Digital Footprints as Collateral for Debt Collection

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Current Version: September 2020

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Abstract

We study the role of borrowers' digital footprints in debt collection. Using a large sample of personal loans from a fintech lender, 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, although these borrowers even have a higher likelihood of delinquency. The use of digital footprints can remain legitimate even under stringent privacy protection regulations and fair debt collection practices. Our findings suggest that digital footprints, as a new type of collateral, ultimately can enhance financial inclusion by facilitating the lender's collection of delinquent loans.

JEL classification: D14, G14, G23, G51

Keywords: Delinquency, Collateral, Debt collection, Digital footprints, Fintech

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 the U.S., and 8.4% was more than 90 days delinquent. Similarly, Chinese credit card holders accumulated a comparable amount of $13 billion overdue for more than six months by 2019. This enduring problem of loan delinquency calls for new tools to help creditors to obtain repayments. In recent years, the wide use of smartphones and internet services generates a new type of information about the online traces of users, such as the contacts that they maintain, the mobile applications that they use, and the websites that they visit. We refer to such information as digital footprints and propose the use of debtors' digital footprints potentially as a novel channel to facilitate creditors' debt collection.

Creditors' efforts in the loan process mainly include 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 by the debt literature as a commitment device to enforce 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 cannot provide any 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 the process of debt collection for at least two reasons. First, by using the information of borrowers' digital footprints, lenders may know exactly whom borrowers often contact via mobile phones, email, or instant messaging applications, and thus might be able to identify borrowers' social networks. When a loan is delinquent, the

[1] Digital footprints are referred to the information that borrowers leave online 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).

lender can contact the 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 ask them to urge the borrower to repay. Either possibility would 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 would be incentivized to repay the loan (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 enables 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 often exercise liens to seize goods from the borrower's dwellings or other addresses.[3] Moreover, if the delinquent borrower knows that the lender has her address information, additional pressure may be imposed on the borrower because of a reduced psychological distance and a heightened threatening stimulus (McGraw et al. 2012; Williams, Stein, and Galguera 2014; Boothby et al. 2016). Therefore, when the delinquent borrower receives a phone call from the debt collector with her address information, she will believe that 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 would motivate her 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 contained in digital footprints may simply reflect

[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 bonding individuals' social capital to facilitate personal borrowings through social networks.

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

borrowers' characteristics such as age, income, and gender, which renders digital footprints less incremental information in facilitating debt collection. Second, data about borrowers' digital activities could be noisy, leading to the poor information quality of digital footprints and thus making the corresponding 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 the data of personal loan contracts from a leading fintech company in China. The fintech company only asks the individual borrower to provide her mobile number and national identity number. With such information, the lender can obtain from the third-party data providers other information about the borrower, such as the borrower's credit score, the balance of her online payment account, and the historical record of her past loan applications. Then, the lender computes the internal credit score using an automatic algorithm and evaluate the borrower's creditworthiness for loan decisions.

More importantly, this fintech creditor can also obtain the borrower's digital footprints from data providers, including her frequent mobile contacts and delivery addresses for online shopping. 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 such digital collateral available 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 as the treatment group to those without collateral as 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

[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). In three months after the delinquency, if the borrowers still fail to make repayments, the lender will hand over the cases to debt collection agencies to further contact the borrowers and collect the debt (Fedaseyeu and Hunt 2018; Fedaseyeu 2020).

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 the address information.[5]

Second, in a timeline after delinquency, the lender will make the five rounds of phone calls to borrowers in the following quarter: the fourth day after the repayment due date (hereafter, Day 4), following by another four dates (i.e., Day 16, Day 31, Day 61, and Day 91). Then, the delinquent loans will be handed over to external debt collection agencies for further collection efforts after Day 93.[6] We examine the likelihood of repayment in several six-day windows centered around the dates when delinquent borrowers receive phone calls from the lender. This enables us to compare the changes in the likelihood of repayment after 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 phone 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 of 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 centered on 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 re-perform the DID tests in a placebo sample period for the six-day window centered on the repayment due date, during which the lender makes no call but only sends 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 period. Second, to ensure that our baseline findings are not simply driven by chance, we conduct simulation by artificially constructing pseudo borrowers with digital collateral. We randomly assign half of our sample borrowers as the pseudo

[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.

borrowers with digital collateral to the new treatment groups and the remaining half of them to the pseudo control groups. We generate the randomized pseudo samples for 1,000 times and then reconduct the DID analyses. We find that the mean and median values of the pseudo coefficients are statistically insignificant and also 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 suggest a marginal decline in the coefficients on collateral proxies 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 a 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 strictly 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 the 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 the veneration events of honoring ancestors more frequently, they are 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 the areas with stronger law enforcement systems, compared to their counterparties, the availability to their physical locations to the lender can better incentivize them to make repayments because of the potential judicial enforcement (Djankov, McLiesh, and Shleifer 2007; Djankov et al. 2008) and additional psychological pressures (Williams, Stein, and Galguera 2014; Boothby et al. 2016). These results are corroborating with our main findings and consistent with the two economic channels.

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 would 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 show that the incidence of delinquency is even 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, the balance in her payment account, and the historical record of her past loan applications. This finding suggests an incremental effect of digital collateral on the 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 determining the loan approval, 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 the 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; 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 footprint and debt collection. Section 5 reports the additional tests for 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 the 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 of loan delinquency likelihood. In similar veins, 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 from delinquent debtors.

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 the debt collateral backed by assets can mitigate the likelihood of delinquency. The literature on debt collection has documented the determinants of the recovery of delinquent loans, including the information technology development (Drozd and Serrano-Padial 2017), debt collection agencies (Fedaseyeu and Hunt 2018; Fedaseyeu 2020), and lenders' communication to 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 prior research by documenting an effective role of digital collateral backed by borrowers' social and physical capital in enforcing debt repayments after delinquency.

Fourth, our paper sheds light on an emerging stream of literature that examines the relation between fintech and traditional lenders. Prior studies have shown that fintech lenders can act as substitutes for banks (Tang 2019) and fill the gaps in lending markets left by traditional lenders (Erel and Liebersohn 2020). For example, the extant research suggests that fintech lenders tend to fill the credit supply gap 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 themselves tighten credit standards (Allen, Shan, and Shen 2020). Moreover, fintech lenders 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, deviating from the traditional banking model, from the debt collection perspective.

3. Institutional background, variables, and descriptive statistics

In this section, we describe the institutional background of our research setting and present the definitions and summary statistics of 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 the staff assisting the loan applicant in the application process. Figure 1 illustrates the process of the loan application, approval, repayment, and collection.

[Insert Figure 1 Here]

A borrower can apply for the loan from the fintech company's terminal, a tablet mobile device with a touchscreen display designed for the submission of loan applications to the fintech lender. The information filled in the loan application includes the customer's mobile number and national identity card. Then, by using the applicant's mobile number and national identity number, the company can 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.[7] 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 within ten minutes.

After the loan application is approved, the borrower will obtain money from the fintech company, and either use it to purchase goods immediately or keep the cash for future use. Then, 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.

[Insert Figure 2 Here]

[7] 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.

As shown in the timeline, in a four-day window [-3, 0] before the repayment due date (Day 0), the lender starts to send mobile messages as reminders to borrowers. When 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 used by financial institutions and public services in China. In principal, it would be hard for a person with a low credit score to obtain future mortgage loans and even travel with high-speed trains and airlines.

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 information from her digital footprints, the lender will tell the borrower that debt collectors would come to the borrower's place to collect the loan and probably also report it to the borrower's neighborhood committee.[8] Further, the lender will warn the borrower with the penalties forced by the police and the 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, if the borrower still does not make the loan repayment in the coming quarter, the lender will call the borrower and her frequent contacts if available, again on Day 16, Day 31, Day 61, and Day 91. Finally, following the last chasing call, after Day 93, the case of the delinquent loan will ultimately be handed over from the fintech lender to a third-party debt collection agency, who makes 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 all 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

[8] 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.

the provinces in China.[9] As indicated in the figure, the sample of applications is widely spread over the country and well represents the population in China.

[Insert Figure 3 Here]

Within 97,783 approved loans, 41,711 borrowers experience at least one time of loan delinquency. Our 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 0 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 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 the two measures as the metrics 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 a few filers to identify frequent contacts: 1) a frequent contact number should not be a phone number from 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 have been made for more than 20 seconds.

Second, we construct the digital collateral metric, *Address*, as an indicator variable if a borrower's physical address can be obtained from her digital footprints. Specially, the fintech

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

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 neither seem to be the borrower's residential or office addresses nor are useful to identify 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 the delivered shopping 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 our sample borrowers to the new treatment groups as if they have the corresponding 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 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 transferred to the logarithm value in regressions. We expect the 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 transferred 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' demographic characteristics, 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 directly 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 high-risk profile (*Score*), the balance of a borrower's *Alipay* account from *Alibaba* in Chinese Yuan (*Wealth*), and the number of loan applications of a borrower rejected by other online lending platforms (*History*). All these credit quality proxies are transferred 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%, lower than the repayment likelihood in the window [1, 93]. This suggests that not all repayments fully recover the outstanding loan payments. Indeed, in untabulated statistics, we find that among all the delinquent loans, 73.8% of borrowers make payments equal to or above the outstanding loans, accounting for 123.6% of the outstanding amounts,[10] while 12.0% of borrowers make underpayments equal to 29.0% outstanding loans. 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 for our analyses on digital collateral. 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, suggesting a right-tailed skewness distribution. With regard to the physical address, the lender

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

can find the address information from digital footprints among 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 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 28 May 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, typically with no collateral. The annual nominal interest rate is 29.5%, substantially higher than the prime loan rate at 4.3% between 2017 to 2019, but lower than the cut-off rate for the usurious loan equal to 36.0% as per statute in China.[11]

The average age of borrowers 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 female percentage in the full sample equal to 19.2%, 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, personal wealth in the Alipay's account amounting to 4.22 Chinese Yuan, and has been rejected by other online lending platforms by 0.12 times.

[Insert Table 1 Here]

4. Main results

Our main analysis is conducted using a difference-in-difference approach by matching borrowers with digital collateral available as the treatment group to those with no collateral as the 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

[11] 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.

We employ 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 treatment borrower would have no match in the control group when her distance of propensity score to any control borrower is not the least compared to all other treatment borrowers.[12]

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 the ones without the address information as the control group.

Table 2 presents the 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 treatment borrowers encounter higher interest rates (*Rate*) and have lower balances of online payment accounts (*Wealth*), compared with control borrowers. 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 treatment borrowers with digital collateral are more likely to make the repayments, while the higher interest rates and lower wealth balances, on the contrary, would make it more difficult for borrowers to repay the outstanding loans.

[Insert Table 2 Here]

[12] 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.

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 the information of 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.

After the fintech lender makes calls made on Day 4, the treatment borrowers have a significantly higher repayment likelihood (9.5%) in the window [4, 6] than the control borrowers (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 an increase in the repayment rate for a magnitude of 21.5% (1.7%/7.8%) in the post-call period.

[Insert Table 3 Here]

Our findings are similar around the second wave of phone calls on Day 16 for 4,412 borrowers who remain delinquent on Day 13.[13] Specifically, the lender will warn the treatment borrowers (*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 with the frequent contact information have a significantly higher repayment rate (3.7%) than those with no such information (2.5%), with the difference equal to 1.2% and significant at the one percent level. This finding is also economically significant. Compared to borrowers with no frequent contact, the treatment borrowers have an increase in the repayment rate for 46.0% (1.2%/2.5%).

[13] 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.

The further DID analyses 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 the treatment and control 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). Similar results are found for the second wave of phone calls on Day 16 (*DID*=1.0%, and *t*-statistic=3.72).

Moreover, these results also hold in Panel B for 9,994 treatment borrowers 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 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%, also 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 actions to enforce loan repayments at the borrower's physical address. It is also likely that the treatment borrowers will face more pressure psychologically due to reduced psychological distance and heightened threatening stimulus, with their address information known by the lender. However, the lender will only warn the control borrowers on the potential damages on their credit scores. In addition, we examine the second wave of calls, when the lender will call the treatment borrowers (*Address*=1) with physical addresses again on Day 16 and find similar results for 3,459 borrowers who remain delinquent until Day 13 (*DID*=0.9%, and *t*-statistic=3.20).

Lastly, we illustrate the patterns of prepayment likelihood discussed above in Figure 4 and Figure 5. From both figures, we find the larger increases in periods after the fintech lender makes the chasing calls to the digital-collateral-backed borrowers than those with no digital collateral.

[Insert Figure 4 and Figure 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 model, with Day s indicating the date for the lender to make chasing calls:

$$Paid_t = \alpha + \beta_{CD\times DC}\ Chasing\ Day_s \times Digital\ Collateral\ Proxy$$
$$+ \beta_{CD\times Control}\ Chasing\ Day_s \times Control\ Variables + \beta_{FE}\ Fixed\ Effects + \varepsilon, \quad (1)$$

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]. *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 *Chasing Day* $_s$ with *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 indeed plays an effective role in facilitating debt collection.

We conduct the analyses in the matched samples, as described in Table 3. In Equation (1), *Control Variables* represents a vector of control variables of loan and borrower characteristics, as described in Section 2.2, which are interacted with *Chasing Day* $_s$ to account for any effect of chasing calls that moderate the impact of control variables on the repayment likelihood. We also include *Fixed Effects*, the borrower and day fixed effects, to control for any cross-sectional and time-series omitted factors and cluster standard errors at the borrower level.[14]

We perform the DID tests based on Equation (1) for the first two rounds of chasing calls in Table 4. Around the first chasing call on Day 4, for 14,768 treatment borrowers with frequent mobile contacts, the matched sample in the DID analyses consists of 177,216 borrower-day observations for both treatment and control groups in the six-day window (14,768×2×6). For 9,994 treatment borrowers with the information of physical addresses, the matched sample being tested include 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 treatment borrowers, who have not made repayment until Day 13, with contact and address information. 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 suggest the usefulness of digital collateral in the debt collection process. For example, in Model 1, we find that delinquent borrowers with frequent contact information have

[14] 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 do not control for the main effects of control variables, because the interaction terms have absorbed them. We find similar results when we drop the interactions and only control for the main effects of control variables.

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 $Chasing_{Day\ 4} \times Contact$ is equal to 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].

Regarding our control variables, we find a significantly positive impact of chasing calls 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 potentially indicates that old and risky borrowers are more concerned about the possible detrimental impacts on their credit scores if they do not make the repayments. In contrast, there is a significant and negative reciprocal effect of chasing calls on loan repayment for loans with large amounts (coefficient on $Chasing_{Day\ 4} \times Amount$=-1.92 and *t*-statistic=-4.62) and 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 are less motivated to repay the delinquent loans (coefficient on $Chasing_{Day\ 4} \times Gender$=-2.29 and *t*-statistic=-5.72).

We find similar results when we either examine *Address*. For example, in Model 2, the coefficient on $Chasing_{Day\ 4} \times Address$ is 1.79 and significant at the one percent level (*t*-statistic=5.00). 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 magnetically smaller 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 may suggest that borrowers who remain delinquent after the first round of calls are less responsive to further calls, because they are less concerned about the potential loss of their social capital and about being chased by debt collectors through their physical locations.

Taken together, the results in Table 4 provide supports for an effective role 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 perform two placebo tests to alleviate this concern.

First, we re-run the DID analysis in 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 of digital collateral in this placebo test. That is, borrowers with the information about frequent mobile contacts or physical addresses have an increase in the repayment likelihood from the window [-2, 0] to [1, 3] than those with no such information.

In Panel A of Table 5, we find that the coefficient on $\textit{Chasing Day}_1 \times \textit{Contact}$ is -0.074 and insignificant (t-statistics=-0.40) in Model 1. This suggests that before receiving chasing calls, the delinquent borrowers with key contact information in digital footprints are indifferent from those with no such information in terms of loan repayment. Similar results are found for treatment borrowers with physical address information in Model 2 (coefficient on $\textit{Chasing Day}_1 \times \textit{Address}$=-0.266 and t-statistic =-1.22). Therefore, we find supportive evidence mitigating the concern about the 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 simulation by running the 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 treatment borrowers 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, $\textit{Contact}_{\textit{pseudo}}$ ($\textit{Address}_{\textit{pseudo}}$). The unassigned borrowers are considered as those in the pseudo control groups with $\textit{Contact}_{\textit{pseudo}}$ ($\textit{Address}_{\textit{pseudo}}$) denoted zero.

We generate 1,000 randomly assigned samples for pseudo borrowers and then reconduct the DID analyses based on the chasing calls made on Day 4 in these samples. Panel B of Table 5 presents the mean values and distribution percentiles of the coefficients on $\textit{Chasing}_{\textit{Day 4}} \times \textit{Contact}_{\textit{Pseudo}}$ and $\textit{Chasing}_{\textit{Day 4}} \times \textit{Address}_{\textit{Pseudo}}$ based on 1,000 times of regression estimation.

If our baseline findings are largely driven by chance, we may find our main results close to the mean and median values reported in Panel B.

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

Collectively, the findings in these placebo tests suggest that either the time trend effect or the by-chance explanation cannot be the main force that predominantly drives 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

In Table 6, we replace our main metrics of digital footprints regarding the presence of borrowers' contact and location information with the amount of digital information, to investigate whether the variation of information amount exerts an effect on debt collection.

On the one hand, more relevant information extracted from digital footprints can allow the lender to reach a larger group of a borrower's family members and friends, and to locate her physical addresses more completely. On the other hand, given the time and resource constraints faced the lender's staffs, a large amount of 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, 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. Consistent with our main results, we find a positive impact of $Contact_{Number}$ and $Address_{Number}$ 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 and both 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 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 staffs 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 pick up some contacts to make chasing calls rather than reaching all the contacts. However, these selected contacts can be less important than 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 two coefficients is statistically insignificant.

In sum, the results suggest that the likelihood of loan repayment increases with the amount of digital collateral, and this increase may not be linear. Especially when there is a large number of borrowers' digital footprints, the lender can potentially spend more time identifying the key information, which, in turn, would reduce the effectiveness of digital collateral.

[Insert Table 6 Here]

4.5.2. Sequence of chasing calls

In the main analyses, we focus on the first two rounds of chasing calls on Day 4 and Day 16. In this subsection, we first investigate the overall effect of digital collateral on the repayment rate along the whole timeline before the lender hands over delinquent loans to external collection agencies. Then, we conduct the analyses to compare the effect of digital collateral in the first two rounds of chasing calls with that in the next three rounds of chasing calls on 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 treatment borrowers with frequent contact information in digital footprints, who remain delinquent in 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.[15] For treatment borrowers with physical location information, the sample consists of 241,812 observations, because the number of borrowers with physical location information varies across the five calling days equal to 9,994, 3,459, 2,696, 2,102, and 1,900, respectively.[16]

Table 7 presents the results on the above test. In Models 1 and 2, we find an overall effect of digital collateral, facilitating the debt collection process in the five six-day 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).

Then, 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. Psychology literature suggests that repeated notifications may results 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, the coefficients on $Chasing_{Day\ 4,16} \times Contact$ and $Chasing_{Day\ 31,61,91} \times Contact$ are 1.40 and 0.63 in Model 3, significant at the one percent level (t-statistics=6.46 and 4.89). Consistent with our expectation, the differences in coefficients are statistically significant between $Chasing_{Day\ 4,16}$ and $Chasing_{Day\ 31,61,91}$ (z-statistics of difference=3.11 and 2.04) in Models 3 and 4.

These findings indicate 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 the calls on Day 4 and Day 16. A potential explanation is that delinquent borrowers, who have been warned using digital

[15] 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.

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

collateral but fail to make repayments after the first two calls, are bored and less concerned about their digital collateral (Bornstein 1989; Bornstein, Kale, and Cornell 1990). Therefore, 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 by one type of digital footprints rather than the other. To address this concern, we conduct additional tests to separate out the effects of the two types of digital footprints.

Specifically, we start with 14,768 treatment borrowers 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 and 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 treatment borrowers 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 manger 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).

We next investigate a sample with 15,334 treatment borrowers who have both frequent contact and physical address information in Model 3. 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 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, 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 in Model 4. The sample includes 255,264 borrower-day observations used in Models 1 to 3 (34,968+36,288+184,008). We find the positive and significant coefficients of 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 the debt collection process, 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 effect of digital collateral on debt collection operates through the *social capital channel* and the *physical location channel*. In this and next subsections, we conduct the cross-sectional analyses to validate these two economic mechanisms.

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 China Household Finance Survey and Research Center (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.[17] We construct two social capital metrics, $Social_{Spending}$ and $Veneration_{Ancestor}$, based on the 2017 CHFS data.

[17] 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?"

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 to establish and maintain personal social networks in China (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 the veneration events of honoring ancestors at the province-year level. Ancestor veneration and worship can stress social unity and are associated with familism, the basic 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 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.[18] 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), are more concerned about the potential impairment on their social capital and thus are more likely to make repayments when the lender reaches their frequent contacts.

[18] 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.

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).[19]

Talen 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, e.g., debt contracting (Hasan, Hoi, and Zhang 2017), management compensation (Hoi, Wu, and Zhang 2019) and corporate innovation (Gupta, Raman, and Shang 2020).

[Insert Table 9 Here]

5.2. Cross-sectional analyses of physical location channel

Then, we perform the cross-sectional analyses on 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, including 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 defaults (Mian 2006). Also, lenders tend to cut lending for long-distance borrowers during the financial crisis (De Haas and Van Horen 2013), and demand collateral and grant loans of short maturity (Beck, Ioannidou,

[19] The sum of the subsamples can be slightly smaller than that in our main analysis, because not all the provinces in our main sample are surveyed in the CHFS data.

and Schäfer 2018). Therefore, we expect that it would be more likely for the lender to recover the delinquent loan when a borrower is geographically closer. Furthermore, a close-by borrower may psychologically face more threatening pressures from the lender (McGraw et al. 2012). This leads to a weaker digital collateral effect through the *physical location channel*, because the close-by borrower will be nevertheless 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 borrower remote from the lender, 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 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, $\textit{Litigation}_{\textit{Confidence}}$, and match it to a borrower's physical location in digital footprints. The rating varies between one to 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 more satisfactory in terms of law enforcement (Djankov et al. 2008). This is because the delinquent borrowers perceive that the lender will make use of the information of their physical locations to pursue judicial enforcements, leading to judgment liens placed on borrowers' assets by the courts.

The results are presented in Panel B of Table 9. Consistent with the *physical location channel*, we find a stronger effect digital collateral effect for borrowers in subsamples with long $\textit{Distance}_{\textit{FinTech}}$ and high $\textit{Litigation}_{\textit{Confidence}}$ (in Models 1 and 3, coefficients=2.56 and 2.55 and *t*-statistics=5.41 and 5.16, respectively) than the 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 equal to 2.39 and 1.97 for $\textit{Distance}_{\textit{FinTech}}$ and $\textit{Litigation}_{\textit{Confidence}}$.

Overall, these findings are corroborating with our main results and provide further support to the *physical location channel*. We document the scenarios under which delinquent borrowers will face pressures 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. This subsection will investigate the impact of digital collateral through chasing calls on the amount of debt recovery. This analysis can provide important profitability implications for the lender (Karlan and Zinman 2010). When a delinquent borrower makes loan repayment, she may underpay the overdue amount because of a shortfall of cash or make payment more than 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 repayment contingent on the repayment is made.

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 amount required to be paid by the due date, 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 in a sample of 41,711 delinquent borrowers:

$$Repayment_{Ratio} \,/\, Repayment_{Complete} = \alpha + \beta_{DC}\, Digital\ Collateral\ Proxy$$
$$+\, \beta_{Control}\, Control\ Variables + \beta_{FE}\, Fixed\ Effects + \varepsilon, \quad (2)$$

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* represent the province and year fixed effects to control for the cross-sectional variations across geographic areas and also 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 pay off the delinquent amounts fully. The coefficients on *Contact* is 1.22, and that on *Address* is 5.21, 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 the 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 investigating 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:

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

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 reported 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 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 older and female borrowers less likely to involve in delinquency, because older people may have built up a long-term credit record, and female borrowers could be less aggressive in making lending 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 more likely to experience delinquency. For example, in Model 1, the coefficient on *Wealth* is -1.86 (*t*-statistic=-27.36), and 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 decision of loan approval 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 iOS mobile operating system, have predictive power for a fintech lender's loan approval decisions 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 acquired through digital footprint. For example, we find the coefficients on *Contact* and *Address* are 0.97 and 4.67, significant at the one percent level (*t*-statistics=3.17 and 14.42).[20] Concerning the economic magnitude, these results imply that borrowers with frequent mobile contacts (physical address

[20] 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.

information) have an increased approval likelihood of 2.21% (11.27%) higher than those with no digital collateral, compared to the sample mean.

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

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

[Insert Table 12 Here]

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 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, which would give consumers the right to know how personal information was used, did not pass after facing a forceful opposition campaign from the technology companies at Silicon Valley (Harmon 2013). Subsequently, the California Consumer Privacy Act was passed by the state legislature in 2018, which provides the California residents with the rights to understand and control the use of their personal data effectively from January 2020 (Hautala 2020). Similarly, the European Union passed the General Data Protection Regulation on data privacy protection in 2016, which became effective from 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 borrowers' privacy leading to a negative reciprocity effect.[21]

Practically, to maintain the 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 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 and credit score information from other financial institutions. The applicant further 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 the 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 on April 10, 2019, as a measure to protect personal information privacy when the Personal Information Protection Law was still 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 better.

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

[21] 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 in selective dates. On the contrary, the lender in our paper applies one collection strategy consistently to all the borrowers by making the phone calls on several given days after delinquency, exogenous to loans and borrowers' characteristics.

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. As reported by the Consumer Financial Protection Bureau (CFPB 2020), there were about approximately 75,200 debt collection complaints received by the Bureau in 2019. 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 FDCPA, when borrowers owe debts, the U.S. debt collectors cannot disclose the information to third parties, such as borrowers' contacts and employers.[22] 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, the collectors might expect that reaching borrowers' contacts would make them 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 effectively facilitate debt collection.

In the Internet Appendix, we further conduct the analyses in the subsamples of 20 provinces that had implemented the province-level rules to regulate the fintech lenders' abusive behavior by April 2018.[23] We match the province regulation information to our baseline sample by borrowers' hometown information in their national identity cards.[24] We consider borrowers

[22] Our discussion in this section mainly refers to the debt collection practices by lenders. For studies on third-party debt collectors, see Fedaseyeu and Hunt (2018) and Fedaseyeu (2020).
[23] The information about the province-level regulation implementation was collated in a survey as reported by the online media outlets such as the Sina Corporation. See, e.g., the coverage by Sina in Mandarin on April 8, 2018: https://cj.sina.com.cn/articles/view/6298435788/1776a80cc019006p67 (accessed September 9, 2020).
[24] We choose to use borrowers' hometown information in the matching process because the potential future lawsuit against a delinquent borrower as the defendant will be judged in her hometown, and the physical address in digital footprints is not available to all the borrowers.

in these subsamples to be better protected against the lender's potential aggressive debt collection practices, because the 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 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 report by World Bank, only seven percent of adults in developing economies have credit cards; however, they have essential reasons for borrowing, i.e., 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 the 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 can boost financial inclusion, especially in countries where standard personal credit scores are unavailable and 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 report underscores that inclusion needs to be promoted properly and responsibly, and the overextension of credit at any cost 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.[25] Traditional financial institutions rely on physical collateral (i.e., income and assets) to overcome default risk in the retail debt markets. Given information asymmetry between the lender and individual borrowers, collateral in general allows for hedging against borrowers' potential moral hazardous behavior.[26] Our study provides an alternative mechanism 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 are likely to be those with 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 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 future debt collection when borrowers fail to make repayments. The role of digital collateral in debt collection is operated through two potential channels, that is, the possible damages to borrowers' social capitals, and the accessibility to their physical locations. Our findings add to the fintech literature by documenting evidence that technological

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

[26] In the event of 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 are difficult to secure a loan from conventional financial institutions, resulting in the inefficiency of resource allocation and low financial inclusion (Gine, Goldberg, and Yang 2012; Lin, Prabhala, and Viswanathan 2013; Hildebrand, Puri, and Rocholl 2017).

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.

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 loan payment by 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 to 5. Higher value of the rating indicating more satisfaction.

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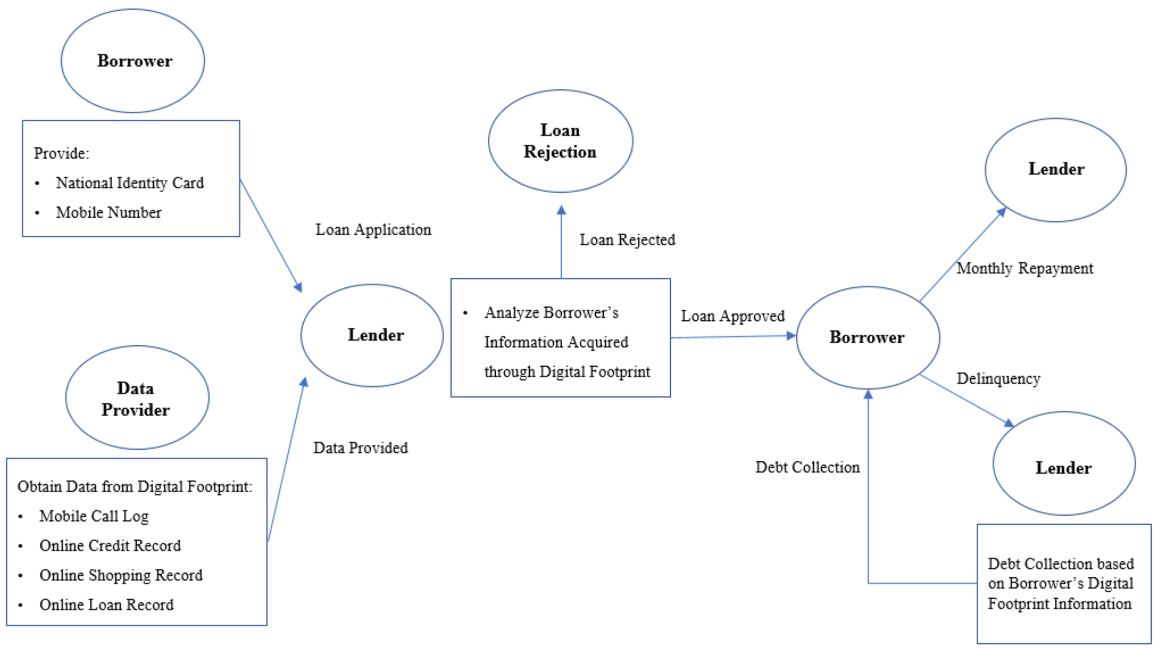
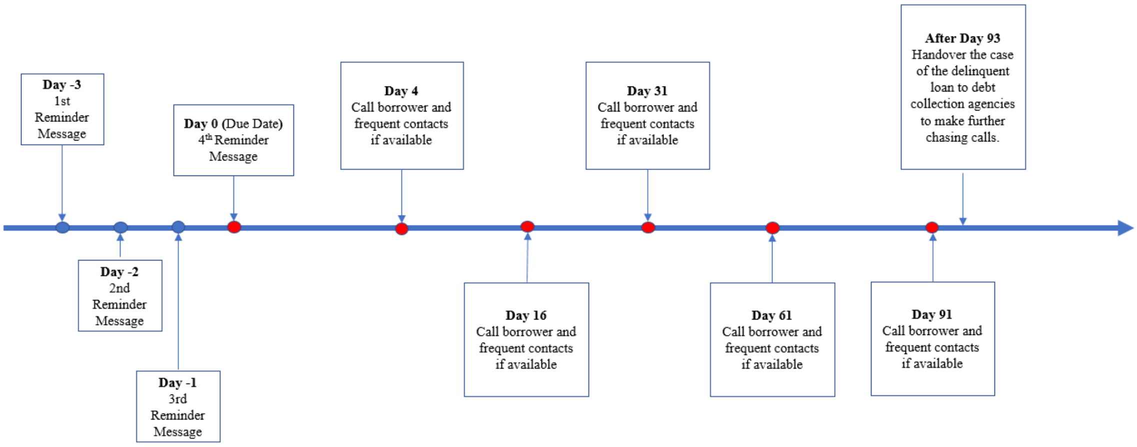
Figure 1 The Process of Loan Application, Approval, Repayment, and Collection



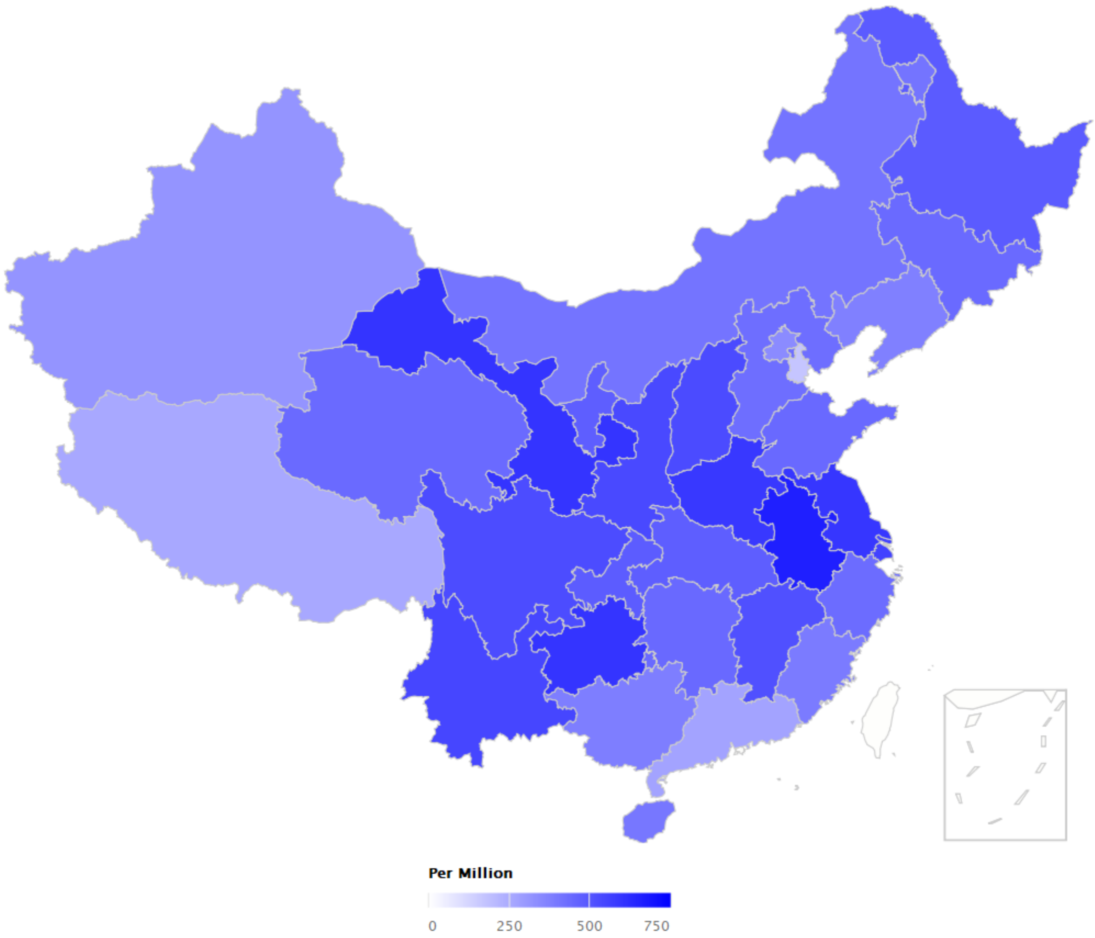
This figure illustrates the process of loan application, approval, repayment, and collection executed by the fintech lender. The sample analyzed in this paper includes 236,967 loan applications submitted to the fintech lender from July 2017 to November 2019, among which 97,783 loan applications have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

Figure 2 Timeline of Debt Collection



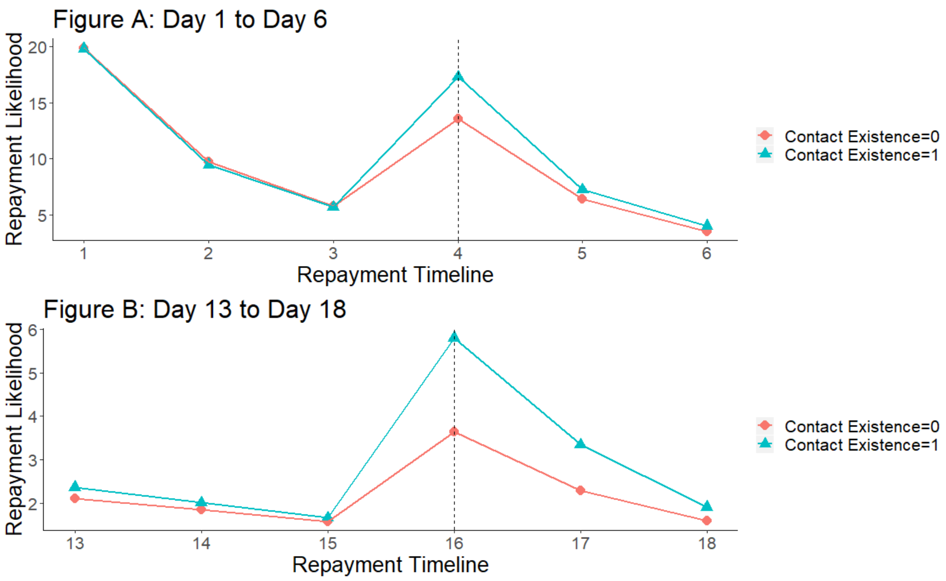
This figure presents the timeline of debt collection executed by the fintech lender, in which the Day *Zero* is the due date of month loan payment. The sample analyzed in this paper includes 97,783 approved loans from July 2017 to November 2019, among which 41,711 loans experience borrower's delinquency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

Figure 3 Geographical Distribution of Loan Application



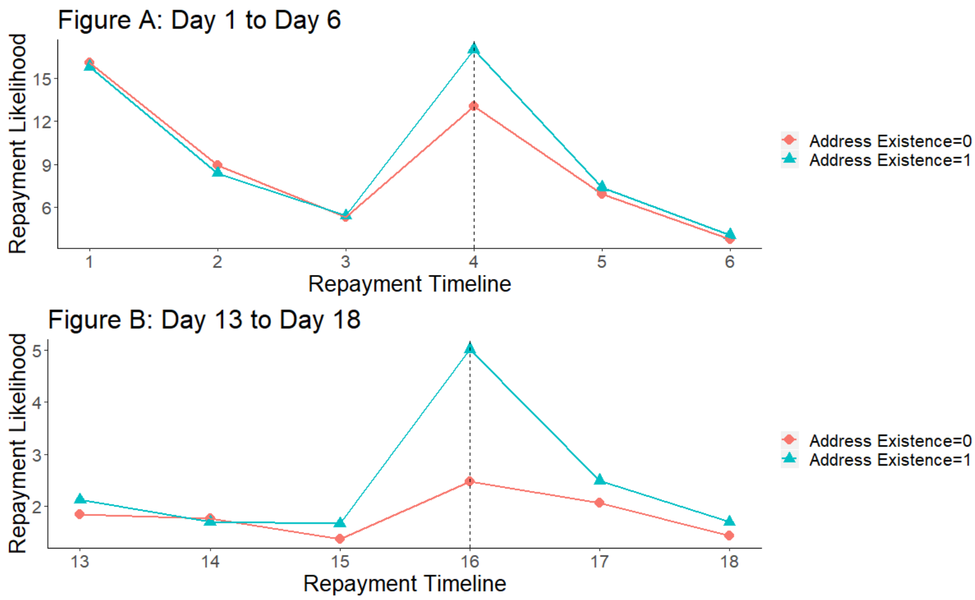
This figure plots the geographical distribution of loan applications submitted to the fintech lender. The color depth denotes the application density regarding the number of applications per million population in a province of China. The sample analyzed in this paper includes 236,967 loan applications submitted between July 2017 and November 2019, among which 97,783 loan 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 in Day *zero*. The repayment likelihoods of both 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 analyzed 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 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 analyzed 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 25^{th} (*25%*), median (*Median*), and 75^{th} 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 as defined in the Appendix.

Table 2 Treatment and Control Groups under Propensity Score Matching

Panel A: Propensity Score Matching based on *Contact*				
	Contact = 1	*Contact* = 0		
	Mean	*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	*Address* = 0		
	Mean	*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 group and control group 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 footprint. In Panel B, the treatment (control) group includes delinquent borrowers who have at least one online shopping delivery address (no delivery address) in digital footprint. The samples of 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 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 footprint. In Panel B, the treatment (control) group includes delinquent borrowers who have at least one online shopping delivery address (no delivery address) in digital footprint. 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-difference analyses of the daily loan repayment likelihood based on lender's first two rounds of chasing calls made on Day 4 and Day 16. 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. 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)
$Chasing_{Day\ 1} \times Contact$	**−0.074**	
	(−0.400)	
$Chasing_{Day\ 1} \times Address$		**−0.266**
		(−1.220)
$Chasing_{Day\ 1} \times Amount$	1.074***	0.956***
	(4.219)	(3.507)
$Chasing_{Day\ 1} \times Rate$	5.977***	10.981***
	(5.281)	(8.508)
$Chasing_{Day\ 1} \times Age$	−4.664***	−3.804***
	(−13.662)	(−10.232)
$Chasing_{Day\ 1} \times Gender$	1.566***	1.048***
	(6.312)	(3.559)
$Chasing_{Day\ 1} \times Score$	−4.144***	−4.014***
	(−13.515)	(−9.839)
$Chasing_{Day\ 1} \times Wealth$	0.419***	0.305***
	(10.831)	(3.934)
$Chasing_{Day\ 1} \times History$	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 $_{Day\ 4}$ × *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 $_{Day\ 4}$ × *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* $_{Day\ 4}$ × *Contact* $_{Pseudo}$ and *Chasing* $_{Day\ 4}$ × *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. Day *Zero* is the due date of loan repayment. ***, **, * 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 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. 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$_{All}$×*Contact*	**1.170*****			
	(6.683)			
Chasing$_{All}$×*Address*		**1.188*****		
		(6.151)		
Chasing$_{Day\ 4,16}$×*Contact*			**1.401*****	
			(6.461)	
Chasing$_{Day\ 31,61,91}$×*Contact*			**0.631*****	
			(4.893)	
Chasing$_{Day\ 4,16}$×*Address*				**1.376*****
				(5.643)
Chasing$_{Day\ 31,61,91}$×*Address*				**0.804*****
				(5.417)
Chasing$_{All}$×*Amount*	−1.054***	−0.801**	−1.049***	−0.798***
	(−4.484)	(−3.371)	(−4.465)	(−3.357)
Chasing$_{All}$×*Rate*	−6.745***	−8.850***	−6.725***	−8.827***
	(−6.431)	(−7.848)	(−6.415)	(−7.832)
Chasing$_{All}$×*Age*	2.571***	2.475***	2.578***	2.447***
	(8.583)	(7.821)	(8.610)	(7.830)
Chasing$_{All}$×*Gender*	−1.349***	-0.699***	−1.349***	−0.695***
	(−5.707)	(−2.644)	(−5.717)	(−2.630)
Chasing$_{All}$×*Score*	2.148***	2.046***	2.141***	2.040***
	(6.207)	(4.725)	(6.186)	(4.713)
Chasing$_{All}$×*Wealth*	-0.166***	-0.057	-0.165***	-0.057
	(-4.248)	(-0.786)	(-4.242)	(-0.773)
Chasing$_{All}$×*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)
$Chasing_{Day\ 4} \times Contact_{Only}$	**2.567*** **			**1.933*** **
	(3.625)			**(4.040)**
$Chasing_{Day\ 4} \times Address_{Only}$		**1.397** **		**2.371*** **
		(2.186)		**(5.261)**
$Chasing_{Day\ 4} \times Collateral_{Both}$			**1.437*** **	**1.390*** **
			(4.416)	**(4.273)**
$Chasing_{Day\ 4} \times Amount$	-1.537*	−1.416***	-1.749***	-1.632***
	(−1.843)	(−1.708)	(-3.923)	(-3.826)
$Chasing_{Day\ 4} \times Rate$	−19.441***	−19.945***	-11.942***	-15.162***
	(−5.216)	(−5.322)	(-6.068)	(-7.961)
$Chasing_{Day\ 4} \times Age$	4.992***	3.739***	5.702***	5.499***
	(4.436)	(3.244)	(9.352)	(9.535)
$Chasing_{Day\ 4} \times Gender$	−1.918**	−1.614***	-2.172***	-2.105***
	(−2.416)	(−1.868)	(-5.053)	(-5.008)
$Chasing_{Day\ 4} \times Score$	2.953**	2.752**	3.173***	3.420***
	(2.490)	(2.353)	(5.776)	(6.355)
$Chasing_{Day\ 4} \times Wealth$	-0.213	0.043	-0.318***	-0.256***
	(-1.283)	(0.191)	(-4.639)	(-3.732)
$Chasing_{Day\ 4} \times History$	-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***	5.124***
	(7.788)	(7.853)
Rate	13.355***	13.959***
	(6.377)	(6.862)
Age	−8.993***	−8.918***
	(−7.152)	(−6.688)
Gender	−4.097***	−4.042***
	(−6.892)	(−6.902)
Score	11.412***	11.223***
	(16.788)	(17.010)
Wealth	−1.857***	−1.807***
	(−27.360)	(−28.662)
History	3.195***	3.683***
	(5.152)	(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***	−15.119***
	(−20.758)	(−20.931)
Rate	107.984***	107.514***
	(18.402)	(18.538)
Age	−7.820***	−6.317***
	(−7.952)	(−6.291)
Gender	12.066***	11.950***
	(27.097)	(27.367)
Score	−35.251***	−34.888***
	(−95.932)	(−97.897)
Wealth	3.222***	3.014***
	(83.566)	(82.717)
History	−9.259***	−9.482***
	(−13.538)	(−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 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 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)
$Chasing_{Day\ 4} \times Contact$	**1.078*** **	
	(2.659)	
$Chasing_{Day\ 4} \times Address$		**1.059*** **
		(3.111)
$Chasing_{Day\ 4} \times Amount$	-2.044***	-1.591**
	(-3.382)	(-2.215)
$Chasing_{Day\ 4} \times Rate$	2.842	1.362
	(1.022)	(0.377)
$Chasing_{Day\ 4} \times Age$	6.213***	6.772***
	(8.332)	(7.917)
$Chasing_{Day\ 4} \times Gender$	-1.642***	-0.328
	(-3.008)	(-0.455)
$Chasing_{Day\ 4} \times Score$	2.297***	1.188
	(3.274)	(1.122)
$Chasing_{Day\ 4} \times Wealth$	-0.387***	-0.183
	(-4.757)	(-1.097)
$Chasing_{Day\ 4} \times History$	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 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 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.