IS THE LEADERBOARD INFORMATION USEFUL TO INVESTORS? : THE LEADERBOARD EFFECT IN P2P LENDING

Research-in-Progress

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Abstract

P2P (Online Peer-to-Peer) lending provides an open marketplace where borrowers make requests for loans by lenders who subsequently decide whether to bid or not following an examination of the relevant information posted by borrowers. In this P2P lending context, the leaderboard, where popular loan requests are displayed at the web's front page, provides information for lenders to use when evaluating the requests. We empirically examine the effects of leaderboard information regarding the most popular existing loan requests. Our results show that the leaderboard information works ex ante in attracting additional bids to get loan requests successfully financed. However, it does not work ex post in improving the performance so that it has less potential for default.

Keywords: P2P lending, leaderboard, Information Asymmetry, Wisdom of Crowds

Introduction

P2P lending has recently become a popular business research field not only because it has witnessed substantial growth, but also because information asymmetry issues exist and result in investors having a limited amount of information with which to distinguish between good and bad borrowers (e.g., Puro et al. 2010; Puro et al. 2011). Signaling is expected to mitigate the adverse selection problem in Akerlof's "lemon" market and P2P lending (Akerlof, 1970; Spence, 1973; Lin et al. Forthcoming). Regarding the P2P lending site investigated in this study, the leaderboard which contains existing loan requests is displayed on the site's front page. This unique method of sharing information regarding the choices of others offers the ideal environment in which the existence of signaling effects can be tested. Although the bestseller effect has previously been addressed in studies in the fields of economics (e.g., Sorensen 2007; Banerjee 1992; Bikhchandani et al. 1992; Cai et al. 2009) and IS (e.g., Duan et al. 2009) and herding behavior in P2P lending market has been explored (e.g., Zhang and Liu. 2012; Herzenstein et al. 2011), this paper is the first to explore the impact of the leaderboard effect in the context of P2P lending. We empirically study the relationship between the likelihood of being financed and loan performance and the information on the leaderboard.

P2P lending represents an open marketplace for loans provided not by a bank, but by individuals online taking advantage of P2P architecture. In P2P lending, financial transactions are facilitated directly between individuals ("peers"). Potential borrowers create and post listings with an overview of their need for a loan, while potential lenders place bids on listings they would be interested in funding. A borrower is then provided a loan only in the case that his or her listing garners enough bids to exceed a predefined amount or to fulfill a loan request by a number of lenders. A market study by the Gartner Group forecasts that the scope of P2P lending will soar by at least 66% to US$5 billion in outstanding loans by 2013 (Gartner 2010). The wisdom of crowds is said to enable businesses to make profits when social networks try to establish the concept of a community into the decision making process. The underwriting decisions assessing the risk of each loan on a micro-lending site are made by individuals, while the value of a loan is established through lender bidding. When considering the context of borrowers, such lending decisions, which are attributed to the "wisdom of crowds" (Surowiecki, 2004; Bonabeau, 2009), are expected to be superior to the same decisions currently made by loan officials at banks as the collective intelligence experiment shows (Wolley at al., 2010).

Before we take the wisdom of crowds in haste, it is better to consider literature on adverse selection and signaling that is applicable to the P2P lending market in which there exist information asymmetry problems. Akerlof's (1970) used car "lemon" market crowds out sellers of high quality cars, leading to market failure. Even though the difficulty exists that quality discovery of non-standardized and complex products will increase transaction costs, many successful electronic auction markets deal in seemingly typical "lemon" goods. Signaling is expected to mitigate the adverse selection problem in the lemon market according to Spence (1973). In his job market model, education is a signal of quality. High quality workers signal their quality through education. The implication is that educated workers should have better ex-ante outcomes, i.e. getting employed and ex-post results, and thus have better job performance. Lin et al. (Forthcoming) apply this theory to the borrower's friendship signal in P2P lending to show that if a borrower's friendship signals better borrower quality, borrowers with friends should have a higher likelihood of getting their requests financed, while ex-ante and borrowers with friends should default less given their higher intrinsic quality, ex-post.

The leaderboard of existing loan requests is displayed on the P2P lending site's front page. It displays information about the "Top 8" most financed requests in terms of the percentages for the respective requested amounts so that all potential lenders can easily find popular loan requests. We intend to examine the effect of the leaderboard on the likelihood of being financed and loan performance.

Following the aforementioned description, our research questions are as follows:

1. Does the leaderboard information influence whether a loan request is financed successfully?

2. Does the leaderboard information have predictive power regarding the loan's performance or the default rate?

The results show that the leaderboard information works ex ante, thus attracting additional bids to get requests financed. However, it does not work ex post and lacks a correlation with the default rate.

This paper is organized as follows: Studies related to the theories of information asymmetry and adverse selection, are briefly reviewed. Previous research on the effects of leaderboard, as well as reviews of studies on P2P lending is briefly presented. The data set used in this study is then introduced. After we describe the construction of the model and introduce the underlying methods, the results are presented. The discussion follows.

Literature Review

On a P2P lending web site, the information provided by the intermediary is likely to work as a signal as potential lenders face and struggle to overcome information asymmetry issues due to limited information on the credit of potential borrowers. Another approach to mitigate issues related to information asymmetry in the loan market is credit rationing as presented by Stilglitz et al. (1981). Social networks with Web 2.0 features found in P2P lending sites have been analyzed in the research of Lin et al. (Forthcoming), which explained the effects and patterns of social networks on the fundability and appropriateness of a repayment. The intervention and coordination of groups and group leaders play a key role in full funding and loan performance according to the study by Freedman and Jin (2011), while Collie and Hampshire (2010) pointed out signals enhancing community reputation in order to reduce adverse selection and moral hazard risk. Lending strategies in P2P lending have also been analyzed in regard to the effectiveness of the group's reputation. Findings have shown that having a low final rate and getting the loan funded, as well as bidding behavior, is not homogeneous among bidders (Puro et al. 2011). Herzenstein et al. (2011) analyzed the incentives to herd and found herding behavior in P2P lending to be sub-optimal and that lenders show strategic herding behavior up to a threshold point. Shen et al. (2010) found that P2P lending site users follow herds rather than profit. That is, herding takes place when lenders make investments on loan listings, rather than on more rational investments based on risk and returns. Lee and Lee (2012) investigates herding behavior empirically in the P2P lending market in which seemingly conflicting conditions and features of herding exist.

Theory regarding observational learning and information cascading presents a social learning mechanism (Banerjee 1992, Bikhchandani et al. 1992). These theories show that individuals make decisions with incomplete and inaccurate information. Consequently, people refer not only to their own information, but also to the actions of predecessors without any knowledge of the predecessors' decision making process. The value of online reviews works as a good source of information. Dellarocas et al. (2007) find that the characteristics of online reviews can be a good predictor for box office sales of new released motion pictures. Zhu and Zhang (2010) find that the reviews are more influential and valuable for less popular product and consumers who are more internet-savvy. Herd behavior is particularly prominent in the IS field. Computer users frequently adopt popular software products consequently making them even more popular (Brynjolfsson and Kemerer 1996). Bid participation in eBay auction shows the herding pattern (Dholakia and Soltysinki, 2001). Duan et al. (2009) empirically examined the impact of leaderboard information in the context of software adoption, while Ghose et al. (2009) found empirically that the monetary value of a click is not uniform across all positions in a search result. Herding behavior in the crowd-funding markets is empirically examined in terms of network externality (Burtch, 2011). Specifically in the P2p lending, Zhang et al. (2012) distinguish the rational herding and rational herding to find that obvious defects such as poor credit grades grow the herding momentum while favorable borrower characteristics like friend endorsements reduce the herding effect.

Hypotheses

While observational learning and herding may help attract bids and subsequently improve a loan's chances of getting financed, a lender's final profit depends on the quality of the loan decision. Herding can be found in many cases and investors may imitate investment decisions made for peculiar reasons. For example, restaurant patrons may choose to go to a busier restaurant with the expectation of higher quality. Herding is found to be a factor in non-diagnostic decisions in the context of online auctions (Simonsohn et al. 2008). Thus, it can be inferred that requests with more bids have a higher probability of being funded if requests are high on the leaderboard. In this light, the following statement is presented:

H1: Lenders' choice of participation in bidding is significantly affected by the leaderboard.

It is reasonable to infer that the more lenders participate in bidding, the more likely requests get financed. To cross check the leaderboard effect on getting financed, we present the following statement.

H1a: The likelihood for requests to get financed is significantly affected by the leaderboard.

Loan performance is measured by the likelihood of default. This study investigates the impact of the leaderboard through observational learning and herding in regard to the qualification assessment of borrowers. In other words, we examine whether a decision by lenders supported by observational learning really improves the quality of the decision when selecting the investment most likely to see repayment of invested funds and interest successfully. If the leaderboard is able to screen which borrowers are more likely to default, loans highly ranked on the leaderboard are more apt to be paid back in a timely manner. Positive association between herding in the P2P lending and its loan performance is found (Herzenstein et al., 2011). To clarify the effects of leaderboard, we present the hypothesis on loan outcomes relating to our investigation:

H2: Requests which remain on the leaderboard longer have a lower likelihood of default and subsequent loss of loan.

Data and Method

Popfunding.com, one of the biggest P2P lending sites in Korea, presents an ideal environment for this study in that the site's P2P lending market follows the rule of Dutch auctions for borrowers' requests in the same format as found on Prosper.com and Zopa.com. This study focuses on transaction data collected from registration dates between July 1 and December 31, 2009.

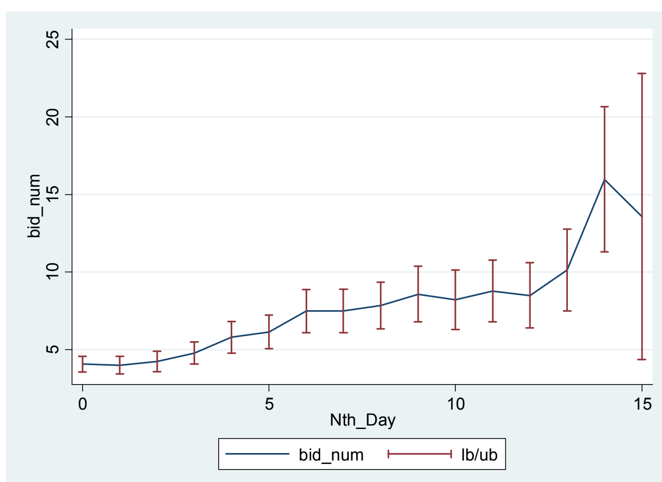

Figure 1. Average number of bids on Nth day

*bid_num = the number of bids, lb/ub = lower bound / upper bound

For the entire period, 2,470 requests for funding are generated, while 39,722 bids are made for those requests all outstanding over 15 days. Figure 1. shows the average number of bids on N^{th} day during the bid period.

Bid Participation and the Likelihood of Being Financed

The empirical attempt to quantify the effect of the leaderboard is found to be difficult due to the identification issues described by Manski (1993) in that the relationship between the leaderboard and the number of bids could be bi-directional. In this study, the panel data set is constituted to clarify the causality of the number of bids from the leaderboard effect based on the fixed estimation model. The differences between two groups of on-the-leaderboard and others taken from previous dates are what are examined. Dummy variables, $\text{Leaderboard}_{it-1}$, $\text{Leaderboard}_{it-2}$,..., $\text{Leaderboard}_{it-14}$ exhibit these differences where $\text{Leaderboard}_{it-k}$ is 1 if the loan request appears on the leaderboard on the day t-k, and zero if otherwise.

$$Y_{it} = \beta_0 + \beta_1(leaderboard_{it-1}) + \beta_2(leaderboard_{it-2}) + \ \dots\ + \beta_{14}(leaderboard_{it-14})$$
$$+ a_i + d_1(request\ fixed\ effect_i) + d_2(week\ fixed\ effect_t) + d_3(weekend_t) + d_4(N^{th}\ day_t) + \varepsilon_{it} \tag{1}$$

where y_{it} is the dependent variable of the number of bids observed for each request i at time t, $Leaderboard_{it-k}$ ($1 \leq k \leq 14$) is the binary variable to identify if the request i is on the leaderboard on the day $t-k$ and α_i is the unobserved individual effect. The assumption that α_i is not independent of $Leaderboard_{it-k}$ in that the requests are expected to be affected by specific daily situations and the specific context of the request, as well, is made. Total participation fluctuates along dates for various reasons. In order to control such variance, a panel negative binomial regression with fixed effect is included. Furthermore, dummy variable of *request fixed effect*$_i$, is included to control the request specific unobserved effects. The influences of specific weekly changes, daily changes on the N^{th} day from the bid starting point, as well as the weekend effect, are investigated. Dummy variables of *week fixed effect*$_t$, N^{th} day_t from the bid starting point at time t and binary variable of $weekend_t$ at time t are also added.

To examine the influence of the leaderboard on the likelihood of being financed, the relationship between the number of days in the leaderboard and the likelihood of being financed is analyzed using a logit model. The dummy variable to hard and soft information and control variables are added as was done in previous research in P2P lending.

$$Y_i^* = \alpha(The\ Number\ of\ Days\ in\ the\ Leaderboard_i) + d_1(leaderboard_i)$$
$$+ \beta_1(Hard\ Info._i) + \beta_2(Soft\ Info._i) + \beta_3(Control\ Variables_i) + \varepsilon_i \tag{2}$$

The probability that $Y_i = 1$ is given in Equation (2), where β is the vector of coefficients to be estimated.

$$P(y_i = 1|x_i) = \frac{\exp(x_i'\beta)}{1+\exp(x_i'\beta)} \tag{3}$$

Discrete dependent variable in (3) represents the likelihood of being financed.

Loan Performance

Requests staying longer on the leaderboard are expected to have lower default rates. The relationship between the number of days on the leaderboard and the likelihood of default is analyzed using a logit model for the requests which succeeded in getting funded. Hard and soft information and control variables are added here, as well.

$$Y_i^* = \alpha(The\ Number\ of\ Days\ in\ the\ Leaderboard_i) + d_1(leaderboard_i)$$
$$+ \beta_1(Hard\ Info._i) + \beta_2(Soft\ Info._i) + \beta_3(Control\ Variables_i) + \varepsilon_i \tag{4}$$

The probability that $Y_i = 1$ is given in Equation (3), where β is the vector of coefficients to be estimated. Discrete dependent variable in (3) represents the likelihood of default.

Furthermore, to release selection issues regarding the correlation between the error terms in equation (2) and (4), we perform Heckman estimation as we observe the loan performance only when the requests are financed.

Results

Regarding the results of testing the hypotheses, firstly for H1, the number of bids is found to be significantly affected by whether the request appeared on the leaderboard for the previous 7 days. The dynamic panel regression of System GMM, as well as the panel and OLS regression, consistently show that the leaderboard effect from the previous day to 7 days prior influences the number of bids significantly, while the leaderboard effect of the previous day is interpreted as most influential as shown in Table 1. The reason that *leaderboard_14* is dropped is that no request is listed on the leaderboard on day 1 as new requests tend to need more than a day to attract enough bids to get in the leaderboard. The coefficient for *leaderboard_12* is stastistically significant prominently, which is presumed for new requests on the leaderboard to attract the interests of lenders, who would bookmark and participate in bidding toward the end of an auction.

The number of bids made during the weekend is found to be fewer than those made during the week when the coefficients of the weekday dummies are statistically evaluated, thus inferring that lenders are participating in bids on weekdays rather than on weekends. Such a finding could be attributed to lenders being involved in P2P lending on business days rather than on non-business days.

Table 1. Estimation of the Number of Bids Equation

	(1) OLS	(2) Panel Regression with Fixed Effects	(3) System GMM
L_number_of_bids			0.916*** (0.0451)
leaderboard_1	9.541*** (0.543)	6.279*** (0.551)	1.817** (0.8)
leaderboard_2	5.397*** (0.692)	5.557*** (0.646)	3.861*** (0.776)
leaderboard_3	1.943** (0.77)	3.528*** (0.715)	1.772** (0.849)
leaderboard_4	1.145 (0.868)	2.825*** (0.802)	2.483*** (0.936)
leaderboard_5	0.714 (0.978)	2.389*** (0.907)	2.170** (1.042)
leaderboard_6	1.759 (1.134)	3.258*** (1.052)	3.604*** (1.2)
leaderboard_7	2.227 (1.397)	3.950*** (1.301)	4.247*** (1.468)
leaderboard_12	20.31*** (5.946)	20.48*** (5.555)	21.76*** (6.455)
weekend dummy	-3.624*** (0.356)	-3.821*** (0.346)	-4.972*** (0.486)
Observations	4,780	4,780	3,160
R-squared	0.289	0.323	
Number of Requests	903	903	662

a. Dependent variable is the number of bids. The values in parentheses are standard errors. All tests are two-tailed with * = 10%, ** = 5%, and *** = 1% significance.

According to the results of the study, it is easily inferred that requests having more bids are more likely to be financed. For H1a, the likelihood of being financed is found to be significantly affected by the number of days in the leaderboard. The Logit regression shows that the coefficients for the number of days on the leaderboard and the dummy variable to identify whether the requests are on the leaderboard more than once are both statistically significant as shown in Table 2. Therefore, it is understood that the leaderboard information positively influences the lenders' willingness to participate in bidding and the number of bids caused by the leaderboard effect will help requests on the leaderboard to get funded. Additonally, to examine the effect of soft and hard information pointed out in a previous study (Freedman et al. 2011), we find that the number of supporting documents submitted by borrowers is statistically significant.

Table 2. Results for Testing the Likelihood of Being Financed				
		(1)	(2)	(3)
days on the leaderboard		0.224*** (0.0485)	0.0853* (0.049)	0.188*** (0.056)
leaderboard dummy		3.284*** (0.442)	2.696*** (0.417)	1.647*** (0.479)
Terms	*requested amount*	-5.39e-07** (2.25E-07)		-1.70e-06*** (3.13E-07)
	repayment period	-0.00802 (0.0364)		-0.00953 (0.0485)
	interest	-0.145*** (0.048)		-0.315*** (0.0803)
Soft Info.	*replies on the bulletin board*		0.001 (0.002)	0.001 (0.002)
	comments on the bulletin board		0.001 (0.003)	0.005 (0.003)
	vote		0.085*** (0.013)	0.131*** (0.017)
Hard Info.	*supporting documents*		0.267*** (0.078)	0.526*** (0.101)
Control	*age dummy*	Yes	Yes	Yes
	male	0.134 (0.217)	0.117 (0.235)	-0.063 (0.27)
Observations		903	903	903

b. Dependent variable is Getting Financed (1=Financed, 0=Not). The values in parentheses are standard errors.
All tests are two-tailed with * = 10%, ** = 5%, and *** = 1% significance.

However, for the H2, a request's long stay on the leaderboard does not guarantee a lower likelihood of loan default in that we find no correlation or negative correlation between the number of days on the leaderboard and the likelihood of default. Heckman estimates on Table 3. consistently show that the leaderboard effects are not influential to the loan performance statistically.

Table 3. Results for Testing the Likelihood of Default					
		(1)	(2)	(3)	(4) Heckman
Financed(Select)					17.72 (2.084e+07)
days on the leaderboard		-0.175* (0.0986)	-0.107 (0.110)	-0.397** (0.160)	-0.015 (0.011)
leaderboard dummy		1.181 (1.238)	0.608 (1.3)	1.682 (2.276)	0.099 (0.117)
Terms	*requested amount*	1.01E-07 (4.45E-07)		1.56e-06* (9.20E-07)	3.95e-08 (5.64e-08)
	repayment period	0.125 (0.0808)		0.260* (0.133)	Yes
	Interest	-0.0289 (0.24)		0.06 (0.275)	0.006 (0.026)
Soft Info.	*replies on the bulletin board*		-0.004 (0.003)	-0.008 (0.005)	-0.0002 (0.0003)
	comments on the bulletin board		0.008 (0.008)	0.006 (0.0114)	0.0002 (0.0004)
	Vote		0.0751** (0.032)	0.038 (0.039)	0.003 (0.003)
	Q&As		-0.016*** (0.003)	-0.024*** (0.005)	-0.0004*** (8.63e-05)

Hard Info.	*supporting documents*		-0.0637 (0.205)	-0.31 (0.263)	-0.011 (0.017)
Control	*age dummy*	Yes	Yes	Yes	Yes
	Male	-0.293 (0.482)	-0.990* (0.578)	-0.78 (0.655)	-0.055 (0.047)
Observations		196	196	196	199(Uncensored) 704(Censored)

c. Dependent variable is the likelihood of default (1=Repaid on Time, 0=Default).
The values in parentheses are standard errors. All tests are two-tailed with * = 10%, ** = 5%, and *** = 1% significance.

The variables of the information presented on the P2P lending website, including the hard information which is significant for likelihood of being funded, are found not to have a clear correlation with the likelihood of default even though information on the friends' networks of borrowers is identified as an effective signal in differentiating the borrowers who will have lower likelihood of default in a previous study (Lin et al. Forthcoming).

Discussion

In this study, we have attempted to analyze the respective impacts of leaderboard information by empirically investigating the impact of the leaderboard, which depends on changes in the percentage for the requested amount. Such analyses are done in the context of P2P lending, which provides a number of investment choices available to potential lenders as well as ranking chart information that illustrates which funding requests are getting comparatively more bids. While the P2P lending market represents an extreme case of information overload in which only a limited amount of information regarding borrowers can be seen, information about others' participation in bidding could influence subsequent lenders' decisions. By analyzing the panel and cross section data, we show that the lenders' choice of bids is influenced by a funding request's entry on the leaderboard. The findings are consistent with observational learning that show that individuals are very much influenced by the information inferred from others' behavior in an online market. In P2P lending, the bids of lenders rely on the information provided by the intermediary. However, following the analysis undertaken in this study, it has been found that longer exposure on the leaderboard does not necessarily correlate to the likelihood of default.

Screening mechanism for bad borrowers is one of the most important characteristics of the P2P lending market. However, it is observed in this case that rational screening such as the wisdom of crowds in the P2P lending market does not work properly when the leaderboard forces bidders to obtain certain information regarding requests. Instead, a type of irrational herding caused by given information occurs as a signaling effect. While the analysis in this study focuses mainly on lenders' participation in bids for funding requests by potential borrowers, the results from the analysis have implications for e-commerce intermediaries, as well. It is recommended that an intermediary should manage the ranking information and review the feasibility of underwriting to verify loan requests to the extent possible by providing lenders with a sense of assurance, as well as with an anti-fraud index. Effective underwriting is hard to realize, requires a large input of labor, and is thus consequently expensive. As such, providing underwriting information on a P2P lending site will act as a 'double-edged sword,' both securing asset stability while at the same time not allowing the customer base to grow within a short amount of time. As Venkatesan et al. (2007) show, market characteristics should be considered together with retailer characteristics for the better performances of online markets. From the perspective of this research, an intermediary may well provide the underwriting information about requests that are on the leaderboard.

In light of the results of this study, there are many areas which can be improved upon in future studies. Future studies should extend to a more thorough analysis of the slot effect within the leaderboard and any comments posted along with the requests, as well as those on the community bulletin board. The empirical analysis undertaken in this study is not able to distinguish totally rational and irrational herding. Herding resulting from informational cascades is rational in that decision makers integrate antecedents' actions into their own decisions (Duan et al., 2009). The development of a measurement apparatus for non-rational herding should be a suitable topic for further exploration in later studies.

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