The Power of Non-Monetary Incentive: Experimental Evidence from P2P Lending in China

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Abstract

The adoption of reputational sanctions in the online P2P lending industry in China offers a unique opportunity to test the impact of reputational concerns on repayment behavior in a clean experimental setting. In a privately implemented randomized controlled trial, we test a novel reputation-based incentive both in parallel to and coupled with accommodative monetary incentives on the repayment decision of 18,000 late borrowers vis-*à*-vis ex-post reminders. Within 24 hours, we find that late borrowers are sensitive to the generosity of the monetary incentive but equally responsive to a warning of reporting delinquent behavior to mobile contacts and a full late fee waiver. In joint schemes, the social incentive neutralizes the benefits of increasing the generosity of the monetary incentive. Ex-post reminders and monetary punishment are largely ineffective. Borrowers who respond to early incentives largely pay-off the loan on time. The social incentive affects repayment behavior through the power of a credible announcement.

Keywords: Peer-to-Peer Lending, Incentives, Loan Payments, Reputational Concerns, China

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1. Introduction

Access to finance and poor credit information are primary concerns in developing economies. In China, online peer-to-peer lending (P2P lending) services have flourished as a response to these issues over the last decade by extending the provision of credit to players other than traditional banks.[1] P2P platforms mitigated high barriers to credit access by transforming the financing of widespread unmet consumption and entrepreneurial needs in the fast-growing economy into an appealing investment opportunity for private investors. The design of effective policies to enhance the loan repayment likelihood became pivotal for the survival of these platforms, which facilitate the provision of credit to low-income and largely inexperienced borrowers and operate in a highly opaque and competitive market. Digital technologies and the availability of mobile/online data access became critical tools to overcome severe market failures. Amid fragilities, this industry experienced exponential growth since inception in 2007, was already four (ten) times the absolute size of the U.S. (U.K.) counterpart back in 2015 (Citi (2016)) and currently features about 50 million users and 1.3 trillion yuan ($195 billion) of outstanding loans. An emerging literature in Finance examines various aspects of this phenomenon (see Jiang, Liao, Wang and Zhang (2018), Du, Li, Lu and Lu (2018) and Liao, Martin, Wang, Wang and Yang (2018)).[2]

In this paper, we use confidential data from a successful player in the consumer finance segment of this industry to study whether an early provision of incentives persuades late borrowers to repay and reduces delinquency over time. Educating borrowers to develop sound repayment habits is a primary concern in China, where financial literacy is 35% among Millenials (15-34) and 28% among adults (Lusardi and Oggero (2017)). We test a novel

[1] P2P lending refers to the practice of providing loans to online users (individuals or small businesses) via virtual platforms that directly match savers with borrowers without the intermediation of a financial institution.

[2] A broader and growing body of work focuses on the advantages of the digital economy for credit-related purposes in mature economies. Contributions document the power of mere digital footprints to predict consumer default (Berg, Burg, Gombović and Puri (2019)) and the superior screening abilities of peer lenders (Iyer, Khwaja, Luttmer and Shue (2015)) and sophisticated investors (Vallee and Zeng (2019)) on major U.S. online lending platforms. De Roure, Pelizzon and Tasca (2016) show that in Germany the P2P lending market substitutes banks for the provision of high-risk consumer loans. Chava, Paradkar and Zhang (2017) and Di Maggio and Yao (2018) examine credit dynamics on major marketplace lending platforms.

reputation-based incentive from this industry in parallel to and combined with a more traditional monetary incentive in a sample of 18,000 late borrowers vis-à-vis ex-post reminders. Participants are late in repaying the first monthly installment of a micro-consumer loan and are randomly selected on the fifth day of delay among those who award the highest credit score during the internal screening process. Borrowers randomly receive a policy by SMS text message around 9 am. We track the repayment decision over a conservative 24-hour window after notification. Several studies across disciplines administer SMS text messages to study the impact of policies on individual behavior (see Kaplan (2006) and Cadena and Schoar (2011)).[3]

The social incentive enhances ex-ante monetary punishment from late fees via social punishment, where social punishment is the perceived damage associated with a discredited reputation. This incentive consists in the announcement to proceed with the implementation of the reputational sanctions embedded in the loan contract in 24 hours. By loan contract and via a recorded phone call, our data provider requires all borrowers to authorize the disclosure of private information about their borrowing status to third parties in case of delinquent behavior. Third parties specifically belong to the mobile contact list of the borrowers, but the agreement is silent on the exact timing of their involvement. In China, it is common practice to require mobile/online data access as a pre-condition for P2P loans. Crucially, there is no actual involvement of the third parties within the 24-hour horizon of the test.

Besley and Coate (1995) were the first to postulate that peer pressure enhances the willingness of borrowers to repay by acting as an additional penalty function for defaulting borrowers participating in a joint-liability lending scheme. In a joint liability scheme, group members suffer for the misconduct of an insolvent borrower and social pressure acts through the wrath of group members and the potential reporting of misbehavior to others. In our set up, third parties are mere recipients of news and social pressure acts through the anticipation

[3]The experiment was conducted over two years at the time the consumer finance market started its rapid expansion in 2013. The P2P platform facilitates the financing of micro-consumer loans for the purchase of mobile phones (primary) or small media products (minor).

of negative social feedback associated with the actual circulation of news through the inner circle of the delinquent borrower. Breza and Chandrasekhar (2019) document that having regular meetings with a designated member of the village ("monitor") in rural India enhances individual savings and generates substantial social network effects. Within 24 hours, the social incentive creates a plethora of implicit credit monitors, who are neither formally appointed nor aware of their role but can affect repayment behavior through their prospective involvement. The social incentive is also prone to induce feelings of guilt but the mechanism differs from the guilt aversion literature, where guilt usually involves damage to social ties (Baumeister, Stillwell and Heatherton (1994), Battigalli and Dufwenberg (2007)). Micro-finance studies find that social interactions are effective collateral in various forms.[4] By design, the social incentive provides a direct and clean metrics to measure whether and the extent to which reputational concerns affect repayment choices. The reputational channel is notoriously hard to pin down in empirical work due to multiple factors simultaneously affecting the outcome variable (Breza and Chandrasekhar (2019)).[5]

The monetary incentive reduces ex-ante monetary punishment from late fees and consists in a 24-hour discount on the monetary penalty. We distinguish between a moderate discount (50%) and a full waiver (100%).

Borrowers in the control group receive ex-post reminders. Reminders are increasingly popular across disciplines and can rationalize the hypothesis of limited attention (Karlan, McConnell, Mullainathan and Zinman (2016)). Cadena and Schoar (2011) find that ex-ante reminders are as effective as generous financial incentives, like cash-backs and large interest rate reductions, in enhancing the probability of paying a loan on time. Du et al. (2018) find

[4] Examples include joint-liability to induce mutual insurance (Rai and Sjöström (2004)) and weekly group meetings to enhance the interaction among individual borrowers (Feigenberg, Field and Pande (2013)). Variables like geographic proximity and cultural similarity (Karlan (2007)) and trust between group members (Cassar, Crowley and Wydick (2007)) are associated to improved loan repayment rates. In the context of major U.S. online platforms, variables like online friendships (Lin, Prabhala and Viswanathan (2013)) and more trustworthy appearance in photographs (Duarte, Siegel and Young (2012)) increase the probability of successful funding.

[5] Breza and Chandrasekhar (2019) argue that reputational concerns likely contribute to the findings of a variety of micro-finance studies on peer effects that even abstract from a joint liability scheme (e.g., Feigenberg et al. (2013), Breza (2014)).

that behavioral reminders that convey lenders' positive expectations about repayment have long-term effects on the repayment likelihood in China, while those which emphasize the adverse consequences of missing payments are short-lived.[6] Since treated borrowers receive an enriched version of this reminder, we view this policy as a natural control. We also obtain a simultaneous independent random sample of late borrowers, who do not receive any policy (i.e., "hold-out" group).

We start by showing that in the absence of intervention the daily repayment likelihood sharply and monotonically declines to less than 1% in five days and barely moves up to 30 days after the first due date. Monetary punishment is associated with a negligible repayment likelihood and the mere existence of reputational sanctions weakly discourages late repayments. Limited attention well rationalizes the five-day pattern, but the presence of financially constrained and/or intentionally delinquent borrowers plausibly explain poor debt collection within a month from the first due date.

We find that both the reputation-based incentive and the monetary incentive statistically outperform ex-post reminders on the fifth day of delay. In terms of magnitude, the odds of making the pending payment are 3.31 times higher for borrowers who receive a moderate monetary incentive, 4.37 times higher for borrowers treated with a social warning and 4.92 times higher for borrowers who receive a late fee waiver, than borrowers in the control group. Statistically, repayment gains are increasing in the generosity of the monetary incentive, but the social incentive is as effective as a full late fee waiver. The repayment likelihood for the control group is 1.60%. This finding confirms that inattention is a weak explanation for pending payments and suggests that borrowers who respond to the social incentive do not repay for their own sake (reminder) but to prevent reputational damage (social incentive). We conclude that pure incentives effectively alter the cost/benefit trade-off of delaying the first payment.

The effectiveness of the social incentive is intriguing for two reasons. Firstly, the text

[6] In contrast to our treatment, these policies do not alter the cost-benefit trade-off of a late payment.

message does not contain news about punishment but simply announces the intention to proceed with agreed-on punishment. Like the U.S. credit card owners forget about late fees until they are actually charged the penalty (Agarwal, Driscoll, Gabaix and Laibson (2008)), borrowers in our sample may forget, or simply ignore, social punishment until they are actually warned of the social penalty. Secondly, while the monetary incentive dispenses an actual benefit, the social incentive does not inflict actual punishment but successfully generates an expectation of punishment. Granted mobile data access is key, as it ensures the ability to identify the borrower's network and promptly and potentially pervasively report delinquent behavior through such network.

Next, we turn to joint incentives. The literature on prosocial behavior often finds that reward and punishment are conflicting schemes and their combination reduces the total benefits (Benabou and Tirole (2003), Bénabou and Tirole (2006)).[7] We find that joint treatment is more effective than single treatment and the social incentive neutralizes the benefits of incremental monetary incentives. Combining a moderate discount with a social warning improves the repayment odds by 35% relative to a pure social incentive, 79% relative to a pure moderate monetary incentive and 20% relative to a pure late fee waiver. We infer that the social incentive can attract, among others, the subset of "expensive" borrowers, that is those who respond to a full discount but reject a moderate discount. This result reinforces the power of the social incentive to enhance the repayment likelihood at a lower cost.

We also characterize the borrowers who respond to pure incentives. Consistent with the hypothesis that monetary incentives attract borrowers who are sensitive to small perturbations in credit constraints, we find that the response is statistically more pronounced for borrowers who exhibit lower income, face smaller payments and combine smaller payments with shorter loans, smaller loans, no other outstanding mortgages, and lower indebtedness. Interestingly, borrowers in cities exhibit larger reactions to the social warning than those

[7] For a review of this literature see the surveys in Frey and Jegen (2001) and Bowles and Polania-Reyes (2012).

in rural areas. Though speculative, this finding is consistent with predominant tight family connections in the countryside and more formal social connections in cities, which may amplify the importance of reputational concerns. As expected, borrowers who are plausibly financially constrained, that is those who feature a high product price-to-income ratio, monthly payment-to-income ratio and down payment-to-income ratio, do not respond to any incentive.

Our ultimate question is whether delinquent payments diminish over time. To shed light, we collect information on the repayment decision at the due dates of the third and the last installment of the loan. We find that between 76.88% and 83.46% of the borrowers who promptly respond to early incentives make the third payment on time and the interval slightly decreases to 71.86%-79.23% at loan maturity. Our major findings remain statistically robust. For borrowers who do not respond promptly and are subject to further action, the shares are about 64% (third payment) and 54% (last payment).[8] Although we are unable to pin down a causal interpretation of their subsequent repayment choices, these borrowers are not statistically different from persistently late borrowers based on observables. We therefore reject high financial constraints as a major explanation for persistently delayed payments and also large down payments as an explanation for temporarily delayed payments. We conclude that the benefits of an early provision of incentives are long-lasting and prompt intervention induces borrowers who largely lack past credit experience to learn over time how to timely fulfill their financial commitments.

The rest of the paper is organized as follows. Section 2 briefly reviews the phenomenon of P2P lending in China and the risk-control policies of our data provider. Section 3 describes the experimental design. Section 4 characterizes the borrowers in our sample and presents balance tests. Section 5 discusses the results of the field experiment. Section 6 concludes.

[8]All borrowers receive incentives once. Further action includes direct calls and the implementation of reputational sanctions after 30 days from the first due date. Subsequent intervention is homogenous across experimental groups.

2. Institutional Setting

We start with a quick review of the phenomenon of P2P lending in China with a focus on individual borrowers. Jiang et al. (2018) provides a broader overview of the Chinese P2P lending market. We next introduce our data provider and present the screening process and the forms of punishment for delinquent payments.

2.1. P2P lending in China

P2P platforms are virtual marketplaces, which match lenders with borrowers without credit intermediaries, like banks. In China, the emergence of P2P lending anticipated the traditional banking system in abating high barriers to credit access and tackling the widespread inability to develop creditworthiness. Although the central bank initiated the building of the credit system via the collection of credit information from licensed financial institutions in March 2006, coverage remained fairly limited over the subsequent years. The World Bank Global Findex Survey reports that credit card ownership was 8% in 2011, despite 64% of the Chinese respondents had an account with a financial institution at the time. Credit card ownership merely reached 21% in the next six years.

P2P platforms transformed the financing of widespread unmet consumption and entrepreneurial needs in the economy into an appealing high-rate-of-return investment opportunity for investors. On the demand side, low-income households and small-to-medium enterprises were largely excluded from the traditional banking channel. On the supply side, the rapid economic growth spurred a large accumulation of funds and banks offered low interest rates on deposits. The combination of high barriers to credit access, a large supply of funds from investors and the escalating penetration of the Internet sustained the fast expansion of the industry since inception in 2007 (Huang (2018)). According to the China Internet Network Information Center, the Internet penetration rate climbed from 10% in 2007 to 53.2% in 2016, where the 2016 rate was 3.1 percentage points higher than the world average and comprised 731 million Internet users with 95% access from mobile phones. Thanks to the Internet, access to credit became viable and affordable. Simultaneously, the profitability of the novel practice attracted new players in the market.

This industry retains the classic fragilities of broadening access to credit in a developing country. High information asymmetries, weak punishment for late or forgone repayments and the provision of unsecured loans to low-income and largely inexperienced borrowers translate into high-risk investments. Before the change in regulation in 2016, Chinese platforms mitigated the lack of trust between lenders and borrowers by following the "principal guarantee", which is the practice to guarantee the principal back to investors in case of borrowers' default (Jiang et al. (2018)). By shifting default risk from lenders to the platform itself, platforms enhanced the uncertainty about their own survival likelihood. This practice combined with the highly dispersed and competitive market urged individual platforms to identify effective policies to enhance the loan repayment likelihood to beat competitors and remain solvent over time. While in the United States and the United Kingdom the market is highly concentrated, in China platforms are largely operated by small and medium-sized firms (Huang (2018)). Platforms intensively exploited the availability of digital information and the widespread use of mobile phones to overcome classic market failures.

The year 2013 became the turning point in the development of the industry. For the first time, Chinese authorities allowed third parties to conduct credit investigation on individuals, with the explicit aim to "enhance the building of the social credit system" (Article 1).[9] Third parties started selling authorized data on consumer behavior to Fintech companies, which intensively relied on artificial intelligence to process the acquired information and improve the screening of the applicants. On the supply side, P2P platforms started offering refined screening as a service to the lenders. On the demand side, individual borrowers were eager to share information on spending habits and provide mobile/online data access to signal creditworthiness and obtain credit access.[10] The ability to mitigate high information

[9]The State Council issued the "Regulation on the Administration of Credit Investigation Industry" in January 2013 (effective March 15, 2013). The full text is available at www.lawinfochina.com.

[10]A 2015 survey conducted by the Association of Chartered Certified Accountants (ACCA) on Paipadai, which is the first P2P platform in China, reveals that 51% of the individual respondents declared "to accumulate creditworthiness" as the main purpose of the loan request, while the next 20% reported "to meet basic needs". See Deer, Mi and Yuxin (2015) for details about the survey.

asymmetries between lenders and borrowers accelerated the growth of the industry between 2013 and 2015. The consumer finance industry, for example, started its rapid expansion in 2013.

The regulation was fairly lenient in the early years and the government explicitly encouraged the development of Internet Finance to stimulate economic growth. The combination of loose regulation and high-risk profile of the industry encouraged some players to favor the short-term benefits of the first-mover advantage rather than the long-term benefits of sound risk management policies. Available statistics report that the number of platforms was 15 in 2010, peaked to 3844 in 2015 and collapsed to 1931 in 2017. Mass defaults by borrowers coupled with poor risk controls and liquidity issues contribute to explain the sharp drop in the number of platforms since 2015. Authorities issued the first set of official guidelines in 2015 and deeply tightened the regulation in 2016 in the attempt to clean up the market from several cases of fraud and "Ponzi schemes".[11] Although bad practices contaminated the industry, platforms which learned how to effectively tackle market failures established a solid position over the years and spurred large economic benefits. These platforms anticipated the banking sector in tackling first-order concerns in the developing stage.

2.2. Data provider

We examine the effectiveness of an early provision of incentives to late borrowers through a confidential partnership with a medium-sized player in the Chinese P2P lending industry. Our data provider conducted the experiment over two years, at the time it entered the consumer finance market in May 2013. The consumer finance industry emerged in China in 2009 and is projected to grow to 1.6 trillion by the end of 2020. The "Pilot Administrative Measures for Consumer Finance Companies" promulgated by the China Banking Regulatory Commission (CBRC) in 2009 define consumer finance companies as non-financial institutions

[11] The central bank jointly with other nine regulatory authorities issued the "Guiding Opinions on Promoting the Healthy Development of Internet Finance" in July 2015. The China Banking Regulatory Commission and other authorities promulgated "The 2016 Interim Measures on Online Lending" in August 2016. See Huang (2018) for details about the development of the P2P industry in China and changes in the regulatory framework over the years.

that provide small consumption-oriented loans to domestic residents. Our data provider manages P2P micro-consumer loans for the purchase of mobile phones (primary) or small media products (minor). For reference purposes, our data provider resembles HomeCredit, which is currently the major consumer finance player and was among the firsts to enter the market.[12]

The P2P platform follows a “loan-agency” model. Lenders earn an interest and provide funds to individual borrowers through the platform, while individual borrowers request a micro-consumer loan through the loan agency. The platform facilitates the matching between lenders and borrowers, while the loan agency, or the so-called “focal” company, handles loan applications, screens and pre-selects qualified borrowers, arranges the loan agreement and provides post lending service, such as debt collection. Both the platform and the loan agency retain risk-control functions during the screening process. Our data provider is the loan agency, which provides exclusive services to the platform and fully guarantees for delinquent borrowers. The platform does not conduct any debt collection.[13]

The matching process starts with the loan agency, which conducts the preliminary credit evaluation and submits the applications of the qualified borrowers to the platform. The platform conducts further independent screening and assists lenders in choosing the appropriate matching. Once the matching is complete, the platform collects the principal from the lender and transfers the sum to the loan agency, which transfers the capital to the shop in charge of the delivery of the target product. The shop delivers the funding to the borrower, who simultaneously makes the down payment, signs the loan agreement and collects the target product. Each month, the borrower repays the principal, the administrative fee and agreed-on interests on the loan by installment to the loan agency, which transfers the appropriate payment to the platform for final delivery to the lender. The interests and administrative

[12]Players in this market include P2P lending platforms, banks, licensed consumer finance companies, Internet giants, E-commerce, start-up companies and industry enterprises.

[13]Confidential data are subject to the anonymity of the platform and the loan agency. For privacy concerns, our data provider reserves the right to disclose partial information. Our data provider is not a “cash-loan company”, as shops do not retain cash-flows. Funding is fully provided by P2P lenders.

fees are 1.33% and 1.67% of the loan size per month, respectively, regardless of credit score. The volume of loans was tens of millions per month at the time of the experiment.

Jiang, Liao, Lu, Wang and Xiang (2019) find that a credit score computed from a set of 3,000 variables not available to traditional credit lenders (i.e., "big data credit score") substantially outperforms a traditional internal score in predicting P2P consumer loan delinquency in China. In a similar vein, the loan agency collects pervasive information on mobile/online credit behavior and adopts machine learning techniques to identify qualified borrowers beyond self-reported credentials. The loan agency retrieves digital information from the mobile phone of the applicants and also acquires data from authorized third parties. Granted mobile/online data access is a standard pre-condition for P2P loans in China and is requested through the loan application form. Table 1 reports the five-step screening procedure and the inputs of the algorithm in detail. Although screening is not the focus of the paper, a careful screening ensures a reliable pool of participants to the experiment and rules out the hypothesis that poor loan repayment rates are inflated by a massive presence of junk borrowers in the sample.

The initial steps involve the identification of the applicants through ID information, mobile phone information and bank debit or credit information. Financial account details include past or outstanding loans, but this information is sparse and of limited value in the light of the high barriers to credit access in China. The platform verifies that the submitted information is formally correct and rejects applicants who belong to available blacklists. Since P2P companies are not allowed to access the "Basic Information Management System of Personal Credit Collecting" managed by the central government, our data provider obtain a wide array of ad-hoc blacklists through third parties (e.g., credit card, lawsuit, and interest lending blacklists).[14] Next, a proprietary algorithm processes large-scale information and assigns a credit scoring between A (low-risk) and F (high-risk) to each applicant. Large-scale

[14]Third parties include Baidu, Zhi Ma Credit, Tong Dun, and Qian Hai Credit. Baidu is one of the largest artificial intelligence and internet companies in the world. Zhi Ma Credit is a credit service provided by Zhi Fu Bao, that is the counterpart of Paypal with a customer base of 870 million (i.e., more than half of the Chinese population volume).

information includes classic variables, such as demographics and payments through banks or third parties, and media indicators on a wide array of credit-related activities. These indicators comprise searches through Baidu, that is the major search engine in China, activity on the two major Chinese e-commerce websites (i.e., Jingdong and Taobao) and the usage of multi-loan applications, like Lending App. The platform obtains further soft information via the social media of the applicant, like the presence of friends in available blacklists and the frequency of access to the websites of lending or credit score card companies. Subject to undisclosed risk tolerance, the loan agency selects the subset of qualified borrowers and submits their applications to the platform. Applicants received a pass/rejection decision from the loan agency in less than 30 minutes, which was the average time for middle and top loan agencies in the consumer finance market at the time of the experiment.

In the P2P industry, players have limited ability to punish negligent borrowers. The loan agency implements standard monetary punishment by charging increasing late fees, starting from the fifth day of delay. The penalty late fee is 0.25% of the overdue amount per day for a delay between 5 and 30 days, 0.50% of the overdue amount per day between 30 and 60 days and there is an additional late fee of 19% of the principal amount after 60 days. Fees are charged until all payments (including principal, interests and all penalties) are paid off. The loan agency also charges a preliminary fee of RMB10 (about $1.45). In addition to monetary penalties, the platform or the loan agency files a lawsuit or initiates an arbitration against insolvent borrowers at maturity. However, the effectiveness of these legal actions is limited due to poor law enforcement. Since P2P platforms are not able to report insolvent borrowers to the central government due to denied access to the official credit database, our data provider reports insolvent borrowers to third parties that compile P2P blacklists, like Zhi Ma Credit. Although this policy reduces the likelihood of a further provision of P2P funding to delinquent borrowers, late or forgone P2P repayments do not translate into a negative impact on credit records in China. Overall, conventional punishment for misconduct is weak and the environment is conducive to delinquent payments.

Our data provider exploits mobile data access to tackle moral hazard. Condition number 5 in the loan contract authorizes both the lender and the loan agency to disclose private information about the conduct of a negligent borrower to third parties to enforce the loan. The third parties specifically belong to the mobile contact list of the borrower, but the agreement is silent on the exact timing of their involvement. The loan agency makes a phone call to each borrower to clarify this condition after loan approval and records the dialogue on mp3 files. The call informs the borrower that a debt collector will report delinquent payments, if any, to third parties, such as family members, the employer, and friends of the borrower, by phone in due course. Mobile data access is acquired through the loan application form. The loan contract conceives the reputational damage associated to a release of negative information to others as a social collateral for unsecured high-risk loans. Reputational sanctions play the same penalty-role of the late fees but exploit the power of reputational concerns as a deterrent for delayed repayments in the presence of weak conventional punishment for misconduct.

3. Experimental Design

An early provision of incentives aims to induce borrowers to promptly rectify negligent behavior and develop diligent repayment habits over time. The experiment targets borrowers, who are late in repaying the first monthly installment of the loan and receive the highest credit scores during the internal screening process, that is A-rating or B-rating. These borrowers are the ideal candidates for responding to early incentives, as they are the most likely to be able to afford the payment and the least likely to be truly maliciously delinquent based on the screening process. Early incentives complement standard monetary punishment via late fees.

The randomized controlled trial involves 18,000 borrowers, who signed the loan contract between May 29, 2013 and April 24, 2015. This sample period excludes any major change in the regulatory framework and coincides with the early years of the expansion of the consumer finance industry and the adoption of mobile/online data to tackle the opaqueness of the market. Borrowers enter the sample via daily random draws on their fifth day of delay. The loan agency does not charge any penalty up to four days of delay and introduces late fees on the fifth day. All borrowers in the first draw signed the contract on May 29, 2013, agreed on making the first monthly repayment by June 29, 2013, and joined the sample on July 4, 2013. Similarly, all borrowers in the last draw signed the contract on April 24, 2015, agreed on making the first monthly repayment by May 24, 2015, and joined the sample on May 29, 2015. Henceforth, we refer to this sample as the experimental sample. The experiment is conducted immediately after each draw. Borrowers homogeneously join five treatment groups and one control group by random assignment and receive an ad-hoc policy via SMS text message around 9am. Text messages are concise and direct in the delivery of information, low-cost and ensure that all participants are notified simultaneously. A growing literature across disciplines uses SMS text messages to study the impact of policies on individual behavior (see Kaplan (2006) and Cadena and Schoar (2011)). To establish causal effects in a clean setting, we track the repayment decision over a conservative 24-hour window after notification. This choice minimizes confounding effects from factors other than policies as a trigger for repayment.

We also obtain a simultaneous and independent random sample of 1,000 late borrowers, who join this sample via daily random draws on their first day of delay. These borrowers do not receive any policy. We use this sample to compile the baseline repayment likelihood for late borrowers, that is the one observed in the absence of further intervention up to 30 days after the first due date. Borrowers in the first draw signed the contract on May 29, 2013 and entered the sample on June 30, 2013. Borrowers in the last draw signed the contract on April 24, 2015 and entered the sample on April 30, 2015. Henceforth, we refer to this sample as the "hold-out" group.

Ex-post reminder. Borrowers in the control group receive an ex-post reminder. The text message states that the debt is overdue, there is a suspect of malicious arrears and requests the execution of the pending payment within 24 hours.[15] Reminders rationalize the hypothesis of limited attention (Karlan et al. (2016)) and their effectiveness received wide support across disciplines in recent years. In contrast to other studies, our reminders are issued after the due date (i.e., ex-post) rather than before the due date (i.e., ex-ante). This policy signals a neutral debt collector, who raises the possibility of intentional misconduct, but does not take immediate action. Since treated borrowers receive an enriched version of this text message, we view reminders as a natural control in our setting. By testing the effectiveness of incentives relative to ex-post reminders, we ensure that treatment effects measure the response of the late borrower to an incentive and are not contaminated by his potential response to a plain reminder.[16]

Text messages for the treated borrowers start with the notification of a suspect of malicious arrears and proceed with the description of the treatment.

Monetary incentive. The monetary incentive consists in a discount on the monetary penalty for delayed payments. Borrowers in treatment group 1 receive a moderate discount equal to a 50% rebate (i.e., *Mod*). Borrowers in treatment group 2 receive a full discount, which is a 100% late fee waiver (i.e., *Full*). In both cases, the discount applies to payments executed in 24 hours. Since late fees are small in absolute value, this scheme tests the sensitivity of low-income borrowers to small perturbations in credit constraints. This incentive is accommodative and signals a benevolent debt collector, who reminds misconduct to late borrowers but is willing to compromise on the first payment.

Social incentive. Borrowers in treatment group 3 receive a non-monetary or social incentive (i.e., *Social*), that consists in the announcement to proceed with the implementation of reputational sanctions embedded in the loan contract in 24 hours (see Section 2.2). The text

[15] The text message reads “Dear sir/madam, your debt is overdue, suspected of malicious arrears. In order to avoid damage to your interests, please deal with it within 24 hours: *** (amount). Thank you!”

[16] Du et al. (2018) test whether behavioral reminders sent before the first due date or to borrowers who are late in paying off the P2P loan affect repayment behavior in China. Their reminders are text messages that convey lenders’ positive expectations about repayment or emphasize the adverse consequences of delayed payments. In contrast to our treatment, behavioral reminders do not alter the cost-benefit trade-off of a late payment.

message states that the loan agency will call third parties and inform them about the pending payment, in the event the suspect of malicious arrears will not cease within 24 hours.[17] This policy signals a resolute debt collector, who enhances ex-ante monetary punishment via social punishment on the fifth day of delay. Social punishment is the perceived damage associated with a discredited reputation. It is a perception because there is no actual involvement of the third parties over the 24-hour horizon of our tests. Any payment made in response to the reaction of the third parties to information received from the loan agency and any potential financial support received from the third parties fall outside the horizon of our tests. The social incentive offers a novel and direct metrics to measure whether and the extent to which the anticipation of negative social feedback affects repayment behavior, where feedback precisely stems from the release of private information to third parties, who specifically belong to the inner circle of the delinquent borrower. Isolating the impact of reputational concerns on individual behavior is notoriously hard in empirical work due to multiple factors simultaneously affecting the outcome variable. Breza and Chandrasekhar (2019) argue that reputational concerns likely contribute to the findings of a variety of microfinance studies on peer effects (e.g., Feigenberg et al. (2013), Breza (2014)) and provide clean evidence on the effectiveness of reputational concerns for savings decisions.

The social incentive presents commonalities with past work, but also peculiar differences. The idea that reputational concerns act as a social penalty is in the spirit of Besley and Coate (1995), who postulate that peer pressure enhances the willingness of borrowers to repay by acting as an additional penalty function for defaulting borrowers participating to a joint-liability lending scheme. Besley and Coate (1995) suggest the "wrath of other group members" and the potential reporting of misbehavior to "others in the village" as plausible forms of social penalties. The social incentive explicitly models the latter channel. As an important departure, in a joint-liability lending scheme group members suffer from the mis-

[17] The text message reads: "Dear sir/madam, your debt is overdue, suspected of malicious arrears. Please deal with it within 24 hours: *** (amount). Otherwise we will call your family and tell them about your loan problems. Thank you!"

conduct of an insolvent borrower, while in our setting third parties are mere recipient of news over the 24-hour horizon of the test. Breza and Chandrasekhar (2019) show that frequent reporting of progress to designated "monitors" in rural India substantially enhances individual savings over time. Monitors are also found to report information to others with consequent positive network effects. In a similar vein, within 24 hours, the social incentive creates a plethora of invisible credit monitors, who are neither formally appointed nor aware of their role but can indirectly affect the repayment decision through the borrower's anticipation of negative social feedback. As in Besley and Coate (1995) and Breza and Chandrasekhar (2019), once notified, third parties may further report negative information to others and amplify social punishment through negative network effects. The social incentive is also prone to induce feelings of guilt but the mechanism differs from the guilt-aversion literature, where the trigger for repayment usually involves a damage to social ties (see Baumeister et al. (1994) and Battigalli and Dufwenberg (2007)).

Joint treatment. Borrowers in the last two treatment groups receive joint treatment, which is the combination of a monetary incentive and the social incentive. The text message for treatment group 4 (i.e., *Mod&Social*) contains both a moderate discount and the social incentive. The one for treatment group 5 (i.e., *Full&Social*) includes both a late fee waiver and the social incentive. *These schemes test whether there are synergies to exploit in combining reward (monetary incentive) with punishment (social incentive).*

Before delving into the results of the experiment in Section 5, we characterize the experimental sample and verify that the randomization procedure is successful in creating five treatment groups that are comparable to the control group along a number of characteristics.

4. Data

Table 2 characterizes the experimental sample and offers a rich description of the population of late P2P borrowers in China.[18] Panel A summarizes the demographics, Panel B

[18]Our sample well matches the socio-demographic statistics reported in the 2015 ACCA survey on Paipaidai, which is the first online P2P lending platform in China (see Section 2). The comparison is indicative but corroborates the view that our sample is representative and our findings are of broad interest.

presents the loan characteristics, and Panel C reports phone-related characteristics, such as the type of product financed by the loan, its price, the monthly spending on phone calls and the tenure of the phone number. Borrowers disclose this information in the loan application form. For each variable, the table presents the mean, standard deviation, 25th percentile, 75th percentile, and the number of available observations. Monetary variables are reported in Chinese yuan (RMB), but major monetary statistics are also presented in U.S. dollars for ease of interpretation.

Panel A shows that borrowers are typically male (70%), living in rural areas (60%) and young (23). Despite age varies between 18 and 63 in the sample, senior borrowers are rare: 93% of the borrowers are 30 or less. Consistent with the young age, most of the borrowers are not married (85%) and about half of them is a student (46%). The majority of borrowers (55%) report income in a "low-income range", which is between RMB2000 and RMB5000 a month. A further 32% reports income even below this range. This statistic captures students, who most likely have part-time or temporary jobs. "Mass middle-class" representatives (RMB5000 to RMB10000) are a minority (8%) and wealthy borrowers (>RMB10,000) are sporadic (less than 1%).[19] The sample is fairly split between A-rating and B-rating borrowers. Education completes the demographic profile. About 60% of the borrowers has tertiary education, that is an associate degree (42.18%) or a bachelor/graduate school degree (19.95%), while the remaining ones hold a high school diploma (12.06%) or less (25.81%).

Turning to Panel B, the loan size is about RMB3367 on average (i.e., $517) and 85% of the loans are in a magnitude comparable to a monthly income in the low-income range. Borrowers make a down payment and face a schedule of monthly repayments. The minimum number of installments is 6, the average is 14 and the number of repayments mostly varies between 12 and 18. As a gauge of the severity of the debt, we report two ratios: monthly payments to monthly income and loan size to monthly income. These ratios underestimate

The ACCA survey reports 342 responses from individual borrowers.

[19]About 4% of the participants report zero income. These borrowers are students, unemployed and farmers, who were not able to formally prove to have income.

the actual indebtedness of the borrowers, because do not include interests and administrative fees. The first ratio is on average 15% and varies between 7% (10th percentile) and 25% (90th percentile). The second ratio is 1.56 on average. These statistics jointly indicate that the indebtedness of the borrowers is nontrivial, as loans are small in absolute terms but borrowers are low-income. The share of borrowers who declare the existence of another loan or an extinguished one is 22%. Although borrowers may hide negative past credit experience due to self-reporting, this statistic well illustrates the issue of high barriers to credit access in China. Among the borrowers with a second line of credit, 38% declare no outstanding balance, while the remaining ones disclose monthly payments that are in size comparable to the ones under study.

Lastly, Panel C shows that the primary target of the loan is a mobile phone. The popular choice is an Apple smartphone (57.23%), followed by a Samsung phone (17.19%). A minority of the sample chooses a computer (6.58%), while the remaining borrowers pick other products, like a digital camera or a laptop (18.99%).[20]

Table 3 presents balance tests with respect to several demographic and loan characteristics. For each variable, the table reports mean difference tests for the difference in means between a given treatment group and the control group. Associated t-statistics are in brackets. We report analogous tests for a richer set of variables in Table A.1 in the appendix. We find that means are similar in magnitude across groups and tests widely do not reject the null hypothesis of equality at the 1% confidence level. Since exceptions are rare, we conclude that our sample is well randomized and sporadic irregularities can hardly explain our findings. Table X in the Appendix reports analogous balance tests for the hold-out group against the experimental sample. We confirm that the two samples are comparable with respect to all major covariates.

[20] Over the two-year period of the experiment, Statista reports an increase in the mobile phone penetration rate in China as a share of the population from 71.1% to 75.9% and in the share of smartphone users among mobile phone users from 43.0% to 50.9%. The Global Mobile Consumer Survey by Deloitte reports an increase in the smartphone penetration rate from 70% to 77%.

5. Incentives and repayment choices

In this section, we present our empirical findings. Firstly, we show that monetary punishment is associated with a negligible repayment likelihood and the mere existence of reputational sanctions weakly discourages late first repayments. Secondly, we find that both the monetary incentive and the social incentive trigger repayments within 24 hours, while ex-post reminders are largely ineffective. Over the same horizon, joint incentives outperform pure incentives and, in joint schemes, the social incentive fully accounts for the benefits of increasing the generosity of the monetary incentive. Thirdly, we document heterogeneous treatment effects. Lastly, we present descriptive evidence for subsequent repayments. We conclude that the benefits of an early provision of incentives are long-lasting and prompt intervention induces late borrowers to learn over time how to timely fulfill their financial commitments.

5.1. Hold-out group

We start by reporting experimental evidence on the natural or baseline repayment likelihood for late borrowers, up to 30 days after the first due date. We define the natural repayment likelihood, as the share of late borrowers who repay the first installment of the loan without any further intervention of the loan agency. We draw this inference from the hold-out group.

Figure 1 shows that about 16% of the borrowers in this sample repay the first installment of the loan the day after the due date, a further 7% makes the payment in two days, and the share sharply and monotonically declines to less than 1% in five days. On the fifth day, late fees start to apply and the likelihood of collecting the first pending payment becomes negligible. Both standard monetary punishment and the mere unconventional introduction of reputational sanctions in the loan contract weakly discourage borrowers from delaying or even forgoing the first repayment. Poor repayment rates for the first installment of the loan illustrate the urgency in the P2P lending industry to identify effective policies to enhance the individual loan repayment likelihood and induce late borrowers to develop diligent repayment habits over time. Limited attention plausibly rationalizes the five-day pattern, but other explanations likely account for the inability of the loan agency to collect a substantial share of late repayments within a month from the first due date.[21]

A straightforward possibility is that borrowers delay the first repayment due to their inability to afford the payment. This outcome is consistent with both highly financially constrained borrowers, who benefited from information asymmetries, and poor management skills of first-time low-income borrowers, who simply did not save properly in the first month. Although both types of borrowers are unlikely to respond to incentives within 24 hours, the first type is prone to default, while the second type may develop sound repayment habits over time. Prompt intervention targets the latter type.

A second possibility is that late borrowers can afford to repay, but rationally decide to postpone the payment due to economic convenience. Economic models assume that borrowers pay late when the benefits of late payments are greater than the costs (Campbell and Cocco (2015); Stango and Zinman (2009)). Both the monetary incentive and the social incentive alter the cost-benefit trade-off of a delayed payment to induce late borrowers to revisit their choice.

The lack of credible punishment may also induce borrowers to act maliciously, that is to collect the loan but forgo repayments. The social incentive, and more broadly the adoption of reputational sanctions, tackle this issue. The monetary incentive is plausibly ineffective, as the discount is small and applies to the monetary penalty rather than the payment itself.

Finally, first-time borrowers may sincerely miss the first due date due to inattention. Ex-post reminders address this problem.

The results of the experiment (Section 5.2) and heterogenous treatment effect (Section 5.4) shed light on the validity of these hypotheses. In the absence of intervention, the repayment likelihood on the fifth day of delay is 0.7%.

[21]The loan agency reports a repayment likelihood of 51% at the first due date. Figure 1 implies that the repayment likelihood for the first installment of the loan reaches 65% in five days and barely improves over the remaining part of the month. These low figures well illustrate the issue of poor loan repayment rates in the Chinese P2P industry.

5.2. *"Pure" incentives*

We test the effectiveness of "pure" incentives vis-*à*-vis ex-post reminders via the following logit regression:

$$D_{Repayment,i} = c + \beta_{Mod} D^{+}_{Mod,i} + \beta_{Full} D^{+}_{Full,i} + \beta_{Social} D^{+}_{Social,i} + \epsilon_i, \tag{1}$$

where the dependent variable is a dummy variable taking a value of 1 if the borrower i makes the pending payment within 24 hours from notification and 0 otherwise, and the three regressors are dummy variables taking a value of 1 if the borrower i receives single treatment and 0 otherwise. Single-treated borrowers receive a moderate monetary incentive (*Mod*), a full monetary incentive (*Full*) and the reputation-based incentive (*Social*), respectively. The suffix "+" indicates that dummy variables exclude borrowers who receive joint treatment. The sample size is 12,000 borrowers.

Estimated coefficients are in Table 4. For each coefficient, we report the log odds repayment ratio for treatment group T over the control group C, where $T = Mod/Full/Social$ and $C = Reminder$. t-statistics are in brackets.

Panel A shows that both the monetary incentives and the social incentive are effective, as the three estimates are all positive and statistically significant. In terms of magnitude, the odds of making the pending payment are 3.31 times higher for borrowers treated with a moderate discount, 4.92 times higher for borrowers treated with a late fee waiver, and 4.37 times higher for borrowers treated with a social warning than borrowers in the control group.[22]

Both a punitive approach via social punishment and an accommodative approach via monetary benefits trigger a repayment and outperform a plain ex-post reminder. It may

[22] For ease of exposition, we refer to odd ratios rather than log odds ratios in the text. For example, for borrowers treated with a moderate discount, the log odds ratio is $\beta_{Mod} = 1.195$ and the odds ratio is 3.31, that is:

$$exp^{\beta_{Mod}} = 3.31 = \frac{(\frac{p}{1-p})^T}{(\frac{p}{1-p})^C} = \frac{(\frac{5.10}{100-5.10})}{(\frac{1.60}{100-1.60})},$$

where p denotes the repayment likelihood. We report the repayment likelihood for treatment (T) groups and the control (C) group in Figure 2.

not sound surprising that low-income borrowers respond to monetary incentives, but we find intriguing that the mere prospect of a release of negative information to others persuades late borrowers to promptly execute the pending payment. Our argument is twofold.

Firstly, the social warning does not contain news about punishment, but simply announces the intention to proceed with agreed-on punishment. Agarwal et al. (2008) find that, in the United States, credit card owners learn to avoid future fees by paying late fees, though learning partially fades away over time. Like borrowers tend to forget about monetary punishment until they are actually charged the penalty, borrowers in our sample may forget about the involvement of the third parties until they are actually warned of the social penalty.

Secondly, while borrowers who respond to monetary incentives receive an actual discount, those who respond to the social incentive do not experience actual punishment. The effectiveness of this scheme suggests that borrowers perceive a delayed payment as an act of financial misconduct and anticipate negative feedback from others when assessing the consequences of misconduct. Since the social incentive outperforms a plain reminder, borrowers do not simply make the payment for their own sake (reminder), but repay to prevent a reputational damage. By successfully generating an expectation of punishment, the social incentive achieves the desired outcome in the absence of actual punishment. Granted mobile data access anchors the expectation of punishment, as the loan agency is in the position to retrieve the borrower's network and to proceed with the circulation of sensitive information through such network. In expectation, the social penalty is severe, as the dissemination of information is potentially rapid and pervasive.[23] Consistent with Breza and Chandrasekhar (2019), we find that reputational concerns affect individual behavior.

Panel B investigates whether monetary incentives and the social incentive are equally successful in outperforming the ex-post reminder. We present statistical tests for the equality

[23]According to the same principle, the "credibility hypothesis" in monetary economics postulates that central banks can achieve a disinflation without bearing the cost of a period of high unemployment by making fully credible announcements (Blinder (2000)).

of the estimated coefficients and report, for each test, the null hypothesis, the F-statistic and the associated *p-value* (in parenthesis).

The first test rejects the hypothesis of equality between the two monetary incentives, which is $\beta_{Mod} = \beta_{Full}$. Repayment gains are statistically increasing in the generosity of the monetary scheme and the full waiver is more effective than the moderate discount in enhancing the repayment likelihood. We infer that there are two types of borrowers, who respond to monetary benefits. Naive borrowers accept a moderate discount, while demanding borrowers require a more generous incentive to convert a delayed payment into a prompt repayment.

The second test rejects the hypothesis of equality between the social incentive and the moderate monetary incentive, which is $\beta_{Mod} = \beta_{Social}$. Since the significance of the rejection is marginal (*p-value*=0.012), our conservative conclusion is that the non-monetary incentive is at least as effective as the moderate monetary incentive.

The third and last test does not reject the hypothesis of equality between the social incentive and the generous monetary incentive, which is $\beta_{Full} = \beta_{Social}$. Statistically, an announcement of reporting financial misconduct to others is as effective as a generous late fee waiver as a prompt trigger for repayment. Monetary incentives present two shortcomings: They are expensive to implement and may be counterproductive over time. Although the text message does not contain any explicit reference to following payments, accounting for the possibility of receiving a similar treatment in the future reduces the cost of delaying a future payment. In contrast, reputational sanctions incentivize on-time repayment behavior over time, as they enhance the cost of any late payment. The social incentive can be implemented at zero cost, preserves the cash-flow from late fees and triggers a repayment via the recognition of misbehavior. Incentivizing on-time repayment behavior is the ultimate goal of the loan agency which bears the "principal guarantee". It is also a primary concern in China, where borrowers have limited past credit experience and suffer from poor financial literacy.

Figure 2 summarizes the findings in terms of repayment likelihood. The 24-hour repayment likelihood is 5.10% for borrowers treated with a moderate monetary incentive, 7.40% for borrowers treated with a full monetary incentive, 6.63% for borrowers treated with the social incentive and 1.60% for the control group. As suggested by Figure 1, the effectiveness of ex-post reminders is limited in our setting. Although ineffective ex-post reminders point to highly financially constrained borrowers, the efficacy of incentives suggest otherwise. Since monetary benefits are small in value, there is no actual involvement of the third parties and the repayment window is short, we can hardly reconcile a repayment over the horizon of the experiment with the hypothesis of insolvent borrowers. We conclude that inattention is a weak explanation for pending first loan repayments and both monetary and reputation-based incentives successfully alter the cost-benefit trade-off associated with the choice of delaying the first payment. Prompt intervention enhances the repayment likelihood as early as on the fifth day of delay. Overall, we view the impact of pure incentives as economically relevant, especially in the light of the short horizon of the experiment and the contemporaneous negligible repayment likelihood in the absence of intervention (i.e., hold-out group).

Finally, we acknowledge that the setting of our experiment may potentially amplify the success of the social scheme due to the primary importance of the concepts of "face" (mianzi) and "social connections" (guanxi) in the Chinese culture. The concept of "face", or self-image, broadly refers to the way a person views him-herself in a social context (Goffman (1955); Ho (1976)). Studies in sociology and psychology on the dynamics of face document feelings like embarrassment and shame when individuals perceive that their face is discredited and the tendency to actively engage to convert a discredited face into a positive face (Goffman (1956), see Kim and Nam (1998) and references therein). In the context of our experiment, the circulation of a suspect of malicious arrears through the borrower's own network results in a discredited face and the prospect of losing face generates embarrassment. Borrowers who respond to the social incentive anticipate a discredited face and promptly repay to preserve a positive face. Cultural psychologists document systematic differences across countries with respect to this concept. In a "Face culture" like China, individuals largely judge themselves by absorbing the evaluation of others, while in a "Dignity culture" like the United States individuals are independent in their own self-assessment and perceive their self-worth as inalienable (see Kim, Cohen and Au (2010) and Kim and Cohen (2010)). Leung and Cohen (2011) discuss the pervasive and powerful role of face in Asia, where shame is perceived as punishment for bad behavior.[24] Although this strand of work well supports our findings, the effectiveness of the reputation-based incentive may be peculiar to the Asian culture, have widespread applications or even operate through a distinct mechanism in a different cultural system. We leave external validity as an avenue for future research.

5.3. Joint incentives versus pure incentives

The efficacy of pure incentives raises the question of whether there are further gains to collect by combining reward (monetary incentive) with punishment (social incentive).

Full complementarities between monetary and social incentives imply that borrowers who respond to one scheme do not respond to the other and pure treatment effects capture independent gains (*Only*). Subject to this hypothesis, treatment effects for the joint scheme are the sum of treatment effects of the two pure schemes and joint treatment strategies dominate single treatment strategies. Full substitution effects imply that borrowers are indifferent between the two schemes and pure treatment effects capture overlapping gains (*Indiff*). Subject to this hypothesis, treatment effects for the joint scheme equal the treatment effects of the two pure schemes and joint treatment strategies are as effective as single treatment strategies. Synergies are amplified if there are borrowers who do not respond to a single treatment, but respond to joint treatment (*NewEntry*), and mitigated if there are borrowers who respond to single treatment but do not respond to joint treatment, due to a perceived conflict (*Exit*). For example, a late fee waiver and a social warning may jointly disorient a borrower, because this strategy combines an accommodative stand on

[24] As informal support for our rationale, a popular Chinese idiom goes: "Men can't live without face, trees can't live without bark".

misconduct (i.e., a discount) with a punitive approach (i.e., the prospect of a discredited reputation). These two opposite signals may crow out and leave the decision of the late borrower unchanged. To summarize, the effectiveness of the joint provision of policy A and policy B is given by:

$$\begin{aligned} A\&B &= A^{pure} + B^{pure} - Indiff + NewEntry - Exit \\ &= (A^{Only} + Indiff) + (B^{only} + Indiff) - Indiff + NewEntry - Exit \\ &= A^{Only} + B^{Only} + Indiff + NewEntry - Exit, \end{aligned} \tag{2}$$

Where *pure* denotes pure treatment effects and other variables are defined above.

We test for the existence of synergies between monetary and social incentives via the following logit regression:

$$\begin{aligned} D_{Repayment,i} = \quad & c + \beta_{Mod} D_{Mod,i} + \beta_{Full} D_{Full,i} + \beta_{Social} D_{Social,i} + \\ & \beta_{ModSocial} D_{Mod,i} * D_{Social,i} + \beta_{FullSocial} D_{Full,i} * D_{Social,i} + \epsilon_i, \end{aligned} \tag{3}$$

where the dependent variable is a dummy variable taking a value of 1 if borrower i makes the pending payment within 24-hours and 0 otherwise, and $D_{Mod,i}$, $D_{Full,i}$, $D_{Social,i}$ are dummy variables taking value of 1 if borrower i receives a moderate monetary incentive, a full monetary incentive, and a social incentive, respectively, and 0 otherwise. The log odds repayment ratio for a joint treatment group over the control group is given by

$$Mod\&Social: \quad \beta_{Mod} + \beta_{Social} + \beta_{ModSocial} \tag{4}$$

$$Full\&Social: \quad \beta_{Full} + \beta_{Social} + \beta_{FullSocial}, \tag{5}$$

where the coefficients β_{Mod}, β_{Full} and β_{Social} measure pure treatment effects and $\beta_{ModSocial}$ and $\beta_{FullSocial}$ capture deviations from the assumption of full complementarities between monetary and social incentives (i.e., $A^{pure} + B^{pure}$), that is the net impact of indifferent borrowers, new entries and borrowers who perceive a conflict. Sample size is 18,000 borrowers, as the sample includes both single treatment groups and joint treatment groups. Estimates are in Table 6. *t*-statistics are in brackets.

Column I rejects the hypothesis of full complementarities between a monetary incentive and the social incentive as both $\beta_{ModSocial}$ and $\beta_{FullSocial}$ are negative and statistically significant at the 1% level. There are therefore borrowers who are indifferent between the two schemes (*Indiff*) and/or respond to pure incentives but do not respond to joint incentives (*Exit*). In terms of magnitude, the coefficient $\beta_{FullSocial} = -1.303$ is in an absolute value larger than the coefficient $\beta_{ModSocial} = -0.893$ and we reject the hypothesis of equality between these two estimates. We conclude that there are statistically smaller offsetting effects in combining a moderate discount with a social warning than a full discount with a social warning. This outcome is consistent with the F-tests in Table 4, which reveal that the social warning marginally outperforms the moderate discount while it is as effective as a full monetary discount. The former result is in line with the existence of synergies, while the latter finding points to substitution effects.

The next two columns investigate whether joint treatment schemes statistically dominate single treatment schemes, despite the existence of offsetting effects. The logistic regressions of interest are:

$$\begin{aligned} D_{Repayment,i} &= c + \beta_{Social} D_{Social,i} + \beta_{ModSocial} D_{Mod,i} * D_{Social,i} \qquad (6) \\ &\quad + \beta_{FullSocial} D_{Full,i} * D_{Social,i} + \epsilon_i \\ D_{Repayment,i} &= c + \beta_{Mod} D_{Mod,i} + \beta_{Full} D_{Full,i} + \beta_{ModSocial} D_{Mod,i} * D_{Social,i} \qquad (7) \\ &\quad + \beta_{FullSocial} D_{Full,i} * D_{Social,i} + \epsilon_i. \end{aligned}$$

We focus on the coefficients associated with the interaction terms, which measure the log odds repayment ratio for a joint treatment group over a single treatment group.[25]

In Column II, we test for the existence of marginal gains from monetary incentives,

[25]For example, the coefficient $\beta_{ModSocial}$ in Equation 6 measures the odds of the Mod&Social policy over

conditional on the social incentive. We find that joint incentives statistically outperform a pure social incentive, as the coefficients $\beta_{ModSocial}$ and $\beta_{FullSocial}$ are both positive and statistically significant at the 1% level. Interestingly, these two estimates are not statistically different from each other. Conditional on a social incentive, there are statistical gains in pairing the social incentive with a moderate discount, but we do not detect incremental gains in further increasing the generosity of the monetary incentive. In joint schemes, the social incentive crowds out the additional gains from a pure late fee waiver. We infer that the social incentive can attract, among others, the subset of demanding borrowers, that is those who respond to a full discount but reject a moderate discount. This finding corroborates the power of the social incentive to enhance the repayment likelihood at a lower cost.

In Column III, we test for the existence of marginal gains from the social incentive, conditional on a monetary incentive. Consistent with our findings above, the improvement in the repayment odds is large and statistically significant for the *Mod&Social* scheme over the *Mod* scheme (coeff=0.581, +79%), and is small and marginally significant for the *Full&Social* scheme over the *Social* scheme (coeff=0.172, +19%). As in Column I, the marginal gains from the social incentive are decreasing in the generosity of the monetary incentive.

Lastly, Column IV eases the comparison between joint treatment groups and single treatment groups by reporting the log odds repayment ratios for joint treatment groups over the control group. The log odds repayment ratio is 1.777 (=1.195+1.475-0.893) for the *Mod&Social* scheme and 1.764 (=1.592+1.475-1.303) for the *Full&Social* scheme. The odds of making the pending payment are 5.91 times higher for borrowers who receive both a moderate discount and a social incentive and 5.84 times higher for borrowers who receive both a full discount and a social incentive, than borrowers in the control group. The corresponding

the odds of the social incentive:

$$exp^{\beta_2} = 1.35 = \frac{(\frac{p}{1-p})^{Mod\&Social}}{(\frac{p}{1-p})^{Social}} = \frac{(\frac{8.77}{100-8.77})}{(\frac{6.63}{100-6.63})},$$

where p denotes the repayment likelihood. We report the repayment likelihood for joint treatment groups in Figure 2, along with figures for single treatment groups and the control group.

figures are 3.31 (*Mod*), 4.92 (*Full*), and 4.37 (*Social*) for pure incentives. Joint incentive schemes dominate pure incentive schemes and are statistically equivalent in enhancing the repayment odds.

Figure 2 summarizes the findings in terms of repayment likelihood. The 24-hour repayment likelihood is 8.77% for the *Mod&Social* scheme and 8.67% for the *Full&Social* scheme. Gains from the provision of joint incentives are economically relevant: The *Mod&Social* scheme enhances the repayment likelihood by about 72% relative to a pure moderate discount and by about 32% relative to a pure social warning. We conclude that this policy maximizes the repayment likelihood at the lowest cost, though the overall gains are constrained by a share of borrowers who are indifferent between the two schemes (*Indiff*) and/or respond to pure incentives but do not respond to joint incentives (*Exit*).

5.4. Heterogenous treatment effects

We show that both the monetary incentive and the social incentive persuade late borrowers to repay within 24 hours and statistically outperform ex-post reminders. In this section, we characterize the borrowers who respond to pure incentives. We start with a graphical overview of the repayment odds by covariates and next formally test for heterogeneous treatment effects.

Figure 3 reports repayment odds for pure incentives over ex-post reminders conditional on a battery of demographic and loan characteristics. Green (yellow) bars denote borrowers who exhibit the covariate of interest; the symbol *** indicates that the estimated impact is statistically significant at the 1% level. To detect heterogeneous responses, we construct a set of dummy variables and define them relative to the sample average. For example, a"small loan" is a loan, which is in size smaller than or equal to the average loan in the sample. Other variables on the x-axis are constructed accordingly. Coefficients are from the logit regression in Equation 1.

The chart shows that the outperformance of incentives over ex-post reminders is statistically widespread, though often heterogeneous in magnitude. Borrowers respond to pure incentives regardless of income (low income), gender (male), marital status (married), size of the monthly payment (small payment), size of the loan (small loan), length of the loan (short loan), cost of the target product (cheap product) and incidence of the down payment (dp) on the price of the target product. We also find support for the hypothesis that borrowers who are plausibly financially constrained do not respond to incentives due to the inability to afford the payment. Coefficients are small and not statistically significant for borrowers who feature high indebtedness, as measured by a high product price-to-income ratio and monthly payment-to-income ratio, and also for those who present a large down payment-to-income ratio. Borrowers who declare a second outstanding mortgage respond to both a full monetary incentive and the social incentive, but do not respond to a moderate monetary incentive. A possibility is that these borrowers rationally decided to delay the first repayment due to financial difficulties in managing the increased credit burden, but the full exemption from the monetary penalty is sufficient to persuade them to repay, perhaps by favoring the new loan over the outstanding loan.

Next, we formally investigate the existence of heterogeneous treatment effects via the following logit regression:

$$\begin{aligned} D_{Repayment,i} &= c + \beta_1 D^+_{Mod,i} + \beta_2 D^+_{Full,i} + \beta_3 D^+_{Social,i} + \beta_4 Z_i + \\ &\quad \beta_5 D^+_{Mod,i} * Z_i + \beta_6 D^+_{Full,i} * Z_i + \beta_7 D^+_{Social,i} * Z_i + \epsilon_i \end{aligned} \tag{8}$$

Where Z_i is a dummy variable taking a value of 1 if borrower i features the covariate Z and 0 otherwise, and the interaction terms measure the heterogeneous response to pure incentives relative to the control group. For example, for the covariate "Student", Z takes value of 1 if borrower i is a student and 0 if is a worker, and each interaction term measures the difference in the response to single treatment between a student and a worker relative to a student/worker in the control group. We report estimates in Table 6. t-statistics are in brackets.

Consistent with the hypothesis that monetary incentives attract borrowers who are sensitive to small perturbations in credit constraints, we find that the response to monetary incentives is statistically more pronounced for borrowers who exhibit lower income, face smaller payments and combine smaller payments with shorter loans, smaller loans, no other outstanding mortgages and lower indebtedness. For all these covariates, we find that both the coefficient β_5 and the coefficient β_6 are positive and statistically significant. A reasonable conjecture is that higher income borrowers can afford the payment but rationally postpone it for convenience, while lower income borrowers delay it for financial reasons. Lower income borrowers may value an immediate relaxation of the monetary penalty more than higher income borrowers, because the progressive accumulation of the monetary penalty affect their credit burden. Monetary punishment may barely matter for higher income borrowers. Small payments and small loans also point to borrowers who may be able to pay off the loan and may have a keen interest in avoiding a delayed payment. Lastly, the lack of other outstanding mortgages and the low indebtedness suggest that these borrowers may be able to afford the payment.

In line with our previous conclusion that there are two types of borrowers who respond to monetary incentives, we identify distinct heterogeneous treatment effects for the moderate discount and the full discount. Borrowers who respond to the moderate incentive are more likely to be students, who tend to have the lowest income in the sample. Their odds of making the pending payment are statistically 2.47 times higher than for workers and we confirm that the response is also statistically more pronounced for students who are low-income ($\beta_5 = 0.752$, t-statistic=2.17) and have a low loan-to-income ratio ($\beta_5 = 0.754$, t-statistic=2.17). Borrowers who are more responsive to the full incentive have a small loan ($\beta_6 = 0.707$, t-statistic=2.06). Table X in the Appendix compares borrowers with small loans with borrowers with small payments, which are those who exhibit heterogeneous responses with respect to monetary incentives of any size. On average, borrowers with small loans are less likely to be students, face higher monthly payments, have shorter loans, higher income and a higher down payment-to-income ratio than borrowers with small payments. These borrowers reasonably benefit from more financial stability due to employment, but also opt for a larger down payment and larger monthly payments and may choose to delay the first payment. Like borrowers who declare a second outstanding mortgage, they can be persuaded to revisit their choice but the compensation should be more than trivial.

Turning to the social incentive, we find that borrowers who live in rural areas are statistically less likely to respond to a social warning ($\beta_7 = -0.805$, t-statistic=-2.19) than borrowers who live in urban areas. Conditional on receiving the social incentive, the odds of making the pending payment are 3.35 times higher for borrowers from rural areas and 7.48 times higher for borrowers from urban areas than borrowers of the same type in the control group. It is plausible that predominant tight family connections in the countryside undermine the impact of a potential circulation of negative news, while more formal social connections in cities enhance the reputational damage. As above, this finding is confirmed for borrowers who also feature a low loan-to-income ratio. A conjecture is that borrowers who respond to the social incentives are students, who potentially hided the loan request from their parents. Against this hypothesis, we do not find that students are more likely to respond to the social incentive than workers. As expected, responses are usually homogenous for monetary variables.

Finally, among the demographics, we do not detect significant heterogeneous treatment effects for sex, marriage and credit risk and we identify marginal effects for education.

5.5. On-time likelihood of paying off the loan

The experiment reveals that both pure incentives and joint incentives trigger the repayment of the first installment of the loan within 24 hours on the fifth day of delay, while ex-post reminders and monetary punishment are marginally effective. Our ultimate question is whether the benefits of an early provision of incentives are long-lasting, that is whether borrowers remain solvent over time and pay-off the loan on time. To address this question, we collect information on the repayment decision of late borrowers in the experimental sample at two subsequent points in time, that is at the due dates of the third payment and the last payment. Although multiple and unobservable factors plausibly influence the repayment decision beyond the initial 24 hours, unobservables equally affect randomized groups over time. Based on this premise, we test the on-time repayment likelihood for the two subsequent payments conditional on a positive response to early incentives. Making the last payment by the due date is equivalent to pay off the loan on time.

Table 7 - Panel I reports the conditional repayment likelihood (in percent) by initial groups. The first row shows our previous results, which is the share of borrowers in each group who make the first payment in the 24-hour window of the experiment (*Response*). The following rows report the share of borrowers in each group who make the first pending payment over the horizon of the experiment and next: i) make the third payment on time (*3rd payment* | *Response*); ii) pay off the loan on time (*Last* | *Response*); iii) make both the third and the last payment on time (*Last* | *(Response and 3rd payment)*); iv) do not make the third and the last payment on time (*No further payments* | *Response*). The second half of the panel reports the same statistics as a fraction of the subset of borrowers who respond to the experiment.

Panel I confirms that repayment gains from incentivizing the first late payment are broadly preserved over time. Between 76.88% and 83.46% of the borrowers who promptly respond to incentives make the third payment on time and the interval slightly decreases to 71.86%-79.23% at loan maturity. The on-time conditional likelihood of paying off the loan is 1.17% for borrowers who initially received a reminder, around 6.50% for borrowers who were initially treated with joint incentives and varies between 4.03% (moderate discount) and 5.83% (full discount) for borrowers who were initially treated with pure incentives.

Table 9 verifies that the conditional repayment gains are statistically robust at loan maturity. The table reports the same regressions of Table 5, but uses the conditional on-time likelihood of paying off the loan (*Last* | *Response*) as the dependent variable. Overall, we confirm our major findings: i) the odds of paying off the loan are statistically higher for borrowers who were initially allocated to a treatment group than borrowers who were allocated to the control group, and this result holds for both single treatment groups (Column I) and joint treatment groups (Column IV); ii) the odds of paying off the loan are statistically higher for borrowers who were initially treated with joint incentives than borrowers who were treated with pure incentives (Column II and Column III); iii) the odds of paying off the loan are statistically equivalent for borrowers who initially received joint treatment relative to borrowers who were allocated to the control group (Column IV); iv) the combination of a moderate discount and the social incentive remains the policy that maximizes the repayment likelihood at the lowest cost (Column II). We conclude that the benefits of an early provision of incentives extend beyond prompt debt collection.[26]

Next, we turn to the large share of borrowers, who do not respond to incentives promptly. These borrowers may be truly insolvent, maliciously delinquent or temporarily financially constrained. To shed light on these hypotheses, we examine their subsequent repayment choices. Although incentives are administered once, persistent delinquent borrowers are subject to further action in the subsequent weeks. Firstly, the loan agency contacts these borrowers directly by phone. Condition 3 in the loan agreement authorizes interaction by mail, email, telephone and mobile phone as loan enforcement measure. Secondly, the loan agency proceeds with a gradual implementation of the reputational sanctions after 30 days of delay, starting from family members (ie., parents, brothers, sisters) and next reaching friends and colleagues, if necessary. Both measures affect groups homogeneously. Table 7 - Panel II reports subsequent conditional repayment shares for this subset of borrowers. Panel III reports unconditional statistics.

Panel II shows that about 64% of the late borrowers who did not respond to incentives promptly make the third payment on time (*3rd payment* | *No response*) and about 54% pays off the loan on time (*Last* | *No response*). As expected, shares are fairly homogenous

[26]In contrast to Table 5, we find that pure treatment effects for a moderate discount and a social warning are statistically equivalent, while pure treatment effects for a full discount and a social warning are statistically different. Unfortunately, we are not able to interpret these results given the limitations of our setting and we cannot exclude that they are merely driven by noise.

across groups. Repayment shares are lower in Panel II than in Panel I, consistent with the hypothesis that borrowers who do not respond promptly are more likely to be financially constrained. Despite an evident discrepancy between panels, repayment shares are quite sizable at loan maturity, even in this subsample. Overall, about 62% of the late borrowers pays off the loan on time. We view this outcome as a substantial achievement, given that by design all borrowers started with a pending payment and the repayment likelihood is negligible for the hold-out group up to 30 days after the first due date. Regardless of the initial response, we also observe that all borrowers who make the last payment on time also made the third payment on time. Although we are unable to provide a causal interpretation of these patterns, Table 7 supports the hypothesis that a large share of late borrowers develop diligent repayment habits by the third due date. Finally, Table 7 shows that about 32% of the late borrowers in the experimental sample do not respond to the initial incentives and also do not make the third and the last payment on time. We interpret this statistic as a proxy for the share of "junk borrowers" in the sample, that is borrowers who could be highly financially constrained or truly maliciously delinquent.

As a final exercise, we investigate whether the decision to repay or to not repay over time is associated with observable characteristics. For example, borrowers with a large down payment-to-product price ratio or down payment-to-monthly-installment ratio may delay the first payment due to temporary financial constraints but subsequently repay on time. Borrowers with a large loan-to-income ratio, another outstanding mortgage or very low income may be persistently late due to high financial constraints. In both scenarios early incentives are ineffective and the subsequent repayment decision is likely independent from any further measure pursued by the loan agency.[27] Table 9 reports a battery of mean difference tests conditioning on the lack of prompt response to incentives. Panel I focuses on the third payment, while Panel II compares solvent borrowers with "junk" borrowers at loan maturity.

[27]The former scenario does not damage the long-term interests of the platform, while the latter plausibly signals borrowers who benefited from the opaqueness of the screening process.

Both panels widely rejects the hypothesis that on-time borrowers and persistently late borrowers are statistically different from each other. We therefore do not find strong support for high financial constraints as major explanation for persistent delayed payments nor for large down payments as explanation for temporarily delayed payments. It is plausible that a share of borrowers in the sample suffered from poor management skills and learned over time how to timely fulfill financial commitments. As in Agarwal et al. (2008), late borrowers may learn through monetary punishment, that is by paying late fees. Late borrowers may also learn through social punishment, that is by experiencing actual punishment after the circulation of news on financial misconduct. Direct calls may also induce inexperienced borrowers to save properly over time. We conclude that the provision of early incentives and prompt intervention in the weeks subsequent to the first due date are crucial to induce late borrowers with poor past credit experience to quickly develop on-time repayment habits and pay off the loan on time.

6. Conclusion

In this paper, we use confidential data from the Chinese P2P lending industry to study the effectiveness of a novel reputation-based (social) incentive both in parallel to and coupled with a more traditional monetary incentive on the repayment decision of 18,000 late borrowers vis-*à*-vis ex-post reminders. To enforce unsecured high-risk P2P loans, our data provider reserves the right to report delinquent behavior to third parties in due course. The loan contract specifies that third parties belong to the mobile contact list of the delinquent borrower, but the timing of their actual involvement is uncertain.

Firstly, we show that a text message announcing the intention to proceed with the implementation of the reputational sanctions persuades late borrowers to repay within 24 hours, while ex-post reminders are largely ineffective. Since late borrowers do not repay for their own sake (reminder) but to prevent a reputational damage (social incentive), we conclude that the anticipation of negative social feedback affects repayment behavior and the prospective involvement of the third parties is sufficient to enforce the loan. Mobile contacts plausibly identify the inner circle of the delinquent borrower and granted mobile data access ensures the credibility of expected social punishment. We acknowledge that the Asian setting of the experiment may amplify the power of this incentive due to the primary importance of the concepts of "face" (mianzi) and "social connections" (guanxi) in the Chinese culture. We discuss related work in the paper and leave external validity as an open question.

Secondly, we show that late borrowers are also sensitive to a discount on the monetary penalty. However, within 24 hours, the social incentive outperforms a moderate discount on the late fee, is as effective as a full late fee waiver and in joint schemes neutralizes the benefits of increasing the generosity of the monetary incentive.

Thirdly, we provide clean evidence on the counterfactual. In the absence of intervention, the loan repayment likelihood for late borrowers drops below 1% in five days and barely moves in the next 25 days. Monetary punishment and the mere adoption of reputational sanctions are therefore ineffective solutions to delayed payments. Since late borrowers receive text messages on the fifth day of delay, we conclude that incentives successfully alter the cost-benefit trade-off of delaying the first repayment.

Lastly, we show that the benefits of an early provision of incentives are long-lasting, as borrowers who respond to incentives largely make the third payment on time and pay-off the loan on time. Among those who do not respond promptly and receive further action, we find that about 50% develop diligent repayment habits over time. These findings suggest that prompt intervention educates borrowers who largely lack past credit experience to learn over time how to timely fulfill their financial commitments.

We view the effectiveness of the social incentive as intriguing. The adoption of reputational sanctions in the Chinese P2P lending market is primarily motivated by the hunt of individual platforms for policies to minimize the burden of the "principal guarantee" and in turn maximize their own survival likelihood. However, effective incentives, and more broadly any measure able to induce diligent repayment habits, serve the long-term purpose of ensuring the sustainable growth of the P2P lending industry in China and the preservation of broad access to credit in the long run. Despite evident fragilities and several scandals since 2015, this industry has fulfilled increasing credit needs in the developing stage by establishing a viable and broadly accessible alternative to the traditional banking channel.

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1 Tables

Table 1
Screening Process

This table summarizes the screening process conducted by the loan agency and presents details about the indicators used to determine the creditworthiness of the applicants.

Step	Description	Details
1. Information verification	Submitted information is correct in format.	Examples: 11 digits for mobile phone number, 6 digits for mail code.
2. Personal identification	Verification of consistency for ID, mobile phone, bank debit/credit information.	a) ID: Name, facial recognition, photo on ID card, ID card number, photo at Ministry of Public Security. b) Mobile phone: Name, ID card number, mobile phone number. c) Bank debit/credit: Name, ID card number, account number.
3. Screening via blacklists	Rejection of applicants in blacklists from third parties.	Credit card/lawsuit/interest lending blacklists. From: Baidu, Zhi Ma Credit, Tong Dun, and Qian Hai Credit.
4. Credit score via proprietary algorithm	Confidential algorithm generates credit scoring from A (low-risk) to F (high-risk) by processing demographics, financial account details and pervasive information on mobile/online credit behavior.	a) Demographics: see Table 2. b) Financial account details: Banks and third payments, debit and credit cards. c) Mobile/online credit behavior: c.1) Mobile phone usage: call bill, name list, SMS contents, roaming. c.2) Search engine usage: Baidu (major one). c.3) Usage of top two e-commerce websites (Jingdong and Taobao). c.4) Mobile phone social network: friends in financial blacklist, frequent access to websites of internet lending or credit score card companies. c.5) Multi-loan applications: Lending App. c.6) Online to offline usage: Baidu Nuomi. (service platform for entertaining, dining, hotels, health& beauty.) c.7) Multi-device usage: Ipad & PC. Wifi usage.
5. Decision	Loan company selects qualified borrowers and submits successful applications to the platform.	Undisclosed risk-tolerance

Table 2
Descriptive Statistics

This table reports mean, standard deviation (std), 25th percentile, 75th percentile, and number of observations (Obs.) for the main variables in the dataset. Panel A presents the demographics. Panel B summarizes the characteristics of the loans. Panel C reports phone-related characteristics, that is the type of product financed by the loan, its price, the monthly spending on phone calls and the tenure of the phone number (in months). Monetary variables are reported in Chinese yuan. Major monetary variables are converted into U.S. dollars ($) at the exchange rate for December 2015, that is $USD1 = CNY6.5138$. Sample size is 18,000 borrowers.

Variables	Mean	Std	25th	75th	Obs.
Panel A: Demographics					
Age	23.20	5.02	20.00	24.00	18,000
Credit risk (A=1, B=0)	0.56	0.50	0.00	1.00	18,000
Education	2.56	1.08	1.00	3.00	18,000
1: Less than high school (25.81%)					
2: High school (12.06%)					
3: Associate degree (42.18%)					
4: Bachelor and graduate school (19.95%)					
Income	2758.17	1728.29	1500.00	3500.00	17,302
($)	423.44	265.33	230.28	537.32	17,302
Male	0.70	0.46	0.00	1.00	18,000
Married	0.15	0.35	0.00	0.00	18,000
Rural residential area	0.63	0.48	0.00	1.00	18,000
Student	0.46	0.50	0.00	1.00	18,000
Panel B: Loan characteristics					
Down payment	806.74	769.12	0.00	1180.00	18,000
Loan size	3367.42	997.95	2698.00	3980.00	18,000
($)	516.97	153.21	414.20	611.01	18,000
Monthly payment	338.34	114.44	265	404	18,000
($)	51.94	17.57	40.68	62.02	18,000
Number of installments	14.31	4.39	12.00	18.00	18,000
Other mortgage	0.22	0.41	0.00	0.00	18,000
with no outstanding balance (37.65%)	0.00	0.00	0.00	0.00	1,460
with outstanding balance (62.35%)	373.62	348.16	255.00	386.00	2,418
Loan size/income	1.56	2.75	0.89	2.10	17,302
Monthly payment/income	0.15	0.28	0.10	0.19	17302
Panel C: Phone-related characteristics					
Loan's purchase	3.13	1.18	2.00	4.00	18,000
1: Others (18.99%)					
2: Computer (6.58%)					
3: Samsung phone (17.19%)					
4: Apple smartphone (57.23%)					
Phone call monthly spending	1.38	0.62	1.00	2.00	18,000
1: Less than RMB100 (63.03%)					
2: Between RMB100 and RMB200 (29.23%)					
3: Above RMB200 (5.46%)					
Phone id tenure	18.51	21.91	3.00	24.00	18,000
Product price	4174.16	1335.71	3350.00	4900.00	18,000

Table 3

Randomization Checks: Mean Difference Tests for Treatment Groups vs. Control Group

This table reports randomization checks for the main variables used in the analysis, that is demographics and loan characteristics. For each variable, the table presents the mean (μ) by group and the mean difference test for the difference in means between any given treatment group (T) and the control (C) group, that is $\mu^T - \mu^C$. t-statistics (t) are in brackets. By design, all borrowers in the sample have a pending payment five days after the due date of the first installment of their first loan. On that day, borrowers are randomly allocated to a control group and five treatment groups. Treatment is a monetary incentive, a reputation-based (social) incentive, or a combination of the two. The monetary incentive is a moderate (50%) or a full (100%) discount on the late fee. The social incentive is a warning to inform third parties about the pending payment. Borrowers in the control group receive a plain ex-post reminder. Sample size is 18,000 borrowers. Groups are equal in size. Monetary variables are reported in Chinese yuan.

	Incentives			Demographics and loan characteristics											
Group	Monetary	Social	Stats	Age	Credit risk	Edu	Income	Male	Married	Rural area	Student	Loan size	Monthly payment	Number of installments	Other mortgage
Control	No	No	μ^C	23.23	0.57	2.55	2746.19	0.70	0.15	0.62	0.46	3367.04	337.74	14.29	0.22
			μ^{T_1}	22.98	0.55	2.57	2751.61	0.70	0.14	0.62	0.47	3376.25	339.55	14.31	0.22
Treatment 1	Moderate	No	$\mu^{T_1} - \mu^C$	-0.25	-0.01	0.02	5.42	-0.01	-0.01	0.00	0.01	9.21	1.81	0.02	0.00
			t	[-1.97]	[-1.01]	[0.87]	[0.13]	[-0.53]	[-0.99]	[0.24]	[0.39]	[0.36]	[0.62]	[0.14]	[0.12]
			μ^{T_2}	23.20	0.54	2.57	2698.46	0.71	0.15	0.63	0.47	3364.67	337.85	14.30	0.21
Treatment 2	Full	No	$\mu^{T_2} - \mu^C$	-0.03	-0.02	0.03	-47.73	0.00	0.00	0.02	0.01	-2.37	0.11	0.01	0.00
			t	[-0.24]	[-1.87]	[0.92]	[-1.13]	[0.28]	[-0.15]	[1.36]	[0.72]	[-0.09]	[0.04]	[0.05]	[-0.35]
			μ^{T_3}	23.23	0.55	2.57	2759.93	0.69	0.15	0.63	0.47	3352.64	337.04	14.28	0.21
Treatment 3	No	Yes	$\mu^{T_3} - \mu^C$	0.00	-0.01	0.02	13.75	-0.01	0.00	0.01	0.01	-14.40	-0.70	-0.01	0.00
			t	[-0.03]	[-1.12]	[0.70]	[0.30]	[-0.84]	[-0.18]	[0.77]	[0.57]	[-0.55]	[-0.24]	[-0.11]	[-0.41]
			μ^{T_4}	23.20	0.57	2.57	2787.46	0.72	0.14	0.64	0.46	3367.62	337.91	14.33	0.21
Treatment 4	Moderate	Yes	$\mu^{T_4} - \mu^C$	-0.03	0.00	0.03	41.27	0.01	0.00	0.02	0.00	0.58	0.17	0.04	-0.01
			t	[-0.20]	[0.16]	[0.93]	[0.91]	[1.22]	[-0.44]	[1.84]	[-0.05]	[0.02]	[0.06]	[0.36]	[-0.63]
			μ^{T_5}	23.34	0.56	2.54	2805.70	0.70	0.15	0.63	0.45	3376.31	339.95	14.32	0.22
Treatment 5	Full	Yes	$\mu^{T_5} - \mu^C$	0.11	-0.01	0.00	59.51	0.00	0.00	0.01	-0.01	9.27	2.21	0.03	0.00
			t	[0.80]	[-0.57]	[-0.18]	[1.29]	[0.03]	[0.47]	[1.04]	[-0.47]	[0.36]	[0.74]	[0.27]	[0.00]

Table 4

Pure Treatment Effects

This table presents logit regressions for the impact of pure monetary incentives and a reputation-based (social) incentive on repayment behavior within 24-hours from notification, relative to a plain ex-post reminder. Panel A reports estimates and Panel B reports Wald tests for the equality of pure treatment effects. The dependent variable is a dummy variable taking a value of 1 for repayment and 0 otherwise. The three regressors are dummy variables taking a value of 1 for single-treated borrowers and 0 otherwise. The monetary incentive is a moderate (50%, D_{Mod}) or full (100%, D_{Full}) discount on the late fee. The social incentive is a warning to inform third parties about the pending payment (D_{Social}). By design, all borrowers in the sample have a pending payment five days after the due date of the first installment of their first loan. On that day, borrowers are randomly allocated to groups (see Table 3) and notified via SMS text messages. Estimates are expressed as log odds ratios. *t*-statistics are in brackets. *p-values* associated with the F-test are in parentheses. The suffix $^{+}$ indicates that dummy variables exclude borrowers who receive joint treatment. Sample size is 12,000 borrowers. Groups are equal in size.

	A: Logit regressions		B: Wald tests		
	$log(\frac{odds^T}{odds^C})$	*t-stat*	H_0	*F-stat*	*p-value*
c	-4.119	[-28.31]			
D^{+}_{Mod}	1.195	[7.14]	$Mod^{+} = Full^{+}$	13.396	(0.000)
D^{+}_{Full}	1.592	[9.87]	$Mod^{+} = Social^{+}$	6.351	(0.012)
D^{+}_{Social}	1.475	[9.05]	$Full^{+} = Social^{+}$	1.350	(0.245)

Table 5

Joint Incentives vs. Pure Incentives

This table presents logit regressions testing the impact of the joint provision of a monetary incentive and the reputation-based (social) incentive on repayment behavior within 24-hours from notification, relative to a plain ex-post reminder. The dependent variable is a dummy variable taking a value of 1 for repayment and 0 otherwise. The regressors are dummy variables taking a value of 1 for treated borrowers and 0 otherwise. Treatment is a moderate monetary incentive (D_{Mod}), a full monetary incentive (D_{Full}) and a social incentive (D_{Social}). Three treatment groups receive a pure incentive and two treatment groups receive the combination of a monetary incentive and the social incentive (see Table 3). The bottom panel reports Wald tests for the equality of the estimated interaction terms. By design, all borrowers in the sample have a pending payment five days after the due date of the first installment of their first loan. The monetary incentive is a moderate (50%) or full (100%) discount on the late fee. The social incentive is a warning to inform third parties about the pending payment. Estimates are expressed as log odds ratios. t-statistics are in brackets. *p-values* associated with the F-test are in parentheses. Sample size is 18,000 borrowers. Groups are equal in size.

	(I)	(II)	(III)	(IV)
Intercept	-4.119	-4.119	-4.119	
	[-28.31]	[-28.31]	[-28.31]	
D_{Mod}	1.195		1.195	
	[7.14]		[7.14]	
D_{Full}	1.592		1.592	
	[9.87]		[9.87]	
D_{Social}	1.475	1.475		
	[9.05]	[9.05]		
$D_{Mod} * D_{Social}$	-0.893	0.302	0.581	1.777
	[-4.61]	[3.09]	[5.53]	[11.16]
$D_{Full} * D_{Social}$	-1.303	0.289	0.172	1.764
	[-6.90]	[2.95]	[1.80]	[11.07]
$H_0 : D_{Mod} * D_{Social} = D_{Full} * D_{Social}$				
F-stat	8.324	0.019	8.324	0.019
p-value	(0.004)	(0.891)	(0.004)	(0.891)

Table 6

Heterogenous Treatment Effects for Pure Incentives

This table reports logistic regressions testing heterogeneous treatment effects for pure incentives. Covariates are a large battery of demographic and loan characteristics, Z. The dependent variable is a dummy variable taking a value of 1 if borrower i repays and 0 otherwise. This variable is regressed on an intercept (c), three dummy variables taking a value of 1 for single-treated borrowers and 0 otherwise, a covariate Z, and the interaction terms between each dummy variable and the covariate Z. Treated borrowers receive a pure moderate monetary incentive (*Mod*), a pure full monetary incentive (*Full*), and a pure social incentive (*Social*). The monetary incentive is a moderate (50%) or full (100%) discount on the late fee. The social incentive is a warning to inform third parties about the pending payment. Borrowers in the control group receive an ex-post reminder. Estimates are expressed as log odds ratios. The suffix $^+$ indicates that dummy variables exclude borrowers who receive joint treatment. t-statistics are in brackets. Group size is 3,000 borrowers.

Z	c	Mod^+	$Full^+$	$Social^+$	Z	$Mod^+ *Z$	$Full^+ *Z$	$Social^+ *Z$
Credit risk	-4.160	1.199	1.699	1.413	0.072	-0.005	-0.196	0.109
	[-18.46]	[4.64]	[6.89]	[5.59]	[0.24]	[-0.02]	[-0.60]	[0.33]
Low income	-3.900	0.754	1.416	1.198	-0.429	0.791	0.353	0.526
	[-19.69]	[3.11]	[6.30]	[5.23]	[-1.47]	[2.33]	[1.09]	[1.60]
High edu	-3.808	0.871	1.353	1.146	-0.567	0.587	0.449	0.595
	[-18.83]	[3.58]	[5.87]	[4.87]	[-1.95]	[1.74]	[1.38]	[1.81]
Male	-4.142	1.204	1.607	1.624	0.033	-0.013	-0.021	-0.220
	[-15.38]	[3.90]	[5.38]	[5.47]	[0.10]	[-0.03]	[-0.06]	[-0.62]
Married	-4.116	1.203	1.626	1.492	-0.018	-0.057	-0.260	-0.123
	[-26.15]	[6.65]	[9.34]	[8.47]	[-0.04]	[-0.12]	[-0.56]	[-0.26]
No d-p	-4.020	1.129	1.513	1.276	-0.440	0.307	0.367	0.784
	[-24.88]	[6.03]	[8.37]	[6.92]	[-1.18]	[0.73]	[0.91]	[1.94]
Outs-2nd-mrg	-4.178	1.290	1.659	1.572	0.367	-0.644	-0.426	-0.679
	[-25.90]	[7.01]	[9.33]	[8.78]	[0.98]	[-1.41]	[-0.99]	[-1.54]
Rural residence	-4.555	1.588	2.007	2.013	0.637	-0.568	-0.604	-0.805
	[-15.70]	[4.95]	[6.42]	[6.45]	[1.90]	[-1.51]	[-1.65]	[-2.19]
Short loan	-4.394	1.589	1.879	1.634	0.414	-0.616	-0.434	-0.231
	[-16.34]	[5.35]	[6.45]	[5.52]	[1.29]	[-1.71]	[-1.24]	[-0.65]
Small payment	-3.864	0.856	1.207	1.342	-0.529	0.683	0.761	0.298
	[-20.23]	[3.74]	[5.50]	[6.17]	[-1.79]	[2.01]	[2.33]	[0.90]
Small loan	-3.925	1.023	1.315	1.311	-0.523	0.470	0.707	0.450
	[-22.33]	[4.96]	[6.57]	[6.55]	[-1.67]	[1.32]	[2.06]	[1.30]
Student	-3.970	0.867	1.427	1.264	-0.357	0.711	0.391	0.485
	[-21.54]	[3.91]	[6.86]	[5.98]	[-1.19]	[2.07]	[1.18]	[1.45]
Low $\frac{d-p}{\text{product}}$	-4.050	0.969	1.456	1.318	-0.151	0.456	0.286	0.335
	[-20.86]	[4.20]	[6.67]	[5.99]	[-0.51]	[1.35]	[0.88]	[1.02]
Low $\frac{d-p}{payment}$	-3.937	1.005	1.359	1.240	-0.325	0.339	0.407	0.411
	[-18.70]	[4.04]	[5.68]	[5.14]	[-1.11]	[1.00]	[1.25]	[1.25]
Low $\frac{d-p}{income}$	-3.178	-0.118	0.875	-0.154	-0.981	1.362	0.750	1.684
	[-5.39]	[-0.14]	[1.23]	[-0.19]	[-1.61]	[1.60]	[1.03]	[1.98]
Low $\frac{product}{income}$	-3.546	-0.118	1.099	0.665	-0.602	1.364	0.519	0.847
	[-6.05]	[-0.14]	[1.61]	[0.92]	[-1.00]	[1.61]	[0.74]	[1.15]
Low $\frac{loan}{income}$	-3.546	-0.118	1.099	0.665	-0.602	1.364	0.519	0.847
	[-6.05]	[-0.14]	[1.61]	[0.92]	[-1.00]	[1.61]	[0.74]	[1.15]
Low $\frac{payment}{income}$	-3.546	-0.118	1.099	0.665	-0.602	1.364	0.519	0.847
	[-6.05]	[-0.14]	[1.61]	[0.92]	[-1.00]	[1.61]	[0.74]	[1.15]

[continued]

Z	c	Mod^+	$Full^+$	$Social^+$	Z	Mod^+ *Z	$Full^+$ *Z	$Social^+$ *Z
Low income & student	-3.973	0.864	1.460	1.291	-0.368	0.752	0.337	0.452
	[-21.91]	[3.97]	[7.15]	[6.23]	[-1.21]	[2.17]	[1.01]	[1.34]
Low income & low $\frac{d-p}{income}$	-3.845	0.692	1.373	1.113	-0.586	0.977	0.486	0.741
	[-20.49]	[2.98]	[6.42]	[5.08]	[-1.97]	[2.84]	[1.48]	[2.23]
Low income & low $\frac{loan}{income}$	-3.868	0.687	1.388	1.154	-0.542	0.985	0.455	0.669
	[-20.62]	[2.96]	[6.51]	[5.29]	[-1.82]	[2.87]	[1.39]	[2.01]
Low income & rural	-4.162	1.107	1.617	1.485	0.128	0.223	-0.075	-0.033
	[-23.00]	[5.24]	[8.04]	[7.32]	[0.42]	[0.64]	[-0.22]	[-0.10]
Rural & low $\frac{loan}{income}$	-4.449	1.448	1.914	1.903	0.505	-0.377	-0.491	-0.675
	[-16.55]	[4.82]	[6.57]	[6.54]	[1.58]	[-1.04]	[-1.40]	[-1.91]
Student & low $\frac{loan}{income}$	-3.970	0.861	1.422	1.237	-0.375	0.754	0.421	0.563
	[-21.90]	[3.95]	[6.94]	[5.94]	[-1.23]	[2.17]	[1.26]	[1.67]
Student & small loan	-4.025	1.069	1.442	1.356	-0.669	0.843	0.951	0.793
	[-26.16]	[5.96]	[8.34]	[7.78]	[-1.41]	[1.62]	[1.89]	[1.56]
Small payment & low income	-3.907	0.915	1.334	1.323	-0.759	0.942	0.881	0.587
	[-23.84]	[4.69]	[7.15]	[7.07]	[-2.12]	[2.38]	[2.29]	[1.51]
Small payment & student	-3.941	0.961	1.363	1.286	-0.774	0.958	0.940	0.809
	[-24.69]	[5.09]	[7.54]	[7.05]	[-1.99]	[2.24]	[2.25]	[1.92]
Small payment & no outs-2nd-mrg	-3.853	0.836	1.228	1.264	-0.681	0.873	0.883	0.564
	[-21.90]	[3.94]	[6.08]	[6.25]	[-2.17]	[2.46]	[2.57]	[1.63]
Small payment & small loan	-3.904	0.933	1.336	1.348	-0.825	0.962	0.942	0.548
	[-24.14]	[4.86]	[7.27]	[7.33]	[-2.22]	[2.35]	[2.36]	[1.35]
Small payment & short loan	-3.904	0.933	1.336	1.348	-0.825	0.962	0.942	0.548
	[-24.14]	[4.86]	[7.27]	[7.33]	[-2.22]	[2.35]	[2.36]	[1.35]
Small payment & low $\frac{loan}{income}$	-3.903	0.879	1.271	1.372	-0.456	0.645	0.652	0.235
	[-20.45]	[3.86]	[5.83]	[6.33]	[-1.54]	[1.90]	[1.99]	[0.71]
Small payment & low $\frac{d-p}{income}$	-3.893	0.884	1.257	1.352	-0.476	0.634	0.676	0.275
	[-20.39]	[3.88]	[5.75]	[6.23]	[-1.61]	[1.87]	[2.07]	[0.83]
Small loan & no outs-2nd-mrg	-3.921	1.038	1.309	1.275	-0.628	0.519	0.844	0.634
	[-23.30]	[5.25]	[6.83]	[6.62]	[-1.87]	[1.38]	[2.32]	[1.72]
Small loan & short loan	-4.053	1.156	1.455	1.389	-0.209	0.125	0.421	0.267
	[-23.43]	[5.79]	[7.52]	[7.12]	[-0.65]	[0.34]	[1.20]	[0.75]
Small loan & low $\frac{loan}{income}$	-3.950	1.031	1.357	1.340	-0.463	0.452	0.619	0.378
	[-22.48]	[5.01]	[6.82]	[6.72]	[-1.48]	[1.27]	[1.80]	[1.09]
Small loan & low $\frac{d-p}{income}$	-3.944	1.029	1.349	1.324	-0.478	0.458	0.635	0.418
	[-22.44]	[4.99]	[6.76]	[6.63]	[-1.53]	[1.28]	[1.85]	[1.20]
Small loan and low income	-3.944	0.980	1.354	1.296	-1.042	1.197	1.272	1.055
	[-25.62]	[5.38]	[7.74]	[7.36]	[-2.20]	[2.35]	[2.55]	[2.10]

Table 7

On-Time Repayment Likelihood: Third Payment and Last Payment

This table presents statistics (in percent) for the likelihood of paying the third and the last installment of the loan on time. Making the last payment by the due date is equivalent to pay off the loan on time. Panel I reports statistics conditional on the subset of borrowers who made the first payment over the 24-hour window of the experiment. Shares are expressed as a fraction of the group size (top half) and of the number of borrowers who positively respond to the experiment (bottom half). The conditional repayment likelihood is computed for: payments made over the horizon of the experiment (*Response*), the third installment of the loan (3^{rd} payment), the last installment of the loan (Last payment), and the last installment of the loan given a third payment on time (Last | (Response and 3^{rd} payment)). The last statistic refers to borrowers who delay both the third and the last payment (No further payments). Panel II reports similar statistics for borrowers who do not respond to policies within 24 hours. Panel III reports statistics for all borrowers in the sample. By design, all borrowers in the sample have a pending payment five days after the due date of the first installment of the loan. On that day, treated borrowers receive an incentive and borrowers in the control group receive a plain reminder. Treatment is a moderate (Mod) or full (Full) discount on the late fee, a reputation-based (Social) incentive, and their combination (Mod&Social, Full&Social). Sample size is 18,000 borrowers.

	Pure incentives			Joint incentives		
	Mod	Full	Social	Mod&Social	Full&Social	Control
I: Late borrowers who respond to initial incentives						
Out of sample size						
Response	5.10	7.40	6.63	8.77	8.67	1.60
3^{rd} payment | Response	4.23	6.10	5.10	6.77	7.23	1.30
Last payment | Response	4.03	5.83	4.77	6.33	6.87	1.17
Last | (Response and 3^{rd} payment)	4.03	5.83	4.77	6.33	6.87	1.17
No further payments | Response	0.87	1.30	1.53	2.00	1.43	0.30
Out of response to the experiment						
3^{rd} payment | Response	83.01	82.43	76.88	77.19	83.46	81.25
Last payment | Response	79.08	78.83	71.86	72.24	79.23	72.92
No further payments | Response	16.99	17.57	23.12	22.81	16.54	18.75
II: Late borrowers who do not respond to initial incentives						
Out of sample size						
No response	94.90	92.60	93.37	91.23	91.33	98.40
3^{rd} payment | No response	61.03	59.93	60.93	58.30	60.00	63.17
Last payment | No response	56.57	56.67	57.23	54.57	56.67	59.10
Last | (No response and 3^{rd} payment)	56.57	56.67	57.23	54.57	56.67	59.10
No further payments | No response	33.87	32.67	32.43	32.93	31.33	35.23
Out of no response to the experiment						
3^{rd} payment | No response	64.31	64.72	65.26	63.90	65.69	64.19
Last payment | No response	53.71	54.48	54.86	51.90	54.44	56.73
No further payments | No response	36.60	36.68	36.38	38.29	35.88	36.11
III: All late borrowers						
Experiment	5.10	7.40	6.63	8.77	8.67	1.60
3^{rd} payment	65.27	66.03	66.03	65.07	67.23	64.47
Last payment	60.60	62.50	62.00	60.90	63.53	60.27
3^{rd} and last payment	60.60	62.50	62.00	60.90	63.53	60.27
No payments	33.87	32.67	32.43	32.93	31.33	35.23

Table 8

Joint Incentives vs. Pure Incentives: Conditional Likelihood of Paying Off the Loan

This table presents the logit regressions of Table 5. The dependent variable is a dummy variable taking a value of 1 for borrowers who pay off the loan and 0 otherwise, conditional on the subset of borrowers who respond to the experiment (Last | (Response and 3^{rd} payment)). The bottom panel reports Wald tests for the equality of the estimated interaction terms. By design, all borrowers in the sample have a pending payment five days after the due date of the first installment of their first loan. Treatment is a moderate monetary incentive (D_{Mod}), a full monetary incentive (D_{Full}) and a social incentive (D_{Social}). Three treatment groups receive a pure incentive and two treatment groups receive the combination of a monetary incentive and the social incentive (see Table 3). Borrowers in the control group receive a plain ex-post reminder. Estimates are expressed as log odds ratios. *t*-statistics are in brackets. *p-values* associated with the F-test are in parentheses. Sample size is 18,000 borrowers. Groups are equal in size.

	(I)	(II)	(III)	(IV)
Intercept	-4.439	-4.439	-4.439	-4.439
	[-26.11]	[-26.11]	[-26.11]	[-26.11]
D_{Mod}	1.270		1.270	
	[6.56]		[6.56]	
D_{Full}	1.658		1.658	
	[8.86]		[8.86]	
D_{Social}	1.445	1.445		
	[7.59]	[7.59]		
$D_{Mod} * D_{Social}$	-0.969	0.301	0.475	1.745
	[-4.31]	[2.64]	[3.99]	[9.39]
$D_{Full} * D_{Social}$	-1.270	0.387	0.174	1.832
	[-5.83]	[3.46]	[1.64]	[9.92]
$H_0 : D_{Mod} * D_{Social} = D_{Full} * D_{Social}$				
F-stat	3.560	0.692	3.560	0.692
p-value	(0.059)	(0.406)	(0.059)	(0.406)

Table 9
On-time vs. Persistent Late Borrowers: Mean Difference Tests

This table presents mean difference tests for borrowers who repay and do not repay the third installment of the loan on time (Panel I) and borrowers who are solvent or "junk" at loan maturity (Panel II). "Junk" borrowers are those who do not respond to incentives and also do not make the third and the last payment on time. For each observable, the table reports the mean for each subset of borrowers, the difference in means (MD) and the t-statistic of the mean difference test. Observables are listed in Column I. All tests are conditional on borrowers who do not respond to incentives promptly.

	I: 3rd repayment | No response				II: At loan maturity | No response			
Observables	Repay	Do not repay	MD	t	Solvent	"Junk"	MD	t
Income	2763.43	2758.78	4.65	[0.16]	2764.89	2758.78	6.11	[0.21]
Loan size	3364.22	3374.42	-10.21	[-0.63]	3365.24	3374.42	-9.18	[-0.56
Product price	4174.18	4177.21	-3.02	[-0.14]	4173.76	4177.21	-3.45	[-0.16]
d-p	809.97	802.78	7.19	[0.58]	808.52	802.78	5.73	[0.45]
d-p/product price	17.65	17.49	0.15	[0.65]	17.62	17.49	0.13	[0.53]
d-p/monthly pay	2.65	2.60	0.05	[0.92]	2.64	2.60	0.04	[0.82]
d-p/loan size	0.27	0.27	0.00	[0.24]	0.27	0.27	0.00	[0.20]
d-p/income	0.35	0.35	0.00	[0.07]	0.35	0.35	0.00	[0.00]
Monthly pay	337.38	339.69	-2.30	[-1.24]	337.70	339.69	-1.99	[-1.06]
Monthly pay/income	0.15	0.15	0.00	[0.62]	0.15	0.15	0.00	[0.67]
Loan size/income	1.57	1.55	0.02	[0.68]	1.58	1.55	0.03	[0.72]
Produce price/income	1.92	1.90	0.02	[0.63]	1.92	1.90	0.03	[0.65]
Number of installments	14.34	14.28	0.06	[0.83]	14.33	14.28	0.05	[0.68]
Other mortgage pay	53.72	50.02	3.70	[1.24]	53.40	50.02	3.38	[1.12]
Other mortgage	0.14	0.13	0.01	[1.26]	0.14	0.13	0.01	[1.09]
Credit score = A	0.56	0.55	0.00	[0.41]	0.56	0.55	0.00	[0.44]
Male	0.70	0.70	0.00	[-0.29]	0.70	0.70	0.00	[-0.33]
Rural residence	0.63	0.63	0.00	[-0.30]	0.63	0.63	0.00	[-0.19]

Figure 1

Hold-out Group: Baseline Repayment Likelihood For Late Borrowers (Month 1)

This chart plots the daily repayment likelihood for the first installment of the loan for a random sample of 1,000 late borrowers, up to 30 days after the due date (i.e., day 0). Borrowers entered the sample on their first day of delay via daily random draws between June 30, 2013 and May 25, 2015. Borrowers in this sample did not receive any policy and were charged late fees from the fifth day of delay (i.e., "hold-out group"). All borrowers are low-risk for the platform, as they obtained top credit scores during the screening process. The dashed vertical line denotes the timing of the experiment (i.e., the fifth day of delay).

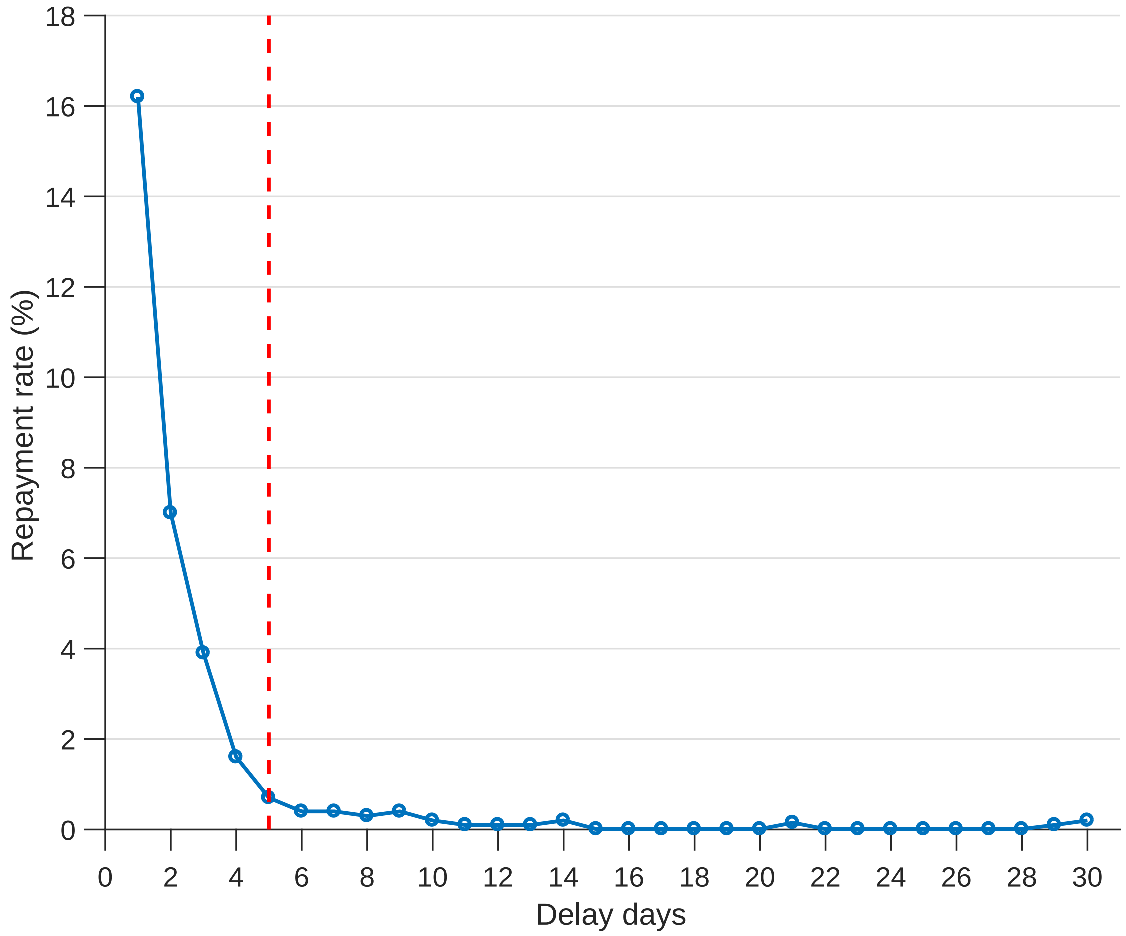


Figure 2
Repayment Likelihood by Policy

This chart reports the repayment likelihood for treatment groups and the control group over the 24-hour window of the experiment. Policies are: a plain ex-post reminder (control group), a moderate discount on the late fee (Mod, 50%), a full discount on the late fee (Full, 100%), a reputation-based incentive (Social), the combination of a moderate discount and the reputation-based incentive (Mod&Social), the combination of a full discount and the reputation-based incentive (Full&Social). The repayment likelihood for each group is reported at the top of each bar (in percent). All borrowers have a pending payment five days after the due date of the first installment of their first loan. Sample size is 18,000 borrowers. Groups are equal in size.

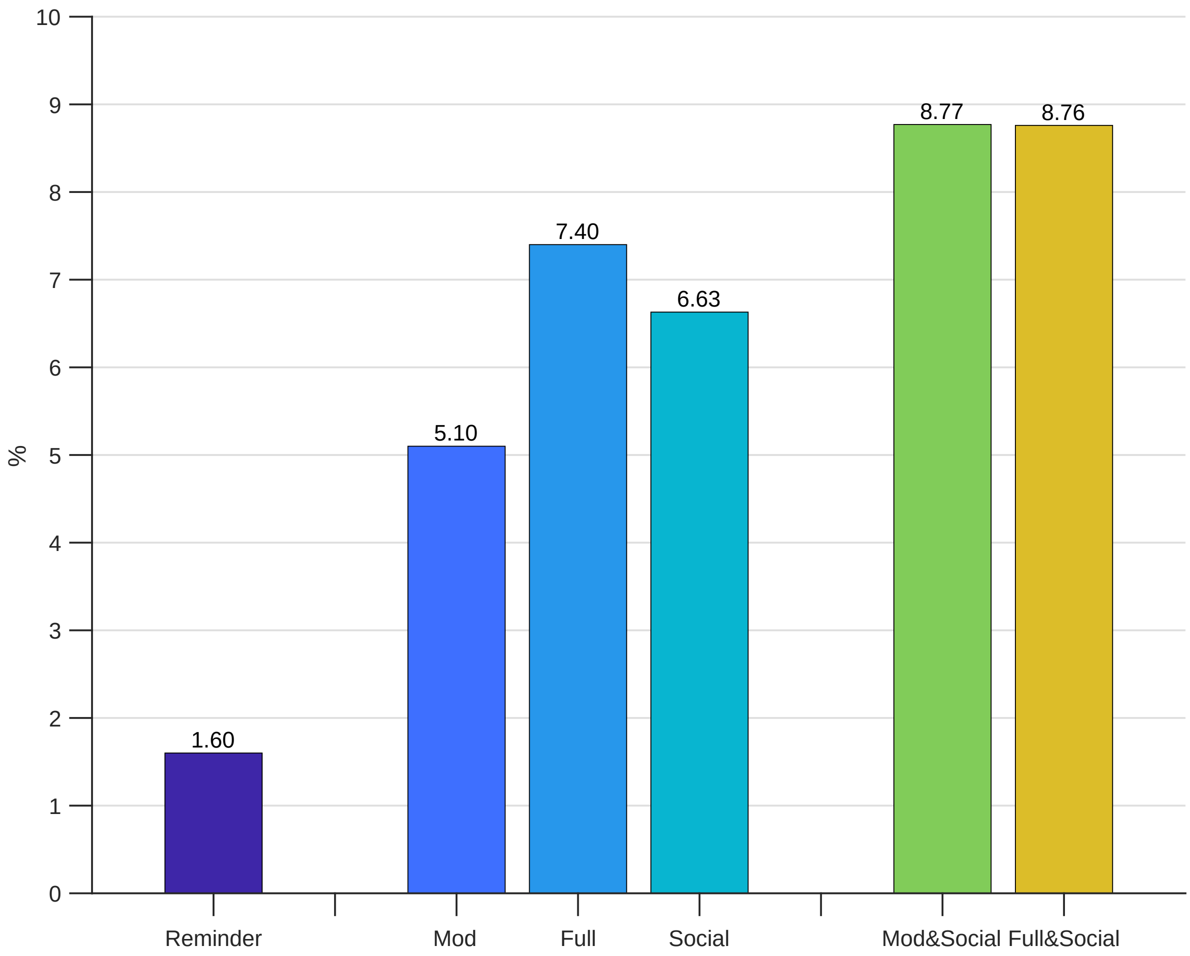
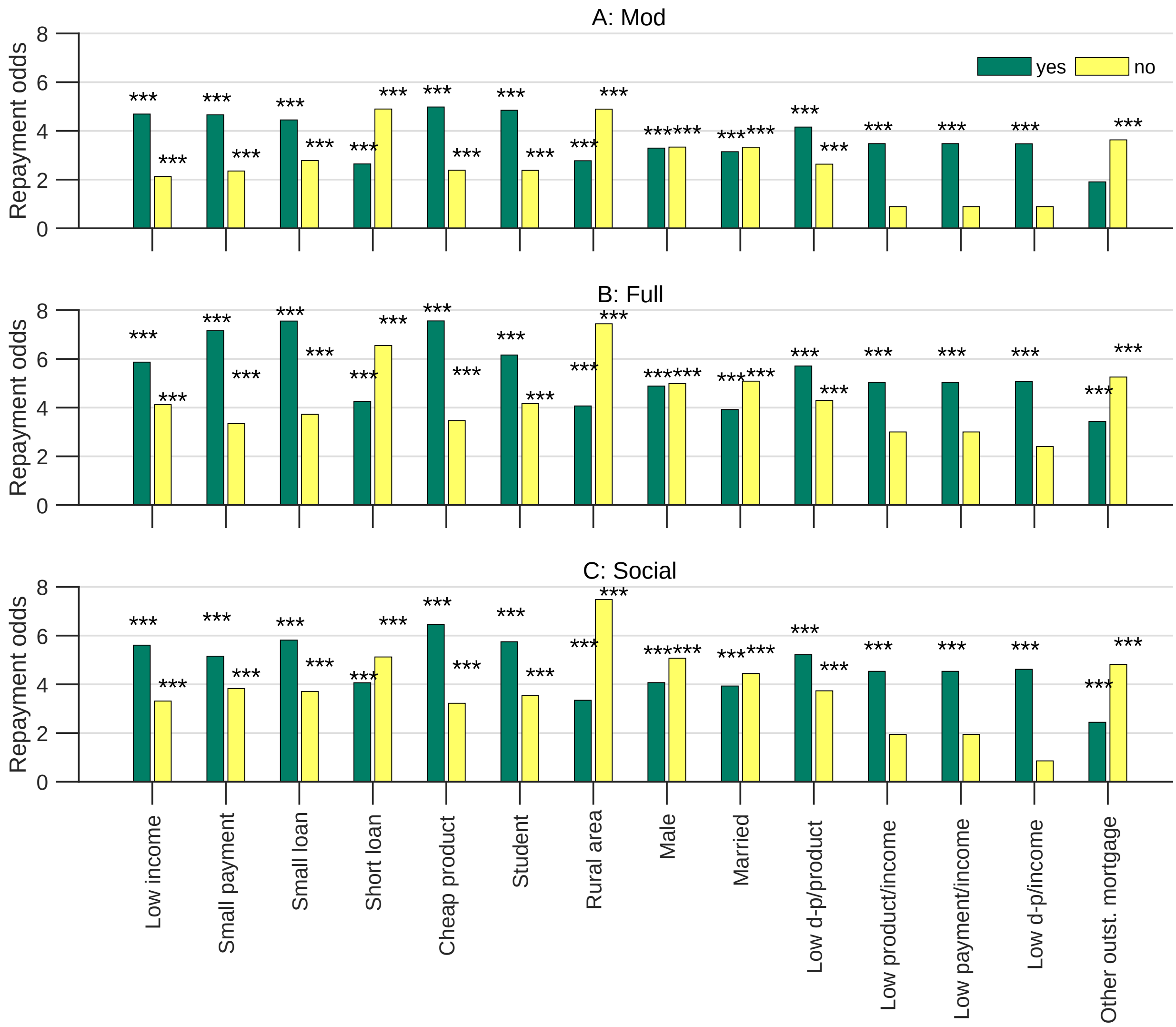


Figure 3

Repayment odds for pure incentives by covariates

This chart reports repayment odds for pure incentives over ex-post reminders by conditioning on a battery of demographic and loan characteristics. Incentives are a moderate monetary incentive (Mod, Panel A), a full monetary incentive (Full, Panel B) and a reputation-based incentive (Social, Panel C). Green (yellow) bars denote borrowers who exhibit the covariate of interest; the symbol *** indicates that the estimated impact is statistically significant at the 1% level.



A Appendix

Table A.1

Additional Randomization Checks

This table reports randomization checks for the variables used in Table 6 and not covered in Table 3. For each variable, the table presents the mean (μ) by group and the mean difference test for the difference in means between any given treatment group (T) and the control (C) group, that is $\mu^T - \mu^C$. t-statistics (t) are in brackets. The number of borrowers is 18,000. The size of each group is 3,000.

Monetary incentive	Social incentive	Stats	Highly educated	Bachelor	Associate	Small loan	Small payment	Short loan	High loan/income	Low Income	Low product/income	Outstanding 2^{nd} mortgage	Cheap product	Apple smartphone
No	No	μ^C	0.62	0.19	0.42	0.43	0.55	0.62	0.38	0.53	0.58	0.14	0.51	0.57
		μ^{T_1}	0.62	0.21	0.42	0.42	0.53	0.61	0.39	0.54	0.57	0.14	0.51	0.58
Moderate	No	$\mu^{T_1} - \mu^C$	0.01	0.02	-0.01	-0.01	-0.01	-0.01	0.00	0.00	-0.01	0.00	0.00	0.01
		t	[0.53]	[1.45]	[-0.65]	[-0.63]	[-1.04]	[-0.72]	[0.37]	[0.31]	[-0.86]	[0.30]	[-0.05]	[0.94]
		μ^{T_2}	0.63	0.20	0.43	0.43	0.54	0.62	0.40	0.55	0.56	0.13	0.52	0.56
Full	No	$\mu^{T_2} - \mu^C$	0.01	0.01	0.00	0.00	-0.01	0.00	0.01	0.02	-0.02	-0.01	0.01	-0.01
		t	[1.04]	[0.91]	[0.29]	[-0.10]	[-0.67]	[-0.05]	[1.14]	[1.45]	[-1.36]	[-0.76]	[0.39]	[-0.68]
		μ^{T_3}	0.62	0.19	0.43	0.43	0.56	0.61	0.38	0.54	0.57	0.13	0.51	0.57
No	Yes	$\mu^{T_3} - \mu^C$	0.01	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00
		t	[0.45]	[0.23]	[0.26]	[-0.26]	[0.80]	[-0.32]	[0.03]	[0.91]	[-0.21]	[-0.19]	[0.15]	[0.08]
		μ^{T_4}	0.62	0.21	0.42	0.43	0.55	0.61	0.38	0.53	0.57	0.13	0.51	0.57
Moderate	Yes	$\mu^{T_4} - \mu^C$	0.01	0.02	-0.01	0.00	0.00	-0.01	0.00	0.00	0.00	-0.01	0.00	0.00
		t	[0.64]	[1.68]	[-0.73]	[-0.16]	[0.29]	[-0.40]	[-0.16]	[-0.36]	[-0.18]	[-0.88]	[0.13]	[-0.36]
		μ^{T_5}	0.61	0.19	0.42	0.42	0.53	0.61	0.37	0.53	0.57	0.14	0.51	0.58
Full	Yes	$\mu^{T_5} - \mu^C$	0.00	0.00	-0.01	-0.01	-0.02	-0.01	-0.01	0.00	-0.01	0.01	0.00	0.00
		t	[-0.27]	[0.29]	[-0.50]	[-0.57]	[-1.24]	[-0.53]	[-0.64]	[-0.36]	[-0.60]	[1.04]	[0.08]	[0.34]

Table A.2

Balance Tests: Hold-out Group vs. Experimental Sample

This table reports balance tests for the hold-out group (HH) against the experimental sample (ES). For each covariate, the table presents the sample means (μ), the mean difference test for the difference in means between the two samples ($\mu^{HH} - \mu^{ES}$) and the associated t-statistic (t).

Covariate	μ^{HH}	μ^{ES}	$\mu^{HH} - \mu^{ES}$	t
Age	23.17	23.20	0.03	0.18
Education	2.58	2.56	-0.02	-0.49
Income	2687.90	2651.51	-36.39	-0.72
Male	0.71	0.70	-0.01	-0.34
Married	0.15	0.15	0.00	0.00
Rural residence	0.63	0.63	0.00	-0.22
Student	0.46	0.46	0.00	0.17
Loan size	3365.76	3367.42	1.66	0.05
Monthly payment	338.30	338.34	0.04	0.01
Down payment (dp)	809.30	806.74	-2.56	-0.11
Number of installments	14.23	14.31	0.08	0.55
Product price	4175.06	4174.16	-0.90	-0.02
Other mortgage	0.20	0.22	0.02	1.19
Loan size/income	1.54	1.56	0.03	0.75
Product price/income	1.88	1.91	0.03	0.70
Monthly payment/income	0.15	0.15	0.00	0.78
Down payment/product price	0.18	0.18	0.00	-0.40
Down payment/income	0.34	0.35	0.00	0.14
Down payment/Monthly payment	2.61	2.62	0.01	0.09
Loan's purchase	3.18	3.13	-0.05	-1.28