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Cheap Talk? The Impact of Lender-Borrower Communication on Peer-to-Peer Lending Outcomes

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ABSTRACT: The limited information provided by peer-to-peer (P2P) lending platforms often is not sufficient for lenders to determine if a borrower is trustworthy and able to repay the loan. Using a unique dataset from a P2P lending platform, which allows lenders to seek information directly from borrowers and borrowers to respond to the questions and comments, we examine the impact of lender-borrower communication on funding outcomes and loan performance. Our results show that not only the amount but also the content of such direct communication matters. Specifically, the number of lender comments is negatively associated with funding success, while the number of borrower responses is positively associated with funding success, although only comments help reduce the final interest rate. The role of the communication is even stronger for listings with poor credit grades. Moreover, lenders are influenced by other lenders' (positive or negative) comments and the quality of the information disclosed in borrower responses can affect funding outcomes. Loan performance (e.g., default ratio), however, cannot be predicted based on the amount

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of lender borrower communication. This research broadens and deepens our understanding of the roles of information disclosure, social influence, information quality, and trust in economic exchanges in online settings.

KEY WORDS AND PHRASES: information quality, lender-borrower communication, online trust, P2P lending, peer-to-peer systems, social influence.

The advance of information technology (IT) has spawned a strong wave of financial innovations in recent years including crowdfunding and social lending, mobile payment, digital currency, blockchain, and thematic investing, among many others. As one of the earliest examples of the "FinTech Revolution," peer-to-peer (P2P) lending has gone through cycles of adventure and development since its emergence around the world in the middle of the 2000s [37, 49].

P2P lending has been enabled by online auction platforms that allow individuals to acquire loans from other people without an intermediary financial institution (e.g., a bank). The greatest challenge facing P2P lenders is information asymmetry, a situation in which one party in a transaction has more or better information than the other [1]. In other words, while borrowers know about their own financial status and repayment capabilities, individual lenders have very little information about who the borrowers are and whether they are trustworthy. In traditional lending transactions, financial institutions such as commercial banks have access to detailed information of borrowers and sophisticated risk-assessment instruments. As a result, they are able to mitigate information asymmetry and reduce risks effectively. In the P2P lending context, however, the information asymmetry between borrowers and lenders is significantly elevated and the adverse selection problem is more severe. Because P2P platforms usually do not offer any guarantees that borrowers would repay the loans on time, lenders must make careful selections from a large number of available loan requests (also called listings) that are subject to a high level of uncertainty, opportunism, and risks [18].

To reduce uncertainty and financial risks, many lenders often strive to find more information about listings and the borrowers who create those listings before making lending decisions. However, due to the virtual nature of the online settings, the information sources that lenders can access are often limited to only the platform and the borrowers. A P2P platform generally provides the hard credit information (e.g., credit score, debt-income ratio) about a borrower. Such hard information is most important for lenders' decision making. In addition, lenders may rely on other "soft" clues, such as social capital (e.g., number of friends a borrower has) [17, 33], demographics (e.g., age, gender, and personal images) [15, 43], and loan descriptions [28, 36] to determine the trustworthiness of a borrower.

A number of research studies have examined P2P lending transactions on various platforms seeking to discover the determinants that affect lenders' funding decisions and the performance of loans [16, 29, 33, 51]. Although considerable progress has been made, a few key questions remain elusive: Does it help mitigate information asymmetry if borrowers provide more information? Do lenders trust borrowers as a reliable information source? Are lenders influenced by the behaviors and opinions of their peer lenders when making decisions?

Our research will examine the effects of direct communication between lenders and borrowers on funding outcomes and loan performance. Because of anonymity on P2P platforms, it is almost impossible for lenders to get any information from borrowers through face-to-face contacts. However, the platform that we study in this research allows lenders and borrowers to engage in direct communication using the "comment" feature on the website, which is not commonly available on other P2P platforms. With this feature, lenders can post questions and request additional information, make comments, or express personal opinions about the listing. The borrower can respond by providing requested information, clarifying outstanding issues, or assuring lenders of timely repayment. Both comments and responses are displayed on the listing page so prospective lenders can view or participate in the discussion.

With this unique feature and its corresponding data set, we will be able to discover how lenders may leverage the information from different sources to reduce uncertainty caused by the information asymmetry problem. Our fundamental research question is: To what extent does the direct lender-borrower communication, as well as the information presented in the conversation, affect funding outcomes and predict loan performance? To address this question, we first attempt to ascertain (1) whether such communication plays a role in affecting funding outcomes, and (2) whether the effect is different for different types of borrowers. We then delve into the contents of the communication to explore (3) whether lenders actually utilize comments posted by other lenders as an information cue during their decision-making processes, and (4) how the quality of the information provided in the responses by borrowers affects lending outcomes. Last, we wonder (5) whether the lender-borrower communication helps predict if a loan will default.

Our research is different from other P2P lending studies in two aspects. First, our research focuses on the direct communication between lenders and borrowers, which has been understudied in the prior literature. Only one study has briefly touched upon this question based on data from a Korean P2P lending platform, which reports that the number of messages posted by borrowers on a QA bulletin board is positively associated with funding outcomes during the period of late repayment of borrowers [51]. This type of dynamic interaction we study in this research is different from other passive forms of information presentation (e.g., images and loan descriptions) and can facilitate lenders' information-seeking and borrowers' trust-building goals. It may also help plant the seeds for forming future social relationships between lenders and borrowers. Second, while most prior research has investigated P2P platforms in developed countries (e.g., Prosper.com in the United States), the platform we study is in China, which has a disparate financial environment (e.g., the lack of a nationwide credit system), legislation, and regulation systems, and culture compared to developed countries. Under greater uncertainty than their western counterparts, Chinese lenders may have different patterns of trust in information provided directly by borrowers. A recent survey notes that trust in borrowers is more important than trust in an intermediary in affecting lenders' willingness to lend in China's P2P context [10]. Unanswered is whether lenders trust borrowers and are willing to lend money based on the information from the borrowers in P2P marketplaces in China.

Literature Review

P2P Lending

The lending processes on most P2P platforms are rather similar. We use Prosper.com, which is one of the largest P2P platforms in the United States, as an example to illustrate the process. On Prosper.com, a borrower can create a loan request, called listing, with an amount between $2,000 and $35,000. The borrower must also specify the maximum interest rate he or she is willing to pay. Lenders can bid on the listing by contributing a certain amount (with a minimum of $50) and specifying the minimum interest rate they are willing to accept. A listing is closed as soon as it receives 100 percent of the funding. A listing may remain active for up to seven days. If the listing is not fully funded before the end of the seven-day period, the listing is considered failed and closed.

A fully funded listing will be materialized into a loan. On Prosper.com, each loan has a fixed maturity of 36 months and each monthly payment made by the borrower is distributed among the winning lenders based on their contribution proportions. The status of a loan that has been repaid up to the payment schedule is "current." A loan's status can also be "one month late" or "two months late." A loan that is late for three or more months is considered to be in default.

The true identities of users (i.e., borrowers and lenders) are never publicly disclosed on Prosper.com. However, to engage in a borrowing or lending transaction, a user's identity must be verified by the platform based on the user's social security number, driver's license number, and bank account number. In addition, Prosper.com assigns each borrower a letter credit grade from AA (high quality) to HR (low quality) based on the borrower's credit report from Experian. Prosper.com publishes several metrics about a borrower including the debt-to-income ratio, home ownership, past and present delinquencies, current credit lines, bankcard utilization, and so on. The platform also allows a borrower to enclose additional information (e.g., location, gender, age, marital status, and a self-portrait image), and a brief text description about the loan (e.g., the purpose, the proof of repaying abilities, etc.). Such information, however, is not subject to verification by Prosper.com.

Platforms may vary in some of the operations in the lending process. For example, on some platforms, if a listing is fully funded before the seven-day period expires, lenders can compete and bid down the final interest rate. The loan maturity period may also vary from 3 to 36 months.

Hard and Soft Information

As information asymmetry is the major concern in P2P lending, the prior literature mostly focuses on how lenders make investment decisions based on various types of information. Petersen [42] categorized financial information into two types: hard information and soft information. Hard information refers to information about an individual's financial status that can be objectively verified and used as a signal of quality. This type of hard information often includes a borrower's credit grade, debt-to-income ratio, number of bank cards, number of credit inquiries on the borrower, credit history length, and home ownership [33]. Because the hard information is based on the financial history of a borrower, it is naturally the most credible source of information that lenders tend to rely on when making lending decisions. Accordingly, research has shown that most factors in the hard information category can significantly affect funding outcomes, which are often captured by funding success and final interest rate of a loan request [20, 29, 33, 52]. Borrowers with a high credit grade and low debt-to-income ratio can get their listings fully funded with a lower final interest rate relatively easily. An exception is home ownership, the impact of which has been found to be nonsignificant probably because it is not a strong sign of financial security after the subprime mortgage crisis in the United States in the late 2000s [20, 52].

Soft information refers to informational cues other than the above-mentioned hard measures [33]. Based on the elaboration likelihood model, Greiner and Wang [18] examined the cognitive process of decision making of lenders and confirmed that hard information and soft information are processed via different routes (central vs. peripheral) and have varying influence on lenders' trust and bidding behavior. Soft information usually cannot be objectively verified and quantified, but may be "hardened" by information technology into usable forms for lenders. For example, social capital, a most commonly studied type of soft information, has been measured using the number and type of friends a borrower has. Most P2P platforms allow users to create friendship links with one another and specify the types of the relationships (e.g., online only, schoolmates, relatives, etc.). Accordingly, the social capital of a borrower and the number of friend endorsements that his or her listing receives may become a signal of listing quality that influences the funding outcomes [17]. Research has shown that this effect is more significant for listings with lower borrower credit grades, for which lenders have to make more subjective assessments of the potential risks [33]. Lenders may also derive signals of quality from other types of soft information such as images, demographics, and the preparedness of listings [37, 18]. For example, Duarte et al. [15] coded perceived trustworthiness based on the self-portrait images posted by borrowers and found that borrowers who appear to be more trustworthy are more likely to get their listings funded. Similarly, Pope and Sydnor [43] studied several individual characteristics (e.g., race, gender, age, attractiveness, etc.) based on borrower images and found that black borrowers are less likely to receive funding than white borrowers with similar credit profiles.

Regarding loan performance, measured by the likelihood of default or default rate, it has been found that hard scores are significant predictors of loan performance [13, 33, 48]. Most studies have reported that borrowers with better credit grades tend to have lower default rates [15, 21, 43]. Lin et al. [33] estimated that the odds of a borrower's defaulting decreases by 9 percent on average if the borrower has friends in their social network with verified identities and who act as lenders. However, other studies have found that borrowers with good personal or social capital may not necessarily perform well in their ex post loan payments and tend to default more often than those with good hard scores [43, 52].

In addition to the verifiable hard information and soft information such as social capital and demographics, the optional loan descriptions, which borrowers provide along with their listings, have also been shown to affect lenders' decision making. In the loan description section on a listing page, a borrower can write a brief narrative to state the purpose of the loan, explain the reasons for a poor credit history, justify repaying abilities, or disclose other personal information that the borrower wants the lenders to know. Studies have shown that lenders tend to believe in what is disclosed in loan descriptions and trust the borrowers to some extent. Herzenstein et al. [21] found that the more identity claims (i.e., trustworthy, economic hardship, hardworking, successful, moral, and religious) a borrower makes in his or her loan descriptions the more likely for the listing to be funded. However, lenders' trust based on the identity claims may cause lenders negative consequences as the number of identity claims is positively associated with defaults in the loan performance analysis. Sonenshein et al. [48] examined loan descriptions through the theoretical lens of social accounts and found that lenders react to different social accounts differently. Descriptions combining explanation with acknowledgment or explanation with denial raise the perceived trustworthiness of the borrower and further increase the likelihood of positive funding outcomes. Larrimore et al. [28] reported that the linguistic features in loan descriptions (e.g., extended narratives, concrete descriptions, and quantitative words) are indicators of trustworthiness and are positively associated with funding success. Moreover, spelling mistakes, text length, and even the use of emotional words in the descriptions may also affect funding outcomes [14]. Michels [36] found that listings with more disclosures can attract more bids and lower the final interest rate, but often perform poorly in the repayment process with a higher likelihood of default.

Our research investigates a different type of information source that has not been studied in the prior literature—the direct communication between lenders and borrowers. Such communication provides an extra venue through which the information asymmetry problem may be mitigated. It makes it possible for lenders to actively seek information from borrowers and for borrowers to strategically build lender trust. In this research, we study the comment feature available on a P2P lending platform and the impact of the direct communication. We posit that as lenders and the borrower of a listing engage in direct communication, more information about the borrower and the listing will be disclosed during the conversation, helping reduce uncertainty; and consequently, the funding outcomes will likely be affected. However, before analyzing the content of the messages, we cannot further predict the direction of the association because based on more information, lenders may be able to make more rational decisions either to fund a promising listing or to discover potential risks in a listing.

Hypothesis 1 (Direct Communication—Funding Outcome Hypothesis): The amount of direct lender-borrower communication on a listing is associated with the listing's funding outcomes.

Decomposing the lender-borrower communication into lender comments and borrower responses, we hypothesize that both types of messages will affect funding outcomes. The prior literature has used funding success and final interest rate to represent funding outcomes. We thus refine our H1 as:

Hypothesis 1a: The number of lender comments on a listing is associated with listing's funding success.

Hypothesis 1b: The number of borrower responses to comments is associated with listing's funding success.

Hypothesis 1c: The number of lender comments on a listing is associated with a loan's final interest rate.

Hypothesis 1d: The number of borrower responses to comments is associated with a loan's final interest rate.

Lenders tend to rely more on soft information–based quality signals (e.g., social capital) if a listing is risky (i.e., with a poor credit grade) [33], and borrowers with a lower credit grade tend to make more identity claims and use more social accounts to enhance lenders' trust [21, 48]. Our second hypothesis thus is intended to ascertain the strength of the impact with respect to a listing's risk level.

Hypothesis 2 (Credit Grade—Funding Outcome Hypothesis): The impact of the direct communication is stronger for listings with a lower credit grade.

As in H1, we investigate this hypothesis in both the lender aspect and borrower aspect:

Hypothesis 2a: The impact of lender comments on the funding success is stronger for listings with a lower credit grade.

Hypothesis 2b: The impact of borrower responses on the funding success is stronger for listings with a lower credit grade.

Hypothesis 2c: The impact of lender comments on the final interest rate is stronger for listings with a lower credit grade.

Hypothesis 2d: The impact of borrower responses on the final interest rate is stronger for listings with a lower credit grade.

Social Influence

Whether it is hard or soft, the information that has been examined in most of the prior studies primarily concerns the types of quality signals that lenders may derive from the static attributes available on a listing page. Additionally, lenders may also be influenced by watching and observing the actions and behaviors of their peers (i.e., other lenders) during the dynamic bidding process. Prior research has shown that social influence is common in many decision-making processes. In the contexts of electronic transactions in general and P2P lending in particular, social influence may manifest itself in various forms such as herding and customer reviews.

The P2P lending literature on the impact of social capital has shown that lenders usually take a borrower's social capital (e.g., number of friends) as a quality signal and that the more endorsements a listing receives from a borrower's friends, the more positively lenders perceive a listing [19, 33]. Furthermore, a borrower's affiliation with a social group may also impose certain pressure on the borrower and engender stronger incentives for repayment [27].

More important, as a type of crowdfunding, a P2P lending transaction usually involves multiple lenders, which naturally makes it a social process. Thus, a lender's decision about whether to bid on a listing and how much to contribute to it may to some extent be affected by the behaviors of other lenders. A phenomenon that clearly manifests such a social effect is herding, which is also called a "bandwagon effect." That is, in addition to relying on the available hard and soft information, individuals may also make their lending decisions based on the number of people who have already bid and the total amount they have contributed [6, 52]. For example, by analyzing the bidding transactions on Prosper.com, several studies have found direct evidence of herding behaviors among lenders on various P2P platforms [9, 29]. Further, this herding behavior pattern has been found to follow a power law, which implies that the more bids a listing has already received, the faster it attracts more bids [46]. Greiner [16] reported that factors such as the uncertainty, lenders' experience, and search costs significantly influence lenders' herding behavior. Zhang and Liu [52] differentiated between rational and irrational herding and discovered that, although both are socially influenced, these two types of behaviors involve different patterns and lead to different outcomes. Rather than following their peer's decisions (irrational herding), rational lenders actively observe and learn from other lenders to make better decisions using available borrower and listing information. So loans selected based on rational herding perform better than those on irrational herding.

The effects of social influence have been frequently documented and studied in the electronic commerce literature. A few studies report that on eBay, one of the largest online auction sites in the United States, buyers tend to bid on items that have already received many bids [47] and the evaluation of the trustworthiness by other buyers, as represented by the seller rating, has a significant impact on item prices [22]. On Amazon and other online retailer websites, product reviews by customers have become a form of electronic word-of-mouth that influences many consumers' purchase decisions [53]. Customers frequently take into consideration product ratings, and feedback and opinions written by other customers before they make purchases [38] and their purchasing intentions increase as the number of reviews increases [40]. Sometimes, customers trust peer-generated reviews more than expert reviews [54].

Customers use product reviews and ratings because when they face incomplete information (e.g., when it is impossible to directly examine the physical characteristics and quality of a product), individuals have to seek information from other sources to make decisions in order to reduce risks and uncertainty [38]. Believing that others may possess additional, private information, individuals perceive the decisions and opinions of others as an important quality signal. Specifically, peer-generated reviews can provide diagnostic information about a product and the review extremity (positive or negative) [38] and the amount of information provided in the review content significantly affect other customers' perception of the usefulness and helpfulness of the reviews [26]. In particular, positive reviews often lead to the growth of product sales [32, 55] and negative opinions can strongly discourage other customers from making purchases [30, 45].

Our research investigates the direct communication between lenders and borrowers. Any questions or comments posted by a lender can be accessed and viewed by all other prospective lenders. From the perspective of a lender, other lenders' opinions and comments may signal the quality of the listing, given the possibility that other lenders may hold private information about the listing and the borrower. Our third hypothesis concerns the social impact that lenders have on their peer lenders:

> *Hypothesis 3 (Lender Comments—Funding Outcome Hypothesis): The content of lender comments has a significant impact on funding outcomes.*

For example, a lender's request for information about a borrower's income data may signify that the listing is not well-prepared or that the borrower is even intentionally hiding such critical information from the lenders. Similarly, a negative comment in a skeptical tone may turn many other lenders away. On the other hand, a lender's positive comment supporting the borrower may imply that the lender has a good reason to trust the borrower. With these quality signals identified from the content of lender comments, we can better posit the direction of their impacts on lending outcomes. Note that a positive outcome means that a listing is successfully funded with a lower interest rate, and vice versa.

> *Hypothesis 3a: The number of lender inquires is negatively associated with the funding success.*

> *Hypothesis 3b: The number of positive comments is positively associated with the funding success.*

> *Hypothesis 3c: The number of negative comments is negatively associated with the funding success.*

Hypothesis 3d: The number of lender inquiries is positively associated with the final interest rate.

Hypothesis 3e: The number of positive comments is negatively associated with the final interest rate.

Hypothesis 3f: The number of negative comments is positively associated with the final interest rate.

Having received comments or questions from lenders, a borrower can post responses to the comments on his or her listing page. All lenders would be able to view the responses. These borrower responses may serve as an additional information source for the lenders to make quality judgment. Thus, the quality of the information disclosed in borrower responses may affect lenders' decisions as well.

Information Quality

Information quality has long been an important research subject in the information systems (IS) literature [4]. It is regarded as one of the most essential measures for information systems success [12]. Our review of the literature suggests that information quality is not an atomic construct but a complex, multidimensional concept. Prior research has identified various dimensions of information quality. Zmud [56] in his pioneering study first investigated the concept of information and proposed that quality information should have several merits such as accurate, factual, reliable, and reasonable. Wang and Strong [50] proposed a comprehensive model for information quality and identified and categorized information quality attributes into four types: intrinsic, contextual, representational, and accessibility dimensions. Intrinsic components (believability, accuracy, objectivity, and reputation) concern the quality of information in its own right. The contextual dimension represented by attributes such as relevancy and timeliness, completeness, and amount of information, is evaluated with respect to the requirements of the task at hand. Representational and accessibility dimensions highlight the role of the information systems that produce the information. Many more recent studies have sought to refine these information quality models or empirically validate the structure of the hierarchical model by Wang and Strong [7, 8, 31]. Among these models, a few attributes have been consistently regarded as the core quality indicators of information such as accuracy, completeness, timeliness (relevancy), and credibility (reliability). According to Bovee et al. [7], accuracy means that the information is true or error free with respect to some measured values; completeness refers to the information having all required parts; timeliness measures how long the information has been recorded; and credibility concerns whether there is sufficient information for the user to believe it.

Information quality has also been found to be an important explanatory variable in system adoption and acceptance research. In particular, user-perceived information quality has been shown to have an impact on users' risk assessment and trusting beliefs, which further influence their intentions to use systems [25, 39, 44]. For example, Almahamid et al. [2] reported a significant positive relationship between perceived information quality and users' intention to use e-government systems.

In our context, the information disclosed in borrower responses is an alternative source accessible to the lenders in addition to the limited amount of hard and soft information. Although lenders have no means of verifying and determining the credibility and reliability of the borrower-provided information, the extent to which they perceive the information to be accurate, complete, timely, and adequate may impact their trust of the borrower and their lending decisions. However, as previously mentioned in the Direct Communication—Funding Outcome Hypothesis (H1), reduced information asymmetry and uncertainty may lead to either positive or negative funding outcomes. Our next hypothesis concerns the quality of the borrower-disclosed information in the communication:

Hypothesis 4 (Information Disclosure—Funding Outcome Hypothesis): The quality of information disclosed in borrower responses is associated with funding outcomes.

In our studies, we use four attributes to capture the quality of borrower disclosed information in their responses: perceived accuracy, perceived completeness, timeliness, and amount of information. The first three attributes are among the most widely used information quality measures [4, 31, 39, 50]. The last one, amount of information, has also been recognized as an important intrinsic quality attribute [50] and an indicator of message complexity [23]. We hypothesize that:

Hypothesis 4a: The perceived accuracy is associated with the funding success.

Hypothesis 4b: The perceived completeness is associated with the funding success.

Hypothesis 4c: The timeliness of response is associated with the funding success.

Hypothesis 4d: The amount of information in borrower responses is associated with the funding success.

Hypothesis 4e: The perceived accuracy is associated with the final interest rate.

Hypothesis 4f: The perceived completeness is associated with the final interest rate.

Hypothesis 4g: The timeliness of response is associated with the final interest rate.

Hypothesis 4h: The amount of information in borrower response is associated with the final interest rate.

Much attention has been paid to the impact of lender-borrower communication on the ex ante funding outcomes. We also attempt to see if such communication has any influence on the ex post performance of loans. Our final hypothesis asks if the direct communication is related to a loan's performance.

Hypothesis 5 (Direct Communication—Loan Performance Hypothesis): The amount of direct communication is associated with the loan performance.

Methods and Data

Study Context

The platform we study in this research, LendingMarket, is one of the largest P2P lending marketplaces in China.[1] Launched in 2007, LendingMarket has attracted over 55 million users with more than ¥70 billion in funded loans as of September 2017. The process for listing loan requests and bidding for loans is quite similar to that at Prosper.com. LendingMarket allows lenders to compete and bring down the final interest rate for a listing after it has received sufficient funding; and the loan maturity period is not fixed but may range from 3 to 36 months.

Because China does not have a nationwide credit system, it is not possible for the platform to quantify the credibility of a borrower based on the borrower's credit history. To address this problem, LendingMarket calculates each borrower's credit score based on the borrower's background information (e.g., education level and degrees, professional certificates, etc.), and assigns each borrower a letter credit grade from A (High Quality) to HR (High Risk).

To help lenders seek more information when making decisions, LendingMarket provides two types of online features to facilitate direct lender-borrower communication. One feature is the comment section on each listing page, where lenders can ask questions, make comments, or request that the borrower provide more information about the listing and the borrower. The borrower can decide which comments to respond to and how to respond. Another feature is the public forums where all users can share experiences and lessons learned, seek or provide investment advice, and discuss P2P related topics. There is a dedicated forum for borrowers to promote their listings. Listing advertisements posted in other forums often are deleted by the system administrator. Our research focuses on the comment feature.

Data and Content Analysis

LendingMarket provided a data set with 53,742 listings made by 26,940 borrowers on the platform from June 2007 to December 2011. In addition to listing information, bidding transactions, user profiles and friends, and loan payment records, the data set also contains, for each listing, all the messages posted by lenders (comments) and the borrower (responses), the lenders' IDs, and the posting dates and times. Among all listings, 39,694 (73.9 percent) are valid listings with either a success or failure status. Listings that failed to enclose verifiable supporting documents (e.g., pay stubs, certifications, etc.) or were withdrawn by the borrowers were considered invalid and unqualified for auction. In the sample of valid listings, 9,771 (24 percent) were successfully funded and the remaining 29,923 (76 percent) listings failed to receive sufficient funding. We call the sample with 39,694 valid listings Sample 1. About 40.4 percent (16,055) of valid listings have lender comments and only 68.2 percent (10,952) of these listings have borrower responses. The sample containing 16,055 listings with comments (and responses if applicable) is referred to as Sample 2.

To investigate the possible effects of social influence among lenders, the Lender Comments—Funding Outcome Hypothesis (H3), through comments and the quality of information provided in borrower responses, the Information Disclosure—Funding Outcome Hypothesis (H4), we need to analyze the content of the lender-borrower communication. Using a stratified random sampling approach, we used roughly 20 percent of lender-borrower listings communication in Sample 2 for each credit grade. The resulting Sample 3 consists of 2,973 listings with 11,508 lender comments and 7,998 borrower responses.

Based on our literature review we developed a coding schema to categorize lender comments into four types: (1) Inquiry: asking questions or requesting additional information and documents, (2) Positive: providing support or expressing a positive attitude toward the listing or borrower, (3) Negative: being skeptical or expressing a negative attitude toward the listing or borrower, and (4) Irrelevant: message content being unrelated to the listing or borrower (e.g., advertisement of products and services).

Two dimensions of perceived information quality are also captured through our content analysis of borrower responses: *Perceived Accuracy* and *Perceived Completeness*. Perceived accuracy involves whether borrower responses carry information about some key factors (e.g., business revenues and yearly cash flows) in a detailed, concrete form (e.g., quantities, numbers, business names and locations, etc.). Perceived completeness involves whether the borrower response has provided all requested information or answers to the questions posted in the lender comments. Note the perceived accuracy and completeness are subjective in nature. It is possible that a borrower may intentionally manipulate the information to gain resources [48] and it is the lenders' call to judge the integrity of the information.

Additionally, according to Herzenstein et al. [21], borrowers may use narratives (the response in this case) to build trust by constructing various identity claims (e.g., trustworthy, successful, hardworking, economic hardship, moral, and religious). In this research we also coded these identities if they were present in borrower responses. Moreover, according to the trust literature, benevolence of one party may increase the other party's trust [35]. During our coding process, we noted gratitude expressed in borrower responses that thanked the lenders for their supports and contributions, which we thought might have helped enhance the lenders' trust in the borrowers.

Two assistants manually coded the messages (19,506 total) in Sample 3. During the training sessions, they were presented with the coding schemas and a number of coding examples. They independently coded 87 randomly selected listings with 1,014 messages. The disagreement on coding results was resolved by in-depth discussion between the authors and the two coders. The two coders then each coded half of the remaining messages in Sample 3. The coding schema with code definitions, message examples, and intercoder reliability values are presented in the Appendix. Each code is binary with 1 indicating its presence and 0 indicating its absence. The definitions of the five identities are adapted from Herzenstein et al. [21]. Since we did not find any instance of religious identity we did not include it in this table.

For the loan performance analysis, LendingMarket provided payment information for only 6,415 funded listings (i.e., listings with funding success). Based on the payment information we identified 2,184 (34 percent) loans that had defaulted by the time of data collection and calculated the number of months before default.[2] We refer to this as Sample 4. Table 1 summarizes the four samples used in this study.

Results

Variables and Descriptive Statistics

Two dependent variables are used to represent funding outcomes: *Funding Success* and *Final Interest Rate*. The funding success is coded 1 if a listing is fully funded and 0 otherwise. *Time to Default* measures the number of months before a loan default occurs and is used as the dependent variable for the loan performance analysis. The reason for using time to default instead of a binary variable is that Sample 4 is a right-censored data set [52]. That is, by the time of data collection, some loans had not reached maturity and it was unknown whether they defaulted later or not. For instance, for listings posted in December 2011, the deadlines of the first monthly payments had not passed by the time of data collection (December 31, 2011). So no payment information was available for those listings.

The independent variables are found in the prior literature to have a significant impact on funding outcomes: *Amount Requested, Borrower Interest Rate, Credit*

Table 1. Samples Used in Hypotheses Testing

Sample	Description	# Listings	# Messages	Used in Hypotheses
1	All valid listings with either success or failure status.	39,694	91,666	H1
2	Valid listings that have at least one lender comment.	16,055	91,666	H2
3	Listings with message content manually coded.	2,973	19,506	H3 and H4
4	Successfully funded loans with payment information.	6,415	18,428	H5

Grade, and *Number of Friends*. Table 2 reports the descriptive statistics of variables (means and standard deviations in parentheses). All the means are significantly different between funded and unfunded listings using independent-sample *t*-tests. The variable reflecting the most important hard credit information is *Credit Grade*, which is a categorical variable in our samples. The majority of listings (71.5 percent) are in the "risky" categories (i.e., grade E or HR); and only about 28.5 percent of listings are in grade D or higher. The proportions of risky listings in the funded and unfunded sets are 63.5 percent and 77 percent, respectively. In Table 2 we convert the credit grades into numerical values (e.g., A = 6, HR = 1, etc.) and report the means. We use a single variable, the *Number of Friends* a borrower had at the time that a listing was created, to capture the borrower's social capital.

The two independent variables for measuring the amount of direct lender-borrower communication are *Number of Comments* and *Number of Responses*. The number of comments posted on a listing by lenders ranges from 0 to 117, with a mean of 1.08.

Table 2. Descriptive Statistics of the Variables (Samples 1 and 3)

Variables	All (StdDev)	Funded (StdDev)	Unfunded (StdDev)
# Listings	39,694	9,771	29,923
Amount Requested	13,400 (22,100)	6,867 (9,053)	15,533 (24,557)
Borrower Interest Rate	17.49 (5.97)	17.79 (4.50)	17.30 (6.37)
Credit Grade (numerical)	2.03 (0.96)	2.92 (0.73)	1.74 (0.84)
# Friends	19.29 (51.95)	58.35 (83.53)	6.54 (25.31)
# Comments	1.08 (2.45)	2.00 (3.98)	0.78 (1.56)
# Responses	0.49 (1.66)	1.26 (2.79)	0.24 (0.93)
# Inquiries	1.90 (1.98)	1.76 (2.27)	1.99 (1.79)
# Positive	0.61 (1.36)	0.92 (1.75)	0.43 (1.05)
# Negative	0.29 (1.01)	0.23 (0.85)	0.32 (1.09)
# Irrelevant	0.78 (2.28)	1.19 (2.87)	0.55 (1.83)
# Perceived Accuracy	0.25 (0.65)	0.29 (0.69)	0.24 (0.62)
# Perceived Completeness	0.83 (1.21)	0.92 (1.28)	0.78 (1.17)
Average Response Time (Days)	0.37 (0.83)	0.17 (0.48)	0.48 (0.95)
Total Response Length	116.90 (198.50)	126.90 (199.40)	111.30 (197.80)
# Gratitude	1.00 (1.48)	1.20 (1.65)	0.89 (1.37)
# Identities	0.02 (0.35)	0.01 (0.32)	0.03 (0.37)
Listing Title Length	18.70 (6.04)	19.45 (6.06)	18.27 (5.99)
Listing Description Length	207.70 (244.20)	219.20 (273.00)	202.00 (228.20)
Listing Duration (Days)	7.14 (2.83)	6.98 (2.64)	7.24 (2.94)
Loan Maturity (Months)	5.83 (3.80)	6.03 (3.67)	5.70 (3.86)
Borrower Age	29.20 (6.20)	31.10 (5.58)	29.13 (6.46)

The mean number of responses made by borrowers is 0.49 (max = 117), 1.26 (max = 117), and 0.24 (max = 47) for all listings, funded, and unfunded.

Four variables are used to account for the characteristics of lender comments on a listing, namely, *Number of Inquiries* (mean = 1.9, max = 33), *Number of Positive Comments* (mean = 0.61, max = 19), *Number of Negative Comments* (mean = 0.29, max = 28), and *Number of Irrelevant Messages* (mean = 0.78, max = 40). It can be seen that funded listings generally receive fewer inquiries, more positive comments, and fewer negative comments than do the unfunded listings. Interestingly, funded listings also get more irrelevant posts than the unfunded listings.

Four variables for representing the information quality of borrower responses are: *Number of Perceived Accuracy, Number of Perceived Completeness, Average Response Time*, and *Total Response Length*. As illustrated in the Appendix, perceived accuracy and perceived completeness are subjective measures and were coded during the content analysis of Sample 3. The other two information quality attributes, timeliness and amount of information [50], are objectively measured by *Average Response Time* and *Total Response Length*, respectively. *Average Response Time* (mean = 0.37 day, i.e., approximately 9 hours) is operationalized by the difference between the posting time of a comment and the time when the borrower made a response to the comment. We operationalize *Total Response Length* by counting the number of characters (words) in each response. Our data show that, on average, information provided in responses by funded borrowers is generally perceived to be more accurate and complete. Funded borrowers are also more responsive and reply to comments faster and with longer texts.

We also include in our analysis a number of control variables reflecting other characteristics of listings and borrowers. These control variables are used as covariates together with the independent variables in our analyses. Although they are not what we are particularly interested in, they may to some extent relate to the dependent variables. Models without appropriate control variables may fail to account for possible confounding factors and the relationships discovered may be spurious [41].

Variables for representing listing characteristics are *Length of Loan Maturity* (length of loan repayment period: mean = 5.83 months, max = 36), *Listing Duration* (number of days a listing remains active before closing: mean = 7.14 days, max = 38), *Listing Title Length* (number of characters in the title: mean = 18.7 characters, max = 41), *Listing Description Length* (number of characters in the loan description text: mean = 207.7 characters, max = 1,942), and two categorical variables indicating whether a borrower filled out the optional sections on the listing page for income sources and expenses.

LendingMarket strongly encourages borrowers to specify their loan purpose, such as business, automobile, home improvement, personal, short-term capital, student loan, and other, while creating listings. We thus include *Loan Purpose* as a control variable. In addition, a small proportion of borrowers had collaterals for their listings either from the platform (2.8 percent) or other individuals (0.9 percent), while most listings (96.3 percent) were not collateral loans. We use a categorical variable *Collateral* for this information.

To control for possible variations in lender-borrower communication, based on our content coding results, we include *Number of Identities* (number of distinctive identities claimed in the borrower responses: mean = 0.02, max = 5), and *Number of Gratitude* (the borrower messages in which gratitude was explicitly expressed: mean = 1.0, max = 20) to count the number of thanks by the borrowers.

Variables for borrower demographical characteristics are *Age* (mean = 29.2), *Gender* (Male: 54 percent, Female: 10 percent, N/A: 36 percent), *Education Level*, and *Marital Status* (Married: 29.3 percent). In addition, we use *Monthly Effect*, which is a simple counter of the number of months since the inception of the platform, to capture the effect of any platform-wide shocks, such as the increase in the media exposure of the platform [24]. All categorical variables are represented using dummies in our analysis except for the testing of the Credit Grade—Funding Outcome Hypothesis (H2), in which *Credit Grade* is converted into numbers.

Hypothesis Testing

Regression analyses were used on Sample 1 to test if the amount of lender-borrower communication, measured by the *Number of Comments* and *Number of Responses*, has any impact on the funding outcomes in the Direct Communication—Funding Outcome Hypothesis (H1). Logistic regression is a type of statistical analysis for testing models with categorical dependent variables and has been widely used in the P2P lending literature when the dependent variable is funding success (a binary variable) [43, 48, 51]. In our analysis, we employ the forward stepwise procedure in which the block of hard information, soft information, and control variables was entered into the model at the first stage and the block of communication variables was added at the second stage. Reported in Column (1) in Table 3 is the stage-2 result of logistic regression of *Funding Success* on the two communication variables, the hard and soft information, and major control variables. The odds ratios (exponentiated coefficients) of these two communication variables indicate that the amount of direct communication, above and beyond the impact of hard and soft quality of a borrower and listing, does affect the funding success. However, the two variables exhibit different effects in terms of direction and size. For a listing, since the odds ratio (0.97) of the number of comments is less than 1.0, lender comments are negatively associated with the listing's funding success. The odds of getting funded drop by 3 percent for an additional lender comment. Thus, H1a is supported. On the other hand, the number of responses' odds ratio (1.36) is greater than 1.0, which means that if the borrower chooses to respond to the comments then each additional response will increase the odds of funding success by 36.4 percent. So H1b is also supported.

Consistent with findings from prior studies, the odds of funding success are negatively associated with the requested amount but positively associated with the

Table 3. Results for Testing Hypothesis 1 (Sample 1)

		Dependent Variables			
		1	2	3	4
		Funding Success	*Final Interest Rate*	*Percent Funded*	*# Bids*
Hard Information	Ln *(Amt. Requested)*	0.61***	–0.17***	–7.67***	7.93***
	Borrower Rate	1.04***	1.01***	0.006	0.05*
	Credit Grade				
	A	18.89	–0.55	25.77*	12.65*
	B	991.87***	0.95***	53.43***	32.09***
	C	482.56***	0.64***	55.04***	15.57***
	D	384.66***	–0.23***	53.67***	9.91***
	E	11.41***	0.28***	–11.45***	–1.77***
Soft Information	*# Friends*	1.01***	–0.001***	0.076***	0.02***
Communication	*# Comments*	0.97*	–0.034***	–1.11***	0.32***
	# Responses	1.36***	0.003	3.05***	1.29***
Control	*Listing Title Length*	1.05***	–0.006**	0.37***	0.18***
	Listing Duration	0.81***	0.15***	–1.22***	–0.62***
	Loan Maturity	0.88***	0.06***	–0.43***	–0.41***
	Loan Purpose[3]	***	***	***	***
	Collateral				
	Individual	316***	0.23	19.38***	–6.54***
	Platform	265***	0.73***	13.82***	–5.28***
	Age	1.02***	–0.006*	0.22***	0.024
	Gender (Male)	1.38***	0.02	–3.5***	–0.08
	Education Graduate	2.58***	Not signif.	6.57***	Not signif.
	Marital Status				
	Single	0.69*		3.16*	2.24***
	Married	1.17**	0.02	3.06*	2.32***
	Monthly Effect	1.10***	0.03***	0.58***	0.53***
Adjusted R^2		0.77	0.88	0.62	0.48

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

borrower rate; and hard credit grades can significantly affect the funding success. With respect to the HR grade (the reference category), the odds of getting fully funded are several hundred times greater for borrowers with higher grades, indicating that lenders primarily rely on credit grade information to infer borrower credibility while making decisions. Merely upgrading to level E will cause the funding success likelihood to increase by a factor of 11. However, we found that Grade A is not significant probably because only a small percent (0.003 percent) of listings are in this grade. Soft social capital information also affects lending decisions with a 1.2 percent increase in the odds of funding success for each additional friend.

Control variables for listing characteristics exhibit different effects. Specifically, the length of the listing title has a positive yet minor effect and each additional character will increase the odds of funding success by 5 percent. It also shows that the longer a listing remains open, the less likely it will receive sufficient funding (each additional day decreases the odds by 19 percent). Similarly, a longer maturity period may increase risks of default (each additional month decreases the odds by 12 percent). Unsurprisingly, a collateral either by the platform or other individuals significantly reduces the default risk and greatly enhances the trustworthiness of a borrower and the chance of funding success. Lenders also tend to take into consideration the extra information presented in the loan purpose category (in Table 3 we only present the significance level without listing all eight coefficients for *Loan Purpose*). It turns out that lenders prefer listings without explicitly specified loan purposes. Among the listings with loan purposes, student loan and home improvement loan requests are least favored by lenders. The impact of listing description length and the optional information about borrower income and expenses is nonsignificant. This may be because less than 10 percent of listings have the optional income and expense fields filled out.

Borrower characteristics (i.e., gender, age, education, and marital status) also have varying effects on the funding success. Overall, lenders prefer to invest on listings by older, male, married borrowers. Among all education levels (e.g., college, associates, etc.), only a graduate degree has a significant effect on the likelihood of funding success. Table 3 also reports the adjusted R^2 (Nagelkerke R^2 in the case of logistic regression) for all models. An R^2 of 0.77 for the logistic regression model indicates that the model fits the data well.

As *Final Interest Rate* is a continuous variable, we use linear regression to analyze this price aspect of funding outcome. Column (2) in Table 3 lists the variable coefficients in a linear regression with *Final Interest Rate* as the dependent variable. It shows that each additional comment by a lender can help reduce the final interest rate by 0.034. However, the number of borrower responses does not play a role in reducing the final interest rate. As a result, H1c is supported while H1d is not supported. Other independent variables and control variables have effects similar to those on the funding success.

In summary, the Direct Communication—Funding Outcome Hypothesis (H1) is partially supported, meaning lender-borrower communication is associated with funding outcomes. Specifically, lenders comments can lower a listing's likelihood of being funded; but if the listing receives sufficient funding, more lender comments will help reduce the final interest rate. Borrower responses can significantly increase a listing's likelihood of funding success, while making no difference on the final interest rate.

To test Credit Grade—Funding Outcome Hypothesis (H2) regarding listings with different risk levels, we use the numerical values to represent *Credit Grade* (A = 6, B = 5, C = 4, D = 3, E = 2, HR = 1). Two interaction variables, *Number of Comments* × *Grade* and *Number of Responses* × *Grade* are created and used on Sample 2. Columns (5) and (6) in Table 4 report the results of the logistic regression on funding success and the results of the linear regression on the final interest rate, respectively. Both interaction terms are significant in column (5), indicating that the amount of communication has a different impact on funding success in different credit grades. More specifically, both lender comments and borrower responses have a stronger impact on funding success for listings with lower credit grade. That is, as a listing becomes more risky, more comments may signify poor listing quality and lenders have to rely more on the information provided by borrowers when making decisions. Thus, both H2a and H2b are supported. In Figure 1, we plot the fitted values of the odds of funding success (in natural logarithm) against the number of comments for listings with low credit grades (D, E, and HR). It is obvious that when a listing is riskier, more lender comments (or borrower responses) will reduce (or

Table 4. Results for Testing H2 (Sample 2)

		Dependent Variables			
		5	6	7	8
		Funding Success	*Final Interest Rate*	*Percent Funded*	*# Bids*
Hard Information	*Ln (Amt. Requested)*	0.62***	–0.15***	–6.20***	8.28***
	Borrower Rate	1.04***	1.01***	–0.103*	0.02
	Credit Grade (numeric)	16.31***	0.06**	26.77***	5.74***
Soft Information	*# Friends*	1.01***	0.00	0.08***	0.03***
Communication	*# Comments*	0.86*	–0.09***	–6.24***	–1.16***
	# Responses	2.78***	–0.08*	14.27***	1.82***
Interaction Variables	*# Comments × Grade*	1.05*	0.02	1.74***	0.52***
	# Responses × Grade	0.77***	0.03	–3.68***	–0.20*
Adjusted R^2		0.76	0.88	0.57	0.48

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

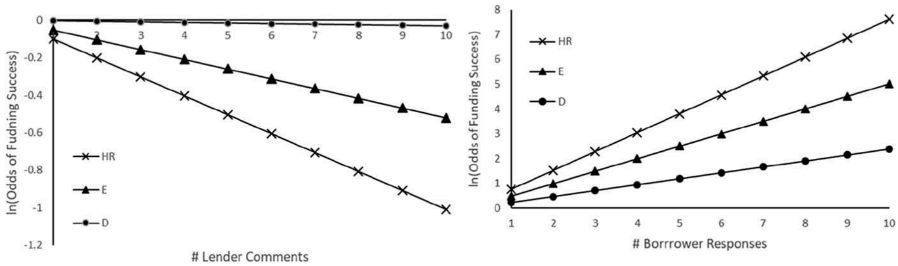

Figure 1. Effects of Interaction Variables on the (Natural Logarithm of) Funding Success Odds

enhance) the likelihood of funding success faster. For the final interest rate, these two interaction terms are not significant. Thus, neither H2c nor H2d is supported. So, the Credit Grade—Funding Outcome Hypothesis (H2) is partially supported. To test the Lender Comments—Funding Outcome Hypothesis (H3), we use Sample 3 with content coding results and perform logistic regression on *Funding Success* and report the results in column (9) of Table 5. For the sake of space, we report only the

Table 5. Results for Testing H3 and H4 (Sample 3)

		Dependent Variables			
		9.	10.	11.	12.
		Funding Success	*Final Interest Rate*	*Percent Funded*	*# Bids*
Lender Comment (Social Influence)	*# Inquiries*	Not Sig.	–0.003	–2.13**	0.59*
	# Positive Comments	1.39***	–0.11**	7.21***	2.46***
	# Negative Comments	0.74***	0.04	–5.13***	–0.90*
	# Irrelevant Messages	1.08**	–0.08***	2.68***	0.297
Borrower Response (Info Quality)	*# Perceived Accuracy*	1.42***	0.09	2.54***	–0.61***
	# Perceived Complete	Not Sig.	–0.05	7.29	2.21
	Average Resp. Time	0.69***	–0.03	–4.79***	–0.46
	Total Resp. Length	Not Sig.	0.000	–0.03**	0.002
Adjusted R^2		0.46	0.84	0.28	0.38

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

effects of the independent variables that capture the characteristics of the content of lender comments and borrower responses, but leave out other independent variable and control variables whose impacts are largely unchanged. In column (9), the exponentiated coefficients of nonsignificant variables are not reported as the regression analysis software (IBM SPSS) automatically removed them from the model without outputting their coefficients. It is quite clear from this column that different types of lender comments have different effects on the likelihood of funding success. The increased number of positive comments, after controlling for other hard and soft characteristics, increases the odds of funding success by 39 percent. Thus, H3b is supported. In contrast, each additional negative comment reduces such odds by 26 percent, which supports H3c. Questions and inquiry type of comments do not seem to affect the funding success. Therefore, H3a is not supported. It is also interesting to see that although some messages are totally unrelated to a listing, they seem to help increase the visibility and "popularity" of the listing among lenders and thus can also increase the funding success by 8 percent. However, it may be that because these listings are popular, they tend to attract irrelevant posts.

Column (10) presents the results of the linear regression on *Final Interest Rate*. Similar to the results in column (9), the effect of lender inquiries is not significant (H3d is not supported). Positive comments and irrelevant messages help reduce the final interest rate by 0.11 and 0.08, respectively (H3e is supported). Negative comments, on the other hand, do not have much impact on the final interest rate. Therefore, H3f is not supported.

Columns (9) and (10) also report the coefficients of the four variables capturing the information quality of borrower responses. It can be seen that if a borrower's responses provide concrete, detailed information about some key aspects of the listing or the borrower (e.g., incomes and expenses, business revenues, and profits, etc.), the odds of funding success will be higher. In this sense, H4a is supported. In addition, lenders welcome timely responses and each 24-hour delay in response will reduce the odds of success by 31 percent. Therefore, H4c is supported. However, H4b and H4d are not supported, which implies that providing complete answers to lenders' inquiries and writing longer posts may not necessarily help the borrower to attract funding. None of the four variables can significantly affect the final interest rate. That is, H4e to H4h are not supported. Two other control variables related to the content of borrower responses, *Number of Gratitude* and *Number of Identities*, are found to have no significant impact on the funding success and final interest rate. Although their means are significantly different between funded and unfunded listings (see Table 2), these variables do not help explain the variance of the model.

We examine the *Time to Default* using the Cox proportional hazards model when testing the Direct Communication—Loan Performance Hypothesis (H5) based on Sample 4. This model is a type of survival model in statistics that relates the time that elapses before an event (default in this case) to some explanatory variables and is especially appropriate for addressing the right-censoring problem in sample data [11]. This model has been widely used in P2P lending studies to analyze loan performance [33, 37, 43, 52]. When using the time to default as the dependent variable, this analysis actually models the risk of default (i.e., default rate) of a listing and the exponentiated coefficients are called default ratios [52]. The regression coefficients and *p*-values, which are not reported here, show that neither the number of lender comments nor the number of borrower responses has any significant impact on the loan performance. In other words, the amount of lender-borrower communication cannot predict whether a loan will default. Thus, H5 is not supported. Unsurprisingly, the most significant predictor of loan performance is the credit grade; and the number of friends has no impact on the default (hazards) ratio. Table 6 summarizes the hypothesis testing results.

Robustness Checks

The independent variables were checked for multicollinearity and all VIF values are less than 10. We also tested H1–H4 using alternative specifications of the dependent variables regarding funding outcomes. Columns (3) and (4) in Table 3, (7) and (8) in Table 4, and (10) and (11) in Table 5 report the results of linear regressions using the *Percent Funded* and the *Number of Bids* received by each listing as proxies for funding outcomes [36, 48]. The conclusions remain largely the same. We summarize the results next.

First, the amount of lender-borrower communication is significantly associated with funding outcomes measured by *Percent Funded* and *Number of Bids*. Specifically, each additional lender comment reduces the funding percentage by 1.11 percent but attracts 0.32 more bids. Each additional borrower response increases the funding percentage by 3.05 percent and attracts 1.29 more bids (see Table 3). We performed an analysis of the relationship between lender comments and bids. We found that the number of small bids (with an amount less than or equal to ¥100) and the number of comments a listing receives are moderately correlated (Pearson correlation = 0.29). That is, lenders tend to contribute only small amounts to listings with more comments.

Table 6. Summary of Hypothesis Testing Results

Hypothesis	Description	Support
H1	The amount of direct lender-borrower communication on a listing is associated with the listing's funding outcomes.	Partially supported
H2	The impact of the direct communication is stronger for listings with a lower credit grade.	Partially supported
H3	The content of lender comments has a significant impact on funding outcomes.	Partially supported
H4	The quality of information disclosed in borrower responses is associated with funding outcomes.	Partially supported
H5	The amount of direct communication is associated with the loan performance.	Not supported

Second, the impact of lender comments on *Percent Funded* and *Number of Bids* is stronger for better credit grades and weaker for poor grades. In contrast, the impact of borrower responses is weaker for good credit grades but stronger for risky listings (see Table 4).

Third, the content of lender comments also affects the percent of funding received and total bids. As with *Funding Success*, each additional positive comment and irrelevant message increases *Percent Funded* by 7.21 percent and 2.68 percent; but each additional negative comment reduces the percentage by 5.31 percent. It is interesting to note that the number of inquiries also has a negative impact on this outcome. Positive and negative comments play similar roles on *Number of Bids* and *Percent Funded*. The number of inquiries can slightly increase the total bids as well; but irrelevant messages do not help attract bidders.

Discussion

Information asymmetry is an inevitable challenge that P2P lenders must face when making investment decisions. To reduce uncertainty and risks, lenders strive to seek more information from more sources. In the context of online P2P marketplaces, the only alternative source of information, in addition to the platform, seems to be the borrowers. However, because of anonymity, it is usually impossible for lenders to identify the borrowers, let alone contact them and get information from them. This article studies a unique online feature that allows lenders and borrowers to engage in direct communication regarding loans. Our research aims at unfolding the impact of such online communication on the funding outcomes of a loan request and the loan performance. We attempt to ascertain (1) whether such communication matters and, if it does, to what extent, (2) whether lenders' decisions are affected by other lenders' opinions, and (3) whether the quality of information provided by borrowers makes lenders trust borrowers as a useful information source. We also ask if such communication can serve as a predictor of loan defaults.

Our analysis results show that lender-borrower communication does matter. More specifically, measured by the odds of funding success, the funding outcome is negatively affected by the number of lender comments and positively affected by the number of borrower responses. In other words, the more comments a listing receives, the less likely the listing will get funded; and the more responses a borrower makes to the comments, the more likely the listing will attract sufficient funding. However, this does not necessarily mean that more comments are bad because, as shown in our analysis, lender comments may help reduce the final interest rate by increasing the visibility of a listing and attracting more lenders to bid down the interest rate. We have also found that the impact of the communication varies with the borrower's credit grade and that the effects of lender comments and borrower responses are stronger for riskier loans (in lower credit grades).

Our content analysis uncovers the specific mechanisms through which lender-borrower communication affects funding outcomes. We have found that lenders are socially influenced by other lenders' opinions and treat other lenders' comments as quality signals. Positive comments supporting a borrower or expressing confidence and trust in a borrower boost the funding success likelihood. In contrast, negative comments significantly reduce the chance of getting sufficient funding. Interestingly, we have found that even irrelevant messages such as advertisement that is completely unrelated to a listing may help increase the listing's visibility and draw the attention of more lenders. However, the effect could also be the other way around, that is, the popularity of a listing may attract more ads and irrelevant postings. On the other hand, although the number of inquiries and requests for additional information may not necessarily affect the overall likelihood of funding success, it does reduce the amount (and percentage) of funding that a listing can possibly receive.

From a borrower's perspective, the most important task is to enhance lenders' trust so that they will bid on his or her loan. To gratify lenders' need for more information, borrowers may craft textual messages to supply information that appears to be credible and relevant. Our analysis reveals that when borrowers disclose detailed, concrete data requested by lenders (i.e., perceived accuracy is high), lenders tend to trust them and are willing to chip in. Lenders also like borrowers' timely responses and feedback. However, the perceived completeness and information quantity do not seem to make a difference, implying that lenders pay more attention to the content of the responses and the quality of listings.

The data do not support our conjecture about the impact of lender-borrower communication on the possibility of loan defaults. This suggests that what is discussed between lenders and borrowers during the auction process does not influence the loan repayment process that takes place in a much longer period of time afterward. Nevertheless, our research contributes to both the theory and practice related to P2P lending, online trust, social influence, and perceived information quality.

Theoretical Implications

This study broadens and deepens our understanding and knowledge about how lenders make decisions in the P2P lending context. Specifically, it reveals the role that the direct lender-borrower communication plays in mitigating the information asymmetry problem. Naturally lenders prefer to fund listings with higher credit grades. However, most borrowers in P2P marketplaces have low credit grades, because individuals with good credit history often can borrow from traditional commercial banks. On P2P lending platforms, a small number of highly competitive listings are often quickly funded and closed. As a result, many prospective lenders have to turn to borrowers with lower credit grades. Getting involved in such arm's-length transactions, lenders become more vulnerable to information asymmetry and adverse selection problems. Without knowing the true identity of a borrower, lenders have rather limited means to find more information and assess the borrower's willingness and ability to repay the loan.

Uncertainty reduction theory predicts that when involved in interactions with strangers, individuals are motivated to exchange and collect information from each other [5]. The availability of the commenting feature enables the lenders to seek information directly from borrowers and the borrowers to build trust. The findings about the amount of communication, especially the number of borrower responses, is in agreement with the prior literature [36, 48–14], which reports that lenders do take into consideration borrower-generated narratives (e.g., text descriptions) during decision making, although the information disclosed is not verifiable. This implies that the direct communication is not simply a type of cheap talk but serves, to some extent, as a signal for the quality of the loan request.

Our study also shows that in addition to the effects of friend endorsement, group membership, and herding, there is another possible channel through which lenders may be socially influenced by others' behaviors. Diagnostic information regarding the quality of a loan may be embedded in lender comments. Unlike customers who write online product reviews based on their actual experience, lenders who post comments may not necessarily have more and better knowledge about a listing or a borrower. Nevertheless, the subjective opinions and assessments seem to have an impact on other lenders' decisions. Such a social effect is not exactly like herding in which people simply follow the crowd's behavior. Instead, lenders read the content of those (negative or positive) comments, presuming that people who wrote the comments maintain private information or knowledge related to a loan request or borrower. For example, a negative comment on a listing that requests funding for a business start-up may assert that the market for the proposed business is deteriorating and it is hard to make a profit (and repay the loan). This assessment would very likely discourage other lenders from bidding on the listing. This is not surprising, as in the context of electronic commerce, consumers have similar behavioral reactions to negative product reviews. Indeed, people tend to consider negative opinions to be more objective and trustworthy [3]. Viewed via the elaboration likelihood model [18], identifying and inferring quality signals from other lenders' messages requires cognitive effort and tends to occur on the central information-processing route.

Our research contributes to the IS literature by demonstrating that information quality is not only important for user behaviors such as systems acceptance and adoption but also critical for a broader range of decision-making tasks. Even in situations where the credibility of a source and the veracity of the content are difficult to assess objectively, a presentation with factual, concrete, or quantified facts increases the perceived trustworthiness of the source. In addition, the significant effect of information timeliness implies that lenders may have associated a borrower's diligence in responding to comments and questions with the borrower's willingness and ability to repay the loan.

This study also updates our understanding of online trust. It reveals that in the P2P lending context, lenders have rather different patterns of trust in information sources than in regular economic exchanges (e.g., purchase of products). Traditional consumer behavior theories predict that as a purchasing situation becomes more uncertain and risky, buyers tend to trust the seller less [34]. However, our finding suggests that lenders (i.e., the buyers of a loan) rely even more on the borrower (i.e., the seller of a loan) as a source of information when the borrower's credit grade is poor. This finding is consistent with several prior P2P studies [21, 33, 48]. We believe that this different pattern is due to the lack of alternative information sources and reputation systems (e.g., seller ratings on eBay) in P2P lending transactions. Unlike purchasing a product (e.g., a car), during which a buyer can find product quality information from various sources other than the seller (e.g., online reviews, friends' recommendations, expert evaluations), P2P lenders have only two information sources (the platform and the borrower). In this case, the more risky the listing, the more likely lenders will have to seek information from the borrower and the more they have to trust the borrower.

Furthermore, our study contributes to the research on online trust in an investment setting that is rather different from that in developed countries. The lack of a nationwide credit system in China implies that if a borrower provides misleading or false information in a loan request or even defaults in the repayment process, the consequence to the borrower is minimal. The borrower's misbehavior will have little impact on his or her credit records and future chances of getting loans. In this situation, Chinese P2P lenders face much higher risks than their western counterparts do. Interestingly, our results show that even in such a disadvantageous circumstance, lenders still tend to trust the unverifiable information provided by borrowers. However, they may trust different types of borrower messages to different degrees. For instance, unlike previous studies (e.g. [24]), which report that more identity claims made by a borrower are positively associated with funding success, our analysis has found no impact of identity claims on funding outcomes, and the average identity claims in unfunded listings is even more than that in funded listings. This may have been caused by cultural differences; that is, Chinese lenders believe in actual, factual information more than they do in self-claimed identities.

Practical Implications

Our research has implications for P2P platforms, lenders, and borrowers. For the P2P lending platform, our study shows that the commenting feature on the platform website can facilitate lenders' decision making by helping them gather more information about borrowers. P2P platforms other than LendingMarket may adopt this idea and implement similar features. Moreover, P2P platforms may consider designing and providing more communication channels for their users. Open forums and chat rooms can create more opportunities for lender-borrower communication while preserving anonymity.

From the lenders' perspective, we suggest that they take more advantage of communication features available on a P2P platform. By posting questions and participating in discussions they may get more useful information about a listing and its borrower, thereby reducing uncertainty. However, lenders should be quite careful about what is disclosed by borrowers as the information is voluntary and unverifiable. The information presented in borrower responses may be subject to manipulation and deception (e.g., concealment and distortion). Lenders may make a better judgment on the borrower's trustworthiness by scrutinizing the contents of the responses or conducting reality checks.

Direct communication allows borrowers to present favorable images of themselves. This is critical when lenders post concerns and questions about them. By diligently responding to the questions, providing additional data and facts, making clarifications, and offering explanations, a borrower can manage to reduce the negative impact of the lender comments on the funding outcomes. However, we discourage borrowers from abusing the feature by posting deceptive information. Such misbehavior will ruin the trust of lenders and deteriorate the investment environment in P2P marketplaces.

Limitations and Concluding Remarks

There are several limitations in our research. First, we have studied only one platform in one country (China), which has significantly different culture, financial environment, laws, and regulations from many other countries. Further work is needed to investigate whether the findings from this work are generalizable to a wide variety of platforms in other countries. Second, the data set we analyzed is small compared to the large number of P2P lending transactions that have taken place. It is possible that the sample we studied is not as representative as we wished and the conclusions are only valid for the small sample. Third, in our analysis, we focused on four types of lender comments (i.e., inquiry, positive, negative, and irrelevant comments), and four information attributes of borrower responses (i.e., perceived accuracy, perceived completeness, timeliness, and amount of information), but did not study other lender information-seeking and borrower trust-building behavior that may have influenced the dependent variables.

Our work extends the stream of research on P2P lending and makes several contributions to the literature on topics such as online financial transactions, social influence, information quality, and consumer trust. Our findings suggest that the seemingly cheap talk between lenders and borrowers is actually not cheap—it has a concrete economic impact on lenders and borrowers. We also show that P2P lending platforms, by employing the right information technologies and implementing proper features, can serve as an intermediary to facilitate the exchanges of various resources (e.g., fund, information, trust) between parties in financial transactions.

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Notes

1. We use a fictitious company name for data confidentiality.
2. Default means being late with payment for at least three months by the end of the time period of the sample (December 2011).
3. We do not list the coefficients of all eight loan purposes in this table for succinctness of presentation.

References

1. Akerlof, G.A. The market for "lemons": Quality uncertainty and the market mechanism. *Quarterly Journal of Economics*, *84*, 3 (1970), 488–500. doi:10.2307/1879431.

2. Almahamid, S.; McAdams, A.C.; Kalaldeh, T.A.; and Al-Sa'eed, M. The relationship between perceived usefulness, perceived ease of use, perceived information quality, and intention to use e-government. *Journal of Theoretical and Applied Information Technology*, *11*, 1 (2010), 30–44.

3. Amabile, T.M. Brilliant but cruel: Perceptions of negative evaluators. *Journal of Experimental Social Psychology*, *19*, 2 (1983), 146–156.

4. Ballou, D.P., and Pazer, H.L. Modeling data and process quality in multi-input, multi-output information systems. *Management Science*, *31*, 2 (1985), 150–162.

5. Berger, C.R., and Calabrese, R.J. Some exploration in initial interaction and beyond: toward a developmental theory of communication. *Human Communication Research*, *1*, 2 (1975), 99–112.

6. Berkovich, E. Search and herding effects in peer-to-peer lending: evidence from Prosper.com. *Annals of Finance*, *7* (2011), 1–17.

7. Bovee, M.; Srivastava, R.P.; and Mak, B. A conceptual framework and belief-function approach to assessing overall information quality. *International Journal of Intelligent Systems*, *18*, 1 (2003), 51–74.

8. Bovee, M. Empirical validation of the structure of an information quality model. In *Proceedings of the 9th International Conference on Information Quality*. Cambridge, MA: MIT Press, 2004, pp. 358–372.

9. Ceyhan, S.; Shi, S.; and Leskovec, J. Dynamics of bidding in a P2P lending service: effects of herding and predicting loan success. In *Proceedings of the International World Wide Web Conference Committee*. New York: ACM Press, 2011, pp. 547–556.

10. Chen, D.; Lai, F.; and Lin, Z. A trust model for online peer-to-peer lending: A lender's perspective. *Information Technology and Management*, *15*, 4 (2014), 239–254.

11. Cox, D.R. Regression models and life-tables. *Journal of the Royal Statistical Society, Series B*, *24*, 2 (1972), 187–220.

12. DeLone, W.H., and McLean, E.R. Information systems success: The quest for the dependent variables. *Information Systems Research*, *3*, 1 (1992), 60–95.

13. Do, H.; Jeon, S.; Banker, R.D.; Lee, B.; and Yoo, B. Is the leaderboard information useful to investors? The leaderboard effect in P2P lending. In *Proceedings of the 33rd International Conference on Information Systems*. Atlanta, GA: Association for Information Systems, 2012, pp. 3820–3829.

14. Dorfleitner, G.; Priberny, C.; Schuster, S.; Stoiber, J.; Weber, M.; De Castro, I.; and Kammler, B. Description-text related soft information in peer-to-peer lending: Evidence from two leading European platforms. *Journal of Banking and Finance*, *64* (2016), 169–187.

15. Duarte, J.; Siegel, S.; and Young, L. Trust and credit: The role of appearance in peer-to-peer lending. *Review of Financial Studies*, *25*, 8 (2012), 2455–2484.

16. Greiner, M. Determinants and consequences of herding in P2P lending markets. In *Proceedings of the 19th Americas Conference on Information Systems*. Chicago, IL: Association for Information Systems, 2013, pp. 1–13.

17. Greiner, M.E., and Wang, H. The role of social capital in people-to-people lending marketplaces. In *Proceedings of the 13th International Conference on Information Systems*. Atlanta, GA: Association for Information Systems, 2009, p. 29.

18. Greiner, M., and Wang, H. Building consumer-to-consumer trust in e-finance marketplaces: An empirical analysis. *International Journal of Electronic Commerce*, *15*, 2 (2011), 105–136.

19. Herrero-Lopez, S. Social interactions in P2P lending. In *Proceedings of the 3rd Workshop on Social Network Mining and Analysis* (Article No. 3). Paris, France: ACM Press, 2009.

20. Herzenstein, M.; Dholakia, U.M.; and Andrews, R.L. Strategic herding behavior in peer-to-peer loan auctions. *Journal of Interactive Marketing*, *25*, (2011), 27–36.

21. Herzenstein, M.; Sonenshein, S.; and Dholakia, U.M. Tell me a good story and I may lend you money: The role of narratives in peer-to-peer lending decisions. *Journal of Marketing Research*, *48* (2011), S138–S149.

22. Houser, D., and Wooders, J. Reputation in auctions: Theory and evidence from eBay. *Journal of Economics and Management Strategy*, *15* (2006), 353–369.

23. Jones, Q.; Ravid, G.; and Rafaeli, S. Information overload and the message dynamics of online interaction spaces: A Theoretical model and empirical exploration. *Information Systems Research*, *15*, 2 (2004), 194–210.

24. Kim, K., and Viswanathan, S. The experts in the crowd: the role of reputable investors in a crowdfunding market. In *Proceedings of the 41st Research Conference on Communication, Information and Internet Policy*. Arlington, VA, 2014.

25. Komiak, S. The effects of perceived information quality and perceived system quality on trust and adoption of online reputation systems. In *Proceedings of American Conference on Information Systems*. Atlanta, GA: Association for Information Systems, 2010, p. 343.

26. Korfiatis, N.; García-Bariocanal, E.; and Sánchez-Alonso, S. Evaluating content quality and helpfulness of online product reviews: The interplay of review helpfulness vs. review content. *Electronic Commerce Research and Applications*, *11*, 3 (2012), 205–217.

27. Krumme, K.A., and Herrero, S. Lending behavior and community structure in an online peer-to-peer economic network. In *Proceedings of International Conference on Computational Science and Engineering*. Los Alamitos, CA: IEEE Computer Society Press, 2009, pp. 613–618.

28. Larrimore, L.; Jiang, L.; Larrimore, J.; Markowitz, D.; and Gorski, S. Peer to peer lending: The relationship between language features, trustworthiness, and persuasion success. *Journal of Applied Communication Research*, *39*, 1 (2011), 19–37.

29. Lee, E., and Lee, B. Herding behavior in online P2P lending: An empirical investigation. *Electronic Commerce Research and Applications*, *11*, 5 (2012), 495–503.

30. Lee, J.; Park, D.-H.; and Han, I. The effect of negative online consumer reviews on product attitude: An information processing view. *Electronic Commerce Research and Applications*, *7*, 3 (2008), 341–352.

31. Lee, Y.W.; Strong, D.M.; Kahn, B.K.; and Wang, R.Y. AIMQ: A methodology for information quality assessment. *Information and Management*, *40*, 2 (2002), 133–146.

32. Li, X., and Hitt, L.M. Self-selection and information role of online product reviews. *Information Systems Research*, *19*, 4 (2008), 456–474.

33. Lin, M.; Prabhala, N.R.; and Viswanathan, S. Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science*, *59*, 1 (2013), 17–35.

34. Locander, W.B., and Hermann, P.W. The effect of self-confidence and anxiety on information seeking in consumer risk reduction. *Journal of Marketing Research*, *16*, 2 (1979), 268–274.

35. Mayer, R.C.; Davis, J.H.; and Schoorman, F.D. An integrative model of organizaitonal trust. *Academy of Management Review*, *20*, 3 (1995), 709–734.

36. Michels, J. Do unverifiable disclosures matter? Evidence from peer-to-peer lending. *Accounting Review*, *87*, 4 (2012), 1385–1413.

37. Mollick, E. The dynamics of crowdfunding: an exploratory study. *Journal of Business Venturing*, *29*, 1 (2014), 1–16.

38. Mudambi, S.M.; and Schuff, D. What makes a helpful review? A study of customer reviews on Amazon.com. *MIS Quarterly*, *34*, 1 (2010), 185–200.

39. Nicolaou, A.I., and McKnight, D.H. Perceived information quality in data exchanges: Effects on risk, trust, and intention to use. *Information Systems Research*, *17*, 4 (2006), 332–351.

40. Park, D.-H.; Lee, J.; and Han, I. The effect of on-line consumer reviews on consumer purchasing intention: The moderating role of involvement. *International Journal of Electronic Commerce*, *11*, 4 (2007), 125–148.

41. Pedhazur, E.J., and Schmelkin, L.P. *Measurement, Design, and Analysis: An Integrated Approach*. Hillsdale, NJ: Lawrence Erlbaum, 1991.

42. Petersen, M.A. Information: Hard and Soft. Chicago: Northwestern University, 2002.

43. Pope, D.G., and Sydnor, J.R. What's in a picture? Evidence of discrimination from Prosper.com. *Journal of Human Resources*, *46*, 1 (2011), 53–92.

44. Rieh, S.Y. Judgement of information quality and cognitive authority in the Web. *Journal of the American Society for Information Science and Technology*, *53*, 2 (2002), 145–161.

45. Sen, S., and Lerman, D. Why are you telling me this? An examination into negative consumer reviews on the Web. *Journal of Interactive Marketing*, *21*, 4 (2007), 76–94.

46. Shen, D.; Krumme, C.; and Lippman, A. Follow the profit or the herd? Exploring social effects in peer-to-peer lending. In *Proceedings of IEEE International Conference on Social Computing*. Washington, DC: IEEE Computer Society Press, 2010, pp. 137–144.

47. Simonsohn, U., and Ariely, D. When rational sellers face non-rational buyers: Evidence from herding on eBay. *Management Science*, *54*, 9 (2007), 1624–1637.

48. Sonenshein, S.; Herzenstein, M.; and Dholakia, U.M. How accounts shape lending decisions through fostering perceived trustworthiness. *Organizational Behavior and Human Decision Processes*, *115*, 1 (2011), 69–84.

49. Wang, H., and Greiner, M.E. Prosper: The eBay for money in lending 2.0. *Communications of the Association for Information Systems*, *29*, 1 (2011), 243–258.

50. Wang, R.Y., and Strong, D.M. Beyond accuracy: What data quality means to data consumers. *Journal of Management Information Systems*, *12*, 4 (1996), 5–34.

51. Yum, H.; Lee, B.; and Chae, M. From the wisdom of crowds to my own judgment in microfinance through online peer-to-peer lending platforms. *Electronic Commerce Research and Applications*, *11*, 5 (2012), 469–483.

52. Zhang, J., and Liu, P. Rational herding in microloan markets. *Management Science*, *58*, 5 (2012), 892–912.

53. Zhang, J.Q.; Craciun, G.; and Shin, D. When does electronic word-of-mouth matter? A study of consumer product reviews. *Journal of Business Research*, *63*, 12 (2010), 1336–1341.

54. Zhang, Z.; Ye, Q.; Law, R.; and Li, Y. The impact of e-word-of-mouth on the online popularity of restaurants: A comparison of consumer reviews and editor reviews. *International Journal of Hospitality Management*, *29*, 4 (2010), 694–700.

55. Zhu, F., and Zhang, X. Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, *74*, 2 (March 2010), 133–148.

56. Zmud, R.W. An empirical investigation of the dimensionality of the concept of information. *Decision Sciences*, *9*, 2 (1978), 187–195.

Appendix: Content Coding Schema and Intercoder Reliability

Content Code	Definition	Message Examples	Intercoder Reliability
		Lender Comment	
Inquiry	The lender asks questions regarding the listing or borrower or requests additional documentations and information.	• 你在什么国家机关工作呢？ • Which government agency do you work for? • 你提一提你的收入来源吧。 • Provide your sources of income.	95.9%
Positive	The lender explicitly supports the borrower or expresses a positive attitude toward the listing or borrower.	• 加油，看好你噢！有必要的话我会加投！ • Support! I believe you will make it. I will contribute more if necessary!	94.8%
Negative	The lender is skeptical or expresses a negative attitude toward the listing or borrower.	• 你将期限压到 2 个月， 2 个月你就有能力还掉信用卡了？ • You set your repayment period to be two months. Are you sure you will be able to pay back in just two months?	95.9%
Irrelevant	The message content is irrelevant to the listing.	• 网络借贷 QQ 群 XXXX ，现在交易免一切费用! • eLoan QQ Group XXXX, no fees!	94.8%
		Borrower Response (Information Quality)	
Perceived Accuracy	The response carries information about some key facts in a concrete, detailed form (e.g., numbers, names, etc.)	• Question: 银行流水上有笔柜台存现 7000 元，是什么？ • Response: 是公司支付的湛江地区跟茂名地区的劳务费，每个地区3500. • Question: what is the direct deposit of ￥7,000 on your bank statement?	86.9%

		• Response: It is the labor charge the company paid for Zhanjiang and Maoming areas. Each area is ￥ 3,500.	
Perceived Completeness	The response provides all information requested by the lender.	• Question:提供的是你本人签的场地租赁合同么？与其他证明中的缴款人不是一个人吧？高尔夫车是谁的？ • Response:合同是我自己签的. 还有营业执照也是我的名字, 车子是我老公的, 买了4年了. • Question: Was the rental contract you provided signed by yourself? Was that the same person who signed other documents? Who owns the golf car? • Response: I signed the contract, the business license, and other documents. The golf car is my husband's and he bought it four years ago.	84.1%
		Borrower Response (Identity)	
Trustworthy	The borrower assures the lenders that he or she is a trustworthy person.	• 我讲信誉，会及时还款的！ • I am trustworthy. I will repay the loan!	97.1%
Successful	The borrower has a successful business, job, or career.	• 来这里我也只是抱着试试的心理，加上并不是非常缺钱。 • I am here just to explore and try. I am not short of money.	99.6%
Hardworking	The borrower will work hard to repay the loan.	• 我会靠自己的勤劳来改变自己的命运！ • I will work hard to bring changes to my life!	99.6%
Economic Hardship	The borrower has difficult situations, bad luck, or other misfortunes that are not under his or her control.	• 刚毕业经济上现在相当困难。 • I have just graduated and have a lot of financial difficulty.	97.7%
Moral	The borrower is an honest or moral person.	• 我觉得欠了别人的钱不还是一种可耻的行为。 • I believe it is a shame not to repay a debt.	98.7%
Gratitude	The borrower expresses gratitude toward the lenders.	• 非常感谢！ • Thank you very much!	99%