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Judging online peer-to-peer lending behavior: A comparison of first-time and repeated borrowing requests

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ABSTRACT

The past decade has witnessed a growing number of business models that facilitate economic exchanges between individuals with limited institutional mediation. One of the important innovative business models is online peer-to-peer lending, which has received wide attention from government, industry, and researchers. Using the signaling theory, we compare the effects of various signals on the likelihood of successful funding in three models (i.e., first-time borrowing, repeated borrowing without prior lending, and repeated borrowing with prior lending). Using data collected from PPDAI.com, we verify the three proposed models by employing logistic regression. Results and implications are analyzed and discussed.

1. Introduction

The past decade has witnessed a growing number of business models that facilitate economic exchanges between individuals with limited institutional mediation. One of the important innovative business models in digital finance is online peer-to-peer (P2P) lending, which has received wide attention from government, industry, investors, and researchers [13,14,17,18,23]. P2P lending is a new and innovative platform for financial transactions that bypasses conventional intermediaries by directly connecting borrowers and lenders [36]. Leveraging the "collective efforts" by allowing multiple lenders to collectively fund a loan, online P2P lending is part of a large crowd-funding movement that uses the Internet to rally donors for collective funding [4,24]. The first P2P lending platform, Zopa, was launched in 2005. Powered by technological advances and rapidly changing customer behavior, online P2P lending is dramatically gaining popularity worldwide as a convenient way of financing and is probably becoming a better alternative to the traditional banking system for many users [2,11]. Founded in 2007, PPDAI (www.ppdai.com) is now one of the largest online P2P lending platforms in China. Similar to Prosper.com, PPDAI serves as an information dissemination platform with no offline business. It is a typical representative of a pure intermediary and online service provider. By the end of 2014, there were more than 600,000 registrants on PPDAI, with more than 2.6 million successful borrowing requests and more than 12 million RMB in successful investments (loans). The revenue of PPDAI mainly comes from service fees and compensation but with no guaranteed return of the lender's capital or protection against bad-debt expense risk.

Although P2P lending markets have enjoyed rapid development in recent years, some problems exist in the development of this business model. One of the most prominent problems is information asymmetry [23,36]. This asymmetry may expose lenders to high investment risk and tends to distort their bidding decisions [5,36]. Several solutions have been proposed in extant research. Herzenstein et al. [18] suggested that the market inefficiency induced by information asymmetry can be, to an extent, alleviated using methods such as disclosure of the borrower's financial and personal information and the development of mutual trust between borrowers and lenders. Yum et al.'s [36] suggested solution was a portfolio that consists of a large number of microloans with diverse risk levels, but with an inherent risk of default on loans made via the online media to strangers without collateral. The key to resolving the information asymmetry problem may be found in the decisions of P2P-lending participants. The fundamental problem is how lenders make their investment decisions on online P2P platforms [14,23]. To understand the decision-making process, prior academic attention has been devoted to the investigation of factors that may affect lenders' bidding strategies, which are mainly measured by the success rate of funding. For instance, researchers found that the offered interest rate and the borrow amount had a positive impact on the funding success rate [11,28]. The impact of credit grading and the financial history of the borrower on successful funding have also been empirically verified [16,36]. In addition, the impact of demographic

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information and photos from the borrower on the funding success rate is evident in the literature [10,13,28].

However, although a set of variables that may affect the success of funding has been identified in the literature, little research has been conducted to compare the antecedents of successful funding for different types of borrowing requests. Specifically, although the importance of the borrowing history (including borrowing and lending) of a borrower has been documented [36], little research has been conducted to investigate the potential differences between first-time borrowing requests and repeated borrowing requests. A deeper understanding of the factors that lead to the success or failure of funding for first-time borrowing requests and repeated borrowing requests, respectively, and how the different sets of factors may differ remain elusive in P2P-lending literature. For instance, first-time lending might concern how to "break the ice" and make people willing to lend their money for the first time, and repeated lending is important to ensure the sustainability of the platform. Understanding both may allow a more holistic strategy to be derived. In addition, besides the borrowing history of a potential borrower, his or her lending history could be of importance. Because the history may reflect the seriousness of the borrower in the platform community, it is given that a unique nature of P2P lending is that an individual can be both borrower and lender on these platforms. Therefore, considering the borrowers' lending history may offer a more complete picture of the factors influencing the loan success rate.

Therefore, the objective of this research is to investigate how lenders process the information when they are presented with different types of borrowing requests. In particular, by comparing the effects from various antecedents in three different models (i.e., first-time borrowing request, repeated borrowing without lending, and repeated borrowing with lending), this study aims to contribute to P2P-lending literature by providing a better understanding of how the provision of different types of information in the borrowing lists may affect the success of funding under different circumstances.

2. Literature review and theoretical background

2.1. Online P2P lending

Online P2P lending has gained wide attention in the past few years. Extant research has largely focused on identifying the economic factors that influence funding success, including interest rates of loan requests, transaction history, etc. [14,18,23,36]. For example, Yum et al. [36] applied the loan funding success status as the dependent variable to explore the influential role of the voting results and transaction history in loan funding success in P2P-lending behavior. The results show that borrowers tried to maintain a good reputation, and direct communication with lenders may adjust incorrect inferences made from hard data when their creditworthiness was questioned.

Economic transactions are often embedded in social relationships [32,33]. Economic factors as well as personal and social factors that can affect P2P borrowing have been explored in the literature. Greiner and Wang [14] identified the economic status of a borrowing request as the major driver for bidding behavior and social capital and listing quality as trust-building mechanisms that influence trust behavior in P2P lending. Herzenstein et al. [18] examined how borrowers' identity claims constructed in their narratives influence lender decisions on unsecured personal loans. Specifically, they investigated loan funding, the percentage reduction in the final interest rate, and loan performance on P2P websites. Their findings suggested that the influence of unverified information on lending decisions was more significant than that of the objective and verified information. Liu et al. [24] investigated how friendships act as pipes, prisms, and herding signals on a large online P2P-lending site. Their findings showed that friends of the borrower, especially close offline friends, could act as financial pipes by lending money to the borrower, and the prism effect of friends' endorsements via bidding on a loan negatively affects subsequent bids by third parties. A brief summary of the recent P2P research is presented in Table 1.

To explain the underlying phenomena in P2P lending, several theoretical lenses have been employed in the literature. Lee and Lee [22] empirically investigated lenders' behavior and found strong evidence of herding behavior and its diminishing marginal effect as bidding advanced. Similarly, several studies reported the existence of the herding effect in P2P lending [17,36]. Further, Greiner and Wang [14] proposed a theoretical model, built on the elaboration likelihood model (ELM), to explain the trust-building mechanisms in P2P-lending marketplaces, and their findings showed the importance of the central route (i.e., economic status) and peripheral cues (i.e., social capital and listing quality) that influence trust behavior. In addition, since information asymmetry has been identified as one of the most critical problems of P2P lending (e.g. [4,36]), prior research has also applied the signaling theory to explain P2P-lending behavior. Collier and Hampshire [7] drew on the theory from the principal-agent perspective to empirically examine the signals that enhance community reputation.

To sum up, some key findings of online P2P lending have been reported. First, a large number of studies agreed that one of the most critical problems in P2P lending was information asymmetry (e.g. [4,36]). Because of this problem, trust and trust building become critical issues in P2P lending [14,18]. In addition, herding behavior in P2P lending has been intensively studied and empirically identified in the context of information asymmetry [14,36]. Although the literature has recognized the importance of transaction history (including borrowing and lending) in trust building [36], little research has been done to investigate the underlying differences between first-time and repeated borrowing requests. First-time borrowing requests could be significantly different from repeated borrowing in terms of the availability of information, lenders' decisions, and many other unidentified factors. Moreover, although transaction history has been identified as an important factor, most research attention has been devoted to the *borrowing* history, and the potential effect of the borrower's *lending* history has largely been neglected.

2.2. Signaling theory

One of the most critical problems in P2P lending is information asymmetry (e.g., [4,36]). When decision makers are faced with information asymmetry, Spence [31] postulated signaling theory, which explains that observable entity attributes can serve as a signal of quality. In his formulation of signaling theory, Spence [31] utilized the labor market to model the signaling function of education. Potential employers lack information about the quality of job candidates. The candidates, therefore, obtain education to signal their quality and reduce information asymmetry. The signaling theory has been applied to a wide range of management studies, including electronic commerce research [25,34], online trust building [35], venture capital financing, electronic word-of-mouth (eWOM) [1], investor decisions [9,19], and P2P lending [23].

A review and assessment of the extant literature on the application of the signaling theory suggest that there are three primary focuses: signaler, signal, and the receiver [8]. In our study, the signaler in P2P lending could be the borrower, P2P website, or other potential lender, and the signals might include various pieces of information the potential lenders are exposed to, and the receiver might be the potential lender.

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Table 1
Summary of Recent P2P Lending Research.

References	Dependent variables	Main independent variables	Supporting theory	Method/data
[7]	Interest rate	Structural signals (community size, community rating, and community selection criteria); Individual signals; Behavioral signals (community endorsements, community stake in transaction, and community coaching)	Signaling theory	Data from Prosper.com
[14]	Trusting behaviors (likelihood of funding and reduced interest rates)	Economic status(central route) Socialcapitaland listing quality (peripheral cues)	ELM (elaboration likelihood model)	Data from Prosper.com
[18]	Loan funding, percentage reduction in final interest rate, and loan performance	Borrower's identities (trustworthy, successful, hardworking, economic hardship, moral, religious)	Identity claims	Data from Prosper.com
[12]	Loan value, time until loan filled	Borrower group size, unfilled loan size, loan term, field partner risk rating, borrower gender, borrower country characteristics, death rate, power distance, individualism, masculinity	Prosociallending	Data from Kiva
[17]	Relative time elapsed, number of bids	Starting interest rate, requested loan amount, percent funded, debt-to-income ratio, homeownership, credit grade	Herding behavior	Data from Prosper.com
[30]	Loan funding	Credit grade, amount requested, maximum interest rate, explanation, denial, acknowledgment, unusual explanation	Social account	Data from Prosper.com, laboratory experiment
[10]	Likelihood of a loan being funded	Trustworthiness, attractiveness, financial resources, credit profile information, listing and auction characteristics	Beauty premium	Data from Prosper.com
[22]	Daily market share of bidders, daily market share of bid amounts	Participation rate, number of postings on the Q&A board, number of verified certificates, interest rate, duration for repayment, and the number of past auctions	Herding behavior	Data from Popfunding.com
[36]	Loan funding success	Total number of existing certificates for borrower, past loan requests by borrower, loan investments made by a borrower, delayed payments for the previous funded loan, early repayments for the previously funded loans, articles on b-board borrower posted in payment delay period	Information asymmetry, herding behavior	Data from Popfunding.com
[23]	Funding probability, interest rate, loan default	Online friendship (credit quality)	Signaling theory	Data from Prosper.com
[13]	Lending decision expressed in percentage	Lender attractiveness, lender charisma, age, gender, and image quality	Decision heuristics and judgment biases, beauty premium	Experiment
[4]	Number of lending transactions,lending actions	GDP, common language, distance, cultural differences, disaster, immigration, diversity, MFI risk rating, and lender trust index	Cultural and geographicdistancerelated to IS literature	Data from kiva.org (by country analysis)
[24]	Bid on a listing	Offline/online strong-tie/weak-tie, friendship, number of prior bids	Pipes, prisms, and relational herding	Data from PPDai

The usefulness of a signal to the receiver depends on the extent to which the signal corresponds to the sought-after quality of the signaler and the extent to which the receiver interprets the signals [8]. Because signalers and receivers often have partially competing interests, inferior signalers have an incentive to "cheat," intentionally producing false signals so that the receivers will select them [21]. Davila et al. [9] used the term "credibility" to describe the extent to which the signaler is honest and the signal corresponds to signaler quality. The credibility of the source of information (i.e., the signaler) would affect the trustworthiness of the signals it sends out. From the receiver side, some receivers interpret signals differently from others. In many cases, receivers may apply weights to different signals in accordance with preconceived notions of their importance or cognitively distort signals [27].

Prior research has identified a variety of signals of quality. For instance, a positive reputation over time is a strong signal of underlying quality [6]. Not all signals are equally efficacious. Some signals of quality may be more readily detected by the receiver than others. In other words, signals may be strong or weak [15]. Two important traits for efficacious signals are observability and cost [1,8,31]. While observability is a necessary characteristic of a signal, it is not sufficient for detecting quality. Signal cost is so central to the signaling theory that some refer to it as the "theory of costly signaling"[3]. Some signals are costly to produce but more efficacious. For instance, the introduction of live chat software on online shopping sites might signal the quality to the consumer but might be expensive and time-consuming to employ. In addition, some signals are difficult to obtain. For example, displaying an authentic third-party seal such as that of the Better Business Bureau requires accreditation and compliance with its Code of Business Practices [25].

3. Research model and hypothesis

The aim of this study is to analyze lenders' decision-making in online P2P-lending marketplaces. To obtain observable data, the borrowing request was used as the unit of analysis. The likelihood of successful funding can be represented as the status of the borrowing request (i.e., success or failure), which reflects the opinion of the participating lender. Further, by using the borrowing request as the unit of analysis, the heterogeneous characteristics of the individual lender can be eliminated [36]. On the basis of the signaling theory and prior research, we proposed three research models for the scenarios of first-time borrowing (Model 1), repeated borrowing without lending (Model 2), and repeated borrowing with lending (Model 3). Model 1 relates to the scenario when a specific borrower submits a borrowing request for the first time. Thus, for such a borrowing request, there is no previous transaction history. Both Models 2 and 3 correspond to the scenario of repeated borrowing. We further distinguished two specific repeated borrowing situations in which borrowers only borrow money from the P2P website but never lend out (Model 2), while some have a lending history before or concurrent with their borrowing request (Model 3). For first-time borrowing requests, we did not distinguish two situations (i.e., with/without historical lending), because only a very small number of first-time borrowers had ever lent money to others (based on our data, seven records out of more than 13,000 records, accounting for less than 0.1%). For Model 1, we identified five factors as the antecedents of the likelihood of successful funding, including the interest rate, loan duration, borrow amount, number of verifications, and credit grade. All three models shared these five factors as common antecedents. We added unsuccessful borrowing requests, successful borrowing requests, and overdue repayment for Model 2. For Model 3, we further added the number of previous successful

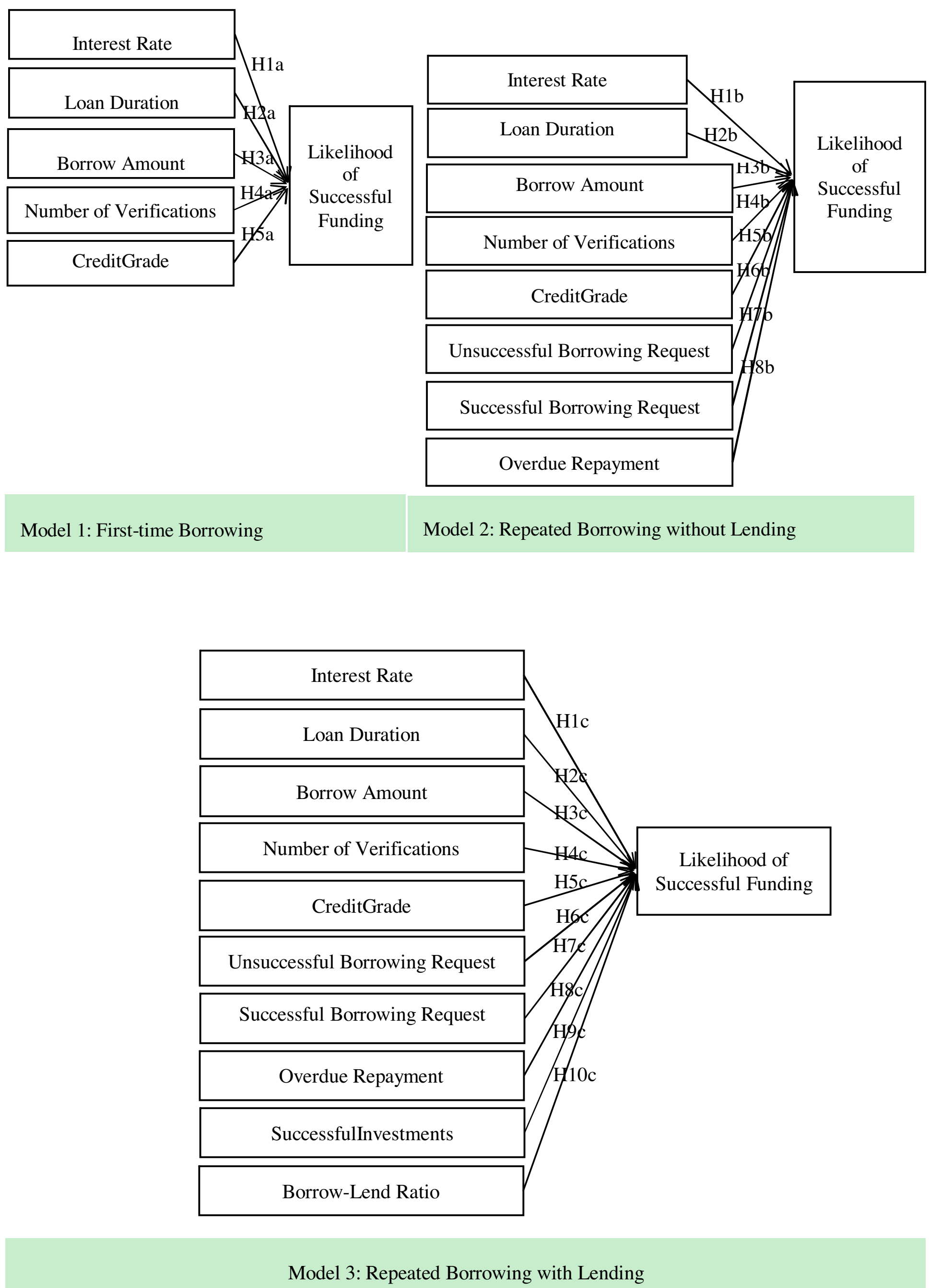

Fig. 1. Research Models.

investments and borrow-lend ratio factors. Three models are illustrated in Fig. 1. We will further justify each hypothesis in these models in more details.

Signal cost is central to the signaling theory and is important in predicting the efficaciousness of signals [1,31]. A signal would be costly if the monetary spending associated with it is high. For instance, a real-time product comparison chat feature might be expensive [25]. In online P2P lending, the interest rate a borrower is willing to pay represents the monetary cost. Further, a signal might also be costly if it takes a long time to build and maintain. According to Ippolito [20], a credible signal should have a "bonding" component, such that the firm incurs a cost if the signal is false. Reputation and commitment are examples of costly (credible) signals because they take a long time to build. In online P2P lending, for individuals with repeated borrowing, their previous successful borrowing may serve as a costly signal of their trustworthiness, because it takes time to build and maintain. In the context of online P2P lending, the source of information might also affect the cost of a signal. The sources of information about a borrowing request vary, including the borrower, the P2P website, other lenders, or a combination of these. While some information is provided by the borrower himself, other information provided by the borrower is verified by the P2P website, for example, the number of verifications. The P2P website may also decide on the credit grade by using the information it has collected. Other information such as successful borrowing requests (i.e., transaction history) is provided by the website according to the behavior of other lenders. A successful borrowing request might be a costlier signal because it is less likely to be fake.

We first identify the interest rate, loan duration, borrow amount, number of verifications, and credit grade as antecedents of the likelihood of successful funding. These five factors are common across the three models, i.e., even when a borrower is new, his or her borrowing requests contain that information. A description of variables is presented in Table 2.

When all other factors are equal, the higher the interest rate, the more favorable a borrowing request becomes (e.g., [14,17]). In accordance with prior literature, we hypothesized that the interest rate will increase the likelihood of successful funding. We also expected the interest rate to be an efficacious signal for a borrowing request because it represents the monetary cost a borrower is willing to pay. Such a signal might be costly and thus strong. In addition, when a high interest is offered by a borrower, it indicates not only the potential financial benefits a lender can obtain but also the borrower's confidence in economic status and thus in turn gives lenders greater confidence to lend their money to the borrower.

H1a(b, c). A higher interest rate will increase the likelihood of successful funding for first-time borrowing (repeated borrowing without lending history, repeated borrowing with lending history).

The effect of loan duration on the likelihood of successful funding could be mixed. Given a fixed interest rate, the financial benefit for lenders is positively related to the loan duration. However, it is also highly possible that longer loan duration may increase the risk of a borrowing request. Because the P2P market is developing and changing rapidly, lenders may prefer short-term investments to reduce risk. Galak et al.'s [12] empirical results showed that loan term is negatively related to the investment return and loan remaining time. Lee and Lee [22] also suggested that a borrowing request with a shorter payback period attracted more bids. While the former argument (loan duration relates to financial benefits for lenders) has not been empirically verified, in line with prior empirical results, we hypothesized a negative relationship between loan duration and the likelihood of successful funding.

H2a(b, c). A longer loan duration will decrease the likelihood of successful funding for first-time borrowing (repeated borrowing without lending history, repeated borrowing with lending history).

While the effect of the interest rate on borrowing success is relatively straightforward, the effect of the borrow amount could

Table 2
Descriptions of Key Variables.

Variable	Descriptions
Interest Rate	Interest rate offered in the borrowing request (auction)
LoanDuration	Duration for repayment of received loanby the borrower (represented in months)
Borrow Amount	Amount of money requested in an auction
Number of Verifications	The number of verifications borrowers have (verified and issued by the P2P website). There are four verifications in the PPDAI.com, including identity card verification, video verification, academic degree verification, and mobile phone number verification.
CreditGrade	The credit grade is provided by the P2P platform foreach specific borrowing request. It is calculated based on a very large number of data related to the borrower and borrowing requests, including borrowing/lending history,personal debt, credibility history,number of verificationsand third-party data, etc. However, the platform does not publish the detailed algorithm.In this study, the lowest credit grade is coded as 1, and the highest is coded as 8.
UnsuccessfulBorrowingRequests	The number of unfulfilled borrowing requests (auctions) ofa specific borrower
SuccessfulBorrowingRequests	The number of fulfilled borrowing requests (auctions) ofa specific borrower
Overdue Repayment	The number of requests (auctions) that were not fully repaid within 15 days of the lapse of the due date
Number of Successful Investments	The number of successful investments in other borrowing requests (auctions)
Borrow-lendRatio	The ratio of the amount of money requested to the total amount of recent investments (maximum 12 recent investments) for a specific borrower
Successful Funding	Adummy variable. If a borrowing request is fully funded, we code it as 1, otherwise as 0.

be complicated. Lenders could consider the borrowed amount as a risk factor and/or as a credit cue. On the one hand, lenders may intuitively prefer to lend money to borrowers who request smaller amounts for the following two reasons: First, if a lender is sensitive to the risk of the investment, he or she may avoid lending a large amount of money to control risk; second, borrowing requests with smaller requested amounts may be easier to fulfill because they generally make the request of fewer lenders. For the above reasons, some empirical evidence has suggested that it is more likely that a larger borrow amount would decrease the funding success rate [11,28].

However, while the role of the requested amount as a risk is straightforward, sometimes it could also serve as a credit cue of borrowers. Some P2P websites set strict rules on the amount that a specific borrower can request. If the amount requested is strictly examined and verified by the P2P website, or the lenders believe it to be so, it is possible that the amount requested becomes a signal of credibility. This indicates that a larger borrow amount may also signal the ability of the borrower to engage in bigger and more promising businesses, which will convince lenders to invest more money. Since this signal is verified by the P2P website, if lenders tend to trust the platform more than individual borrowers, such a signal might be efficacious for lenders.

Further, lenders can decide the investment amount that they are willing to lend to a specific borrowing request. The amount of investment can be lower than the overall amount requested and not proportional to the requested borrowing amount. That is, even if the amount requested is large, lenders can still choose to lend a smaller amount to the borrower, such that the risk can be reduced. In a recent study by Herzenstein et al. [17], the borrowing amount was not a significant predictor of the likelihood of a partially funded loan auction receiving an additional bid, and this alternative explanation was refuted by their data. Therefore, we would like to adopt the “borrow amount as credit cue” reasoning and expect a positive relationship between the borrow amount and the likelihood of successful funding.

H3a(b,c). A larger borrow amount will increase the likelihood of successful funding for first-time borrowing (repeated borrowing without lending history, repeated borrowing with lending history).

There are four verifications in PPDAI.com, including identity card verification, video verification, academic degree verification, and mobile phone number verification. PPDAI.com also provides a credit grade for each specific borrowing request. It is calculated using a very large amount of data related to the borrower and borrowing requests, including borrowing/lending history, personal debt, credibility history, number of verifications, third-party data, etc. These factors are believed to mitigate potential investment risks for lenders and increase the trustworthiness of the borrowers [10,16,17,36]. Lee and Lee [22] posited that a borrowing request with more verifications attracts more bids. If the request is guaranteed by users who have good credit or the borrowing request had an excellent credit grade, lenders would be more confident. Therefore, in line with prior research, we expected these two factors to positively affect the likelihood of successful funding.

H4a(b,c). The number of verifications will increase the likelihood of successful funding for first-time borrowing (repeated borrowing without lending history, repeated borrowing with lending history).

H5a(b,c). A higher credit grade will increase the likelihood of successful funding for first-time borrowing (repeated borrowing without lending history, repeated borrowing with lending history).

For repeated borrowers, transaction history is an important signal for potential lenders [36]. For potential lenders, the predicted outcome of investing in a specific borrowing request can be regarded as an expectancy, which is based on experiences of many similar situations. That is, lenders may tend to look at past transaction results as a basis of future expectancy. A record of unsuccessful and successful borrowing requests is a signal of what the borrower and what other potential lenders did in the past. Unsuccessful borrowing requests may be interpreted by the potential lenders as a signal that the borrower offered less favorable terms in past requests or that other potential lenders did not have confidence in the repayment ability of this borrower. No matter how lenders interpret this information, it is a negative signal. On the contrary, successful borrowing requests are positive signals based on similar reasoning. For borrowers with a history of repeated borrowing, previous unsuccessful/successful borrowing may have great impact on their trustworthiness since many lenders have entrusted them with their money.

Records on overdue repayment create an unfavorable transaction history for a borrower. When lenders make a decision about investing in a specific borrowing request, a history of overdue repayments will suggest higher risk to lenders [36]. Similar to unsuccessful borrowing requests, overdue repayment is a negative signal. From a lender's perspective, a borrower's inability to repay prior borrowing requests may signal a weak economic status of a borrower. Therefore, lenders may tend to believe that a borrower who delayed repayments in the past will be more likely to delay repayment in the future. In fact, this notion is supported by Schreiner's research on microfinance, which suggests that those who fell into repayment arrears for more than 15 days on their previous loan were 2.8% more likely to delay repayment for at least 15 days on their current loan [29]. Therefore, we suggest the following:

H6b(c). More unsuccessful borrowing requests in the past will decrease the likelihood of successful funding for repeated borrowing without lending history (repeated borrowing with lending history).

H7b(c). More successful borrowing requests in the past will increase the likelihood of successful funding for repeated borrowing without lending history (repeated borrowing with lending history).

H8b(c). More overdue repayments in the past will decrease the likelihood of successful funding for repeated borrowing without lending history (repeated borrowing with lending history).

For repeated borrowers with lending, that is, those borrowers who had invested their money through the P2P platform before or concurrent with borrowing, there is more information available for potential lenders to examine. Two of the key factors are the number of successful investments in the past and the borrow-lend ratio. More successful investments in the past indicate that the borrower has more experiences and engagements in the platform, and he or she had more interactions with other users. In addition, Yum et al. [36] have verified that borrower's loan would positively influence the success rate of getting a loan. Further, if this borrower had lent out a certain amount of money through the same P2P platform, a low borrow-lend ratio may signal the borrowers' commitment to the community by reciprocating through lending to others, which indicates their seriousness and trustworthiness. Given that this entails high costs to the borrowers, it may then serve as a particularly efficacious signal that can lead people to lend their money to the borrowers. In particular, given a certain loan amount, when a borrower made more investments to others, this will lower his or her borrow-lend ratio, and the likelihood of successful funding will be increased. This result is consistent with the effect of investments while given a certain loan amount. Therefore, we hypothesize the following:

H9c. More successful investments in the past will increase the likelihood of successful funding for repeated borrowing with lending history

H10c. A higher borrow–lend ratio will decrease the likelihood of successful funding for repeated borrowing with lending history

4. Data

We collected data from PPDAI.com, one of the largest P2P-lending platforms in China. On the PPDAI website, borrowers can post borrowing requests—called listings (auctions)—with a title, description, amount requested, interest rate, number of monthly repayments, etc. We obtained data by crawling the PPDAI website in September 2015. Through the website, 13,000 borrowing requests (auctions) were returned as search results. A large number of these were still under verification by the website and some records had incomplete values. After removing such “noisy” records, we retained 5069 records (borrowing requests), including 2860 first-time borrowing requests without lending, 1964 repeated borrowing requests without previous lending, and 245 repeated borrowing requests with previous lending.

5. Empirical results

We employed logistic regression in SPSS to verify our research models. All data for independent variables were normalized before conducting the regression analysis. Before estimating our models, we conducted a regression analysis for the three models. The variance inflation factors associated with all variables were below 10, indicating that there was no evidence of the existence of multicollinearity [26].

Since this research focused on investigating the potential differences between first-time borrowing requests and repeated borrowing requests, as well as the differences between borrowing requests with and without prior lending behavior, we first verified that there were indeed significant differences in the success likelihood among these three types of borrowing requests.

We first assessed the difference between first-time and repeated borrowing. We pooled Data sets 1 and 2 (Data set 1 for first-time borrowing without lending and Data set 2 for repeated borrowing without lending), added one binary variable (first or repeated borrowing, FRB) distinguishing first-time and repeated borrowings, and included the five common variables for Models 1 and 2 as control variables. Results from the logistic regression showed that the effect of FRB was significant ($\beta = 1.278$, $P = 0.000$, and Nagelkerke $R^2 = 0.75$). In addition, we pooled Data sets 2 and 3 (Data set 2 for repeated borrowing without lending and Data set 3 for repeated borrowing with lending), added one binary variable (with or without lending, WWL) to distinguish repeated borrowing with and without lending, and included the eight common variables for Models 2 and 3 as control variables. Results from the logistic regression showed that the effect of WWL was also significant (β=0.421, $P = 0.026$, and Nagelkerke $R^2 = 0.63$). Therefore, we proceeded to analyze the three different models for different scenarios.

5.1. Model 1: first-time borrowing requests

In Model 1, we included five independent variables in the research model. The mean, standard deviation of independent variables, and the correlation matrix are presented in Table 3. The average borrow amount was 1376 RMB, with an average interest rate of 13%, and the average loan duration was 11.6 months. Each borrower had an average of 1.24 verifications and the average credit grade was 2.27.

Hosmer and Lemeshow conducted a typical statistical test for the goodness of fit of logistic regression models. It evaluated whether the observed event matched the expected event in the subgroups of the model. Thus, if the result of the test was not significant, it indicated that the observed event matched the expected event well. In this study, the results of this test (i.e., $\chi^2 = 0.446$, Sig. = 0.931) indicated that the observed event matched the expected event well. The results of the logistic regression are illustrated in Table 6. The results indicate that for a first-time borrowing request, the borrow amount (β=0.56, $p = 0.010$), interest rate (β=4.96, $p = 0.007$), number of verifications (β=0.98, $p < 0.001$), and credit grade (β=5.69, $p = 0.003$) were positively associated with the likelihood of successful funding. However, the hypothesized relationship between loan duration and the likelihood of successful funding was not significant ($\beta = -0.12$, $p = 0.54$).

It is interesting to see that the relationship between the borrow amount and the likelihood of successful funding was significant ($\beta = 0.56$, $p <= 0.010$), and it was consistent with our hypothesis. On the basis of prior literature, there are three lines of reasoning for this relationship. First, the amount of money a specific lender invests in a borrowing request may not be proportional to the overall amount requested. Accordingly, the borrow amount might not be a significant predictor of the likelihood of successful funding. Herzenstein et al.’s [17] empirical results have provided some guidance in this line of reasoning. Second, the borrow amount should be a significant predictor of successful funding because it could be a signal of risk, and requests for small amounts are more easily fulfilled. Some prior research provides empirical support for the negative relationship between the borrow amount and successful funding [11,28]. Third, the borrow amount could be a signal of credit. Some P2P websites set strict rules on the amount that a specific borrower may request. If the amount requested is strictly examined and verified by the P2P website or lenders believe such a proposed borrow amount has been examined by the P2P platform and they trust the platform, the borrow amount would likely be a positive signal. Our hypothesis was proposed on the basis of this line of reasoning. Therefore, for first-time borrowing, it is likely that this effect plays a major role in our study.

5.2. Model 2: repeated borrowing requests without lending

In Model 2, we included eight independent variables in the model. The mean, standard deviation of independent variables, and the correlation matrix are presented in Table 4.

The results of the Hosmer and Lemeshow test ($\chi^2 = 5.191$, Sig. = 0.737) indicated that the observed event matched the expected event well. The results of the logit regression are shown in Table 6. The results indicate that for repeated borrowing requests without lending, interest rate (β=1.64, $p < 0.001$), credit

Table 3
Descriptive Analysis for Model 1 Data Set.

	Mean	S.D.	BA	IR	LD	NV	CG
Borrow Amount (RMB)	1376.09	1261.22	1				
Interest Rate	0.13	0.03	0.30	1			
Loan Duration	11.60	1.78	0.07	−0.58	1		
Number of Verifications	1.24	0.51	0.53	0.22	−0.06	1	
Credit Grade	2.27	1.41	0.53	−0.07	−0.12	0.45	1

Number of Valid Records (borrowing requests): 2860.

Table 4
Descriptive Analysis for Model 2 Data Set.

	Mean	S.D.	BA	IR	LD	NV	CG	UBR	SBR	OP
Borrow Amount	3324.86	4792.86	1							
Interests Rate	0.14	0.05	−0.05	1						
Loan Duration	9.47	3.52	−0.03	−0.36	1					
Number of Verifications	1.90	0.79	0.31	0.00	−0.16	1				
Credit Grade	4.01	2.41	0.39	−0.38	−0.26	0.46.	1			
Unsuccessful Borrowing Requests	1.49	1.38	−0.23	−0.04	0.14	−0.21	−0.40	1		
Successful Borrowing Requests	1.70	2.15	0.40	0.074	−0.22	0.43	0.55	−0.42	1	
Overdue Repayment	0.07	0.49	−0.01	−0.054	−0.05	0.08	0.13	0.06	−0.02	1

Number of valid records (borrowing requests): 1964.

grade (β=1.07, $p < 0.001$), unsuccessful borrowing requests (β=−1.10, $p < 0.001$), and successful borrowing requests (β=0.34, $p < 0.001$) had significant effects on the likelihood of successful funding. However, the effects of loan duration (β=0.13, $p = 0.065$), borrow amount (β=−0.05, $p < 0.445$), number of verifications (β=0.11, $p = 0.178$), and overdue repayment (β=−9.49, $p < 0.993$) on the likelihood of successful funding were not significant.

When potential lenders are evaluating a repeated borrowing request, it is likely that they make decisions differently from the ones when evaluating a first-time borrowing request. First, the amount of information, or number of signals, is different because more information is available. Second, the importance of some signals might decrease since more official signals are available for repeated borrowings. Compared to the number of verifications, the credit grade provided by the platform could be a more efficacious signal because it is more systematic and seriously endorsed by the platform. In addition, records on successful borrowing are efficacious because many lenders have entrusted the borrower with their money and they are difficult to obtain. Records on unsuccessful borrowing are also efficacious because they are also part of the transaction history and could be even more efficacious than successful borrowing.

For the insignificant relationship between overdue repayment and the likelihood of successful funding, we had expected it to be significant and negative because overdue repayment contributes to an unfavorable transaction history. However, potential lenders could think differently. Although the history illustrates the number of times this borrower has failed to fully repay the money within 15 days of the lapse of the due date, it also indicates that the borrower ultimately repaid the full amount. It is likely that some lenders would not place much importance on the arrears since ultimately the full amount was repaid.

5.3. Model 3: repeated borrowing requests with lending

In Model 3, we included ten independent variables in the model. The mean, standard deviation of independent variables, and the correlation matrix are presented in Table 5.

We noticed that the correlation between credit grade and interest rate was very high (−0.92). According to the PPDAI.com platform, to a certain extent, the credit grade would affect the interest rate approved by the platform; that is, the higher the credit grade a borrowing request has, the lower is the approved interest rate. In addition, the correlation between successful investment requests and successful borrowing requests was also relatively high (0.78). Such results were consistent with our hypothesis that when a borrower invests more on a platform, it is more likely that his or her borrowing requests will be more easily fulfilled. We also explored the reasons behind such high correlations. In the data analysis, we removed each variable one by one and examined the results. For example, we removed credit grade and investigated the effect from interest rate, and vice versa. Regardless of whether an effect is significant, the result remains unchanged.

The results of the Hosmer and Lemeshow test ($\chi^2 = 13.079$, Sig. = 0.109) indicated that the observed event matched the expected event well. The results of the logit regression are illustrated in Table 6. The results indicate that for repeated borrowing requests with lending, interest rate (β = 1.23, $p = 0.017$), credit grade (β = 0.85, $p = 0.003$), unsuccessful borrowing requests (β = −0.36, $p = 0.020$), and borrow–lend ratio (β = −0.36, $p = 0.040$) had significant impacts on the likelihood of successful funding.

However, consistent with results from the two prior models, the effect of loan duration (β = −0.24, $p = 0.150$) was not significant. Consistent with results from Model 2, the effects of borrow amount (β = 0.03, $p = 0.883$) and number of verifications (β = 0.06, $p = 0.703$) were not significant. Further, the effect of successful borrowing requests (β = −0.22, $p = 0.382$) was also not significant. It is possible that when lenders make decisions using a larger set of signals, the signals that are costlier might have greater effects, and effects from less costly signals become weaker and even insignificant.

In addition, the effect of overdue repayment was again not significant (β = −0.19, $p = 0.353$). A possible reason is that some lenders thought that it was not important since ultimately the full amount was repaid.

Table 5
Descriptive Analysis for Model 3 Data Set.

	Mean	S.D.	BA	IR	LD	NV	CG	UBR	SBR	OP	SI	BLR
Borrow Amount	6806.64	5137.09	1									
Interest Rate	0.13	0.05	−0.03	1								
Loan Duration	6.99	3.68	0.18	0.23	1							
Number of Verifications	2.29	0.87	0.05	0.20	0.15	1						
Credit Grade	6.20	1.88	0.08	−0.92	−0.28	−0.20	1					
Unsuccessful Borrowing Requests	1.52	2.08	−0.13	−0.01	0.09	0.23	−0.01	1				
Successful Borrowing Requests	33.14	84.45	0.11	−0.23	−0.21	0.06	0.26	0.17	1			
Overdue Repayment	0.08	0.51	−0.09	0.13	0.14	0.03	−0.15	0.12	−0.05	1		
Successful Investments	1062.87	2622.71	0.09	−0.32	−0.30	−0.03	0.35	0.14	0.78	−0.06	1	
Borrow-Lend Ratio	29.43	52.99	0.26	0.12	0.25	−0.00	−0.12	−0.09	−0.16	0.01	−0.19	1

Number of validrecords (borrowingrequests): 245.

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Finally, our hypotheses suggested that the amount of money lent by the borrower through the same platform could increase the credit of a borrower. It is likely that a reciprocity mind-set is appreciated by potential lenders, such that lenders may consider whether the borrowers made a return to the community after they had obtained loans. However, the effect of number of successful investments was not significant (β=0.15, p = 0.595), but the effect of the borrow–lend ratio was significant (β = −0.36, p = 0.040). A possible reason could be that potential lenders focus more on *how much* the borrower invests through the platform than on *how many times* he or she invests. It is also likely that although both a borrow–lend ratio and successful investments could signal a borrower's commitment to the P2 P platform, successful investments could have been completed long before, but the borrow–lend ratio indicates that there is a certain amount of money receivable by the borrower. Such receivables could be treated as some kind of gauge and accordingly potential lenders feel safer. Moreover, compared with the mere number of successful investments, the borrow–lend ratio may encapsulate more information, as it reflects how much they lend in relation to how much they get. The different borrow–lend ratios may reflect the different characteristics of the borrowers. For example, a borrower with a low borrow–lend ratio tends to be more trustworthy. A better understanding of the characteristics of the borrower will be helpful to assist the investment decision-making.

5.4. Summary of empirical results and discussions

The empirical results of the three research models are summarized in Table 6.

Analyzing the results of the three models, we found that two variables were consistently important. Regardless of whether the borrowing request was made for the first time or repeated, interest rate and credit grade had significant effects on the likelihood of successful funding. The stable effects of these two variables are consistent with prior literature [30,36]. The interest rate indicates the benefit of the investment, and the credit grade is central to the potential lenders' control of risk.

The effect of loan duration was consistently insignificant in the three models, which is contrary to prior literature (e.g. [10]). We then pooled the three data sets to test the effect of loan duration again. In contrast to the results for each individual model, the effect was significant. We examined the mean and standard deviations of loan duration in the three models and found that they were different. The first-time borrowing requests had an average of 11.60-month loan duration, whereas the average loan durations for repeated borrowing with or without prior lending were 6.99 months and 9.47 months, respectively. It is possible that the variance of loan duration was increased in the three models, resulting in the effects becoming insignificant. However, it also suggested that the three types of borrowing did have great differences among them and it is important to investigate such differences.

Across the three models, the borrow amount had a positive and significant impact on the likelihood of successful funding in Model 1. In addition, this hypothesized relationship was not significant in Models 2 and 3. As we discussed in the hypothesis development section, there may exist multiple explanations for this relationship. Although it is intuitive that a smaller loan amount might be easier to fulfill, the approved borrow amount could also be a credit cue. For first-time borrowing requests, potential lenders have very limited information with which to evaluate the credit of the borrower. Therefore, the borrow amount becomes a credit signal. However, for repeated borrowings, more and stronger signals for credit are available for evaluation. Thus, the effect of the borrow amount as a credit signal becomes weaker and even insignificant. In addition, since we collected data from PPDAI.com, it sets limits on the borrowing amounts for new borrowing requests. For this reason, the positive relationship between the borrow amount and the likelihood of successful funding is more marked for Model 1.

Given that all the factors with highly skewed distributions have been log-transformed, to explore the nonlinear relationship between the borrow amount and the likelihood of success funding, we add the quadratic and cubic terms of the borrow amount in the regression by using the whole data set as a post-hoc analysis. We also included five common variables across the three models in the regression. The results showed that a cubic regression led to the largest R^2 (R = 0.353, P = 0.000). For quadratic regression, R^2 = 0.264, P = 0.000. R^2 from both models are larger than that from the linear model (R^2 = 0.167, P = 0.000). Thus, it is possible that some relationships in our model are nonlinear, and adding quadratic and cubic terms to the model could increase the explanatory power of our model. This would be an interesting future research.

Most importantly, we found that when more information was available, or when "costlier" new signals arrived, those less "costly" signals became less efficacious or even insignificant. Comparing Models 1 and 2, when "costlier" signals like information on unsuccessful and successful borrowing requests were available, the effect of the number of verifications became insignificant. Another example for this finding is that the effect of the credit

Table 6
Results for AllModels.

	Model 1 First-time borrowing model (without lending experience) Nagelkerke R^2 = 0.951	Model 2 Repeated borrowing without lending experience Nagelkerke R^2 = 0.681	Model 3 Repeated borrowing with lending experience Nagelkerke R^2 = 0.217
Interest Rate	4.958**	1.638***	1.233*
Loan Duration	−0.119	0.129	−0.242
Borrow Amount	0.557*	−0.050	0.025
Number of Verifications	0.980***	0.107	0.061
Credit Grade	5.693**	1.068***	0.850**
Unsuccessful Borrowing Requests		−1.100***	−0.361*
Successful Borrowing Requests		0.340***	−0.215
Overdue Repayments		−9.493	−0.192
Successful Investments			0.151
Borrow-Lend Ratio			−0.357*
Constant	−33.794**	−7.481	−4.494*

* $p < 0.05$.
** $p < 0.01$.
*** $p < 0.001$.

grade is stronger and more significant than the number of verifications in Model 2 and 3. One possible reason is that the number of verifications is a result of the borrower submitting photos and ID card's photocopy, etc., while the credit grade is calculated by the website from historical records. Obviously, the credit grade is a "costlier" signal than the number of verifications, as the source of the latter is from the borrower. Similarly, the effect of successful borrowing requests was significant in Model 2. However, with the introduction of the borrow-lend ratio information in Model 3, the effect of successful borrowing request was insignificant.

Finally, unsuccessful borrowing requests had a significant impact in Models 2 and 3, according to our empirical results. These results suggest that this information might be an important signal for potential lenders when making investment decisions. However, the effect of successful borrowing requests was significant in Model 2, but not in Model 3. A comparison between the effects of unsuccessful and successful borrowing requests could possibly imply that an unfavorable transaction history had a more significant impact on the likelihood of successful funding than a favorable transaction history. It has been discussed in Ref. [37] that in the online auction market eBay, a product's faults are more seriously discussed. This also seems to be similar to the results from online WOM studies that suggested that negative comments were more powerful than positive ones [1]. Although such a notion is not conclusive in this study, it could be an interesting topic for future research.

6. Implications

This research offers several implications for theory and practice. From the theory perspective, this study has presented evidence that lenders' investment decisions evolve as more information is revealed. When more verifiable information accumulates, lenders tend to utilize a different set of criteria to support their decision-making. Our research complements the current literature on P2P lending by providing a better understanding of how different types of information provided in borrowing lists may affect the success of funding under different scenarios. Our empirical evidence shows that for first-time borrowing and repeated borrowing with and without prior lending, the effects of different signals vary. More importantly, the signaling theory suggests that signals may be more efficacious when they are costlier [1,8,31]. Our research provides empirical evidence that some "costlier" signals do indeed have greater power in influencing lenders' decisions. In P2P lending, costly signals include those that are costly to produce (e.g., the credit grade system), difficult to obtain (e.g., a borrower's favorable transaction history), and showing commitment to the community by lending money (e.g., the borrow-lend ratio). Finally, although transaction history has been identified as an important factor for the likelihood of successful funding, most research attention has been devoted to *borrowing* history, but the potential effect of the *lending* history of a borrower has largely been neglected. Our research complements the current theory in P2P lending by identifying and confirming the effect of a borrower's lending history on successful funding.

From the practice perspective, there are important implications in the findings for P2P lending. This study suggests that credit grade is a consistent and powerful signal to lenders. It is important for a P2P platform to devote significant effort and resources to develop a sound credit grade framework and system. In addition, this study suggests that there is no evidence that a larger borrow amount will reduce the chance of a borrowing request being fully funded. In contrast, our study suggests that for first-time borrowing, the borrow amount is positively associated with the likelihood of successful funding. Therefore, it is not necessary to limit the borrow amount of first-time borrowers to a small amount for the sake of increasing the chance of successful funding. Finally, our results also provide suggestions for borrowers. A high credit grade is the key to successful funding in all scenarios. For first-time borrowing, obtaining more verifications is important. For repeated borrowing, the transaction history of borrowers is extremely important for a borrowing request to be fully funded.

7. Conclusions

Our results add to the nascent empirical research on P2P lending. Instead of investigating lender's investment strategies, we addressed this issue by examining which factors are powerful signals that make a borrowing request more likely to be fulfilled. Overall, our results confirm the power of a list of signals from the borrowing request. However, this does not simply replicate prior research in a specific P2P-lending platform. More importantly, we extend the theory and research on P2P lending by comparing the effects of different signals in different scenarios. By using the signaling theory, our study shows that for first-time borrowing, repeated borrowing without prior lending experience, and repeated borrowing with prior lending experience, the power of different signals vary significantly.

However, there are still some limitations to the current research. First, we collected only data from one P2P platform (PPDAI) that may have unique characteristics, limiting the generalizability of the proposed model. Second, although we obtained a relatively large data set, the number of records for repeated borrowing with prior lending experience was relatively small; therefore, the results should be viewed as only preliminary evidence with respect to the varying signals that affect successful funding in different scenarios. Finally, the R^2 of the models became substantially lower from first time to repeated borrowing. This may suggest that there are other important factors for these models that have not been considered. Future research should be conducted by including more undiscovered variables in the models.

This research also provides some interesting findings. For first-time borrowing, potential lenders have to make decisions based on very limited information. To evaluate borrowing requests, they mainly rely on information on the interest rate, borrow amount, number of verifications, and credit grade. For repeated borrowings without prior lending, the transaction history of the borrower becomes an important source of information for potential lenders. Historical unsuccessful and successful borrowing requests become important signals on which potential lenders base their decisions. In this scenario, while the interest rate and credit grade still play important roles in deciding the likelihood of successful funding, the effects of the borrowing amount and the number of verifications diminish. Finally, for repeated borrowing with prior lending, the new information on the borrow-lend ratio of borrowers has a significant impact on the likelihood of successful funding. However, the effect of past successful borrowing requests diminishes in this scenario.

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