Day\ 4}$×*Score*	2.297***	1.188
	(3.274)	(1.122)
Chasing $_{Day\ 4}$×*Wealth*	-0.387***	-0.183
	(-4.757)	(-1.097)
Chasing $_{Day\ 4}$×*History*	0.091	-1.232
	(0.120)	(-1.097)
Borrower Fixed Effect	Yes	Yes
Day Fixed Effect	Yes	Yes
Observations	101,688	54,780
R^2_{ADJ}	6.9%	6.2%

This table presents the additional tests for the change of regulation on data privacy and protection, focusing on the subsamples with the loan repayment due dates after the adoption of the China Internet Personal Information Security and Protection Guidelines on April 10, 2019. The analyses are performed at the delinquent-borrower-day level. The dependent variable, *Paid* $_t$, is an indicator variable equal to one if a borrower makes the repayment on the Day t, and zero otherwise. Day zero is the due date of loan repayment. The tests are conducted in window [1, 6], where Day 4 is the date that the lender makes the first round of chasing calls for delinquent loans. *Chasing* $_{Day\ 4}$ is an indicator variable equal to one for days in window [4, 6], and zero for window [1, 3]. The dependent variable, *Paid* $_t$, is regressed on *Chasing*, *Chasing* × *Digital Collateral Proxy* (i.e., *Contact* or *Address*), controlling for the interactions between the *Chasing* dummy and other characteristics of loan and borrower, as well as the borrower and day fixed effects. The matched subsamples based on *Contact* and *Address* consist of 101,688 and 54,780 borrower-day observations from the adoption of the Guidelines to November 2019, respectively. The t-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and borrower-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix of the paper.

Table IA2 Tests for Fintech Lending Regulation

Dependent Variable	$Paid_t$	
	(1)	(2)
$Chasing_{Day\ 4} \times Contact$	**1.625*** **	
	(4.337)	
$Chasing_{Day\ 4} \times Address$		**1.424*** **
		(3.840)
$Chasing_{Day\ 4} \times Amount$	-1.540***	-0.344**
	(-2.999)	(-0.599)
$Chasing_{Day\ 4} \times Rate$	-12.328***	-15.950***
	(-5.553)	(-6.251)
$Chasing_{Day\ 4} \times Age$	6.347***	7.896***
	(9.286)	(10.183)
$Chasing_{Day\ 4} \times Gender$	-2.619***	-2.001***
	(-5.299)	(-3.340)
$Chasing_{Day\ 4} \times Score$	4.177***	3.815***
	(6.733)	(5.003)
$Chasing_{Day\ 4} \times Wealth$	-0.267***	-0.163
	(-3.474)	(-1.515)
$Chasing_{Day\ 4} \times History$	-1.662*	-1.436
	(-1.859)	(-1.416)
Borrower Fixed Effect	Yes	Yes
Day Fixed Effect	Yes	Yes
Observations	116,160	77,976
R^2_{ADJ}	6.7%	7.3%

This table presents the additional tests for the regulation on fintech lenders, focusing on the subsamples of 20 provinces that had implemented the province-level rules to regulate the fintech lending markets by April 2018. The analyses are performed on the delinquent-borrower-day level. The dependent variable, $Paid_t$, is an indicator variable equal to one if a borrower makes the repayment on the Day t, and zero otherwise. Day Zero is the due date of loan repayment. The tests are conducted in window [1, 6], where Day 4 is the date that the lender makes the first round of chasing calls for delinquent loans. $Chasing_{Day\ 4}$ is an indicator variable equal to one for days in window [4, 6], and zero for window [1, 3]. The dependent variable, $Paid_t$, is regressed on *Chasing*, *Chasing* × *Digital Collateral Proxy* (i.e., *Contact* or *Address*), controlling for the interactions between the *Chasing* dummy and other characteristics of loan and borrower, as well as the borrower and day fixed effects. The matched subsamples based on *Contact* and *Address* consist of 116,160 and 77,976 borrower-day observations from July 2017 to November 2019, respectively. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and borrower-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix of the paper.

Table IA3 Tests for Financial Inclusion

Dependent Variable	*Approval*	
	(1)	(2)
Contact	**1.748*****	
	(6.342)	
Address		**7.303*****
		(15.586)
Amount	−15.064***	−15.180***
	(−20.347)	(−20.330)
Rate	79.102***	82.348***
	(17.984)	(18.389)
Age	−7.909***	−5.654***
	(−6.447)	(−4.478)
Gender	11.748***	11.567***
	(20.906)	(21.774)
Score	−34.254***	−33.597***
	(−58.232)	(−61.108)
Wealth	3.303***	2.932***
	(56.082)	(73.669)
History	−10.933***	−10.797***
	(−11.234)	(−11.423)
Province Fixed Effect	Yes	Yes
Year Quarter Fixed Effect	Yes	Yes
Observations	118,484	118,484
R^2_{ADJ}	12.4%	12.8%

This table presents the additional tests for the role of digital collateral in financial inclusion, focusing on the subsamples of loan applicants with low creditworthiness as indicated by their credit risk scores. The analyses are performed on the loan application level. The dependent variable, *Approval*, is an indicator variable equal to one if a borrower's local application is approved by the fintech lender, and zero otherwise. *Approval* is regressed on the *Digital Collateral Proxy* (i.e., *Contact*, or *Address* $_{Number}$), controlling for other characteristics of loan and borrower, as well as the province and year fixed effects. The subsample of loan applications consists of 118,484 observations from July 2017 to November 2019. The *t*-statistics shown in parentheses are based on standard errors adjusted for heteroskedasticity and province-level clustering. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively. All the variables are defined in the Appendix of the paper.