Prosocial Compliance in P2P Lending: A Natural Field Experiment

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Abstract

We implement behavioral mechanisms in a natural field experiment to increase loan repayment rates on a peer-to-peer (P2P) lending website. The results show that text message reminders that convey lenders' positive expectations considerably increase the likelihood that borrowers will repay their loans, whereas reminders emphasizing the adverse consequences of failure to repay loans do not have enduring effects. Our experiment results in an increase in loan repayments in the sample period. In addition, our reminders are cost-free to implement, demonstrating the potential importance of such interventions in enhancing prosocial compliance in P2P lending.

Keywords: Natural Field Experiment, P2P Lending, Prosocial Compliance

JEL Codes: C93, D02, D03, G21.

1. Introduction

Efficiency in bilateral economic relationships is often hampered by moral hazard problems, in which one party in a transaction can perform hidden actions to further their own interests at the price of harming the other party. Moral hazard problems have numerous substantial practical implications. In product markets, such situations include e-commerce fraud; in factor markets, examples include credit default in financial markets and the principal–agent problem in labor markets.

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Imperfect monitoring and transaction costs often render the use of conventional court-enforced solutions to moral hazard problems unfeasible. Moreover, studies have indicated that these conventional (court-enforced) solutions are not only costly but also ineffective because conventional solutions may have a negative impact on one's motivation.[2] Therefore, as alternatives to conventional solutions, recent studies on behavioral economics have focused on developing behavioral mechanisms to mitigate the moral hazard problem; these include abiding by social norms, setting effective examples through social comparison, using reframing techniques in reminders, and reminding opposite parties of potential consequences (Hallsworth et al., 2015; Lu et al., 2016; Chen et al., 2017).

In this study, we implement several behavioral mechanisms in a natural field experiment to alleviate the moral hazard problem. The experiment is conducted on a peer-to-peer (P2P) lending platform. P2P lending, a disruptive innovation in the financial industry, is booming because it is a convenient means of addressing the financing needs of small firms and individuals.[3,4] Similar to conventional financial markets, credit risk is a challenge encountered in P2P markets, although progress in Internet technology has enabled more convenient, efficient, and transparent matching processes for lenders and borrowers on P2P platforms. The risk of default may be higher on P2P platforms than in conventional credit markets, where borrowers must provide collateral to obtain loans (Stiglitz and Weiss, 1981; Freedman and Jin, 2016). Thus, mitigating borrower moral hazard is a salient concern in P2P lending. Because most behavioral mechanisms are cost-free and easy to implement, establishing effective behavioral mechanisms on P2P platforms is a practical means of reducing credit risk.

The first behavioral mechanism examined in this study is whether conveying lenders' *positive expectations* for repayment increases borrower repayment in P2P lending. According to the guilt aversion literature, people are concerned about what others expect of them, and they feel guilty if their behavior

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[2] See Falk and Kosfeld (2006), Fehr and Rockenbach (2003), and Fehr et al. (2007).

[3] Morgan Stanley forecasted that the global P2P lending market will grow to US$490 billion by 2020, with a compound annual growth rate of approximately 50% (Morgan Stanley, 2015).

[4] China's P2P lending market is the largest and the most vibrant in the world, with more than 4,000 providers operating in the market as of September 2016. This number has continued to increase, reaching 5,900 by July 2017, according to wangdaizhijia: http://shuju.wdzj.com/industry-list.html (accessed on August 7, 2017).

falls short of these expectations.[5] Along with guilt aversion, communication may influence people's motivation and behavior by influencing their beliefs about beliefs.[6] Charness and Dufwenberg (2006) experimentally examined the impact of communication on trust and cooperation with hidden action. The evidence is consistent: people strive to meet others' expectations to avoid feelings of guilt.[7] Both behavioral economic theory and laboratory experiments have demonstrated that conveying positive expectations through *ex ante* communications influences behavior in transactions; however, to the best of our knowledge, this behavioral mechanism remains untested in real-world business practice.[8,9]

The second behavioral mechanism examined in our study is whether reminding the borrowers of the *adverse consequences* of failing to repay their debts increases repayments in P2P lending. The consequence-deterring mechanism typically reinforces the adverse consequences that borrowers must bear if their bilateral economic relationships with lenders deteriorate. Much financial compliance research has indicated that issuing threatening reminders to borrowers can increase compliance immediately (Perez-Truglia and Troiano, 2015; Luo et al., 2017). Nonetheless, the adverse consequence mechanism may lead to a feeling of distrust (Falk and Kosfeld 2006), which in turn suppress a borrower's intrinsic motivation for proper conduct and prosocial behavior (Benabou and Tirole, 2006; Falk and Kosfeld, 2006; Fehr and Rockenbach, 2003; and Fehr et al., 2007). Furthermore, the psychological literature has suggested that the fear of potential adverse consequences only matters in the short run (Verduyn and Lavrijsen, 2015; Verduyn et al., 2012). Thus, its effectiveness in regulating human behavior is controversial and understanding it requires more comprehensive and systematic investigation.

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[5] See Baumeister, Stillwell, and Heatherton (1994).

[6] See Battigalli and Dufwenberg (2007).

[7] In this treatment, we issued reminders to add a psychological cost of default to induce compliance. As mentioned in Crockett et al. (2014), Adam Smith argued that the "indelible stain" of guilt is worse than pain in *The Theory of Moral Sentiments* (Smith,1759), and it is common to observe that people dislike causing outcomes that negatively affect others (Kahneman, 2013).

[8] In our paper, "*ex ante* communication" refers to communication that occurred *before* borrowers defaulted, and "*ex post* communication" refers to communication that occurred *after* borrowers defaulted. In our experiment, the website confirms a default 2 months after the final installment's due date as indicated in figure 1. All our experiment observations were made prior to confirmation of default by the P2P platform, so all our reminders in the treatments were *ex ante* communications.

[9] Numerous previous studies have examined how cheap-talk communication raises efficiency in bilateral contracting situations. In addition to Charness and Dufwenberg (2006), examples include Charness and Dufwenberg (2011) and Goeree and Zhang (2014).

Third, we investigate whether *revealing information* of lenders increases the likelihood of borrower repayment. According to Gneezy (2005), people are sensitive to the saliency of harm caused by cheating when deciding whether to cheat. Hurkens and Kartik (2009) also found that people take the harm of a lie to others into account. However, Fischbacher and Föllmi-Heusi (2011) conducted a series of experiments and found that liars and partial lying persist even when stakes, consequences, or anonymity are altered. Thus, it is unclear whether saliency of harm would work in naturally occurring markets.[10] In our case, we conjecture that revealing individual lenders' information may increase the perception of harm caused by cheating compared with when P2P platform information is revealed, given that the platform can bear more losses than the individuals who lend through the platform. Thus, revealing information about individual lenders may lead to a higher likelihood of borrower repayment. In the treatment, we reveal a lender's last name to the borrowers and demonstrate that it is a person, rather than a group of people, who lent them the money; thus, if a borrower defaults, he knows that he is harming a person, not a group of people.[11]

We conducted the experiment between May 2016 and February 2017; we collected a panel dataset of 2,012 loan applicants and their repayment behavior over 10 months. Because the lending website already had a system to send reminder messages before loan repayment due dates, we embedded the behavioral mechanisms into the reminder messages as informal interventions. We designed a 2 × 3 field experiment in which one dimension was the variation in the message content (neutral, positive expectations, or adverse consequences) and the other dimension was whether the lender's identity was revealed. We found that (1) the messages conveying lenders' positive expectations considerably increased the likelihood of borrowers repaying their loans; (2) the messages emphasizing the adverse consequences for those who failed to repay their loans only increased the repayments in the short run (the first month's installment), whereas this effect declines in the long run (the remaining installments); and (3) revealing the lender's

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[10] Another justification of this design is related to the literature on social distance, for example, Hoffman et al. (1996) found that social distance reduces cooperation.

[11] Crockett et al. (2014) conducted a field experiment by pairing subjects with other individuals and found that most people value others' pain more than their own pain.

identity had no impact on whether the borrower repaid the loan. Our experiments resulted in greater adherence to repayment plans in the sample period, and our reminders were cost-free to implement, demonstrating the value of such interventions in enhancing prosocial compliance in P2P lending.

Our paper has three contributions to the literature: (1) This study probably is among the first to empirically analyze and investigate the effectiveness of different behavioral compliance mechanisms on a large online P2P platform. (2) This paper provides tangible empirical evidence of the power of content of text message reminders and reveals that positive expectation messages are more effective than adverse consequence messages. This provides additional evidence of let-down-aversion and guilt aversion behavior in naturally occurring markets.[12] In contrast to the findings of other financial compliance studies, indicating that threatening reminders increase repayment compliance, we found that adverse consequence messages have no significant enduring effect on repayment compliance; nevertheless, adverse consequence messages have immediate effects.[13] This result may provide a potential explanation for the mixed findings of prior studies on adverse deterrence and may also suggest a direction for future research. (3) This paper contributes to the growing market design literature with respect to inducing compliance, proper conduct, and prosocial behavior.

The paper is structured as follows: Section 2 summarizes the relevant literature, Section 3 outlines our hypotheses, Section 4 describes the experimental design and data collection method, Section 5 presents our analysis and results, and finally, Section 6 states our conclusion and discusses some study limitations.

2. Literature Review

Our experiment was based on the knowledge that *ex ante* behavioral communications affect people's

[12] See Gneezy (2005), Charness and Dufwenberg (2006), and Battigalli and Dufwenberg (2007).

[13] Andreoni (2010) conducted experiments on public goods using positive and negative framing and found that subjects are more willing to cooperate when the externality is positive. Gerber and Rogers (2009) found that messages emphasizing high expected turnout are more effective at motivating voters than messages that emphasizing low expected turnout.

behavior.[14] This section discusses the theoretical and experimental literature on this topic.

An increasing number of studies have explored behavioral mechanism implementation to enforce prosocial compliance, such as compliance with law and traffic regulations. For instance, Apesteguia et al. (2013) conducted field experiments on all public libraries in Barcelona and found that users return items earlier after they receive simple emails asking them to do so. Furthermore, the authors found that adding other content to this simple email does not significantly increase compliance. Fellner et al. (2013) conducted a large-scale natural field experiment in Austria by sending mail to potential evaders of television license fees. The researchers included different content in these mailed letters and found that legal threats, but not moral appeals, significantly increase compliance rates. Lu et al. (2016) and Chen et al. (2017) each conducted a large-scale field experiment, in which text messages were sent from the police department to motorists in China. Lu et al. (2016) reported that drivers who receive personalized messages about their traffic tickets committed fewer violations in the subsequent month. Chen et al. (2017) conducted a large-scale field experiment by sending text messages containing different types of social information to drivers and found that drivers reduced future violations after receiving information on the driving behavior of motorists similar to themselves and the driving behavior of motorists with high-status cars.[15]

In terms of behavioral mechanisms for mitigating moral hazard in finance, several studies have used text messages to enforce financial compliance in various fields, including microloan repayment, consumer debt collection, credit card repayment, other debt repayment, and tax compliance. Typically, three types of messages have been used in *ex ante* behavioral communications: informational, positive, and deterrent.

[14] Conventionally, the term "*ex ante*" communication in the economics literature indicates communication that happens before any economic agent takes an action. By contrast, "*ex post*" communication happens after allocations are determined, and the economic agents' actions cannot be altered after such communication. In our study, the action that divides "*ex ante*" and "*ex post*" is the website's confirmation that a loan has defaulted, as explained in footnote 7.

[15] Several other papers have also studied compliance issues in transportation. For example, Dai et al. (forthcoming) conducted an artifactual field experiment using a diversified sample of public transportation passengers and found that simple tests of dishonesty in the lab can predict moral firmness in real life.

Informational messages typically provide information about the minimal due amount and the due date. Cadena and Schoar (2011) conducted a field experiment with a microlender (a bank) in Uganda and found that its effect on repayment rates of sending simple reminder messages 3 days before the loans' due date is similar to that of reducing the cost of the loans by 25%. Karlan et al. (2016) performed field experiments with three banks and found that text messages increase savings deposits among microfinance clients. Pekonen (2014) executed a field experiment in cooperation with a Nordic debt collection agency in which 11,949 short message service reminders were randomly sent to debtors in Finland. The results revealed that text message reminders improved the rate of debt repayment by 3.7 percentage points.

Positive messages contain moral appeals, moral norms, and social connections. Bursztyn et al. (2015) performed a field experiment by sending moral appeal reminders to encourage credit card repayment. Karlan et al. (2015) conducted experiments with microlenders by sending text message reminders about loan repayments; the authors determined that messages that include the account officer's name significantly improve repayment rates. Hallsworth et al. (2014) conducted field experiments and found that including social norms and public goods messages in standard tax payment reminder letters increased tax compliance.

Negative messages contain legal threats, financial penalty warnings, and social pressure. Numerous financial compliance studies have determined that threat reminders can increase compliance. For example, Luo et al. (2017) demonstrated that sending social pressure messages facilitates consumer debt collection. Slemrod et al. (2001) reported the findings of a large-scale field experiment performed by the Minnesota Department of Revenue; the authors found that sending letters warning taxpayers of an increased probability of an audit significantly increased the number of tax returns submitted by low- and middle-income taxpayers, but it had a counterproductive effect on the high-income group. Kleven et al. (2011) obtained similar results from a large-scale experiment by the Danish Inland Revenue Department. However, negative messages may be ineffective, as revealed by several studies. For instance, Wenzel and Taylor (2004) oversaw a large controlled experiment in Australia in which letters of varying content with tax-reporting schedules were sent and found that a mere warning letter achieved no reduction in deduction claims. Employing social pressure penalties may backfire because such penalties may provoke anger or hostility in the recipients (Woodyatt, 2015).

Although the aforementioned research has revealed that specific types of reminder message may be effective in some financial situations, Karlan et al. (2015) argued, "studies have devoted relatively little focus to the influence of content, timing, and other mechanics of such communications." Thus, here, we integrate all three of the aforementioned types of message into one experiment, enabling the comparison of each mechanism's effectiveness. Specifically, in our experiment on the positive expectation treatment, for which we are motivated by guilt aversion research, our messages to borrowers state that lenders expect repayment and strive to invoke guilt aversion and let-down aversion among the borrowers. In our experiment, the adverse consequence treatment explicitly emphasizes the certainty of adverse consequences if a borrower does not repay their debt. This may increase compliance, as suggested by the literature on criminal deterrence (Becker, 1968), or suppress a borrower's intrinsic motivation for proper conduct and prosocial behavior (Benabou and Tirole, 2006; Falk and Kosfeld, 2006; Fehr and Rockenbach, 2003; Fehr et al., 2007).

In addition to *ex ante* communication mechanisms, studies have focused on *ex post* mechanisms that manipulate the content of reminders to induce financial compliance. For instance, Perez-Truglia and Troiano (2015) conducted field experiments by sending letters to tax-delinquent individuals in three US states and ascertained that increasing the salience of financial and shaming penalties reduces tax delinquency overall but that the effects of shaming penalties are only significant for individuals with smaller debts. The evidence on whether framing manipulation has critical economic effects in naturally occurring markets was unknown, until 2015, when Hallsworth et al. conducted a field experiment to increase debt repayment by releasing reminder letters where "omission" was replaced by "commission." This change nearly doubled the repayment rates. Our study is similar to this experiment; in that, we manipulate the content of reminders to induce compliance. However, unlike the *ex post* mechanisms used by Hallsworth et al. (2015), we design and implement *ex ante* mechanisms: we sent reminders *before* the borrowers had defaulted; by contrast, Hallsworth et al. (2015) sent reminders sent *after* the payments were overdue.[16]

Several field experiments have investigated microlenders[17]; however, to the best of our knowledge, no field experiments have been conducted on a commercial P2P lending platform on which private individuals fund loans. Using data from Prosper.com or LendingClub.com, empirical studies have mainly focused on factors, such as those affecting loan approvals or contracted interest rates,[18] those more accurately predicting credit risk, and those related to obtaining loans and repayment.[19] By contrast, relatively few studies have designed and implemented behavioral mechanisms to improve borrowers' repayment behavior on P2P platforms. This study attempts to fill in this gap and elucidates the mechanisms underlying the effects of reminders and thus provides a positive contribution to industry financial compliance practices. Our study not only reveals that a simple text reminder can increase compliance in P2P lending markets but also the type of message content that more effectively increases compliance.

3. Behavioral Hypotheses

Although compliance has been discussed extensively, behavioral mechanisms for inducing

[16] Another excellent example of *ex post* behavioral communication is approval/disapproval messages. Given that economic agents know that they will receive nonmonetary approval/disapproval messages conditional on their economic performance, their economic performance could be affected by different evaluation protocols. Examples include performance evaluation in public good games (Masclet et al., 2003), coordination games (Dugar, 2010), gift-exchange games (Du and Shahriar, 2018), and approval/disapproval from the receiver to the sender in dictator games (Ellingsen and Johannesson, 2008; Xiao and Houser, 2009).

[17] For example, Ai et al. (2016) demonstrated that team membership increases participation and lending for a charitable crowd-lending community, Kiva.

[18] For instance, Ravina (2008) found that appearance matters; Herzenstein et al. (2011b), Larrimore et al. (2011) found that descriptions for the loan application have positive effects on loan approval rates.

[19] For instance, Duarte et al. (2012) found that gender and race are related to delinquency; Pop and Sydnor (2011) also found that race matters in repayment behavior; Gao and Lin (2014) found that borrowers' linguistic features are related to delinquency. Freedman and Jin (2008), and Lin et al. (2013) revealed that borrowers' social networks are related to obtaining loans and repayment behavior. Krumme and Herrero (2009), Herzenstein et al. (2011a), Zhang and Liu (2015) have demonstrated the existence of herding effects in online P2P lending using data from Prosper.com. In more recent work published in Management Science, Lin and Viswanathan (2015) found evidence that home bias exists in Prosper.com; and Wei and Lin (2016) compared the effects of different pricing mechanisms (i.e., posted prices and auctions) in online P2P lending through a game-theory model and empirical analysis, also using data from Prosper.com.

compliance are relatively new concepts requiring further elucidation. In our paper, we designed an easy-to-implement mechanism for a P2P marketplace that does not disrupt the existing platform. Because the platform already sent reminder messages to borrowers before loan repayment due dates, we believed that simply changing the reminder message may effectively induce compliance. Thus, we designed the following three treatments:

The first mechanism is positive expectation. According to psychological studies, such as Baumeister, Stillwell and Heatherton (1994), "if people feel guilt for hurting their partners … and for failing to live up to their expectations, they will alter their behavior (to avoid guilt)." Both theory (Battigalli and Dufwenberg, 2007) and laboratory experiments (Charness and Dufwenberg, 2006) have indicated that trustees are more likely to show their trustworthiness if they believe that the trustors expect them to behave trustworthily.[20] Therefore, we propose the first hypotheses as follows:

<u>Behavioral Hypothesis I (H1):</u> *In P2P lending, sending the borrowers messages conveying lenders' positive expectations regarding repayment increases the likelihood that the loans will be repaid.*

The second mechanism is adverse consequences. According to the studies on crime deterrence and behavioral compliance, messages warning the borrowers of adverse consequences (e.g., legal or social penalties) are effective at inducing compliance (Becker, 1968). Fellner et al. (2013) determined that a legal threat stressing a high detection risk has a significant and highly robust deterrent effect. Perez-Truglia and Troiano (2015) and Luo et al. (2017) have ascertained that messages exerting social pressure induce compliance. Slemrod et al. (2001) and Kleven et al. (2011) have found that letters warning of a high probability of audit induce tax reporting compliance in low- and middle-income individuals. Therefore, we propose the second hypotheses as follows:

[20] Notice that guilt aversion is not a unique behavioral model, which is consistent with "positive expectation" messages. Other alternative behavioral models include image scoring (Nowak and Sigmund, 1998), preference for promise-keeping (Vanberg, 2008), and sequential reciprocity (Dufwenberg and Kirchsteiger, 2004). The main purpose of the "positive expectation" message is to increase the saliency of the borrower's psychological burden when the borrower deviates from the target behavior "to repay on time." Identifying the behavioral models behind this effect is left for future laboratory experiments.

<u>Behavioral Hypothesis II (H2):</u> *In P2P lending, sending the borrowers messages that emphasize the adverse consequences of failure to repay their loans increases the likelihood that the loans will be repaid.*

Furthermore, both life experience and the psychological literature have revealed that one's psychological burden matters in the long run, whereas their fear of potential adverse consequences only matters in the short run (Verduyn and Lavrijsen, 2015; Verduyn et al. 2012).[21] Verduyn and Lavrijsen (2015) examined variability in duration between 27 emotions and found that fear was a shortest duration emotion.

In the psychological guilt aversion literature, when a borrower deviates from the target behavior of "repaying on time," the feeling of failure to meet the "positive expectation" leads to a strong psychological burden, which may have a long-term effect. By contrast, adverse consequence messages only matter in the short run because the resulting feeling of fear lasts only temporarily. We thus formulate the following behavioral hypothesis:

<u>Behavioral Hypothesis III (H3):</u> *In P2P lending, sending the borrowers messages that emphasize the adverse consequences of failure to repay their loans increases the likelihood that the loans will be repaid only in the short run, whereas sending the borrowers messages conveying lenders' positive expectations increases the likelihood that the loans will be repaid both in the short run and in the long run.*

The third mechanism is information revealing of individual lenders. In both theoretical and empirical studies, researchers have found that people's behavior is affected by salience of information revealing. For example, Akerlof (1991) highlighted the critical role of salience for explaining procrastination, and Bordalo, Gennaioli, and Shleifer (2013) developed a theory by considering salience as a driver of consumer choice. Bursztyn et al. (2015) found that rendering moral considerations salient has subtle but powerful effects for inducing compliance in credit card repayment. Karlan et al. (2016) determined that reminders increase savings by making future expenses more salient. In our study, we emphasized saliency

[21] The enduring effect is not only studied in psychology, but also in political studies. For example, Davenport et al. (2010) examined the enduring effects of social pressure to increase voter turnout.

of harm by revealing the identity of the matched lenders to the borrowers. According to Gneezy (2005), people are sensitive to the saliency of harm caused by cheating when deciding whether to cheat. However, other studies have indicated that salience may be ineffective; for instance, Fellner et al. (2013), Blumenthal et al. (2001), and Wenzel and Taylor (2004) have found that rendering a moral appeal salient does not affect compliance behavior. Therefore, herein, we empirically investigate the effects of saliency of harm by manipulating the information-revealing condition. In our case, we propose that the perceived harm caused by cheating individual lenders may be higher than that of cheating P2P platforms, given that such platforms would likely be seen by borrowers as more able to bear losses than most individuals. Thus, revealing lenders' information may increase the perceived harm of cheating and thus lead to higher repayment rates.[22] This is hypothesized as follows:

Behavioral Hypothesis IV (H4): In P2P lending, borrowers are more likely to repay their loans if the identity of the individual lender is revealed.

4. Experimental Design

Many small firms have no or limited access to formal financial services. CreditEase (2011) revealed that only 30% of small firms in China apply for bank loans, and only half of such small business loan applicants receive loan approvals. Thus, informal networks, such as Internet P2P lending, have become key credit providers since 2010. According to Chinanews.com (2013), mainland China has more than 500 microfinancing websites and Internet P2P loans amounting to more than 25 billion RMB had been granted as of June 2013.

[22] In addition to the saliency of harm interpretation, revealing the lender's identity also creates the potential for social sanctions conditional on future interactions, which may effectively curtail socially undesirable behavior, as previous examinations of the effect of social distance and anonymity have suggested (e.g. Hoffman et al., 1994; Hoffman et al., 1996). Prior studies have provided evidence that revealing counterparty identity induces individuals to converge to social norms such as fairness in the Dictator Game (e.g., Bohnet and Frey, 1999) and contributions in a Voluntary Contribution Game (e.g., Kachelmeier and Shehata, 1997). Because laboratory experiments are more appropriate for direct theory testing, different behavioral sources behind identity-revealing treatments may be identified in future studies.

4.1 Experiment Background

We conducted our experiments on a medium-sized P2P lending website in China. This website provides loans to more than 20,000 borrowers and has accumulated transaction volume of more than 200 million RMB. The website's borrowers are postsecondary students from all over China, most of whom are college and university students. Nonetheless, the purpose of their P2P loans is not college tuition, as Chinese college tuition is much more affordable than most other countries. The self-reported loan purposes include travel, high-value consumption (e.g., purchasing iPhones), small business startup funding, wedding, and rent payment. The college student microloan market is very large in China because college students are typically ineligible to apply for credit cards and only receive very low credit lines even if their application is approved.

During our experiment, the platform used only the firm owner's and four managers' money for lending. We argue that the small number of lenders should not be a concern for borrowers because the borrowers and lenders could not contact each other during the lending process. The borrowers only knew that this was one-to-one lending and that their loans were from someone who had invested in the website.[23] An advantage of this setting is that it enabled the inclusion of both reveal and not-to-reveal treatments in our experimental design.

All loans approved by the focal platform during May 1 – 31, 2016, were included in our experiment. To apply for a loan, potential borrowers needed to provide information including a copy of their national identification cards and details of themselves and their contact persons. To authenticate the information provided, an operator spoke with the applicant through an online video call. Once approved, the borrower could select the loan amount and the term of installments t. In our data set, the loan size ranged from 500 to 4,500 RMB, with an average of 2,945 RMB;[24] t ranged from 1 to 7 months, with an

[23] In addition to one-to-one lending, in practice microfinance programs also provide credit through crowd lending (Ai et al. 2016) and liability group lending (Hermes and Lensink, 2007).

[24] The average monthly expenditure of a typical college student in China is approximately 1,500–3,000RMB. Because each loan is small and the monthly repayment amount is only approximately 600RMB for a 3,000RMB loan, it is feasible for students to repay if they can obtain a subsidy from their family in time, or if they have part-time job income or scholarships.

average of 6.36 months; and annual interest rate of each loan was 16% or 17%. The website provided loans with the 16% rate up to May 13, and loans extended subsequently carried the 17% rate. Because the website did not announce that it would increase the interest rate after May 13, the borrowers had no incentive to apply earlier to obtain a lower rate. In China, the annual interest rate of credit cards is approximately 13%. The mortgage rate from major banks is approximately 6%–9%. The website's 16%–17% rate is thus higher than the market bank interest rates, which offsets the risk linked to the higher estimated default probability of microlending (Bhaduri, 1977). Microlending borrowers typically lack collateral and steady employment and verifiable credit histories; thus, for them, borrowing money from banks or other formal financial organizations is difficult. P2P borrowing is among their most optimal alternatives when in need for money.

On the platform used in our study, borrowers are asked to repay the same amount of the required monthly installment for t months based on their loan's annual interest rate, size, and term of installments. The first installment is due 1 month after the loan is received. Once the borrower repays the installment, paying an amount other than the required amount is not allowed. If the borrower defaults (the website confirms default at 2 months after the final installment's due date), the website randomly assigns the case to an operator. The operator decides how to handle the defaulted loan. Potential methods of handling defaulted loans include calling the borrower or the borrower's contact person. Borrowers who default might be sued by the website with a certain probability, and they would be recorded in a shared blacklist. The blacklist is maintained by the website and several other P2P lending platforms. Once on the blacklist, the borrower will never obtain another loan from these P2P lending companies.

4.2 Treatment Design

In our experiment, the website sent three reminder text messages to borrowers' cellphones, as illustrated in Figure 1. For all loan applications approved during May 1–31, the platform sent out the first message immediately after the loan was approved, the second on a day prior to the first due date, and the last at 30 days after the final due date if the loan remained unpaid at that time. In other words, all loan recipients received at least two messages, and only those who had not paid off their loans 30 days after the final due date received a third message. The observation period of our data set was May 1, 2016, to February 17, 2017 (approximately 9.5 months) because the longest term for a loan on this platform is 7 months, and the website only confirms bad debt (i.e., default) 2 months after the final installment's due date. Thus, the repayment process may continue for more than 9 months. In our case, the last installment due date of our observed loans was December 12, 2016. Our observation period, which ended on February 17, 2017, was sufficient to capture the entire repayment process and payoff behavior of the studied loans.

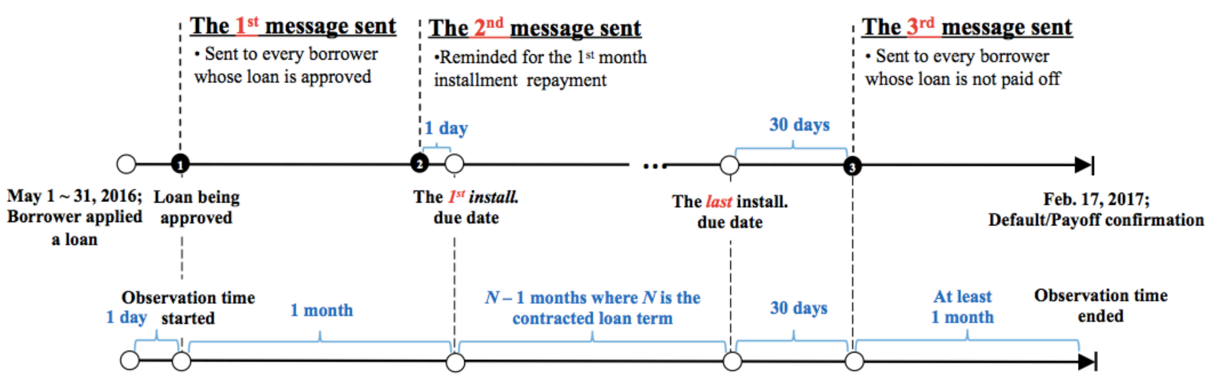

Figure 1. Timeline of experimental intervention

This study varied the content of the messages sent to the borrowers. To investigate our behavioral hypotheses, we implemented a 2 × 3 design in our experiments, in which two factors were varied: (1) whether the identity of the lender was revealed in the message and (2) whether the message sent to the borrower included the lender's positive expectation or the adverse consequences of not repaying on time.[25] In total, 2,012 loans to 2,012 individuals from 1,539 colleges (the maximal number of individuals attending the same college was 45) were randomly assigned to the six treatments (Table 1). The borrowers did not know that they were participating in the experiment.

Table 1. Treatments

[25] Before experiments intervention, the website by default sent neutral reminder messages to the borrowers without revealing the lender identity.

		The content of messages		
		Neutral	*Positive Expectation*	*Adverse Consequences*
The identity of the investor	*Reveal*	362 obs.	331 obs.	341 obs.
	Not to Reveal	332 obs.	331 obs.	315 obs.

The original messages were in Chinese (see Table 2 for the translated messages). The neutral messages were neutral reminders. During the term of a loan, the three reminder text messages sent by the website notified the borrower that the loan had been approved, that the first due date was approaching, and that the debt was so far unpaid. Positive expectation messages included the lenders' positive expectations concerning repayment. Immediately after the loan was approved, the borrower was told, "The lender is helping you when you are in need. Meanwhile, the lender trusts you and anticipates that you will repay the loan on time as you have promised." Before the first due date, the borrower was told, "the lender believes that you will do what you promised, so don't let the lender down." Finally, 30 days after the last due date, if they had not yet paid off the loan, the borrower was told, "Please don't fail to live up to the lender's trust." The adverse consequences messages described the adverse consequences of not repaying on time. Immediately after loan approval, the borrower was told, "If you do not repay your loan on time, on behalf of the lender, the website will press you to repay, inform your contact person, and retain the right to resort to legal measures." Before the first due date, the borrower was told, "Once again, this is to remind you to repay your loan on time. If you do not, on behalf of the lender, the website will take actions to oblige you to repay your loan." Finally, if a borrower had failed to repay 30 days after the last due date, the borrower was warned "This is your final reminder. … If you fail to repay your loan, on behalf of the lender, the website will take legal action to oblige you to repay your loan."[26]

To test the information revealing hypothesis, under the reveal condition, the lender's last name was

[26] We did not send out repeated messages on each due date because they were unlikely to be implemented. The messages after the first due date depended on the borrower's repayment history. For example, for a loan with 6 months term, in each month the borrower could either repay or not repay, resulting in 64 (= 2 × 2 × 2 × 2 × 2 × 2) possible scenarios. It would have been impractical for the website to prepare 64 different sequences of reminder messages.

revealed to the borrower, whereas under the not-to-reveal condition, the phrase "the lender" was replaced by the name of the website in the text messages.[27]

Table 2. Messages

Messages under the *Reveal* Treatment			
	Neutral	**Positive Expectation**	**Adverse Consequences**
After being approved	Hi XXX, your loan is from the lender *Partial name (e.g., Wang XX)*.	Hi XXX, your loan is provided by the lender *Partial name*. *Partial name* is helping you when you are in need. Meanwhile, *Partial name* trusts you and anticipates that you will repay your loan on time as you have promised!	Hi XXX, your loan is provided by the lender *Partial name*. If you do not repay your loan on time, on behalf of *Partial name*, *(the name of the website)* will press you to repay, inform your contact person, and retain the right to resort to legal measures!
The day before the 1st due date	Hi XXX, the first installment of the repayment for the loan that you received from *Partial name* will soon be due. Please login to *(the name of the website)* to make your repayment.	Hi XXX, the first installment of the repayment for the loan that you received from *Partial name* will soon be due. Please login to *(the name of the website)* to your repayment. *Partial name* believes that you will do what you promised, so don't let *Partial name* down!	Hi XXX, the first installment of the repayment for the loan that you received from *Partial name* will soon be due. Please login to *(the name of the website)* to make your repayment. Once again, this is to remind you to repay your loan on time. If you do not, on behalf of *Partial name*, *(the name of the website)* will take action to oblige you to repay your loan!
30 days after the last due date	Hi XXX, the final due date was more than 30 days ago and you haven't fully repaid *Partial name* yet. Please login to *(the name of the website)* to repay your loan as soon as possible.	Hi XXX, the final due date was more than 30 days ago and you haven't fully repaid *Partial name* yet. Please don't fail to live up to *Partial name*'s trust, and login to *(the name of the website)* to repay your loan as soon as possible.	Hi XXX, the last due date is over for more than 30 days and you haven't fully repay *Partial name* yet. This is your final reminder: login to *(the name of the website)* to repay as soon as possible. If you fail to repay your loan, on behalf of *Partial name*,

[27] In the experiment, we only revealed a lender's last name. Borrowers could not infer the lender's gender or ethnic background from this information.

			(the name of the website) will take action to oblige you to repay your loan!
Messages under the *Not to Reveal* Treatment			
	Neutral	**Positive Expectation**	**Adverse Consequences**
After being approved	Hi XXX, your loan from (*the name of the website*) is approved.	Hi XXX, your loan is provided by (*the name of the website*). (*The name of the website*) is helping you when you are in need. Meanwhile, (*the name of the website*) trusts you and anticipates that you will repay your loan on time as you have promised!	Hi XXX, your loan is provided by (*the name of the website*). If you do not repay your loan on time, (*the name of the website*) will press you to repay, inform your contact person, and retain the right to resort to legal measures!
The day before the 1st due date	Hi XXX, the first installment of the repayment for the loan that you received from (*the name of the website*) will soon be due. Please login to *(the name of the website*) to make your repayment.	Hi XXX, the first installment of the repayment for the loan that you received from (*the name of the website*) will soon be due. Please login to (*the name of the website*) to your repayment. (*The name of the website*) believes that you will do what you promised, so don't let (*the name of the website*) down!	Hi XXX, the first installment of the repayment for the loan that you received from (*the name of the website*) will soon be due. Please login to (*the name of the website*) to make your repayment. Once again, this is to remind you to repay your loan on time. If you do not, (*the name of the website*) will take action to oblige you to repay your loan!
30 days after the last due date	Hi XXX, the final due date was more than 30 days ago and you haven't fully repaid (*the name of the website*) yet. Please login to (*the name of the website*) to repay your loan as soon as possible.	Hi XXX, the final due date was more than 30 days ago and you haven't fully repaid (*the name of the website*) yet. Please don't fail to live up to (*the name of the website*)'s trust, and login to (*the name of the website*) to repay your loan as soon as possible.	Hi XXX, the last due date is over for more than 30 days and you haven't fully repay (*the name of the website*) yet. This is your final reminder: login to (*the name of the website*) to repay as soon as possible. If you fail to repay your loan, (*the name of the website*) will take action to oblige you to repay your loan!

Note. For messages under the reveal treatment, the lender's partial name is revealed to borrowers in the messages. The positive expectations are marked in blue and the adverse consequences are marked in red.

5. Results

5.1 Randomization Check

We collected the complete data for the selected 2,012 loan applicants, including loan information and borrowers' characteristics, as well as their monthly installment repayments and payoff behavior records. In total, 12,793 monthly installment repayment (including payoff) observations were obtained for all borrowers. We organized our data at the monthly installment repayment level, rather than at the aggregated loan level, because most P2P platforms, including our focal platform, manage loans by installments. Thus, we conducted our analysis at both the installment and loan levels.

Table 3 lists the results of the randomization check for the six treatments.[28] We compared both demographic and loan characteristics. Among the demographic characteristics, the income was self-reported by the borrowers and thus may have been biased upward given the borrowers' desire to obtain loan approvals. We thus also coded the disposable personal income (DPI) per capita of each borrower's home city (Home DPI) as a complementarity to implement a randomization check. The results indicated similar distributions of gender and educational and income levels among the borrowers in the six treatments. The loan characteristics included four variables, namely purpose, amount, term, and interest rate. The loan purpose was denoted by 1 if the borrowers planned to use the money for high-value consumption, such as shopping and travel, and by 0 if the borrowers had other purposes, such as startup funding or emergency expenses. We found that the loan characteristics across these treatments were also equal. Thus, the data passed the randomization checks for experimental data sets, suggesting that the differences in the results among the treatments were mostly due to the treatment effects.

Table 3. Randomization check of subjects in each treatment

	Obs.	Demographic Characteristics	Loan Characteristics

[28] To check whether the treatments were randomized across May 1–31, we compared the number of loans in each treatment ordered by the week of loan approval. We find that there is no difference in the number of loans across the six treatments. We also compared the number of loans from the perspective of holiday, weekend, and the beginning and end of the month. Again, we do not observe any difference across six treatments.

			Gender (male =0)	Educ-ation*	Self-report Income**	Home City DPI (RMB)	Loan purpose (consumption = 1, other = 0)	Amount (RMB)	Term (month)	Interest Rate (%)
Reveal	Neutral	362	0.23	1.27	1.98	53,809.81	0.61	2,940.88	6.39	16.49
	Pos. Exp.	331	0.23	1.31	2.05	53,131.67	0.66	2,947.13	6.31	16.48
	Adv. Cons.	341	0.26	1.26	2.04	53,010.47	0.70	2,944.87	6.38	16.50
Not to Reveal	Neutral	332	0.25	1.25	1.98	53,323.74	0.64	2,940.36	6.35	16.49
	Pos. Exp.	331	0.22	1.29	2.01	54,218.67	0.66	2,946.53	6.39	16.49
	Adv. Cons.	315	0.23	1.33	1.97	53,786.56	0.68	2,959.37	6.32	16.48

Note. *Education: 1 = junior college; 2 = undergraduate; 3 = postgraduate.

**(Monthly) Income: 1 = less than 1,000 RMB (approximately 155 USD); 2 = 1,000 ~ 2,000 RMB; 3 = 2,000 ~ 3,000 RMB; 4 = 3,000 ~ 4,000 RMB; 5 = 4,000 ~ 5,000 RMB; 6 = more than 5,000 RMB.

We applied four indicators to reflect borrowers' repayment behavior: whether loans were paid off, proportion of monthly installments paid (i.e., repayment rate), whether the monthly installment repayment was made, and monthly installment overdue duration. The focal P2P platform used these variables to monitor the borrowers' compliance toward their microloan contracts and measure the profitability and credibility of each borrower. The definitions of these key variables are exhibited in Table 4.

Table 4. Definitions of main variables

Level	Variables	Definition
Loan Level	Pay-off	Dummy, whether the loan is paid off before Feb 17th 2017; 1 = yes, 0 = no.
	Repayment Rate	# of paid installments / loan term; For instance, for loan A, its loan term is 6 months, somehow the borrowers only repaid 4 times, its repayment rate then is 4/6=66.7%.
Installment level	Monthly Repayment	Dummy, whether the monthly installment is paid; 1 = yes, 0 = no.
	Overdue Duration	# of days delay for monthly repayment (after the last repayment due date); for repayment in advance, = 0 (left censored), for defaulted installment, = 260 (right censored).

5.2 Descriptive Results

Comparison of payoff rates (loan level)

We first compared the payoff rates of borrowers under each treatment condition. Figure 2 indicates that the optimal treatment was the positive expectation message treatment without revealing lender identity, the payoff rate of which was 73.11%. By contrast, the least optimal treatment was the consequence treatment with lenders' information revealed, of which the payoff rate was only 63.64%. We also found that the average payoff rates under the not-to-reveal condition the three treatments were not significantly different. However, when the lender identity was revealed, the average payoff rate for the adverse consequences treatment was significantly lower than those of the other two treatments. This may be because the borrowers perceived a higher level of antagonism when the lenders' information was included in the adverse consequence messages and were hence less likely to repay than when under other conditions.

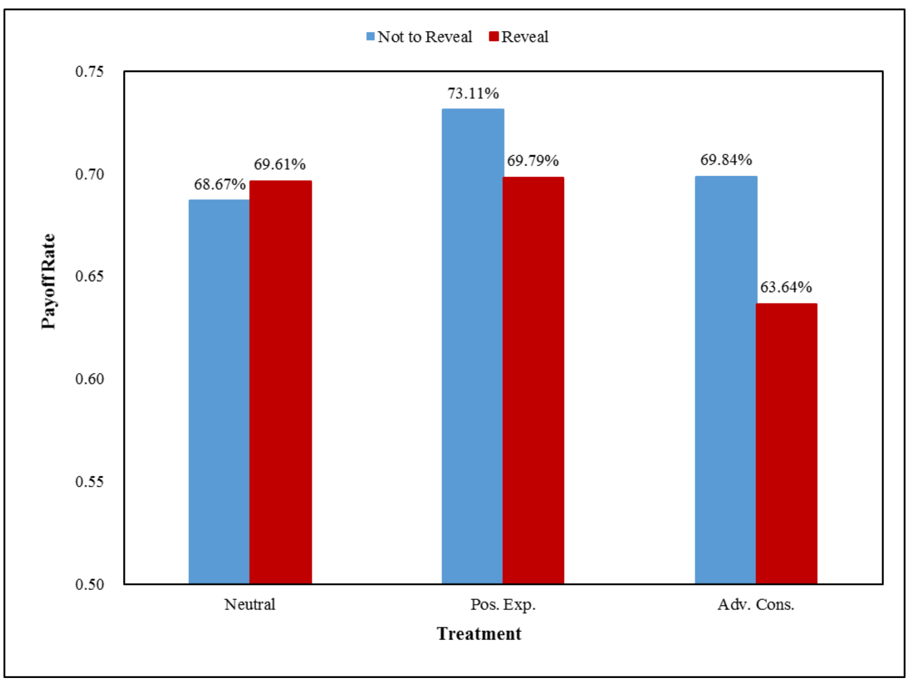

Figure 2. Payoff rates for the six treatments

Table 5 illustrates the mean difference comparison, suggesting that when the lender identity is revealed, the differences between the adverse consequences and positive expectation treatments (p = 0.083) and between the adverse consequences and neutral treatments (p = 0.091) are significant. Note that our experiment comprised multiple treatments and multiple outcomes, and thus, the p value of the unadjusted mean comparison in Table 5 could be biased because it was the test result of a single-treatment setting. We followed the multiple hypothesis test (MHT) method suggested in *Multiple Hypothesis Testing in Experimental Economics* by List et al. (2016) to test the multiple hypothesis simultaneously. The adjusted p values are listed in the final column of Table 5. The results confirmed the difference between the adverse consequences and positive expectation treatments.

Table 5. Comparison of payoff rates for the six treatments

Outcome	Control/Treatment Groups	Difference in Means	Unadjusted *p*-values	Multiplicity Adjusted *p*-values (List et al., 2016)
Payoff Rate	NotRev.×(Neutral) vs. NotRev.×(Pos.Exp.)	0.0444	0.209	0.209
Payoff Rate	NotRev.×(Neutral) vs. NotRev.×(Adv.Cons.)	0.0117	0.748	0.890
Payoff Rate	NotRev.×(Pos.Exp.) vs. NotRev.×(Adv.Cons.)	-0.0327	0.358	0.358
Payoff Rate	Rev.×(Neutral) vs. Rev.×(Pos.Exp.)	0.0018	0.960	0.960
Payoff Rate	Rev.×(Neutral) vs. Rev.×(Adv.Cons.)	-0.0597	0.093*	0.103
Payoff Rate	Rev.×(Pos.Exp.) vs. Rev.×(Adv.Cons.)	-0.0615	0.083*	0.083*

Note. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Comparison of repayment rates (loan level)

The repayment rate comparison in Figure 3 illustrates a similar result, in which the positive expectation message treatment without revealing lender identity was associated with the highest repayment rate of the six treatments at 85.29%, whereas the adverse consequence message treatment with revealed information was associated the lowest repayment rate (77.32%).

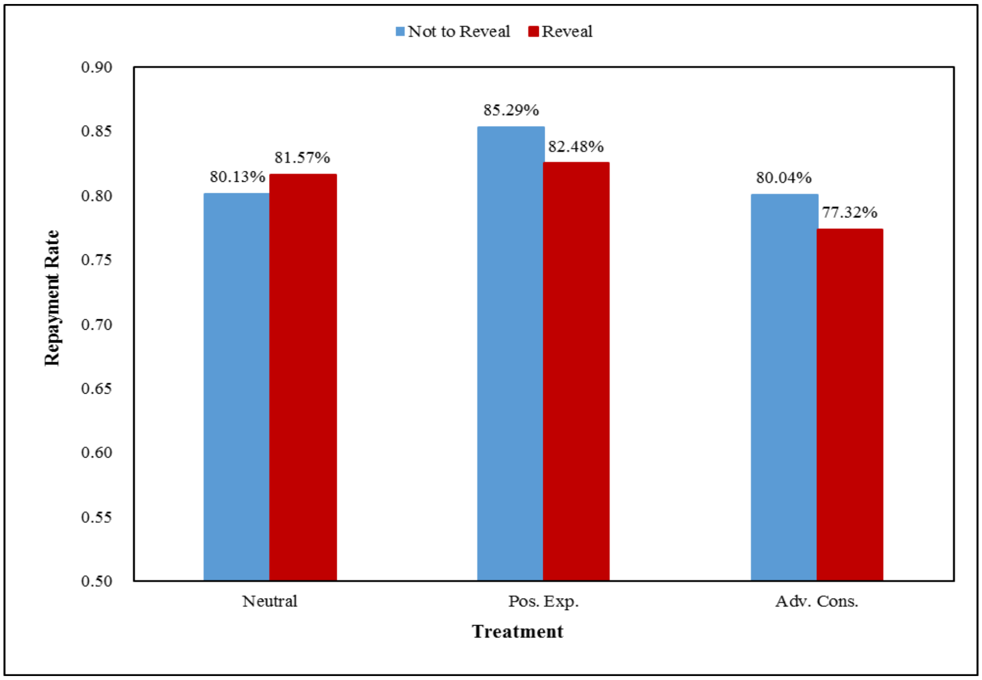

Figure 3. Repayment rates for the six treatments

When lender identity was revealed, the average repayment rate of the adverse consequence message treatment was significantly lower than that of the other two treatments (p = 0.044 between adverse consequence and positive expectation treatments; p = 0.052 between the adverse consequence and neutral treatments). When lender identity was not revealed, the result pattern was only slightly different. The positive expectation message treatment led to a significantly higher repayment rate than the other two treatments (p = 0.038 between prosocial and adverse consequence treatments; p = 0.037 between positive expectation and neutral treatments). The adjusted p value given by List et al. (2016) was consistent with our unadjusted results.

Table 6. Comparison of repayment rates for the six treatments

Outcome	Control/Treatment Groups	Difference in Means	Unadjusted *p*-values	Multiplicity Adjusted *p*-values (List et al., 2016)
Repayment Rate	NotRev.×(Neutral) vs. NotRev.×(Pos.Exp.)	0.0516	0.037**	0.058*
Repayment Rate	NotRev.×(Neutral) vs. NotRev.×(Adv.Cons.)	-0.0009	0.973	0.973
Repayment Rate	NotRev.×(Pos.Exp.) vs. NotRev.×(Adv.Cons.)	-0.0525	0.038**	0.059*
Repayment Rate	Rev.×(Neutral) vs. Rev.×(Pos.Exp.)	0.0091	0.710	0.852

Repayment Rate	Rev.×(Neutral) vs. Rev.×(Adv.Cons.)	-0.0425	0.052**	0.095*
Repayment Rate	Rev.×(Pos.Exp.) vs. Rev.×(Adv.Cons.)	-0.0516	0.044**	0.065*

Note. *p < 0.10, **p < 0.05, ***p < 0.01.

Comparison of monthly repayment and overdue duration (installment level)

Subsequently, we compared the borrowers' repayment behavior at the monthly installment level. We computed the monthly repayment rate and overdue duration for each installment. Figures 4 and 5 illustrate the trend of each treatment.

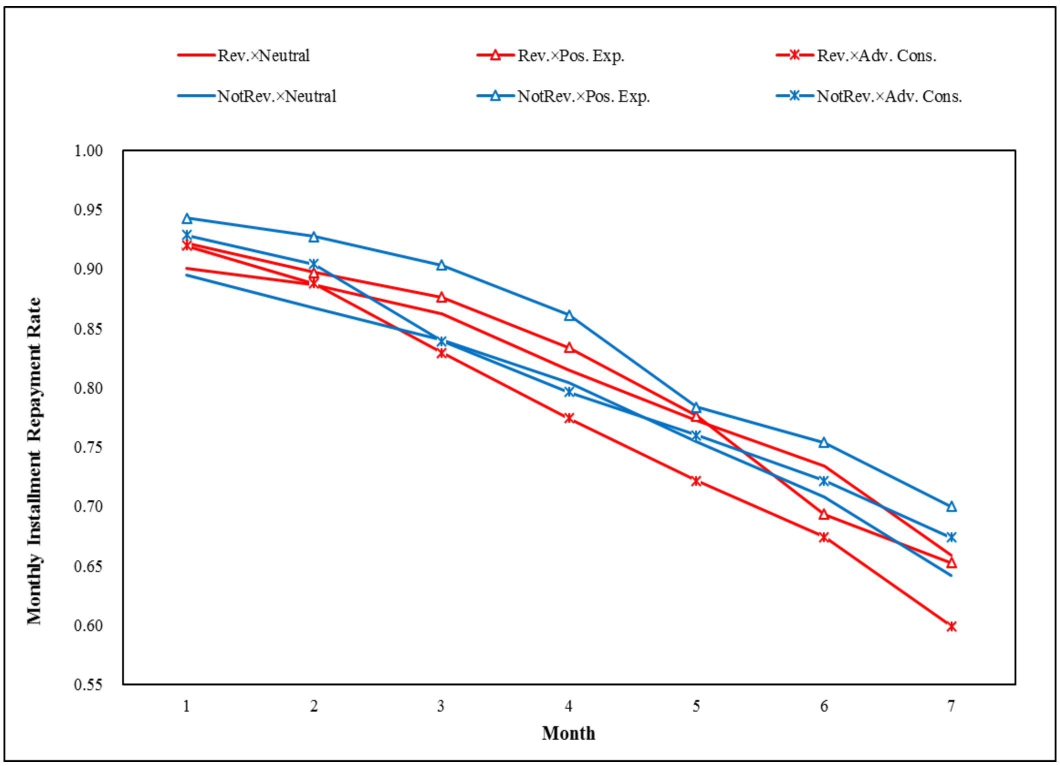

Figure 4. Monthly installment repayment rates across the six treatments

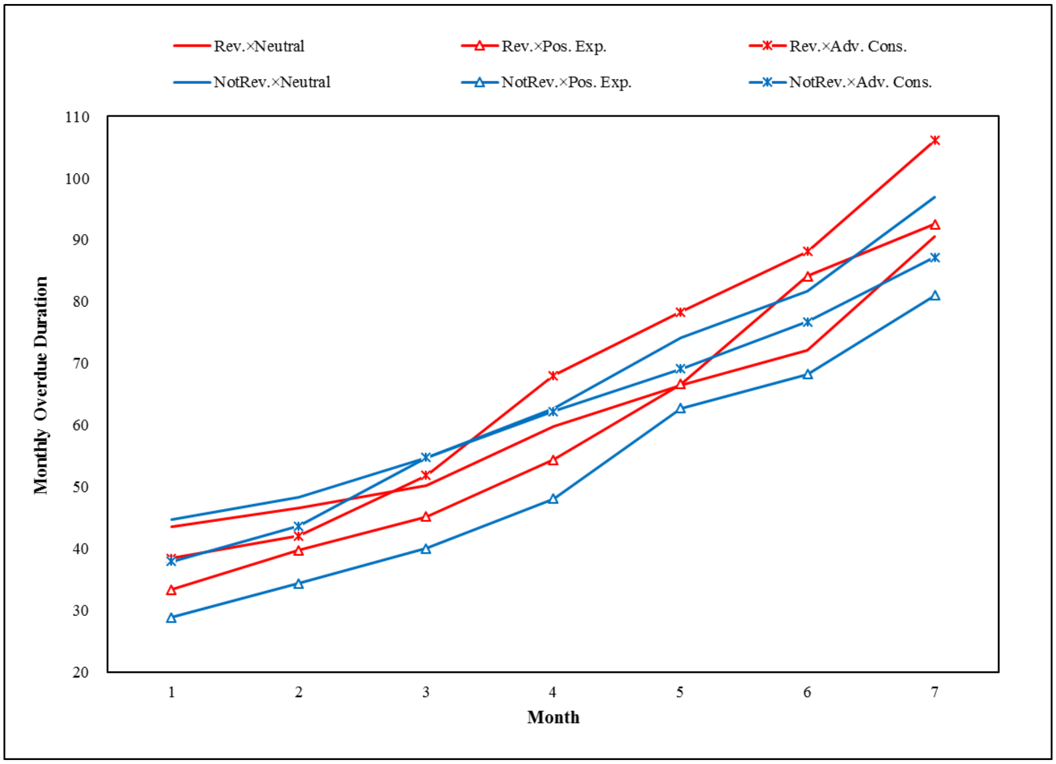

Figure 5. Monthly overdue duration across the six treatments

The results were consistent with those at the loan level. Overall, the positive expectation message treatment without revealing lender identity was associated with the highest repayment rate and the shortest overdue duration, whereas the adverse consequence message treatment with revealed lender information was associated the lowest repayment rate and longest overdue duration.

When we more closely examined the first month's performance for the two adverse consequence treatments (with lender identity both revealed and not revealed), we found that their effects were similar to that of the positive expectation treatments. Thus, we further compared the monthly installment repayment rates and installment overdue durations for the first installment only (i.e., the short-term effect) as exhibited in Figures 6 and 7, which illustrate that the adverse consequence treatments outperformed the neutral treatments. These results further supported the notion that messages emphasizing adverse consequences may only have short-term effects, whereas those emphasizing positive expectation may have enduring effects, consistent with our H3.

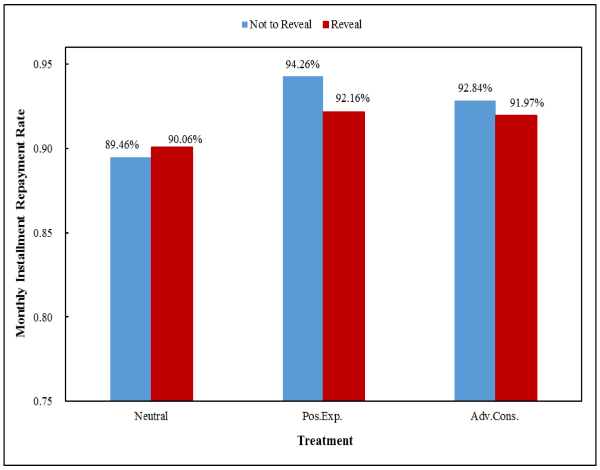

Figure 6. Installment repayment rates of the first installment for the six treatments

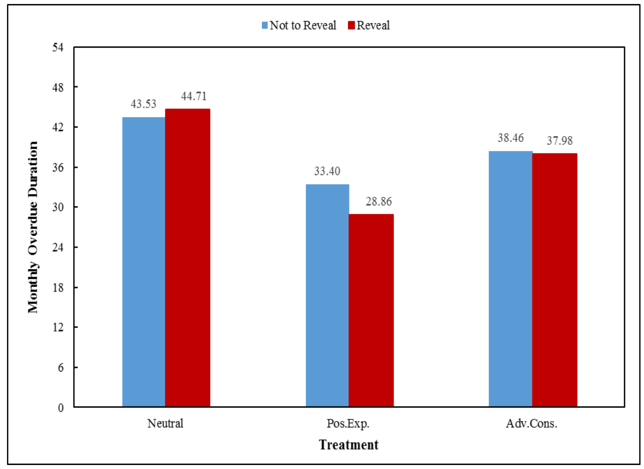

Figure 7. Monthly overdue durations of the first installment for the six treatments

Our descriptive analysis illustrated differences in borrower behavior when exposed to the message content manipulation. Subsequently, we conducted further econometric analysis, as discussed in the next subsection, to illustrate changes in the four variables of interest: whether the loan was paid off, the proportion of monthly installments paid, whether monthly repayments were made, and monthly installment overdue duration.

5.3 Regression Results

The treatment variables of our design were *Reveal*, *Pos.Exp.*, and *Adv.Cons.*. We subsequently applied the following four independent equations to systematically test the effects of reveal, positive expectation, and adverse consequences on the borrowers' repayment behavior. The interactive effects of reveal and positive expectation (i.e., *Reveal* × *Pos.Exp.*) as well as those of reveal and adverse consequences (i.e., *Reveal* × *Adv.Cons.*) were also included in the regression models.

Regression results at loan level

At the loan level, we conducted probit regression analysis to determine the effects of the treatments on borrowers' payoff behavior (Equation 1). Because the second variable of interest (the repayment rate) is a continuous variable, we implemented ordinary least squares regression to test the effects of the treatments (Equation 2). In these two equations, we controlled for the characteristics of the loans and the borrowers that may have affected the dependent variables (i.e., the size, term, interest rate, and purpose of the loan and the gender and education level of the borrowers). We marked all these covariates as $\boldsymbol{X}$, with subscript i indicating an individual borrower.

$$\begin{aligned} \textit{Pay-off}_i &= \beta_0 + \beta_1 \textit{Reveal}_i + \beta_2 \textit{Pos.Exp.}_i + \beta_3 \textit{Adv.Cons.}_i + \beta_4 \textit{Reveal} \times \textit{Pos.Exp.}_i \\ &\quad + \beta_5 \textit{Reveal} \times \textit{Adv.Cons.}_i + \beta_6 \boldsymbol{X}_i + u_i \end{aligned} \tag{1}$$

$$\begin{aligned} \textit{Repayment Rate}_i &= \beta_0 + \beta_1 \textit{Reveal}_i + \beta_2 \textit{Pos.Exp.}_i + \beta_3 \textit{Adv.Cons.}_i + \beta_4 \textit{Reveal} \times \textit{Pos.Exp.}_i \\ &\quad + \beta_5 \textit{Reveal} \times \textit{Adv.Cons.}_i + \beta_6 \boldsymbol{X}_i + \varepsilon_i \end{aligned} \tag{2}$$

Table 7 illustrates the estimation results at the loan level.[29] Because the estimated coefficients of the probit model were not the marginal effects of each independent variable, we applied the partial effects method to calculate the marginal effects of each treatment on the probability of payoff. Considering the example of marginal effect of *Pos.Exp.*, we set other variables at their mean value, and computed the probability of payoff when *Pos.Exp.* = 0 and 1, respectively. Then, the marginal effect of *Pos.Exp.* was the latter probability minus the former one, which can be directly interpreted as the effect of *Pos.Exp.* on the borrower's probability of payoff.

Table 7. Estimation results at the loan level

(Marginal effect in parentheses for probit model)

Variables	**DV: Pay-off**		**DV: Repayment Rate**	
	Probit		**OLS**	
Constant	13.410	13.151	2.414*	2.372*
Reveal	-0.076 (-0.026)	0.038 (0.012)	0.012	-0.016
Pos. Exp.	0.078* (0.027)	0.134* (0.046)	0.046**	0.052**
Adv. Cons.	-0.053 (-0.019)	0.022 (0.008)	-0.025	-0.011
Reveal × (Pos. Exp.)		-0.156 (-0.056)		-0.026

[29] We also include the week dummy, holiday dummy, and weekend dummy as the control variables for our analysis to eliminate the time effects further. We found that the results still hold after controlling for the time effect.

Reveal × (Adv. Cons.)		-0.191* (-0.069)		-0.018
Amount	-0.004*** (-0.002)	-0.004*** (-0.002)	-0.106**	-0.108**
Term	-0.146*** (-0.051)	-0.147*** (-0.051)	-0.012***	-0.011***
Interest rate	-0.637 (-0.223)	-0.625 (-0.218)	-0.076	-0.078
Female	0.052 (0.018)	0.055 (0.019)	0.044**	0.044**
Education	0.162*** (0.056)	0.160*** (0.056)	0.048***	0.047***
Home DPI	0.020** (0.009)	0.024** (0.009)	0.003**	0.003**
Income	-0.009 (-0.003)	-0.008 (-0.003)	-0.010	-0.010
Loan purpose (Consumption)	-0.066 (-0.023)	-0.063 (-0.022)	-0.019	-0.018
R^2 or *Pseudo* R^2	0.228	0.236	0.239	0.245
Number of Observation	2,012	2,012	2,012	2,012

Note. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

The results suggest that after controlling for the covariates, conveying positive expectations in the reminder messages has a significantly positive effect of increasing borrowers' payoff ratio and repayment rate at the loan level. Specifically, when lender information was not revealed, the borrowers who received the positive expectation message had a 4.6% higher payoff probability and a 5.2% higher repayment rate than the borrowers who received the neutral message. Thus, H1 is supported at the loan level. Also, this magnitude is consistent data in Table 5, which for instance, illustrates that the difference between positive expectation and neutral when lender information was not revealed was 0.0444—very close to 4.6%.

Nonetheless, including adverse consequences in the reminders did not have a significant effect on the borrowers' long-term payoff behavior; thus, H2 was not supported. This suggests that as the fear of adverse consequences dampens in the long run, the negative effects of the adverse consequence mechanism on borrowers' intrinsic desire to follow social norms may overshadow its positive deterrence effect. Thus, platforms seeking to mitigate the moral hazard problem should use this mechanism cautiously (Perez-Truglia and Troiano, 2015). Potential negative effects of the adverse consequence mechanism could include borrowers' dislike of adverse consequence messages or their perception of the threat of adverse consequences as a signal of distrust irrespective of their ability or intention to repay their loans. This perception of distrust very likely has a negative impact on the borrowers' motivation to perform well (Falk and Kosfeld, 2006) and willingness to commit (Cho, 2006). Moreover, messages that threatens adverse consequences may signal low repayment rates for the relevant lending platform, which may trigger a behavioral response, reflecting the broken-windows effect (Hinkle and Weisburd, 2008).

We also found that revealing lender's information did not affect the borrowers' repayment behavior, thus H4 was not supported at the loan level.[30] A potential explanation is that in the context of P2P, borrowers who violate the loan contract may perceive individual lenders as less powerful than the platform. Therefore, even though they may perceive higher saliency of harm if they cheat an individual, this perception does not alter their probability of cheating. This is supported by the negative interaction effects between the revealing treatment and the adverse consequence message treatment (column 3 of Table 6); this indicates that revealing lenders' information further reduces the effects of the adverse consequence message (−0.191, $p < 0.10$). This is consistent with the results illustrated in Figures 2 and 3. Both the payoff and repayment rates at the loan level are long-term measurements; thus, we could not test H3 here, and the immediate and enduring effect comparison of the monthly level analysis are elaborated in the next subsection.

Regression results – installment level

At the installment level, we conducted a fixed-effects probit regression analysis to reveal the effects of the treatments on monthly repayment behavior (Equation 3), which indicated whether borrower i repaid the t^{th} installment. The other variable of interest was *overdue duration*, defined as the time taken by a borrower to repay the loan after receiving the message. We implemented a fixed-effects Tobit regression with Equation 4. The regression was left censored at zero for borrowers who repaid their loans before the due date. We set the right censor value of the Tobit regression at 260 because the longest

[30] We acknowledge that only revealing lenders' partial names is a weak implementation of saliency of harm, and this is possibly the reason that the treatment effect of reveal vs. not to reveal was nonsignificant. However, including the characteristics of lenders could potentially complicate the analysis. For example, the prior literature has documented that men and women differ in other-regarding preferences (e.g., Eckel and Grossman, 1998), risk preferences (e.g., Levin et al., 1988), and attitudes toward competition (e.g., Niederle and Vesterlund, 2007).

overdue period that we observed in our data set was 250 days. In both Equations 3 and 4, we controlled for the loans' fixed-effect to capture the additional idiosyncratic characteristics related to each loan. The time-fixed effect was also controlled to capture potential shocks in particular months, which is denoted by $Month_t$. H3 was examined by including the interaction terms between the month dummy and "positive expectation" and "adverse consequences" (i.e., ***Month*** × *Pos.Exp.* and ***Month*** × *Adv.Cons.*). The subscripts *i* and *t* indicate each individual borrower and installment sequence, respectively.

$$\begin{aligned} Monthly\ Repayment_{it} &= \beta_0 + \beta_1 Reveal_i + \beta_2 Pos.Exp._i + \beta_3 Adv.Cons._i + \beta_4 Reveal \times Pos.Exp._i \\ &+ \beta_5 Reveal \times Adv.Cons._i + \beta_6 Month \times Pos.\ Exp._i + \beta_7 \boldsymbol{Month} \times Adv.\ Cons._i + \boldsymbol{X}_i + \boldsymbol{Month}_t + \gamma_i + u_{it} \end{aligned} \tag{3}$$

$$\begin{aligned} Overdue\ Duration_{it} &= \beta_0 + \beta_1 Reveal_i + \beta_2 Pos.Exp._i + \beta_3 Adv.Cons._i + \beta_4 Reveal \times Pos.Exp._i \\ &+ \beta_5 Reveal \times Adv.Cons._i + \beta_6 Month \times Pos.\ Exp._i + \beta_7 \boldsymbol{Month} \times Adv.\ Cons._i + \boldsymbol{X}_i + \boldsymbol{Month}_t + \gamma_i + u_{it} \end{aligned} \tag{4}$$

Table 8 illustrates the estimation results at the installment level, and the marginal effects of the probit model are again included in parentheses. These regression results were similar to the results illustrated in Table 6. Compared with neutral messages, messages conveying lenders' positive expectations increased borrowers' likelihood of repayment and reduced the loan overdue duration; thus, H1 is supported again. The effects of revealing the lender's identity and warning about adverse consequences were nonsignificant; thus, H2 and H4 were not supported at the installment level either.

We found that the first four interaction terms of ***Month*** × *Pos.Exp.* were significant, suggesting that the effects of *Pos.Exp.* could persist for at least four months. This is consistent with H3, which states that positive expectation has a relatively enduring effect. By contrast, the interaction terms of ***Month*** × *Adv.Cons.* were significant only for the first and second month, indicating that the effects of "adverse consequence" messages decay over time. Thus, H3 is supported. The observations from our data set suggest that the adverse consequence treatment has only a short-term effect. However, confirming whether this is also true in other studies requires further meta analysis. Nonetheless, this paper provides a direction for future research that potentially resolves the mixed findings of the previous literature on deterrence.

Table 8. Estimation results at the installment level

(Marginal partial effect in the parentheses for probit model)

Variables	**DV: Monthly Repayment**			**DV: Overdue Duration**		
	Panel Probit			**Panel Tobit**		
Constant	9.800	9.723	9.522	-2,544.598***	-2,536.842**	-2,370.968**
Reveal	-0.046 (-0.018)	0.071 (0.018)	0.071 (0.018)	6.719	-11.318	-10.332
Pos. Exp.	0.111** (0.054)	0.217** (0.054)	0.168** (0.042)	-33.976***	-51.428***	-34.668**
Adv. Cons.	-0.031 (-0.003)	-0.011 (-0.003)	0.022 (0.006)	-16.511	-27.514	-6.620
Reveal × (Pos. Exp.)		-0.207 (-0.056)	-0.201 (-0.057)		34.092	32.181
Reveal × (Adv. Cons.)		-0.155 (-0.042)	-0.155 (-0.042)		21.152	19.803
(Pos. Exp.) × Month 1			0.155*** (0.037)			-45.050***
(Pos. Exp.) × Month 2			0.126*** (0.030)			-14.074*
(Pos. Exp.) × Month 3			0.115*** (0.028)			-17.366*
(Pos. Exp.) × Month 4			0.082*** (0.020)			-22.295*
(Pos. Exp.) × Month 5			-0.012 (-0.003)			-4.079
(Pos. Exp.) × Month 6			-0.054 (-0.014)			-1.879
(Adv. Cons.) × Month 1			0.063** (0.032)			-80.422***
(Adv. Cons.) × Month 2			0.069* (0.025)			-23.926*
(Adv. Cons.) × Month 3			-0.096 (-0.018)			-10.937
(Adv. Cons.) × Month 4			-0.031 (-0.008)			-12.437
(Adv. Cons.) × Month 5			-0.017 (-0.004)			-6.314
(Adv. Cons.) × Month 6			-0.014 (-0.004)			-1.665
Amount	-0.002*** (-0.001)	-0.002*** (-0.001)	-0.002*** (-0.001)	0.113***	0.113***	0.111***
Term	0.044** (-0.011)	-0.043** (-0.011)	-0.043** (-0.011)	-5.347**	-5.101**	-15.498**
Interest rate	-0.485 (-0.124)	-0.484 (-0.124)	-0.472 (-0.121)	134.592**	134.603**	132.956**
Female	0.181** (0.045)	0.184** (0.045)	0.183** (0.045)	-36.317***	-36.573***	-36.855***
Education	0.199*** (0.051)	0.199*** (0.051)	0.199*** (0.051)	-31.176***	-30.973***	-30.636***
Home DPI	0.006** (0.003)	0.006** (0.003)	0.006** (0.003)	0.002	0.002	-0.001
Income	0.029 (0.007)	0.028 (0.007)	-0.028 (0.007)	2.101	2.043	2.075
Loan purpose (Consumption)	-0.072 (-0.018)	-0.071 (-0.018)	-0.071 (-0.018)	11.243	10.867	10.645
Month fixed-effect (Month Dummy)	Included	Included	Included	Included	Included	Included
Loan fixed-effect (Loan Dummy)	Included	Included	Included	Included	Included	Included
Log Likelihood	-5,847.76	-5,842.23	-5,830.51	-24,700.40	-24,699.61	-23,295.26
Number of Observation	12,793	12,793	12,793	12,793	12,793	12,793

Note. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

We also found some considerable results for the control variables. The loan size (the variable *Amount*) and repayment duration of the loan (the variable *Term*) had negative effects on borrowers' repayment behavior, suggesting that borrowers are less likely to repay their loans if the debt is high and the debt repayment period is long. The effects of borrowers' personal characteristics on repayment behavior were also notable. For example, women exhibited a higher likelihood of repayment of installments than did men. This result was consistent with the findings of Pope and Sydnor (2011), who stated that the loan market favors women, who are less likely to default than men are. Education was also positively correlated with the payoff ratio and repayment ratio, which is reasonable because higher levels of education are linked with higher incomes and therefore with superior repayment ability.

Additional analysis

In the regression table, *p* value alone does not provide sufficient evidence to support a given model or the associated hypotheses (Gill, 2018). Thus, other information, such as statistic power, should be considered to formulate rigorous inferences. This paper follows Maniadis et al. (2014) in providing the post-study probability (PSP) information as a supplement to *p* value. Maniadis et al. (2014) suggested that both statistic power and priors would affect the robustness of results. The prior represents the fraction of all observations that are true associations. By using our strongly supported H1 as an example, priors denote that the true proportion of positive expectation is associated with improved repayment behavior, which is unobservable for researchers. We set the prior from extremely small (0.01) to extremely large (0.55) to observe how it changed our results. The power value of two loan-level studies and two monthly level studies was calculated on the basis of the means, standard deviations, and sample sizes of each study. We then computed the PSP of positive expectation for each dependent variable conditional on the power level of our experiment, as illustrated in Table 9.

We found that the PSPs of the monthly level performance measurements were higher than those of the loan-level performance measurements for the same prior probability, thus suggesting that the prediction power of our findings regarding monthly installment level repayment behavior is higher than that of the loan-level repayment behavior. This could be because the measurement of behavior at the loan level was accumulated over 6 months, and the usefulness of such a measurement in predicting behavior may be reduced given that various unobservable factors could be involved over such a long period.

Table 9. PSP estimates as a function of prior probability and power

Pay-off		**Repayment Rate**	
Prior	*Power = 0.19*	*Prior*	*Power = 0.55*
0.01	0.04	*0.01*	0.10
0.10	0.30	*0.10*	0.55
0.35	0.67	*0.35*	0.86
0.55	0.82	*0.55*	0.93
Monthly Repayment		**Overdue Duration**	
Prior	*Power = 0.94*	*Prior*	*Power = 0.97*
0.01	0.16	*0.01*	0.16
0.10	0.68	*0.10*	0.68
0.35	0.91	*0.35*	0.91
0.55	0.96	*0.55*	0.96

6. Concluding Remarks

Moral hazard is a classic problem in financial markets, and it may be even more severe in online financial markets because of the lack of collateral and valid credit checks. We designed and implemented several behavioral mechanisms in a natural field experiment to mitigate the moral hazard problem, based on two dimensions: the content of the messages (positive expectation, adverse consequence, or neutral messages) and revelation of the lender's identity. In general, the evidence favored the adoption of positive expectation messages—we found that the positive expectation treatment is more effective at alleviating the moral hazard than is the adverse consequence or saliency of harm treatment. The adverse consequence treatment also has a positive impact on repayments in the short run, but its effect declines in the long run. This may provide a potential explanation for the mixed findings about adverse deterrence messages in the financial compliance literature. Future meta-studies on adverse deterrence messages may address the mixed results of the previous relevant literature from the temporal perspective.

Our results indicated that *ex ante* communication can affect borrowers' repayment behavior in P2P lending and that managing the content of repayment reminder communications is essential to the success of credit default deterrence. Furthermore, our results demonstrated the potential necessity of behavioral mechanism interventions to enhance prosocial compliance in P2P lending. In contrast to cost-intensive conventional (court-enforced) solutions, behavioral mechanisms to mitigate the moral hazard are cost-free and easy to implement. Supporting this conclusion, the focus P2P lending website implemented the "positive expectation + no revealing" message in its ongoing business operations after we completed this study.

Our findings provide strong evidence that adopting certain behavioral mechanisms increases prosocial compliance in the real world, not only in the laboratory. Beyond the P2P lending context, our findings about positive expectations also have implications for other bilateral economic relationships, such as buyer–seller and employer–employee relationships.

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