LENDERS AND BORROWERS' STRATEGIES IN ONLINE PEER-TO-PEER LENDING MARKET: AN EMPIRICAL ANALYSIS OF PPDAI.COM

Yan Feng
HSBC Business School, Peking University
Rm 758, Peking University HSBC Business School, Xili, Shenzhen, China, 518055
fengyan@phbs.pku.edu.cn

Xinlu Fan
HSBC Business School, Peking University
15/F, NO.100 Pudong South Road, Pudong New District, Shanghai, China, 200120
fanxinlu@cmbc.com.cn

Yeujun Yoon*
HSBC Business School, Peking University
Rm 756, Peking University HSBC Business School, Xili, Shenzhen, China, 518055
yoony@phbs.pku.edu.cn

ABSTRACT

We investigate key factors affecting lenders' bidding strategies using three measurements for the popularity of loans: funding success, number of bids, and funding time. Also, we analyze borrowers' strategy in three groups according to the level of their expertise of online Peer-to-Peer lending: novice borrowers, pure borrowers, and mixed borrowers (as both borrower and lender). We use data from PPDai and find unanimous support for the interest rate, but partial evidence for the loan amount and the loan period. Particularly, we find that a larger loan amount could increase the probability of funding and attract more lenders. This implies that different lenders' strategies exist in the Chinese online P2P market where reliable individual credit information is unavailable. Information related to credit shows significant impact on all three measurements of the loan popularity. For borrowers, we find that different types of borrowers emphasize different components when designing a loan: mixed borrowers seem to put more weight on loan period while pure borrowers consider interest rate and loan amount more. Borrowers who have more expertise tend to propose a loan at a relatively lower cost. Our findings also suggest that Chinese borrowers, especially mixed borrowers, tend to utilize higher credibility to seek larger loans instead of lowering the cost of a loan.

Keywords: Online P2P lending; Lender strategy; Borrower strategy; Borrower types; PPDai

1. Introduction

The peer-to-peer (P2P) lending concept is not at all new in itself, where lenders lend money to borrowers without an intermediary party involved [Herrero-Lopez 2009] .[1] With the growth of the volume for e-commerce and the expansion of the online community, online P2P lending gains popularity as a convenient way of financing and probably a better alternative to the traditional banking system for some people. Online P2P lending basically extends the decision process based on personal credit onto the Internet [Bachmann et al. 2011; Collier & Hampshire 2010; Lin et al. 2009; Lin et al. 2013; Wang & Greiner 2011]. Since the first online P2P lending platform Zopa was established in the UK in 2005, this novel financial business has been growing rather rapidly in many other countries such as the USA, Denmark, Japan, and China. The worldwide online P2P lending business has seen continuous growth at a high speed: in April, 2014, an increase of 30% from March for Prosper (US), 40% for Smava (DE), 10% for Zopa (UK), and etc. (P2P-Banking.com).

Despite the distinctive benefits of the online P2P lending, a high degree of information asymmetry in the market has been considered a substantial problem that hurts the market efficiency. This asymmetry exposes the lenders to a

* Corresponding author.

[1] The first peer-to-peer loans are believed to be facilitated by Zopa, a UK company founded in 2005.

higher risk in their investment and tends to distort their bidding decisions [Chen & Han 2012; Yum et al. 2012]. However, other researchers argue that the market inefficiency induced by information asymmetry can, to an extent, be alleviated by other factors such as the disclosure of the borrower's financial and personal information or the development of mutual trust between the users. [Freedman & Jin 2008; Herzenstein et al. 2011; Iyer et al. 2009; Klafft 2008; Pope & Sydnor 2008; Ravina 2008; William et al. 2009]. We summarize the differences between traditional lending and P2P lending in Table 1.

Table 1: Comparison between the Traditional Loan Financing Market vs. P2P Lending Market

Major Aspects	Traditional Loan Financing	P2P Lending
Interest Rate	Low - Medium	Medium - High
Loan Amount	High	Low
Collateral/Endorsement	Yes	No
Party Involved	Borrower, Bank	Borrower, Lender, Platform
Regulation/Supervision	Strict	Loose
Process	Complex, Long	Simple, Fast
Risk	Low	High
Transaction Cost	High	Low

Along with the market efficiency issue, academic attention has been increasingly focused on the factor affecting the lenders' bidding strategies, which is mainly measured by the fund success rate. For example, researchers found a positive impact of the offered interest rate and the loan amount on increasing the funding rate [Barasinska & Schäfer 2010; Freedman & Jin 2008; Pope & Sydnor 2008]. Also, others found credit scores and the financial history to have a strong impact on successful funding [Klafft 2008; William et al. 2009; Yum et al. 2012]. Furthermore, there has been partial evidence for the impact of demographic information and soft information such as friendship or photos on the funding success rate [Colier & Hampshire 2010; Freedman & Jin 2008; Pope & Sydnor 2008]

While these studies likewise investigate the lenders' bidding strategies, their conventional measurement of the popularity of the loan for the lenders (funding rate or success or failure of funding) seems unsatisfactory. As Chen & Han [2012] argue, most of the loan listings have difficulty attracting even a single lender. Thus, binary discrete measurement of the fund success rate – which is a unitary measurement used for most studies – seems to be insufficient to investigate the lenders' behaviors. Furthermore, among the successful loans, we find a large variation in terms of the number of bidders and the bid closing time. For example, for some loans a large number of lenders rush into the bidding and the bidding is closed and fully funded within one day, while other loans are barely able to attract even a couple of lenders after a long period of time. As a consequence, measurement of the success or failure of funding is likely to yield misleading estimations of the popularity of the loans. Indeed, we found mixed results for some characteristics of the loans such as the amount and the period of loans but consistent support for the impact of the interest rate across our three different measurements of the loan popularity.

In addition, while online P2P lending is distinctive for its interactive functions among the users, the lenders and the borrowers, much of the current literature heavily focuses on the lender-side behaviors. There is very little literature that thoroughly examines the borrowers' behavior. It is noteworthy that the borrowers in this market can design their loans based on their own preferences instead of accepting the terms dictated by the lenders. Therefore, an individual borrower is able to participate in the transaction strategically beyond pure borrowing due to the flexibility of the online P2P lending platform. Also the efficiency of getting a loan can be very different across the borrowers due to the degree of their experience [Freedman & Jin 2008].

In fact, we found strong evidence that "mixed borrowers," who get involved in both borrowing and lending activities, are in a better position to propose a loan with lower cost than the "novice borrowers" or the "pure borrowers". We also found evidence that "mixed borrowers" behave differently compared to the "pure borrowers" when they propose the loans: the former prefers loans with relatively longer time periods whereas the latter emphasizes the loan amount and the interest rate. More interestingly, unlike other types of borrowers, the "mixed borrowers" seem to make fuller use of their credit information.

In this paper, we comprehensively analyze the online P2P market by exploring the bidding/listing strategy of both the lenders and the borrowers with cross-sectional data we collected from PPDai.com, the first and number one online platform of China. For the lenders' bidding strategy, we employed three different measurements to capture the popularity of the listed loans, i.e., success or failure of the loan, number of bidders, and closing time of the loan, which we believe to be more accurate. For borrowers, we categorized them into three groups according to the history of their activities of borrowing and lending. Then we analyzed how they design a loan, respectively. By answering these research questions, we contribute to the online P2P literature by extending our understanding of the lenders' bidding behaviors and shedding light on the borrowers' strategic behaviors. From the next section on, we briefly discuss previous literature on the online P2P lending, and then introduce the data and the models we use in the empirical analysis. Estimation results and discussions will follow, and finally, we provide the conclusions.

2. Literature Review

2.1. Investment Risk of Lenders in Online P2P Lending Market

As Wang & Greiner [2011] argue, there are many reasons for the popularity of online P2P lending: first of all, online matching of financing requests and investment opportunities can be realized with lower transaction costs; secondly, lower costs make smaller loans possible; and finally, splitting large loans into many smaller ones provides a diversifying mechanism for the investors, thus lowering the risk to each individual lender. However, the risk factors associated with online lending can be a serious consideration. Even though the platforms normally provide a decent level of risk protection by checking the borrower's identification, credit records, and other credential proof information, online P2P lending is still characterized by a high degree of information asymmetry ex ante and ex post, and it is still critical to improve the efficiency of the market and the lenders' bidding strategy. The borrowers on an online platform may very well be the individuals who do not have a strong enough credibility to be able to raise money through traditional lending organizations, and even with checking some general credit information, a lender cannot guarantee a low default rate; therefore, possible adverse selection from the borrower side makes online lenders face a high risk as investors. As precautions, in addition to having very strict borrower screening standards, lenders ask for (relatively) higher interest rates. Consequently, funding rates on the lending platforms are not very high. Yum et al. [2012] argue that adverse selection problems lead to high interest rates and low success rates since the lenders are more reluctant to lend money. Chen & Han [2012] find that only 10.5% of the borrowers' loans were funded successfully on Prosper.com in 2008 and the figure was still below 20% in 2012.

Asymmetric information not only causes a risk of adverse selection, but also a risk of moral hazard. Online borrowers who use this market are not necessarily perfectly credible; they may take the money they borrow and never pay it back. While it is too much to assume that every online platform user borrows from his/her peers because they cannot get money from the traditional financial organizations, such as banks, it is still quite reasonable that at least some of them would stand very slim chances obtaining bank loans. In reality, default happens, and with no trivial frequency. The average default rate on Prosper.com has reached 7.42%, much higher compared with an average of 4-5% of bank loans in the US.[2]

One way of alleviating asymmetric information problems is by trying to ask borrowers to disclose as much information as possible, financially and/or personally. Freedman & Jin [2008] study the average funding rates of a 4-year-span from 2005 to 2008. They provide evidence that since Prosper.com began encouraging more financial information disclosure beginning from Feb. 2007 the funding rate has increased. This suggests that the alleviation of information asymmetry improved the market efficiency. William et al. [2009] state that information such as credit ratings also helped to mitigate adverse selection.

In this type of market with a high level of information asymmetry, the buyers (lenders in an online lending context) can infer the credibility of the sellers (borrowers in an online lending context) based on signals, i.e., hard information such as official credit score, more detailed personal information, membership of trustworthy communities, etc. [Collier & Hampshire 2010]. This information, serving as a signal, is believed to impact the lender strategy on an online lending platform. Scholars have identified that lenders make inferences about the borrowers' credibility not just from hard information, which directly indicates repayment ability and the likelihood of default, but also from non-standard signals, especially when the borrower has a poor credit rating [Iyer et al. 2009].

Furthermore, some researchers argue that soft and intangible information such as mutual trust between lenders and borrowers can be helpful for improving the market efficiency of the online P2P market [Greiner & Wang 2010]. McKnight et al. [2002] consider trust to be the lubricant for trading and the foundation for understanding individual

[2] Different sources offered different numbers (based on different calculations) for Prosper, ranging from 2 digits to about 5%. On average Prosper is believed to have a fairly low default rate. We do not have the exact number for bank loans, but from country to country, the average default rate varies a lot due to different mortgage laws, etc., which may make it easier or more difficult for borrowers to default.

behaviors and economic activities. Hence, the more a borrower/lender participates in transactions, the more "trustworthy" he/she is perceived to be, and the easier it is for him/her to borrow, to borrow larger amounts, and/or to borrow for a longer period. Moreover, an experienced borrower/lender learns this and will utilize this as an advantage to plan more strategic loan listings [Freedman & Jin 2008].

2.2. Factors Affecting Online P2P Lender's Bidding Strategy

There has been an increasing volume of studies to verify the factors affecting lender's bidding strategies, predominately measured by the funding success rate of a loan. In this venue, most of the studies focused on the determinants for the success rate of loans, which can be broadly categorized into 4 types: loan characteristics (interest rate, amount of loan, and loan period), user credit/financial information, demographic information, and soft information such as social capital (e.g., friendship network/circle).

Loan characteristics are the fundamental elements of the lenders' investments [Bodie et al. 2012]. Freedman & Jin [2008] and other studies find a significantly positive impact of the offered interest rate for the listed loan on successful funding. Puro et al. [2010] find that smaller loan amounts can help increase the success rate and decrease the interest rate. In addition, Lin et al. [2013] show that it is difficult for loans with a longer period to get funded because it would not provide sufficient liquidity for the lenders.

Typical credit/financial information such as borrowing history, credit rating, bank accounts, house ownership, debt-to-income ratio, and delinquencies impact the success rate of a listed loan. Using Prosper data, Klafft [2008] identifies credit rating as the most important factor affecting the interest rates, debt-to-income ratio takes the second place, and if a borrower has bank accounts then his/her loan requests are more likely to be successful. The findings are also supported by studies such as Freedman & Jin [2008] and Iyer et al. [2009]. Yum et al. [2012] use data from Popfunding.com and argue that borrowing history has a strong effect on the success rate. Borrowers with a successful history are more likely to secure funds, although the impact diminishes as more information is disclosed, with the lenders forming their own judgments about certain borrowers.

Demographics affect the decision of consumers to use or not use online financial platform at all [Lichtenstein & Williamson 2006]. In the context of online lending, the effect of demographic information (such as age, gender, and race) on the success rate and the interest rate seems to be inconsistent across different studies (and for different geographic regions). All in all, women seem to tolerate a lower interest rate from both the borrowing and the lending sides; younger borrowers are in general more successful; and there exists a racial disadvantage in both the funding success rate and the interest rate paid [Barasinska & Schäfer 2010; Herzenstein et al. 2008, 2011; Pope & Sydnor 2008; Ravina 2008].

Research on soft information shows evidences of the impact from "friends", "groups (circle)", "borrower narratives", and "photos". These hard-to-quantify factors influence users' experiences with the platform and serve as the indirect evidence of a user's trustworthiness and thus can influence both the success rate of funding and the eventual interest rate of the acquired loans [Collier & Hampshire 2010; Greiner & Wang 2010; Herrero-Lopez 2009; Herzenstein et al. 2011; Klafft 2008; Michels 2012; Pope & Sydnor 2008; Ravina 2008; Yoon 2012].

2.3. Online P2P Lender's Bidding Strategy in China

China has its own special characteristics that have given rise to a flourishing online lending market. Overall, the tight bank-credit environment in China has helped to push forward the development of P2P lending businesses[3]. Obviously, banks do not finance what they consider to be "trivial" loans because of the costs. Given that the process of the investigation and the approval of a loan project is long and costly, there is little incentive for the banks to consider the relatively small loan requests. For loan requestors, it is also not cost-efficient to apply for small loans, since the interest rate is often higher and the relatively small amount of money does not justify the high transaction costs. China also has a culture (and tradition) of collateral/endorsement lending, meaning that the lending only happens with the borrower offering something of sufficient value that banks can hold [Ma, 2005]. This something can either be collateral or a trustworthy endorsement. In European countries and the US, personal and entity credit scores are collected and provided by professional and independent organizations specializing in credit keeping and calculating; the lending culture in these countries is more of a credit based lending. Whereas in China, no such specialty organization exists and there is basically no mature third party credit rating system.[4] Without access to a

[3] The first online platform, PPDai (www.ppdai.com), was established in 2007 in Shanghai. The cumulative amount of loans transacted through P2P online platforms reached 110 billion RMB by early 2014, and there are currently about 400 active online P2P platforms (2014 China P2P Lending Service White Book)

[4] People's Bank of China has started the collection of credit history and calculation of credit scores, but the credit information is not shared with individuals and non-bank entities. There is literally no independent commercial credit rating organization/entity in China.

trustworthy credit record and collateral /endorsement, banks do not get involved in a loan request.[5] With a need for a cost-efficient small loan and/or having limited credit records, a borrower can only turn to alternative means of financing.

The Chinese P2P lending market has developed rapidly since the end of 2012, as part of the country's unregulated shadow banking system.[6] As well, there is no entry threshold for establishing P2P platforms, nor clear supervision rules. The ambiguity of the rules and the lack of regulations have given rise to concerns over creditors' financial safety. It is not rare to read reports about the closing down of a P2P platform or the founder of a platform just vanishing; relatively recent news about CreditEase has attracted serious attention.[7]

However, compared to its explosive growth in recent years and the distinctive financial system, the literature investigating the online P2P lending market in China is relatively scarce. There is no research specifically addressing borrower behavior, and few studies have used data from PPDai to research the online P2P lending behavior on the lender side, most of which serve as a verification of similar determinants of successful lending online as with platforms in western countries. Chen et al. [2014] use survey data of P2P lending platform users to study the lenders' willingness. They conclude that trust, which is determined by the information of the listed loans and the borrowers, is the most important factor affecting the lender's willingness to lend; perceived risk might impact trust but will not significantly impact lending willingness. This indicates that a successful transaction on online lending platforms is mainly determined by factors other than technical facilities. Li & Zhu [2013] apply OLS model and identify that factors indicating personal credibility, such as credit rating, successful borrowing history, and the amount of a listed loan, affects the interest rate of the successful loans. Song & Han [2013] study factors impacting the success rate and the interest rate based on logit and OLS models and find that the failure history and interest rate have a significant impact. Wen & Wu [2014] also use PPDai data to investigate the factors that lead to successful borrowing. They employ binary logistic model and Monte Carlo simulation and find that borrowing amount, past successful borrowing history, and credit scores are all important factors positively influencing the success rate of funding. According to these studies, Chinese users of the online P2P-lending platforms do not seem to differ from their Western peers.[8]

2.4. Online P2P Borrowers' Strategy

While most literature has extensively investigated the lenders' behavior and strategies, there are very few studies that examine the borrowers' behavior. Most studies have classified the borrowers based on their demographic characteristics or social characteristics such as the social network they belong to, which is not directly involved in online P2P lending from the lenders' perspective. For example, Pope & Sydnor [2008] find that there is a significant difference in successful funding between African American and White borrowers. Ravina [2008] argues that a borrower with similar demographic characteristics to a lender can increase the probability of getting funded. Borrowers can also improve the likelihood of funding by participating in certain groups on the P2P platforms [Freedman & Jin 2008; Herrero-Lopez 2009]. All of these studies examined the borrowers' characteristics as supplementary information for the listed loans to increase the funding rate. However, borrowers could behave more strategically given the unique nature of the online P2P lending business where a borrower is not a passive participant in receiving a fixed interest rate, or at the most, one who is allowed to choose limited numbers of financial products in the traditional financial system. One distinctive feature of the online P2P lending platform is that it allows the borrowers to design their loans and propose them to other parties. Hence, the borrowers are totally free to design the features of the loans in order to attract lenders. In addition, on the online P2P lending platform, the borrowers can be lenders as well. Thus the borrowers are likely to propose differently designed loans consistent with their purposes and different level of expertise. For instance, for borrowers whose purpose is arbitrage, their preference for certain

---

[5] There is a known saying in China that to get a loan from a bank, you need to prove you have money to get money, thus defeating the purpose, not to mention, service from Chinese banks (especially the state-owned big four) is generally sub-par across the board.

[6] According to a Fortune Magazine report (2014, July 9), shadow banking in China has reached about US$4.4 trillion, or about 20 percent of China's total bank assets, and increasingly, the shadow banking has been moving to the Internet.

[7] Guangzhou Daily reported on April 17, 2014 that a Shenzhen-based P2P lending company (wangwangdai.com.cn) has mysteriously vanished, leaving 600 investors unable to claim their 20 million RMB (about 3.2 million USD) investment. According to Net Ease News, in the early half of 2014, there were at least 12 such cases.
According to Hong Kong media, CreditEase has accumulated 0.8 billion RMB (about 128,000 USD) of bad debt, most of which is not recoverable. Allegedly, CreditEase also is involved in usury.

[8] Besides PPDai data, some other authors use data from similar p2p online lending platform and have found so far quite consistent results [Wang 2014; Chen 2014].

loan attributes (e.g. loan period) would be much stronger than for those borrowers who use the platform for pure borrowing. Also, as Freedman & Jin [2008] mention, participants in this new platform of lending could learn more about the nature of the platform and evaluate others' strategies better by accumulating experiences from the involvement in more transactions. Therefore, borrowers who have more experience with online P2P lending can be in a better position to utilize their expertise to design loans more efficiently. Strategic behaviors associated with better experiences of online transactions are documented in research on consumer learning [Liao & Keng 2014; Lu et al. 2014].

3. Theoretical Model and Data

According to the prior literature, we propose a model of lender's bidding strategy to investigate the key factors affecting lender's strategy. Particularly, we employ three different measurements for the popularity of the loans: fund success rate, number of bids, and loan closing time. Also, we propose a model for borrowers' behaviors according to the degree of their expertise. This allows us to analyze how different types of borrowers behave differently when they design the listed loans. A graphic description of the models is presented in Figure 1.

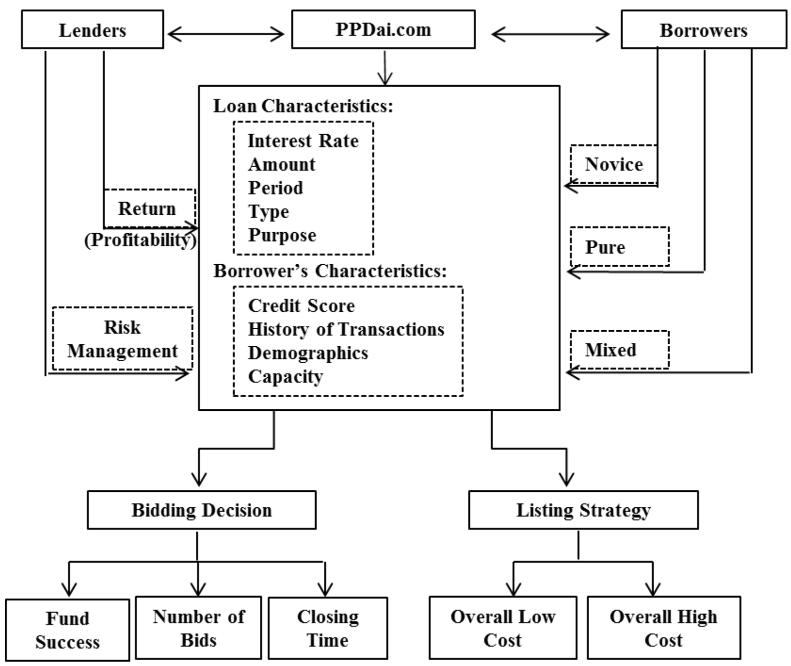

Figure 1: A Visual Indication of the Models

3.1. Model for Lender's Bidding Strategy

3.1.1. Dependent Variable

1) Fund Success (FS): it is a binary variable where it equals one if the raised fund for a loan reaches the requested amount; otherwise it is zero. This is frequently used in previous studies [e.g., Lin et al. 2009; Pope & Sydnor 2008]. Some studies use continuous funding rate as the dependent variable instead of a binary variable of success or failure [Puro et al. 2010]. The binary variable is more relevant to our data set because most loans that failed to be funded did not attract any lenders: only 10 listings out of 717 listings that failed to receive the full amount requested attracted some lenders. However, this binary measurement alone is insufficient to capture the lenders' bidding behavior. For example, for some loans, many lenders rush into a bidding and the bidding is closed within the same day the loan is posted, while other loans are not very successful in attracting many lenders and barely make it after relatively long time period. Indeed, we observed that there was a large variation in the number of bidders and the closing time among the loans that successfully raised fund (Table 3). It is obvious that certain types of listings are more popular and lead lenders to participating in the bidding. Binary variable of success and failure of raising full fund of a loan might not be accurate enough to measure the lenders' likelihood of bidding for the focal loan. Therefore, we propose two additional alternative measurements of the loan popularity, i.e., the "Number of Bids" and the "Funding Time".

2) Number of Bids (NB): this is the number of lenders bidding on the listed loan. The minimum number of bids

is zero. Most of the failed loans do not have a single lender, while there is big variation among the successful loans (Table 3). Popular loan listings can attract more lenders to participate in the bidding. One might argue that a loan is popular if it attracts a single dominant lender who can offer the entire loan amount requested. Thus, the number of bidders might be an indicator of lower popularity, opposite to our intention. This situation is possible, but this is only the case when a loan is successfully closed with a few lenders. In our dataset, we observed that only 15 loans out of total 350 successful loans (4.29%) are successfully closed with less than 5 lenders, it is also a regulation on PPDai.com that a single lender cannot bid for more than 60% of the total loan amount. Furthermore, our correlation analysis (Table 4) shows strong negative correlation between the number of bids and the funding time (explained in the next paragraph). This implies that more bidders can help to close a loan in less time.

3) Funding Time (FT): in order to check the loan popularity further, we employ funding time of the loan as an additional measurement for loan popularity. This is the time of the listing's duration from being launched till the bidding process ends, counted in days. For example, if the borrower achieves full loan funding within the same day it is posted, FT equals zero. The maximum value of FT is 15 because the listing automatically expires on PPDai after 15 days. Therefore, FT ranges from 0-15. More popular listings attract lenders in a shorter time period and can raise the requested amount faster. Conversely, it takes a longer time for less popular listings to become fully funded.

3.1.2 Independent Variables

We include three types of explanatory variables affecting the lenders' bidding decisions: loan characteristics, information related to borrowers' credit, and demographic information of the borrowers.

1) Loan characteristics

The characteristics of the listed loans such as the interest rate, the loan amount, and the loan period are the essential elements relevant to the lenders' investment decision because these are the major determinants of the profit to be generated by the investments [Bodie et al. 2012]. Bachmann et al. [2011] argue that these loan characteristics are considered as the major factors affecting lenders' bidding strategies. For example, a higher interest rate offered by the listed loan can generate higher returns to the lenders, so they are likely to bid for the loan. However, as discussed in the previous section, a higher interest rate might also be interpreted as a signal of a riskier loan, especially in a market with a high degree of information asymmetry, so the lenders might be less interested in loans with higher interest rates [Yum et al. 2012]. Nonetheless, this problem could be mitigated by better/fuller disclosure of borrowers' information. Recently, most online P2P lending platforms require borrowers to reveal more information, and strongly encourage them to do so via various channels. Thus, the lenders become more able to evaluate the borrowers' creditability and this could successfully reduce market inefficiency [Freedman & Jin 2008]. Indeed, studies provide empirical evidence that, with improved information asymmetry, higher interest rates may increase the funding success rate [Barasinska & Schäfer 2010; Freedman & Jin 2008; Pop & Sydnor 2008]. Therefore, interest rate would be a main factor affecting the lenders' bidding decisions.

In the same logic, lenders might prefer larger loans because it generates a higher return if the other conditions are the same [Bodie et al. 2012]. Particularly, the loan amount can act as a secondary indicator of the borrowers' creditability in the online P2P lending market. For example, many novice borrowers who might not have serious motivation with online borrowing will just give it a try by requesting a small loan. Or borrowers with bad credit records might strategically request smaller loans in order to increase the success rate of funding. Based on this, the size of the loan request can determine its attractiveness. However, some researchers argue that lenders might prefer small loans to larger loans for risk management purposes [Wang & Greiner 2011]. By diversifying their investments into various small loans, lenders can effectively manage the potential risk of their overall investments. In this sense, small loans may attract more lenders to the bidding. In fact, Puro et al. [2010] find that a smaller loan amount can help increase the success rate and decrease the interest rate.

Lenders might also prefer shorter loan periods under equivalent conditions because it allows for more liquidity. Liquidity can be a particularly critical issue in online P2P lending market because many lenders are individuals rather than financial institutions. Individuals can be more sensitive to the speed at which their asset being converted to cash because they do not have a large resource base and most of them do not possess advanced risk management techniques [Bodie et al. 2012]. Lin et al. [2013] show that it is difficult for loans with longer periods to get fully funded. Therefore, we include the interest rate, and the loan amount requested, and the loan period as key variables affecting the lenders' bidding decisions. Specifically, they are defined as follows:

a. Interest rate (R): interest rate of the listing is the annual interest rate stated by the borrower on the listing page. Interest rate range can be between 5-24%. According to the Chinese Supreme Court ruling, the interest rate of P2P lending cannot exceed 4 times the basic banking interest rate (around 6%)for similar loan projects.[9]

b. Amount of loan requested (A): the loan amount is the requested amount stated on the listing page, which ranges

[9] Published by People's Bank of China, July 6th, 2012.

from 3,000 to 500,000 RMB (480 to 80,000 USD). The amount of the loan is also one of the main sources for lenders to determine the profitability of the loan.

c. Loan period (P): according to PPDai's regulation, a loan period ranges from 1 to 12 months.

2) Information related to the borrowers' credit

Other key factors affecting lenders' bidding decisions is the information to accurately infer the borrowers' credit status [Iyer et al. 2009; Klafft 2008]. This information is used for the evaluation of the borrowers' reliability, so that the lenders can reduce the risk of investment. Using Prosper data, Klafft [2008] identifies credit rating as the most important factor affecting the interest rates, and debt-to-income ratio is the next most important factor. He also identifies that borrowers with bank accounts are more likely to successfully find funding. These findings are also supported by studies such as Freedman & Jin [2008] and Iyer et al. [2009]. Yum et al. [2012] use data from Popfunding.com and argue that the borrowing history has a strong effect on the success rate. Borrowers with a successful history are more likely to secure funds, although the impact diminishes as more information is disclosed to the lenders, allowing them to form their own judgments about certain borrowers. Hence, information related to the borrowers' credit is likely to lead more lenders to bid for a loan. This information is especially important for the lenders' bidding strategy in China where an individual credit score is not provided to the public and organizational users.[10] There are two types of useful information available for the lenders on PPDai.com:

a. PPDai credit score (CER): it consists of the authentication score, the score for account charging, and the score for repayment record: one time of full repayment earns 1 point and one time of delayed repayment loses 2 points. If delinquency still exists, the borrower cannot launch any new listing. All borrowers have 10 points for authentication at the beginning when they register with their ID number. [11]

b. History of successful bids (HSB): for each loan listing, PPDai provides the number of successful funding/bids and failed funding/bids that the borrower of a loan has experienced up to the point the loan is listed. We use the difference of successful and failed funding/bids to measure the historical success rate of the online borrowers. That is,

$$\text{HSB} = \text{number of successful funding/bids} - \text{number of failed funding/bids}$$

Especially, in the absence of official credit information for borrowers, the aforementioned information can be a useful tool for establishing mutual trust between the borrowers and the lenders. Coleman [1990] suggests that borrower with more successful experience can build up stronger trust with lenders. In addition, this can be used as an alternative measurement of the borrowers' credibility to lenders because it could indicate the serious attitude of a borrower toward the online lending business.[12] Therefore, a loan with PPDai credit score and HSB can have positive impact on the lenders' bidding decisions.

3) Demographic and Social Information

In addition to the credit information, the borrowers' personal information such as age, gender, and race can help the lenders to evaluate the borrowers' reliability. This information is considered more important when the lenders do not see the borrowers' exact credit scores [Pope & Sydnor 2008]. There is abundant research showing that lenders discriminate against borrowers due to demographic factors; however, the effect of demographic information on the success rate seems to be mixed across different studies [Herzenstein et al. 2008; Ravina 2008; Pope & Sydnor 2008]. All in all, women seem to tolerate a lower interest rate from both the borrowing and the lending sides; younger borrowers are more successful; and there exists a racial disadvantage in both the funding success rate and the interest rate paid [Barasinska & Schäfer 2010; Herzenstein et al. 2008, 2011; Pope & Sydnor 2008]. On PPDai.com, the lenders can obtain certain demographic and social information of the borrowers such as gender, age, and occupation. Specifically, we measure the following aspects of the borrowers' demographic information:

a. Gender (M): it is a dummy variable of the male gender. If a borrower is a male, M equals one,otherwise is zero.

b. Age (AG1, AG2, AG3, AG4): according to PPDai's classification method, the borrowers are divided into 4 groups of different ages: 20-25, 26-31, 32-38, and over 39. We represent them with four age group variables: 20-25(AG1), 26-31(AG2), 32-38 (AG3), and over 39 (AG4).

c. Occupation (OC): borrowers are divided into 5 different occupational groups: wage/salary earner, private owner, online seller, student, and others. OC_SAL equals one if the borrower is a wage/salary earner; otherwise it is zero.

---

[10] People's Bank of China provides credit status reports for individual customers but not third parties.

[11] There is PPDai credit score for lenders. It consists of authentication score, score of bidding (One successful bid earns 2 points.), score of return (Receiving principal and interest earns 2 points. If the borrower defaults, the lender will lose 10 points of credit). Similar with borrowers' credit, the minimum is 10. We use this information for classification of borrower types in the next section.

[12] PPDai doesn't provide specific information about whether the success/failure of previous funding/bids are counted as lenders or borrowers. We use this information as an additional measurement for borrowers' reliability.

Similarly, OC_PV, OC_ONS, OC_ST, and OC_Others represent private owner, online seller, student, and others respectively.

4) Supplementary Information

Beyond borrowers' demographic and social information, research identifies the impact of supplementary information such as "purpose of the loan", "friends", "groups (circle)", "borrower narratives", and "photos", which influence the lenders' bidding strategies. These hard-to-quantify factors serve as the indirect evidence of a user's trustworthiness and thus can influence both the success rate of funding and the eventual interest rate of the acquired loans [Collier & Hampshire 2010; Greiner & Wang 2009; Herrero-Lopez 2009; Herzenstein et al. 2011; Klafft 2008; Michels 2012; Pope & Sydnor 2008; Ravina 2008]. On PPDai.com, borrowers are required to reveal their main purpose for the loan. Thus, we include the purpose of loans as an additional factor influencing the lenders' strategies, specifically:

d. Purpose of loan: PPDai requests the borrowers to provide the purpose of the loans in four categories: consumption, business investment, experiencing online P2P lending, and raising credit. We use dummy variables: Pur_CS equals to one if the listed purpose of the loan is consumption; otherwise it is zero. Similarly, Pur_BS, Pur_EX, and Pur_CRE are dummy variables of the listed purposes of business investment, experiencing online P2P lending, and raising credit, respectively.

In summary, we include interest rate, amount of loan, and loan period to capture the loan characteristics and PPDai credit score and history of success for the borrowers' credit. In addition, we include demographic information and the purpose of the loans as additional variables affecting the lenders' bidding strategies. Descriptive statistics and correlation analysis of these key variables in our data are reported in Table 2 through Table 4 respectively.

Table 2: Descriptive Statistics for the Variables

Variable	Min	Mean	S.D.	Max
Observation		1,057		
Fund Success (FS)	0	0.331	0.470	1
Amount of Loan (RMB)	1,000	4,689.77	15,239.05	300,000
Interest Rate (%)	8	14.084	3.073	24
Loan Period (Month)	3	9.207	2.783	12
Funding Time (Day)	0	10.877	6.361	15
Number of Bids	0	7.850	34.468	795
PPDai Credit Score	10	19.489	14.477	96
History of Successful Bids	-7	3.192	28.103	466
Purpose of loan				
Consumption	0	0.368	0.482	1
Business Investment	0	0.377	0.484	1
Credit Raising	0	0.172	0.377	1
Experience	0	0.081	0.273	1
Demographic Info				
Male	0	0.876	0.329	1
AG1 (20~25)	0	0.342	0.474	1
AG2 (26~30)	0	0.360	0.480	1
AG3 (31~38)	0	0.191	0.393	1
AG4 (over 39)	0	0.105	0.307	1
Occupation: Wage Earner	0	0.544	0.498	1
Occupation: Private Owner	0	0.242	0.428	1
Occupation: Online Seller	0	0.046	0.210	1
Occupation: Student	0	0.031	0.173	1
Occupation: Others	0	0.135	0.342	1

Table 3: Descriptive Statistics of Number of Bids and Funding Time for Successful Loans

Variable	Min	Mean	S.D.	Max
Observation	350			
Number of Bids	2	23.708	56.781	795
Funding Time (Day)	0	2.551	4.299	15

Table 4: Correlation Analysis of the Key Variables

	Funding Success	Amount of Loan	Interest Rate	Loan Period	Funding Time	Number of Bids	PPDai Credit	History of Bids
Funding Success	1							
Amount of Loan	0.1578	1						
Interest Rate	0.1967	0.0186	1					
Loan Period	-0.3479	-0.126	-0.0794	1				
Funding Time	-0.9214	-0.1896	-0.2169	0.4076	1			
Number of Bids	0.3236	0.8264	0.1132	-0.1693	-0.3437	1		
PPDai Credit	0.6669	0.2227	0.1611	-0.3439	-0.7156	0.3152	1	
History of Bids	0.1689	0.0282	-0.2042	-0.0655	-0.203	0.0617	0.1792	1

Table 5 lists the key theories and papers that support independent variables in our lender's strategy model.

Table 5: Summary of Key Variables in the Lender's Bidding Strategy Model

Variable	Theoretical Background	Papers	Expected Sign
Loan Characteristics Interest Rate (R) Loan Amount (A) Loan Period (P)	Investment, Information Asymmetry, Portfolio Theory	Bachmann et al. [2011], Barasinska & Schäfer [2010], Bodie et al. [2012], Freedman & Jin [2008], Pop & Sydnor [2008], Puro et al. [2010], Yum et al. [2012]	+/- +/- +/-
Credit Information PPDai Credit Score (CER) History of Bids (HSB)	Signal, Trust	Coleman [1990], Freedman & Jin [2008], Iyer et al. [2009], Klafft [2008], Yum et al. [2012]	+ +
Demographic Information Gender (Male) Age (A1-A4) Occupation	Discrimination, Perception bias	Herzenstein et al. [2008] Pop & Sydnor [2008], Ravina [2007]	- - for younger ?

3.1.3. Model Specification

We adopt three different models along with three different measures of the listed loans. For the binary variable fund success (FS), we use the Logit model specification [Davidson & McKinnon 2004]. Specifically, FS of loan i (FS_i) is a function of a set of independent variables (X_i) described above, and an individual random error term e_i. e_i is assumed to follow a logistic distribution.

$$FS_i = \begin{cases} 1, & \text{if loan } i \text{ is successfully funded} \\ 0, & \text{Otherwise} \end{cases} \quad \text{and } Prob_i(FS_i = 1) = \frac{\exp(X_i\beta)}{1+\exp(X_i\beta)} \qquad (1)$$

For number of bids (NB) and funding time (FT), we employ Tobit model specification [Davidson & McKinnon 2004]: Tobit model with a lower bound for NB and Tobit model with both lower and upper bound for FT.

$$NB_i = \begin{cases} NB_i^*, & if\ NB_i^* > 0 \\ 0, & Otherwise \end{cases} \text{ where } NB_i^* = X_i\beta + \omega_i \quad (2)$$

Similarly,

$$FT_i = \begin{cases} 0, & 0 < FT_i^* \\ FT_i^*, & if\ 0 < FT_i^* < 15 \\ 15, & FT_i^* > 15 \end{cases} \text{ where } FT_i^* = X_i\beta + \varepsilon_i \quad (3)$$

where $X_i\beta = \beta_0 + \beta_1 R_i + \beta_2 A_i + \beta_3 P_i + \beta_4 CR_i + \beta_5 HB_i + \beta_6 M_i + \beta_7 AG1_i + \beta_8 AG2_i + \beta_9 AG3_i + \beta_{10} Pur_{BS\,i} + \beta_{11} Pur_{EX\,i} + \beta_{12} Pur_{CRE\,i} + \beta_{13} OC_{SAL\,i} + \beta_{14} OC_{PV\,i} + \beta_{15} OC\_ONS_i + \beta_{16} OC\_ST_i$

3.2. Model for Borrower's Bidding Strategy

The flourishing development of online P2P platforms can be considered as the evidence of it being an efficient substitute for the conventional financing system for those borrowers who cannot obtain financing otherwise. It also provides convenient financing to small borrowers such as students. However, this platform offers borrowers alternate investment strategies in addition to pure borrowing. For example, a borrower may collect the money from a listed loan and break the money into small portions and then in turn lend the money out to several other borrowers. If we are to very broadly regard the money spent in lending to others (lending part) and the money spent for individual purposes (borrowing part) both as investments, then we can see these mixed types of borrower/lender as the "intermediate financing units" that are expected to invest based on traditional investment theory such as portfolio theory. These types of borrowers then are engaged in achieving "optimal portfolio" [Fama 1970; Mossin 1966; Sharpe 1964]. Additionally, even though it is impossible for us to identify the exact behaviors or detailed use of loans for the mixed borrowers, it is reasonable to assume that apart from trying to come up with a good "portfolio" and hedge the money funded through the platform, these borrowers may also engage in what can be considered as "arbitrage", i.e., some mixed borrowers are at least trying to utilize their ample transaction experiences to make money out of the difference in the length of use and the overall "user cost" between money they borrow and lend out again. Since there are no clear regulations from the platform to prevent this type of transaction, veteran users will be able to discover these opportunities and utilize them. Indeed, in our data set more than one third of borrowers belong to this mixed type of borrower and one fifth belongs to the experienced borrowers participating in pure borrowing.

However, in the online P2P literature, very little attention has been given to the borrower side as most researches focuses on issues on the lender side. Most studies consider the borrowers' socio-demographic dimension from the perspective of the lenders' risk management [Barasinska & Schäfer 2010; Pope & Sydnor 2008]. As was discussed in the earlier section, borrowers can behave differently when they design their loans according to their level of expertise in online P2P lending. Freedman & Jin [2008] argue that lenders can learn from their mistakes and better handle the choice of risky loans. As a matter of fact, this argument might apply to not only the lenders, but also the borrowers. Borrowers also can learn more about the nature of the online P2P platform or the lenders' strategies through "learning by doing". Particularly, the borrowers who have learned the nature of online P2P lending by participating as lenders can have a better understanding of the strategies from both sides. On the other hand, borrowers who lack knowledge or expertise are likely to fail to optimally design their loans. One rational alternative is to imitate the design of other borrowers whose basic information is similar to themselves. This spurious strategy can be particularly appealing to those inexperienced borrowers who have difficulty gauging the level of risk for their own loans or their creditability either because of the complexity of the situation; because they are lacking in the knowledge of the situation they are dealing with; or because they are just unfamiliar with the choices they have to make. Therefore, from the perspective of novice borrowers, they will try to imitate what other loan requesters have been doing within the required framework of the online lending platform they are using [Bikhchandani & Sharma 2001; Devenow & Welch 1996; Herzenstein et al. 2011; Lee & Lee 2012]. Eventually, an interesting phenomenon of online lending is, as is also evidenced by our data, that a listed loan will be more or less similar to other listed loans and will have either very few bidders or a lot of bidders. In our sample, the novice borrowers and the pure borrowers are the two groups of users who exhibit more herding behaviors.

Based on the discussion above, we expect the mixed type of borrowers (indicated by the information listed for the loan requested) to behave differently in the strategy of loan listing compared with the "pure borrower". Therefore, we decompose borrowers on PPDai.com into three groups: the "Novice Borrower", the "Pure Borrowers", and the "Mixed Borrowers". Specifically,

1) Novice Borrower: is a borrower who uses PPDai.com the first time. Operationally, we define this group of borrowers as one who has an observed minimum credit score (10) as both the borrower and the lender that would be automatically given when one registered in PPDai.com. In our data, this type accounts for 45.8% of overall borrowers.

2) Pure Borrowers: is a borrower who uses PPDai.com only for the borrowing intention. This group is defined as

one who has minimum credit score of a lender but higher than 10 as a borrower. This group is 18.9% of overall borrowers.

3) Mixed Borrowers: is a borrower who uses PPDai.com for both borrowing and lending intention. This group of borrowers has more than minimum score as both borrower and lender. This one accounts for 35.2% of overall borrowers. We summarize the borrowers' property in Table 6a through Table 6c.

Table 6a: Characteristics of Borrower Type 1, "Novice Borrower (NB)"

Variable	Min	Mean	S.D.	Max
Observation	484 / 1,057 (45.8%)			
Cost of Loan	235.02	359.81	96.84	804.725
Amount of Loan (RMB)	2,000	2,997.93	45.45	3,000
Interest Rate (%)	13	13.65	1.73	24
Loan Period (Month)	6	10.01	2.38	12

Table 6b: Characteristics of Borrower Type 2, "Pure Borrower (PB)"

Variable	Min	Mean	S.D.	Max
Observation	200 / 1,057 (18.9%)			
Cost of Loan	131.41	383.36	96.84	3,308.58
Amount of Loan (RMB)	3,000	3,337.03	2,704.02	40,000
Interest Rate (%)	13	14.35	2.82	24
Loan Period (Month)	3	9.34	2.67	12

Table 6c: Characteristics of Borrower Type 3, "Mixed Borrower (MB)"

Variable	Min	Mean	S.D.	Max
Observation	372 / 1,057 (35.2%)			
Cost of Loan	98.56	672.04	2,002.773	20,344.29
Amount of Loan (RMB)	1,000	7,622.80	25,371.79	300,000
Interest Rate (%)	8	14.51	4.25	24
Loan Period (Month)	3	8.09	2.94	12

3.2.1. Dependent Variable

In order to investigate borrowers' loan strategy, we employ the measurement of the "cost of loan (CL)" computed by compounding the interest rate of the listed loan [Bodie et al. 2012], that is:

$$CL = A(1 + R)^{P} - A$$

This indicates the total cost that a borrower bears for the requested loan amount (A) under the interest rate (R) for certain time period (P). Table 6 reports the cost of loans for the three groups of borrowers. This measurement is more appropriate to our context because borrowers consider the amount of the loan and the loan period as well as the interest rate to determine the overall cost of a loan when they propose it.

3.2.2. Independent Variables

In order to see how different types of borrowers design the loan, we include three rudimentary components that consist of the total cost of a loan: interest rate (R), amount of loan requested (A), and loan period (P). These are major elements of the loan, which borrowers choose for their specific purpose or preferences. For example, at the same cost, mixed borrowers who have been lenders as well might prefer a loan with a longer time period to obtain a stable source of money to lend. On the other hand, if a user borrows money for pure borrowing purpose, he/she might prefer a certain loan amount to meet their borrowing purpose.

In addition to the design of the loan, which is the choice of the borrowers, there are other factors that influence the efficiency of borrowing. Conventionally, borrowers with a higher credit score propose loans at a lower cost because they utilize their reliability [Freedman & Jin 2008; Iyer et al. 2009; Klafft 2008]. Alternately, this might be exploited to increase the opportunity of borrowing more money [Puro et. al. 2010]. Particularly, the information related to borrowers' credit on PPDai could be more effective to reduce the cost of loans where no official credit information is provided. Also, information of the history of successful bids/funding can influence the loan cost. As Coleman [1990] mentions, repeated actions and successful experiences can help build mutual trust between lenders and borrowers. Thus, borrowers who have more experience with successful funding might benefit from being able to receive a loan at a lower cost because of the higher level of trust from the lenders. Therefore, information related to borrowers' credit, CRE, and HSB are included in our model. Also, we include demographic and social information and the purposes of loans for borrowers' characteristics to control for additional possible factors that may affect the cost of the listed loans.

To investigate the distinctive behaviors between different types of borrowers, we include borrowers' group dummies. This dummy variable captures the efficiency of borrowers' strategies across different types. The different level of knowledge or expertise about online P2P lending business across types of borrowers can lead to more or less efficiently designed loans [Freedman & Lin 2008]. For example, the novice borrowers who have little experience might believe their similarity to similar type of loans as important cues, instead of spending cognitive efforts to analyze the lenders' or other borrowers' strategies [Chaiken 1980; Petty & Cacioppo 1986]. Thus, they are likely to imitate other novice's proposals even if the probability of successful funding is lower; whereas pure borrowers are likely to put forth more cognitive efforts to design their loans more efficiently using their borrowing experience [Bikhchandani & Sharma 2001; Devenow & Welch 1996; Herzenstein et al. 2011; Lee & Lee 2012; Wang & Greiner 2011]. Furthermore, mixed borrowers might have even deeper understanding of the lenders' strategies, so we expect borrowers who have more expertise and knowledge to be more capable of proposing a loan at a lower cost.

The imminent purpose of borrowing among borrowers can also influence their design of the loans. As was aforementioned, different types of borrowers are highly likely to have different intentions in proposing a loan. For example, mixed borrowers need a loan for arbitrage or hedging while pure borrowers need it for a non-speculating intention such as business investment. Those pure borrowers might be relatively more concerned about how much loan they can get as cheaply as possible because they just want the money. However, for those whose intention is arbitrage or composing portfolios for hedging, the interest rate or the amount of loan might be relative matters. Rather, they might be concerned more about how long they can keep this loan because they prefer stable securement of the money. Therefore, we include the interaction terms of interest rate, amount of loan, loan period, and borrowers' credit score with the group dummies. Also, the more experienced borrowers can be in a better position to utilize their credit information to get a loan at a lower cost because they have a better understanding of the lenders' strategies or the nature of the online P2P lending platform. Thus, we also include interaction terms of credit score with each group dummy.

3.2.3. Model Specification

In order to answer research questions related to the borrowers' behaviors according to their types, we propose two models of borrowers: the basic model with key variables that influence the loan cost and the extended model including the interaction terms with borrowers group dummies. Specifically,

1) Basic Model of Borrowers:

$$\begin{aligned} CL_i = {} & \theta_0 + \theta_1 R_i + \theta_2 A_i + \theta_3 P_i + \theta_4 CR_i + \theta_5 HB_i + M_i + AG1_i + AG2_i + AG3_i \\ & + Pur_{BS\,i} + Pur_{EX\,i} + Pur_{CRE\,i} + OC_{SAL_i} + OC_{PV_i} + OC_{ONS_i} + OC_{ST_i} + PBD_i + MBD_i + \epsilon_i \end{aligned} \tag{4}$$

2) Extended Model of Borrowers:

$$\begin{aligned} CL_i = {} & \theta_0 + \theta_{1,NB} NBD_i * R_i + \theta_{1,PB} PBD_i * R_i + +\theta_{1,MB} MBD_i * R_i + \theta_{2,NB} NBD_i * A_i \\ & + \theta_{2,PB} PBD_i * A_i + \theta_{2,MB} MBD_i * A_i + \theta_{3,NB} NBD_i * CR_i + \theta_{3,PB} PBD_i * P_i + \theta_{3,MB} MBD_i * P_i \\ & + \theta_{4,NB} NBD_i * CR_i + \theta_{4,PB} PBD_i * CR_i + \theta_{4,MB} MBD_i * CR_i + \theta_5 HB_i + M_i + AG1_i + AG2_i + AG3_i \\ & + Pur_{BS\,i} + Pur_{EX\,i} + Pur_{CRE\,i} + OC_{SAL_i} + OC_{PV_i} + OC_{ONS_i} + OC_{ST\,i} + PBD_i + MBD_i + \mu_i \end{aligned} \tag{5}$$

where NBD_i, PBD_i, and MBD_i are dummy vectors for Novice, Pure, and Mixed Borrowers, respectively.

3.3. Data

For the analysis, we collected the listing data of 1,057 loans registered on PPDai (www.ppdai.com) from 2014/2/9 to 2014/3/26. PPDai is the first online P2P credit lending platform with the largest number of active users in China. On PPDai, a borrower lists the loan with specific conditions of annual interest rate, the amount of loan, and the time period of repayment and the lenders bid for the loan by submitting a certain portion of the total amount requested (not exceeding 60% of the total requested amount, and no less than 50 RMB, or 8 USD) within a limited time period, namely 15 days.[13] Bidding is closed when either the raised funds fulfill the requested amount or the

[13] According the regulation of PPDai.com, the minimum amount for one single bid is 50 RMB (about 8 USD), the maximum amount should not exceed 60% of the total loan request or larger than 20,000 RMB (about 3,200 USD).

bidding time has passed 15 days. Once the bidding is over, the amount of funds raised toward the listed loan is recorded. In addition, information such as how many bidders participated and the closing time of the bidding is also recorded. For additional information disclosure to the lenders, PPDai requires a borrower to provide the purpose of loans and some demographic and social information such as gender, age, and occupation. Also, PPDai provides the credit score of a borrower using its own criteria: a mixture of the degree of exposure to the borrower's private information and the successful history of payments to the loans he/she secured. Furthermore, PPDai provides information about how many times a borrower has engaged in successful loan funding and failed bids (since a borrower can also act as a lender in different occasions) up to the point he/she lists the sampled loan.

4. Estimation

4.1. Estimation Results of the Lenders' Strategy Model

Among the three major characteristics of the loans, we find unanimous evidence that the interest rate significantly impact the lenders' bidding decisions. A loan with a higher interest rate helps increase the probability of receiving the requested loan and also leads more lenders to participate in the bidding within a shorter time period. However, we find partial support for the amount of loan and the loan period. Table 7 reports the estimation results of the three lenders' models together: fund success (FS), number of bids (NB), and funding time (FT).

Table 7: Estimation Results of Lender Models: Funding Success, Number of Bids, and Funding Time model

Parameter	FS (Logit)		NB (Tobit, lb = 0)#		FT (Tobit, lb = 0, ub = 15)#	
	Estimate	p-value	Estimate	p-value	Estimate	p-value
Interest Rate (R)	0.313***	0.000	2.500***	0.000	-0.698***	0.000
Amount (A)	0.0012*	0.007	0.0017***	0.000	-7.93e-06	0.685
Period (P)	-0.052	0.268	-1.656***	0.002	0.866***	0.000
PPDai Credit (CER)	0.246***	0.000	1.034***	0.000	-0.445***	0.000
History of Bids (HSB)	1.597***	0.000	0.085**	0.037	-0.029***	0.007
Male (M)	-0.908**	0.015	-2.556	0.541	0.636	0.561
Age 20~25 (AG1)	-0.850**	0.025	-14.555***	0.003	4.018***	0.002
Age 26~31 (AG2)	-1.239***	0.001	-17.700***	0.000	4.975***	0.000
Age 32~38 (AG3)	-0.615	0.143	-6.811	0.176	2.494*	0.061
Pur_{BS}	0.756**	0.020	4.330	0.271	-1.868*	0.067
Pur_{EX}	-0.279	0.536	-3.612	0.555	2.153	0.191
Pur_{CRE}	0.356	0.381	13.504***	0.002	-5.563***	0.000
OC_{SAL}	1.82***	0.006	14.554***	0.007	-3.815***	0.005
OC_{PV}	1.075	0.055	8.297	0.159	-4.849**	0.020
OC_{ONS}	1.559**	0.027	31.936***	0.000	-2.411	0.107
OC_{ST}	0.429	0.623	2.220	0.835	-2.559	0.330
Constant	-13.001***	0.000	-72.966***	0.000	29.711***	0.000
Observation	1,057		1,057		1,057	
Log likelihood	-240.65		-1,933.52		-1,493.32	

lb= lower bound, ub = upper bound
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

First, the loan amount shows significant positive impact in the FS and the NB models while is insignificant in the FT model. Large loan might attract more lenders and increase the probability of successful funding, but it might not help reduce the closing time because it needs more lenders to raise a larger fund. The impact of the loan amount on funding success is particularly interesting because it is inconsistent with Puro et al. [2010]'s finding that a smaller loan can help increase the success rate. This might be due to a lack of reliable credit information of the borrowers in China. Unlike the US or other countries, in China, no official credit information related to an individual borrower is provided through any agency, so the lenders have difficulty in finding reliable sources for evaluating the borrowers' credits. Thus, the loan amount can serve as an additional signal to the lenders to indicate the borrowers' credit where most wandering borrowers propose smaller loans. Indeed, many failed loans requested 3,000 RMB (about 480 USD), which is the smallest loan allowed in our data set. In addition, we find positive correlation between the loan amount and the credit information that PPDai provides (Table 4). Another possible reason would be that the lenders feel less risky when they join more lender in a bid [Herzenstein et al. 2011]. However, we might not be able to verify the reasons for the lenders' preference for larger loans with our dataset. Further study is needed to identify the effect of the loan size.

Second, the loan period has a significant impact on the number of bids and the funding time but not on the funding success: a shorter period loan is able to attract more lenders and reduce the closing time. However, our findings indicate that the loan period does not affect the probability of funding success. This implies that the loan period might be a relatively less prioritized component in the lenders' decision making. Overall, we find strong evidence that the interest rate influences the lenders' bidding strategy for the three models and there is partial evidence for the loan amount and the loan period.

We also find partial support that the following two purposes for the loan influence the lenders' bidding decisions: purpose of business investment and raising credit. It is interesting to see that this crude information, self-reported by a borrower, can affect lenders' bidding decisions.

For information related to a borrower's credit (CRE and HSB), we find strong evidence that these variables influence the lenders' bidding behaviors in all the three models. This is consistent with the previous literature: this type of information is of greater importance in the market where the lenders have little information about the borrowers [Iyer et al. 2009; Klafft 2008]. Gender and age also matter to the lenders. It seems that the lenders prefer female borrowers; however, the effect of gender is only significant in the funding success model, while it is not significant in the other two models. Maybe gender is considered to be relatively valuable information, but not too seriously by everyone. Therefore, it might help attract some lenders to participate, but is not enough to cause a listing to become a "rock-star" loan, as is also evidenced by the mixed results for gender effect from previous studies [Barasinska & Schäfer 2010; Pope & Sydnor 2008]. Age also matters to the lenders. They seem to prefer older borrowers (in our case, older than 31). More interestingly, Age group 2 (26-31) has more disadvantage than both the younger group (Age1) and the older group (Age 3 and 4). This somehow indicates a similar pattern to previous evidence of a nonlinear relationship between age and the lenders' evaluation [Pope & Sydnor 2008].[14] Occupation is also considered important information for the lenders' decision. In particular, it seems that being a student does not help attract lenders into bidding.

In short, for the lenders' bidding strategy, major characteristics of the loans play an important role similar to what was identified in previous studies, however, results are not consistent across the three measurement of the popularity of loans. Also, we find unanimous support for the information of the borrowers' credit (CRE and HSB). This result might further imply that revelation of private information can play a role in increasing the reliability of borrowers even if it is not directly related to their credit, but it serves as a signal. Furthermore, we find additional evidence that information related to a borrower's credit can be considered an important factor, i.e., previous successful transaction history itself – it does not matter whether a borrower participated as a borrower or a lender – seems to help increase credibility of a borrower. The impact of information related to the borrowers' attitude toward online lending can be particularly significant in the Chinese market.

4.2. Estimation Results of the Borrower's Strategy Model

Table 8 reports OLS results for the borrowers' basic and extended models. Three components of the loans all have a positive impact on the overall cost of the loans: the higher the interest rate, the longer the loan period, and the larger loan amount leads to higher loan cost. We also find evidence that different types of borrowers tend to be concerned with different components. The effect of the interest rate on the total cost is relatively smaller for the pure borrowers than for the mixed borrowers. However, for pure borrowers, the effect of the loan amount is the largest among all the groups. This implies that the pure borrowers are more concerned with the size of the loans and a lower interest rate than other groups. However, the effect of the loan period is the largest for the mixed borrowers. These findings support our conjecture that different types borrowers focus on different components of a loan according to their intention. Also, results of the group dummies are consistent with what we expected: borrowers who have more expertise and knowledge are better capable of proposing a loan at a lower cost. Mixed borrowers' effect is much lower than that of the pure ones. Pure borrowers' effect is significantly negative to the novice borrowers' effect,

[14] It should be noted that in Pope & Sydnor (2008), they break down the age groups as "<=35", "35-60", and ">60".

which serves as the baseline.

Table 8: Estimation Results of the Borrower Model

Parameter	Basic Model		Extended Model	
	Estimate	p-value	Estimate	p-value
Interest Rate (R)	37.044***	0.000		
R*NBD			24.556	0.143
R*PBD			29.886**	0.048
R*MBD			40.678***	0.000
Amount (A)	0.066***	0.000		
A*NBD			0.234	0.695
A*PBD			0.079***	0.000
A*MBD			0.067***	0.000
Period (P)	62.047***	0.000		
P*NBD			38.653***	0.001
P*PBD			45.275***	0.005
P*MBD			91.405***	0.000
PPDai Credit (CR)	9.155***	0.000		
CR*NBD			-143.78	0.430
CR*PBD			3.582	0.688
CR*MBD			10.549***	0.000
History of Bids (HB)	-0.137	0.844	-0.066	0.924
Male (M)	21.052	0.709	23.605	0.677
Age 20~25 (AG1)	-89.218	0.178	-74.205	0.264
Age 26~31 (AG2)	-54.977	0.395	-44.513	0.492
Age 32~38 (AG3)	25.276	0.722	35.351	0.620
Pur_{BS}	-5.302	0.913	-0.481	0.992
Pur_{EX}	-6.453	0.928	-16.051	0.822
Pur_{CRE}	8.020	0.891	27.166	0.644
OC_{SAL}	-42.251	0.464	-37.445	0.519
OC_{PV}	4.758	0.942	9.800	0.348
OC_{ONS}	105.138	0.308	97.653	0.881
OC_{ST}	-61.906	0.600	-52.437	0.657
PBD	-34.246	0.506	-1162.6***	0.001
MBD	-140.997**	0.026	-1915.7***	0.000
Constant	-1008.00***	0.000	403.0847**	0.029
Observation	1,057		1,057	
F-statistic	183.85		128.35	
R^2	0.761		0.764	
$Adjusted\ R^2$	0.757		0.758	

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

Interestingly also, we found positive impact of the credit score on the cost of loans: a borrower with a higher credit score might have a stronger incentive to request a loan with higher overall cost, e.g., larger amount of loan with similar level of interest rate. Our results do not seem to be consistent with the conventional thought that the credit score is used to gauge the credit risk of a borrower. Indeed, according to a study of individual credit risk by Zheng [2009] using survey data, borrowers with more credit cards and loans are more likely to default. If we reasonably assume that the online users are all rational, they may very well have taken this understanding into account and incur what we have observed in our study. Our proposition to explain this abnormity is that the positive impact might be because some borrowers are able to better leverage their credit information. This different behavior is more obvious if we look at the interaction effect of the major factors with the different groups of borrowers.

5. Conclusion

We used the loan transaction data from PPDai.com to study the key drivers influencing the lenders' and borrowers' strategies when it comes to online peer-to-peer lending in China. We investigated the factors affecting the lenders' bidding strategies using three measurements for the popularity of a loan: funding success, number of bids, and funding time. Our findings suggest that, similar to previous studies, higher interest rates increased the popularity of a loan no matter what we used to measure the popularity. We also find that the larger the loan amount is, the more lenders bid for it, although it might be fulfilled after a longer time. A loan of a shorter period is able to attract more lenders and reduce the time to close the bidding. However, our findings indicate that the key factors do not affect the loan popularity in a unanimous direction for the three measurements we employed. This implies that different lenders' strategies exist in the Chinese online P2P market where reliable individual credit information is unavailable. As was discussed, information related to credit shows significant impact on all three measurements of the loan popularity.

To investigate borrowers' strategy, we grouped them into three categories, namely, novice borrowers, pure borrowers, and mixed borrowers according to the level of their expertise of online P2P lending. We find evidence that different types of borrowers attach a different priority level to different components when they design a loan: the mixed borrowers seem to put more weight on the loan period, while the pure borrowers consider the interest rate and the loan amount to be more important. In addition, borrowers who have more expertise tend to propose a loan at a relatively lower cost. Our findings also suggest that Chinese borrowers tend to utilize higher credibility for the opportunity of receiving larger loan amounts instead of lowering the cost of a loan. This finding is particularly meaningful in online P2P lending literature where most studies are skewed to focus on the lenders' strategies. Our evidence of borrowers' strategic behaviors strongly suggested that studies in online P2P literature must include the borrower side as well as the lenders side.

Our findings also have meaningful implications for practice. First of all, our findings suggest new sources for the lenders to understand the borrowers' behaviors better. Even though recently online P2P platforms have encouraged borrowers to release more information, as Chen & Han [2012] report, the funding success rate in online P2P lending market is still much lower than that of the traditional loan market because of the information asymmetry problem. Hence, lenders are facing an urgent need for more information in order to accurately evaluate borrowers. Therefore, information related to borrowers' experience would be helpful for the lenders to understand the borrower's immanent preferences and practice for better segmentation strategies for their investment portfolio and risk management. This would be more valuable in a market such as China where the lenders struggle with gathering reliable information about the borrowers. Along with the hard and soft information, the information about the borrowers' expertise would be helpful for the lenders to understand the borrowers and lower the risk of their investments. Secondly, for borrowers, our findings suggest that herding behavior might be costly to the new starters in the online P2P lending business because of their lack of knowledge and understanding of the nature of this particular business. They might efficiently improve their funding rates by building long-term strategies instead of targeting a one-shot solution for borrowing. For example, they might begin with a small loan amount first and then steadily increase their borrowing amount. With the accumulation of expertise, the borrowers could design the loan much more efficiently as well as increase their creditability to lenders.

One limitation of our study might be the use of cross-sectional data. To fully understand the lenders' and the borrowers' behavior, we need a more complete set of individual level time series data. With the long panel data, we will be able to explicitly verify the unique property of the lenders' evaluation mechanism. For example, their evaluation procedure could be different over time when borrowers successfully build up their credits. It would be interesting if future studies investigate the hierarchy of the key drivers in lenders' evaluation process.[15] On the borrower side, future studies can also further examine their strategic behaviors in more depth. They can verify the

[15] We thank the reviewers for the suggestion.

borrowers' learning process according to their experience accumulation over time. Also, studies can examine the key drivers for improving the borrowers' expertise in the online P2P lending business. Furthermore, even though we find evidence for the experienced borrowers to utilize their information to secure funding at lower costs, further theoretical and behavioral studies are called for to examine what types of experiences can help develop the expertise of borrowers. In addition, further study is required to investigate the unique property of the online P2P lending business in China. Our findings suggested that lenders are likely to bid on larger amount of loans and increase the funding success rate in the Chinese market, which contradicts previous findings [Freedman & Jin 2008; Puro et al. 2010]. One possible explanation would be that the size of loans can be a positive signal for the borrowers' creditability when there is a dearth of reliable sources of the borrowers' credits. Future research can further examine this potential role of the size of loans on the lenders' bidding strategies in the Chinese market.

REFERENCES

Bachmann, A., A. Becker, D. Buerchner, M. Hilker, M. Kock, M. Lehmann, and P. Tiburtius, "Online Peer-to-Peer Lending - A Literature Review," *Journal of Internet Banking and Commerce*, Vol. 16, No. 2: 1-18, 2011.

Barasinska, N. and Schäfer D., "Does Gender Affect Funding Success at the Peer-to-Peer Credit Markets? Evidence from the Largest German Lending Platform," *Discussion Papers of DIW Berlin 1094*, DIW Berlin, German Institute for Economic Research, 2010.

Bikhchandani, S. and S. Sharma, "Herd Behavior in Financial Markets: A Review," *IMF Staff Papers*, Vol. 47, No. 3: 279-310, 2001.

Bodie, Z., Alex K., and Alan J. M., Essentials of Investments, 9th edition, NY, New York: McGraw-Hill, 2012.

Chaiken, S., "Heuristic versus Systematic Information Processing and the Use of Source versus Message Cues in Persuasion," *Journal of Personality and Social Psychology*, Vol. 39, No. 5: 752-766, 1980.

Chen, X., "A Study of the Private Borrowing Costs—Empirical Analysis Based on P2P Network Borrowing and Lending," *Journal of Finance and Economics*, Vol. 29, No. 1: 37- 48, 2014. (in Chinese)

Chen, D. and C. Han, "A Comparative Study of Online P2P Lending in the USA and China," *Journal of Internet Banking and Commerce*, Vol. 17, No. 2 (Special section): 1-15, 2012.

Chen, D., H. Zhu, and H. Zheng, "Perceive Risk, Trust, and Willingness to Lend: An Empirical Study Based on the Users of PPDai.com," *Management Review*, Vol. 26, No.1: 150-158, 2014. (in Chinese)

Coleman, J. S., Foundations of Social Theory, MA, Cambridge: Harvard University Press, 1990.

Collier, B. C. and R. Hampshire, "Sending Mixed Signals: Multilevel Reputation Effects in Peer-to-Peer Lending Markets," *Proceedings of 2010 ACM Conference on Computer Supported Cooperative Work*, 197-206, GA, Savannah, February, 2010.

Davidson, R. and J. McKinnon, Econometric Theory and Methods, UK, Oxford: Oxford University Press, 2004.

Devenow, A. and I. Welch, "Rational Herding in Financial Economics," *European Economic Review*, Vol. 40, No. 3-5: 603–615, 1996.

Fama, F. E., "Efficient Capital Markets: A Review of Theory and Empirical Work," *Journal of Finance*, Vol. 25, No. 2: 383-417, 1970.

Freedman, S., and G. Z. Jin, "Do Social Networks Solve Information Problems for Peer-to-Peer Lending? Evidence from Prosper.com," *NET Institute Working Paper*, 1-63, 2008.

Greiner, M. E. and H. Wang, "The Role of Social Capital in People-to-People Lending Marketplaces," *Proceedings of the Thirtieth International Conference on Information Systems*, paper 29, AZ, Phoenix, December, 2009.

Greiner, M. E. and H. Wang, "Building Consumer-to-Consumer Trust in e-Finance Marketplace," *International Journal of Electronic Commerce*, Vol. 15, No. 2: 105-136, 2010.

Herrero-Lopez, S., "Social Interactions in P2P Lending," *Proceedings of the 3rd Workshop on Social Network Mining and Analysis* (3), 1-8, FR, Paris, June, 2009.

Herzenstein, M., S. Sonenshein, and U. M. Dholakia, "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*, Vol. 48, Special Issue: 138-149, 2011.

Herzenstein, M., U. M. Dholakia, and R. Andrews, "Strategic Herding Behavior in Peer-to-Peer Loan Auctions," *Journal of Interactive Marketing*, Vol. 25, No. 1: 27-36, 2011.

Iyer, R., A. I. Khwaja, E. F. P. Luttmer, and K. Shue, "Screening in New Credit Markets: Can Individual Lenders Infer Borrower Creditworthiness in Peer-to-Peer Lending?" *HKS Faculty Research Working Paper Series*, John F. Kennedy School of Government, Harvard University, 1-42, 2009.

Klafft, M., "Peer to Peer Lending: Auctioning Microcredits over the Internet," *Proceedings of the 2008 Int'l Conference on Information Systems, Technology, and Management*, 1- 8, Dubai: IMT, 2008.

Lee, E. and B. Lee, "Herding Behavior in Online P2P Lending: An Empirical Investigation," *Electronic Commerce*

Research and Applications, Vol. 11, No. 5:495-503, 2012.
Li, J. and J. Zhu, "An Empirical Study of Determinants of Interest Rate in P2P Lending Market," *Journal of Guangdong University of Business Studies*, Vol. 28 No. 5: 34-40, 2013. (in Chinese)
Liao, T. and C. Kang, "Online Purchase Delay: the Roles of Online Consumer Experiences," *Journal of Electronic Commerce Research*, Vol. 15, No. 2: 133-150, 2014.
Lichtenstein, S. and K. Williamson, "Understanding Consumer Adoption of Internet Banking: An Interpretive Study in the Australian Banking Context," *Journal of Electronic Commerce Research*, Vol. 7, No.2: 50-66, 2006.
Lin, M., N. Prabhala, and S. Viswanathan, "Social Networks as Signaling Mechanisms: Evidence from Online Peer-to-Peer Lending," Working paper, University of Maryland, 1-46, 2009.
Lin, M., N. Prabhala, and S. Viswanathan, "Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending," *Management Science*, Vol. *59*, No.1: 17-35, 2013.
Lu, X., Y. Li, Z. Zhang, and B. Rai, "Consumer Learning Embedded in Electronic Word of Mouth," *Journal of Electronic Commerce Research*, Vol. 15, No. 4: 300-316, 2014.
Ma, F., "Basel New Capital Accord and the Mortgage Culture of Commercial Banks," *Finance and Economics*, Vol.11: 62-64, 2005. (in Chinese)
McKnight, D. H., V. Choudhury, and C. Kacmar, "Developing and Validating Trust Measures for e-Commerce: An Integrative Typology," *Information Systems Research*, Vol. 13, No. 3: 334-359, 2002.
Michels, J., "Do Unverifiable Disclosures Matter? Evidence from Peer-to-Peer Lending," *The Accounting Review*, Vol. 87, No. 4: 1385-1413, 2012.
Mossin, J., "Equilibrium in a Capital Asset Market," *Econometrica*, Vol. 34, No. 4: 768-783, 1966.
Petty, R. E. and T. C. John, "The Elaboration Likelihood Model of Persuasion," *Advances in Experimental Social Psychology*, Vol. 19:123-205, 1986.
Pope, D. G. and J. R. Sydnor, "What's in a Picture: Evidence of Discrimination from Prosper.com," *Journal of Human Resources*, Vol. 46, No.1: 53-92, 2008.
Puro, L., J. E. Teich, H. Wallenius, and J. Wallenius, "Borrower Decision Aid for People-to-People Lending," *Decision Support System*, Vol. 49, No. 1: 52-60, 2010.
Ravina E., "Love & Loans: the Effect of Beauty and Personal Characteristics in Credit Markets," Working paper, Columbia University, 2008.
Sharpe, F. W., "Capital Asset Prices: A Theory of Market Equilibrium," *Journal of Finance*, Vol.19, No. 3: 425-442, 1964.
Song, W. and L. Han, "Influence Factor Analysis of Lending Willingness in P2P Online Lending," *Journal of Southwest University of Nationalities: Natural Science Edition*, Vol. 39, No. 5: 795-799, 2013. (In Chinese)
Wang, H. and M. E. Greiner, "Prosper: the eBay for Money in Lending 2.0," *Communications of the Association for Information Systems*, Vol. 29, No. 1: 243-258, 2011.
Wang, H., "The Lender's Investment Strategy in P2P Lending," *Finance Forum*, No. 10: 29-36, 2014. (in Chinese)
Wen, X. and X. Wu, "An Analysis of Factors to Influence Successful Borrowing Rate in P2P Network Lending-A Case Study of the Paipai Lending," *Finance Forum*, No. 3: 3-8, 2014. (in Chinese)
William, A., E. Liran, and J. Levin, "Liquidity Constraints and Imperfect Information in Subprime Lending," *American Economic Review*, Vol. 99, No. 1: 49-84, 2009.
Yoon, S. "A Social Network Approach to the Influence of Shopping Experiences on E-WOM," *Journal of Electronic Commerce Research*, Vol. 13, No. 3: 213-223, 2012.
Yum, H., B. Lee, and M. Chae, "From the Wisdom of Crowds to My Own Judgment in Microfinance through Online Peer-to-Peer Lending Platforms," *Electronic Commerce Research and Applications*, Vol. 11, No. 5: 469–483, 2012.
Zheng, Y. "An Empirical Research on Individual Credit Risk Using Probit Model," *Shanghai Finance*, Vol.10:85-89, 2009. (in Chinese)