All that Glitters is Not Gold:
The Leaders' Board Effects in P2P Lending

Completed Research Paper

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Abstract

With regards to P2P lending, while it is believed that collective intelligence plays a role in filtering out unreliable borrowers, others point out the existence of herding behavior. In the P2P lending site this study investigates, the leaders' board information of existing loan requests is provided at the front webpage. This unique information sharing of others' choices offers an ideal environment for observational learning. This paper empirically examines whether observational learning in P2P lending leads to herding in bidding and the herding is rational. The results show that the leaders' board information provided by a P2P lending intermediary plays a key role with regards to the number of investors who bid. Ranking information regarding the bid participation rate shows a strong correlation with herding as well as with the likelihood that a loan request would be funded. However, this study shows that a higher ranking does not guarantee lower likelihood of default.

Keywords: P2P lending, observational learning, leaders' board, ranking, herding, collective intelligence

Introduction

An electronic marketplace is said to lower the buyers' costs of acquiring information on seller prices and product offerings(Bakos 1997). The marketplace evolves with the technological advancementof business-to-consumer (B2C), business-to-business (B2B) and peer-to-peer (P2P). In P2P networks, individuals or companies exchange information directly with one another overthe central exchanges. P2P architectures have influenced network structures all through society because of the wide use of the Internet (McAfee 2000; Meyer 2007).

Finance is not an exception. P2P lending is an open marketplace for loans provided not by a bank but by individuals online taking advantages of the P2P architecture. Financial transactions are facilitated directly between individuals ("peers") without any intermediation of a traditional financial institution. On a P2P lending web site, 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 would be provided a loan only in the case that his or her listing garnered 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 their decision making. The underwriting decisions assessing the risk of each loan in micro-lending sites are made by individuals, while the value of a loan is established through lender bidding. For considering borrowers' context, these lending decisions, which are attributed to the 'wisdom of crowds,' are expected to be superior to the same decisions currently made by loan officials at banks (Stalnaker 2008; Libert and Spector 2007).

How can a P2P lending community induce the wisdom of crowds that substitute for financial institutions' organizational knowledge and expertise for loan decision? Social networks and their observational learning are the major enabling mechanism that feeds necessary information to the lenders' community for their decision making. Observational learning could be prevailing in P2P lending markets for two reasons. First, the amount of information about a number of borrowers available on P2P lending sites is enormous for potential lenders to review so it could be the oft-cited information overload on the Web that previous studies have pointed out (Brynjolfsson and Smith 2000; Jones, Ravid, and Rafaeli 2004; Shapiro and Varian 1999). Moreover, potential lenders often find that they lack the knowledge and time to screen the best out of the extremely large number of borrowers on the bulletin board. The observational learning and information cascade (Bikhchandani, Hirshleifer and Welch 1992) suggest that following others' choices can be the most rational and efficient way to make decisions. Secondly, the intermediary provides more information about other lenders' choices and popular requests, consequently making observational learning more likely. Popularity information can be a signal of the earlier adopters' decisions (Duan, Gu, and Whinston 2009). P2P lending web sites seem to strategically encourage this by displaying active requests according to their popularity, ranking auctions based on their funding status in the previous period. This popularity information enables observational learnings to start faster and to grow to a larger population (Bikhchandani, Hirshleifer and Welch 1998).

The objective of this study is to empirically examine the impact of observational learning on bid participation in P2P lending and to test the quality of such decisions by investigating the relationship between observational learning and loan outcomes.

We gather data from Popfunding.com, one of the largest P2P lending sites in Korea. This site provides 'Top 8 ranking chart', a kind of leaders' board listing high ranking loans in terms of bidding participation on its front page so that all potential lenders can easily find popular loan requests. We use this information as well as transactions, to address thefollowing research questions:

(1) What are the factors related with the lenders'participation to bid?

(2) Will the observational learningbe significant in attracting more following participation by lenders for the requests?In other words, in a P2P lending market, are herding behaviors faciliated by observational learning as theory predicts?

(3) Does the observational learning affect the likelihood of the loan being funded?

(4) Are decisions made by herding rational and efficient? That is, do rankings in funding decisions really select good borrowers who will repay loans without default?

Our empirical analysis shows that lender behavior in bidding is consistent with the previous literatures on P2P lending and observational learning. The results of this study show that the ranking information provided by a P2P lending intermediary plays a key role in regard to the number of investors who bid. Ranking information regarding the bid participation rate shows a strong correlation with the number of bids and with the likelihood that funding would ultimately be provided. Furthermore, a higher ranking does not guarantee lower likelihood of default and loss of the loan. This implies that herding behavior is prevailing but does not necessary result in the wisdom of crowds.

This study is organized as follows: Studies related to P2P lending, observational learning and herding behavior are briefly reviewed. The data set used in this study is introduced. We then describe the construction of the model and introduce the underlying methods, and the results are presented. Managerial implications and conclusion are followed.

Literature Review

There exist issues related to information asymmetry in an electronic marketplace where sellers have more knowledge about the quality of the products and services than buyers do. The cost of information asymmetry applies to both the amount the buyers pay additionally and the losses incurred from legitimate businesses existing in the market with the widely known problems of adverse selection and moral hazard (Akerlof, 1970). Banker et al. (2010) empirically show that signals such as reputation are positively associated with the likelihood that a firm survives in a software services electronic marketplace. In P2P lending web site, potential lenders face the information asymmetry issues and struggle to overcome it for the limited information about potential borrowers' credit.

Generally collective intelligence is defined as the synergistic and cumulative channeling of the efforts of many minds towards selecting actions in response to some challenges (Walton and Krabbe 1995). Libert et al. (2007) point out that collective intelligence itself is widely used for systems of crowd reasoning with the adoption of the Internet and social networks. According to Tapscott and Williams (2008), collective intelligence means mass collaboration. In order for this concept to happen, the four principles of openness, peering, sharing, and acting globally are necessary. Interestingly, the borrowers and lenders on newly emerging P2P channel may be differentiated and segmented from those of traditional financial institutions as PC banking customers are more profitable, due to unobservable characteristics extant before they adopted PC banking (Hitt and Frei 2002). If collective intelligence works well in P2P lending web site as a screening process, we will find that they will have low default rates in spite of severe information asymmetry situations.

The rapid emergence of a new type of finance service, P2P lending, has garnered much attention from researchers. A number of research studies have conducted studies based on data provided by Prosper.com, a U.S.-based P2P lending web site. Iyer et al. (2009) also find that lenders refer to not only credit scores that traditional financial institutions look at, but also non-standard subjective information as a credible signal. Social networks with Web 2.0 features found in P2P lending sites have been analyzed in the research of Lin et al. (2009) 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 the full funding and loan performance according to the study of Freedman and Jin (2011). Collie and Hampshire (2010) pointed out signals enhancing community reputation in order to reduce the adverse selection and moral hazard risk.

Lending strategy in P2P lending is also analyzed for the effectiveness of group reputation. A trade off is found between having a low final rate and getting the loan funded and bidding behavior is not homogeneous among bidders (Sanjeev 2007; Puro et al. 2010, 2011). Some studies test the hypotheses about herding in P2P lending. Wang and Greiner (2010) analyze the incentives to herd and find the herding behavior in P2P lending to be sub-optimal. Lenders have strategic herding behaviors up to the threshold point. Shen et al. (2010) find that people in P2P lending site follow herds rather than profit. That is, herding takes place when lenders make investments on loan listings, rather than more rational investments based on risk andreturns. Previous research allows us to have rationale to explore and build hypotheses to understand the behavior of lenders in P2P lending.

Theory regarding observational learning and information cascade presents a social learning mechanism (Banerjee, 1992 and Bikhchandani et al., 1992). This theory explains that individuals make decisions with incomplete and inaccurate information. Consequently the individuals refer to not only their own information but also to their predecessors' actions without any knowledge about their predecessors' decision process. Compared to herd behavior that happens when every individual makes an identical decision considering their private information, an observational learning takes place when individuals ignore their private information during their decision making

(Smith and Sorensen 2000). Herd behavior is particularly prominent in IS area. Computer users frequently adopt popular software products, resulting in making them even more popular (Brynjolfsson and Kemerer 1996). Simonsohn and Ariely (2008) find that bidders repeatedly are in herds, favoring auctions with more existing bids.Duan et al. (2009) empirically examine the impact of ranking chart information in the context of software adoption. The place of the information on the screen is also critical as Ghose and Yang (2009) find that the monetary value of a click is not uniform across all positions in the results of search. From these studies, we examine an idea that leaders' board in the main page of the P2P lending site affects potential lenders decision. In this context, although we surely find the wisdom of crowds as a rational screening process in the P2P lending site, it is likely that they have irrational herding with the information of the leaders' board at the same time.

Complementing this stream of IS research, we empirically explore observational learning among lenders in P2P lending and examine how borrower information influences observational learning. Specifically, we try to clarify the relationship between lenders' participation to bid and the leaders' board that represents other people's previous selections.

Development of Hypotheses

Research Context

Our empirical research is conducted in the context of bid participation at Popfunding.com where borrowers post loan request listings with the amount of money requested and repayment conditions. Lenders bid on specific listings with the amount of money and the conditions that they would offer individually. Typically a loan is funded by a number of lenders, as the individual bid amount is much less the requested amount. A request gets funded if and only if the total amount offered by lenders is bigger than the amount requested by the borrower. After getting funded, the requests start to attract the lenders who would bid down the interest rate.

Research Hypotheses

We would start by verifying previous research on the factors that influence the lenders' participation to bid. Lenders will review all the hard and soft information that is presented with the requests (Lin et al. 2009; Iyer, Khwaja, Luttmer and Shue 2010). Soft information can be defined as the fuzzy, hard-to-quantify information about borrowers other than the hard information such as credit scores or financials of borrowers. Additionally reviews and customer ratings are also influential to the consumers' decisions (Jiang and Chen 2007).

H1: Lenders' choice of participation in bidding is affected by hard information and soft information as well.

We assume that lenders are rational and try to maximize their profit. To be specific, we expect that lenders are more likely to participate in bidding for the requests that look more credible and less risky. The information on how credible the borrowers are will be based on two sources – lenders' own information and information about previous participants. The jump in product adoption is said to be triggered by the condition that the relative popularity of one product excels another (Duan et al. 2009). Basically, ranking is a variable derived from sales and consequently, ranking is expected to have no impact on product adoption after controlling for the influence of sales. Given afore mentioned conditions, herding will take place in P2P lending when other's choices are known to uncertain lenders, which is done through observational learning. Hence, we speculate that loan requests on the leaders' board would attract more bids from lenders. Therefore, we propose

H2a: Lenders' choice of participation in bidding is significantly affected by rankings.

While observational learning and herding may help attracting bids and getting funded, a lender's final profit depends on the quality of loan decision. Collective intelligence is often cited as a screening mechanism for P2P lending (Libert et al. 2007; Weiss2005). Furthermore, the relationship between sales and ranking has been explored in many

related studies (Brynjolfsson, Hu, and Simester2011; Brynjolfsson, Hu, and Smith 2010; Brynjolfsson, Hu, and Smith 2003). Especially, we adopt the negative binomial regression model to analyze the relationship between the sales and rank employed by Brynjolfsson et al. (2011). We take the maximum ranking as a representative value that shows the highest level of attention a request has attracted during the auction period.

H2b: Getting funded is significantly affected by the maximum rankings of the requests.

Herding can be found in many cases. Investors may imitate investing decisions made for peculiar reasons. For example, restaurant patrons may choose to go to a busier restaurant, expecting higher quality. Herding exists behind non-diagnostic decisions in the context of online auctions (Simonsohn et al. 2008). Cai et al. (2009) experimentally show that the observational learning from the best seller lists in the previous week works in choosing the menu at the Chinese restaurants. Values around the positions on the screen vary and the positions on the top are mostly likely to be clicked on by the users (Aggarwal, Feldman, and Muthukrishnan 2006; Athey and Ellison 2009; Ghose et al. 2009; Varian 2006). It can be inferred that the requests with more bids have a higher probability of being funded if requests are high on the leaders' board. So we present

H3: Lenders' choice of participation in bidding is significantly affected by the leaders' board.

Outstanding loans are measured by the timely repayment. We investigate the impact of ranking through observational learning and herding on the qualification assessment of borrowers. In other words, we examine whether the lenders' decision supported by observational learning really improves the quality of decision in choosing the right investment to get the money and interests back successfully. If rankings represent the right information screening the borrowers who have more chances of default, the loans with high rankings will be likely to get paid back in the timely manner. Here follows the hypothesis on loan outcomes relating to our investigation:

H4: The requests with higher ranks would be the ones with a lower likelihood of default and loss of the loan.

Background and Data Description

Popfunding.com, one of the major P2P lending sites, presents an ideal environment for this research because 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. There exists, however, an important difference to be understood that settled interest rate are not varied freely. Potential borrowers cannot make their interest rates over 30% due to the financial regulations in Korea. We find that more than 80% of requests have 30% as their requested interest rate. The reason why the interest rates are skewed to the legal limit is that this site is targeting mostly non-bankable borrowers due to their low credit grades. This implies that information asymmetry lenders face may be lot more acute due to this target customer segments with high risk.

Table 1. Requested Interest Rate

Interest Rate	0%~9%	10%~19%	20%~29%	30%
Frequency	46	75	257	2092
Percentage	1.86%	3.04%	10.40%	84.70%

A potential borrower's requested funding amount is limited to KRW 25 million (roughly equivalent to US$25,000) while each lender's bid amount is limited to less than KRW 100,000 (roughly equivalent to US$100). Normally borrowers request less than KRW 5 million (roughly equivalent to US$50,000) while lenders bid around KRW 20,000(roughly equivalent to US$20). Even though we were allowed to use the whole data set of Popfunding.com, this study focuses on transaction data collected from registration dates between 1st July and 31st December 2009. This period was selected because the period is most stable,thus eliminating noise caused by fluctuation of business performances or events. Moreover, the results (whether the loans were defaulted or not) of requests that were registered in this period could be observed.

We extracted two types of data set, a cross sectional one and a panel. To inquire the characteristics of the 903 requests, we had a cross sectional data at the end of the period. Additionally we constituted the panel data to see the effects of the leaders' board, gettng rid of the specific influences of specific requests and days. Total number of requests for this period were 2,470 and 39,722 bids were generated for those requests. Normally a request has a bidding period from 1 week to 10 days. We had 4,780 day-request combinations. Overall, 14% of total requests got enough number of bids to get funded. As majority of requests do not attract any bid and have no transactions, requests without any bidwere eliminated. Table 2 describes the sample data for our analysis.

Table 2. Sample Descriptive Statistics for Requests, N = 903				
	Mean	Std. Dev.	Min	Max
Reply	11.1008	75.3101	0	1227
Posting	15.2104	53.8674	0	833
Boardview	1390.511	6414.55	0	112407
Recomm	22.7586	108.7409	0	1886
Age	34.8306	6.9284	21	58
Gender	.4784	.4998	0	1
Period	13.3854	5.4239	3	24
Vote	57.8782	18.5649	0	100
Interest	29.7	1.9539	3	30
Document	8.71	2.1218	5	13
amount_d	2.1218	903.7315	1	4
Rankyn	.4164	.4932	0	1
bid_num	.1606	3950.3511	2	224
Financedyn	.2204	.4147	0	1
Performance	-.9524	.2996	-1	1
avg_joinprice	21435.15	11762.51	1000	69500
sd_joinprice	25301.58	11602.99	0	49000
avg_interest	27.7251	2.5068	3	30
Autobid	11.8582	17.0922	0	75
Lendqna	35.9236	136.2098	0	3675
Rankperiod	1.6301	2.5324	0	13
Maxrank	12.866	10.2863	1	49
Sample Panel Descriptive Statistics, N = 4,780				
Rank	14.6050	9.3044	1	51
Rankyn (on the ranking chart =1, else =0)	.3079	.4620	0	1
Max_rank	3.2234	2.3239	1	8
Bid_num	6.5506	12.0548	1	99
Daily_Bid_Amount (KRW)	139,718.8	295,780	1,000	3,850,000

Average_Bid_Amount (KRW)	20,102.6	20,944	1,000	99,000
Total_money (KRW)	2,112,448	769,503	500,000	5,000,000
Funded (yes =1, no =0)	.3297	.4702	0	1
Loan Performance (not funded=-1, default=0, repayment=1)	-.9414	.3297	-1	1
Sample Descriptive Statistics for Financed Requests, N = 199				
Reply	28.7035	142.18	0	1227
Posting	31.9397	87.6531	0	833
Boardview	3326.151	11441.49	0	112407
Recomm	55.1156	199.6419	0	1886
Age	35.4472	6.4695	21	56
Gender	.4623	.4998	0	1
Period	11.3367	4.7971	3	24
Vote	74.5377	9.2331	44	95
Interest	29.9699	.2443	27	30
Document	10.3065	1.4980	6	13
amount_d	199.7602	1.7387	1	4
Rankyn	.0703	.2564	0	1
bid_num	122.5477	34.9471	45	224
Performance	.8744	.3323	0	1
avg_joinprice	20577.51	4896.821	11471.43	39698.8
sd_joinprice	25330.51	4398.006	15863.3	37663.29
avg_interest	27.6194	.9227418	22.1375	28.88542
Autobid	38.0352	15.8568	9	75
Lendqna	139.196	265.4691	15	3675
Rankperiod	4.2513	2.4694	0	13
Maxrank	2.3015	3.3028	1	26

In this period, the default rate of requests is 7%. The lending industry accepts that this rate of default is relatively low, considering the credit levels of potential borrowers. The statistics on the credit level of Popfunding.com arerepresented in Table 3. Most of borrowers have low credit scores, with 84% of potential borrowers level8or lower on Korea's 10 level credit score system. The people under the level 8 are not supposed to have any loans from commercial banks and get qualified for issuing any credit cards. As the credit score information of the borrowers in P2P lending does not represent the credit in reality, a couple of previous studies argue that it can be explained by the usefulness of soft information and a collective screening mechanism (Lin et al. 2009; Collie et al. 2010).

Table 3. Credit Level of Potential Borrowers Collected from a Sample			
Level	Percentage	Level	Percentage
level 0	1.27%	level 6	2.28%
level 1	0.00%	level 7	9.38%

level 2	0.13%	level 8	17.33%
level 3	0.41%	level 9	29.70%
level 4	0.36%	level 10	37.24%
level 5	1.89%	Total	100.00%

The intermediary provides the rankings of requests according the percentage of funds to the requsted amount at the beginning of a day. This information as the form ofranking chart is presented on the front homepage. This chart contains only high ranking bids (up to 8th). Hence, we can observe the effectiveness of this information on the number of bids of the day to a loan request since the ranking data precede the actions of bidding in the persepective of time.

We assume that the bids aquired for a day have no relationship with those on other days. This assumption can be justified as enough number of bids and requests are presented to potential lenders. Typcially requests are renewed, sorted by registered time. Only the ranking chartis presented by the intermediary. Figure 1. shows therelationship between the number of bids and rank through regression analysis. This lead us to inspect the influence of ranking information on the herding in P2P lending.
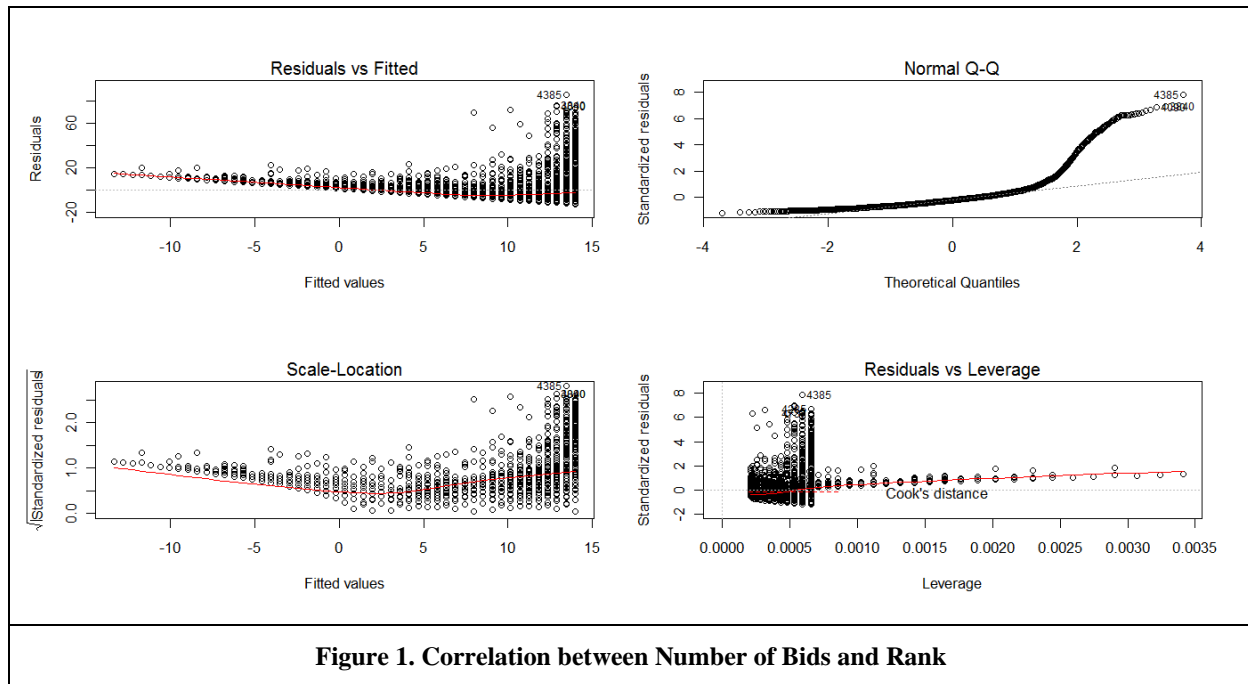

Figure 1. Correlation between Number of Bids and Rank

Method and Model

We now test what information is related with the bid participation of the lenders; and if the leaders' board information of requests attracts more following participation of lenders for the requests; and if the leaders' board information of requests affects their likelihood of getting funded and loan performance. To test H1, negative binomial regression between the number of bids and related variables including control variables such as amount, gender, and age is analyzed. For H2a, negative binomial regression between rankings and the number of bids on the following day in the panel was tested. Probit and Logit models for the relationship between getting funded and maximum ranks with the control variables are used to test H2b. To verify the significance of leaders' board information to attract more following participation of lenders for the requests will be tested by panel regression methods for H3. Finally, to test H4, the effect of the leaders' board information on their loan performance is examined as a discrete dependent model.

Hard information and soft information

We examine the impact of the hard informtion and soft information on the probability that a request is funded using a Probit and Logit model in a line with previous studies of Lin et al. (2009) and Freedman et al. (2008). The variables representing the activities of members on the board such as the number of replies and recommendations are regarded as the soft information, while the number of certified documents for the information of the potential lenders are taken as the hard information. To control the variances resulting from the groups, we add control variables such as amount, gender and age.

$$Y_i^* = \beta_0 + \beta_1 (HardInfo) + \beta_2 (SoftInfo) + \beta_3 (ControlVariables) + \varepsilon_i \quad (1)$$

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

$$P(y_i = 1 | x_i) = \begin{cases} \frac{\exp(x_i'\beta)}{1 + \exp(x_i'\beta)} & \text{for logit} \\ \phi(x_i'\beta) & \text{for probit} \end{cases} \quad (2)$$

where Φ is the cumulative density function for the standard normal. Discrete dependent variables in (2) are the likelihood of getting funded.

Ranking Relatedness

Our next model examine the relatedness between the numbers of bids and ranks which will explain the herding behavior. Based on the panel data of the ranking information at the starting point of a day and the number of bids on the very next day, we have a panel negative binomial regression with fixed effect rather than Poisson analysis as the variance of the counts of the bids within covariate group is not equal to the mean.

$$Y_{it}^s = a(Rank_{it-1}) + \varepsilon_{it} \quad (3)$$

We estimate a negative binomial regression model to understand how rankings affect the lenders' participation to bid. We estimate the following model:

$$f(y_i | X_i) = \frac{e^{-\mu_i} \mu_i^{y_i}}{y_i!}, \quad y_i = 0, 1, 2, 3, \ldots \quad (4)$$

where y_i is the number of bids, X_i is a vector of explanatory variables, $E(y_i | X_i) = \mu_i = \exp(X_i\beta + \varepsilon_i)$ is the conditional mean, and ε_i is the unobserved heterogeneity that follows a log-gamma distribution. This methodology is adopted at the analysis of relationship between revenue and ranks by Brynjolfsson et al. (2011) as well. Additionally the fixed effects model is more appropriate than random effects model that needs a lot more assumptions are unlikely to hold in this setting. The fixed effects model can be described as

$$y_{it} = \beta_0 + X_{it}\beta + Z_i\gamma + \alpha_i + \varepsilon_{it}$$

where y_{it} is the dependent variable observed for each request i at time t, X_{it} is the time-variant regressor, Z_i is the time-invariant regressor, and α_i is the unobserved individual effect. Assumption that α_i is not independent of X_{it}, Z_i in that the requests are somehow affected by daily specific situations and request specific context as well.
The requests with higher ranking are more likely to get funded because the ranking shows the amount of money the request raises. We test this using Probit and Logit model to analyze the relationship between the likelihood of getting funded and the requests' best ranks.

$$Y_i^s = a(Max\_Rank_i) + \varepsilon_i \quad (5)$$

The probability that $Y_i = 1$ is given by Equation (2), where β is the vector of coefficients to be estimated. We obtain the maximum rank value that represents the highest ranking achievement. With Probit and Logit models, the correlation with maximum rank and getting funded is statistically tested.

Leaders' Board Effect

The differences between two groups of on-the-leaders' board and others are what we examine. Dummy variable, $Rank_{it-1}$ will exhibit this difference where $Rank_{it-1}$ is 1 if the loan request appears on the leaders'board on the day t-1, and set to be zero otherwise.

$$Y_{it} = \beta_0 + \beta_1(Rank_{it-1}) + \beta_2(Average\_Bid\_Amount_{it}) + \varepsilon_{it} \tag{6}$$

Total participation fluctuates along dates for various reasons. In order to control such variance, we have a panel negative binomial regression with fixed effect. Furthermore, we investigate the relationship among the leaders' board duration of requests and the variables regarding the requests.

$$Y_t(Number\ of\ days\ on\ the\ leaders'board) = \beta_0 + \beta_1(Regarding\ variables) + \beta_2(Control\ Variables) + \varepsilon_t$$
(7)

Loan Performance

The requests with higher ranking would be more likely to be repaid in a timely manner. Only for the requests which suceeded in getting funded, we test this using Probit and Logit model to see the relationship between the loan performance and the requests' best ranks where the probability that $Y_i = 1$ is given by Equation (2), where β is the vector of coefficients to be estimated.

$$Y_i^* = \alpha(Max\_Rank_i) + \varepsilon_i \tag{8}$$

Results

Results for testing hypotheses are presented in order. Firstly for H1, the likelihood to get funded is significantly related with some soft information (Q&As and Vote) as well as hard information (number of certified documents). The requests with relatively bigger amount are less likely to get funded. The variables representing the group activities such as the number of replies and recommendations on community bulletin board are not statistically significant. The variables such as Posting and Board view are also skipped in the model as those variables are duplicated with the other soft information variables for the effect of community board activities.

Table 4. Results for Testing the Likelihood to Get Funded (1=Funded, 0=Not funded)		
Number of bids (n=903)		
	Probit	Logit
Reply	.0001(.0128)	.0006(.0223)
Recomm	.0052(.0060)	.0092(.0101)
Vote	.1141**(.0469)	.1893**(.0824)

Interest	2.7483*(1.6721)	4.7554(3.0877)
Document	1.0485**(.4537)	1.8962**(.8605)
Lendqna	.2051***(.0560)	.3582***(.1070)
i.amount_d2	-7.9877***(2.5104)	-13.7779***(4.4830)
i.amount_d3	-13.7024***(4.1294)	-23.7840***(7.4195)
i.gender_d1	.9210(.7822)	1.6081(1.4015)
i.age_d2	1.7326(1.8207)	2.8560(3.2771)
i.age_d3	2.6815(2.1141)	4.6002(3.7812)
i.age_d4	-1.9480(215.9084)	-3.4424(49.9018)
Constant	-105.6231***(53.4182)	-183.0652**(98.4591)
Psuedo R^2	.972	.972

a. The values in parentheses are t-statistics. All tests are two-tailed with * = 10%, ** = 5%, and *** = 1% significance.

An interesting point here is that the variable of Autobid is dropped as its correlation with the number of bid is so high as .9. Autobid is defined as the number of bids that participated automatically when conditions of the requestmeet such predefined conditions as interest rate, the number of prior bidders, amount accomplishment, repayment period and requested amount. As the number of bids are closely related with the number of prior bidders and amount accomplishment, this variable works as a 'booster' for the almost funded requests.

Secondly for H2a and H2b, statistical models of negative binomial regression model with fixed effect for panel data show that the count data of the number of bids are signficantly related with the ranks of the requests.

Table 5. Results for Negative Binomial Regression with Fixed Effect for Panel Data	
Number of obs (n=4,627)	Number of groups (n=750)
Obs per group: min = 2avg = 6.2 max = 15	
Rank	-.0311***(.0021)
Constant	.9174***(.0425)
Wald chi2(1)	213.07

b. The values in parentheses are t-statistics. All tests are two-tailed with * = 10%, ** = 5%, and *** = 1% significance.

Max_rank representing the highest ranks of the requests is statistically significant to explain the likelihood of getting funded somehow.

Table 6. Results for Testing the Likelihood to Get Funded (1=Funded, 0=Not funded)	
Number of bids (n=903)	
	Probit	Logit

Reply	.0001(.0195)	.0001(.0328)
Recomm	.0055(.0083)	.0100(.0147)
Vote	.0911*(.0539)	.1504*(.0906)
Interest	3.3331*(1.9881)	5.9733(3.8557)
Document	1.2768**(.5993)	2.368**(1.1837)
Lendqna	.2163***(.0646)	.3853***(.1263)
Max_rank	-.1738*(.1045)	-.3199*(.1901)
i.amount_d2	-8.5461***(2.9886)	-15.2394***(5.8018)
i.amount_d3	-14.4881***(4.7705)	-25.7726***(9.1640)
i.gender_d1	.6205(.8584)	1.0904(1.5038)
i.age_d2	2.308(2.1613)	3.9131(4.1595)
i.age_d3	3.2312(2.4580)	5.6373(4.6485)
i.age_d4	-1.3258(99.3883)	-2.5014(39.5324)
Constant	-123.6386**(63.1840)	-221.233*(123.1964)
Psuedo R^2	.976	.975

c. The values in parentheses are t-statistics. All tests are two-tailed with * = 10%,
   ** = 5%, and *** = 1% significance.

Thirdly for H3, we find the significance of the leaders' board through the negative binomial regression to identify if the number of bids are different depending on whether the requests are on the leaders' board or not. It is statistically significant that the requests within the leaders' board attract more bids than other requests in the model of negative binomial regression model with fixed effect for panel data. Therefore, the leaders' board information which is the result of previous day affects the number of bids the very next day as shown in Table 7.

Table 7. Results for Negative Binomial Regression with Fixed Effect for Panel Data	
Number of obs (n=4,627), Number of groups (n=750)	
Obs per group: min = 2avg = 6.2 max = 15	
Daily Bid Amount	1.11e-06***(1.79e-08)
Rankyn	-.4821***(.0270)
Constant	.8526***(.0362)
Wald chi2(1)	5497.66

d. The values in parentheses are t-statistics. All tests are two-tailed with * = 10%,
   ** = 5%, and *** = 1% significance.

Lastly for H4, the relationship between the leaders' board information and loan performance does not have any significant relationship statistically. Any explanatory variables other than the dummy variable for the age of 40s, are not statistically significant as showed in Table 11. This regression model will not predict the likelihood of default and loss of the loan. From these results, we derive the conclusion that the ranking chart information provided by the intermediary plays a key role for potential bidders to participate in bidding action as a positive signal. Even though

there still exists screening mechanism, the leaders' board provides a strong signal to potential bidders behaving non-rationally. So the information does not necessarily guarantee the repayment likelihood that is directly related with the yield rate. Hence the wisdom of crowds is still elusive in P2P lending market. All that glitters is not gold in that a higher ranking does not guarantee lower likelihood of default.

Table 8. Results for Testing the Loan Performance (1=Repayment, 0=Default)		
Number of obs (n=193)		
	Probit	Logit
Reply	-.0010(.0014)	-.0018(.0024)
Recomm	.0012(.0014)	.0023(.0027)
Vote	.0141(.0142)	.0295(.0261)
Document	.04350(.0895)	.0857(.1642)
Maxrank	-.0154(.0406)	-.0394(.0715)
RankPeriod	-.0700(.05336)	-.1374(.0965)
i.gender_d1	-.2775(.2552)	-.5886(.4835)
_Iage_d_2	.3469(.3469)	.6899(.5216)
_Iage_d_3	.8505**(.8505)	1.8038**(.8867)
Ln_amount	-.1239(.1805)	-.2558(.3295)
Constant	-.1275(1.0797)	-.6167(1.9602)
Psuedo R^2	.0079	.0073

e. The values in parentheses are t-statistics. All tests are two-tailed with * = 10%,
   ** = 5%, and *** = 1% significance.

Managerial Implication and Conclusion

In this study, we have attempted to analyze the respective impacts of collective intelligence, observational learning, and leaders' board information by empirically investigating the impact of changes in ranking on lenders' bids. Such analyses are done in the context of P2P lending which provides a number of investment choices available to potential lenders and 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 cross section and panel data using negative binomial regression model with dummy variables, the results of this study show that the lenders' choice of bids is influenced by a funding request's entry on the leaders' board. The findings are consistent with observational learning that show that individuals are very much influenced by the information inferred from others' behavior in the 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 is found that a high ranking does not necessarily predict a strong loan performance.

Several studies argue that a screening effect is one of the most important characteristics of the P2P lending market as this study reviewed before. However, we observe in this case that rational screening as a collective intelligence in P2P lending market does not work properly when rank list forces bidders to get certain information of requests. It is a type of irrational herding caused by given information as a signaling effect.While the analysis in this study focuses mainly on lenders' participation in bids for the funding requests of potential borrowers, the results from the analysis also 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 in a short amount of time. In the point of view from this research, the intermediary may well provide the underwriting information about the requests that are on the leaders' board at least.

This study leaves many points to be improved. First, only part of data provided by the intermediary has been analyzed due to the technical difficulty of managing such a large volume of transaction data. Surely the scope of data could be expanded upon in later studies. Future studies should extend to the deeper analysis of the slot effect in the leaders' board and the texts posted on the requests as well as the community bulletin board. Second, the use of data from a web site in a specific region may limit generalizability of the results in that both borrowing and lending money could accompany a number of cultural specifics during the transactions. Additional research will be required to verify the result of this study to P2P lending sites in various regions. Third, this empirical analysis is not able to distinguish totally rational and irrational herding. Herding resulting from informational cascades is rational in that decision makers integrate antecendents' actions into their own decisions (Duan et al., 2009). The degrees of rationality in herding information is not easily defined in regard to distinguishing rational herding from non-rational herding at this point of time. The development of a measurement apparatus for non-rational herding should be a good topic for further exploration in extended studies.

Appendix 1. Description of Variables

Description of Variables	
Reply i	The number of the replies of the request i's borrower on the community bulletin board
Posting i	The number of the postings by the request i's borrower on the community bulletin board
Boardview i	The number of the views of the postings by request i's borrower on the community bulletin board
Recomm i	The number of recommendations that request i's borrower received at the postings on the community bulletin board
Age	Dummy variable for age of borrower (1: 20s, 2:30s, 3:40s, 4:50s)
Gender	Dummy variable for gender of borrower (0: Female, 1: Male)
Period i	Repayment Period for request i(Month)
Vote i	Averaged binary ratings for request i by the members(Points/100)
Interest i	Maximum interest rate of request i offered by borrower (%)
Document i	The number of certified documents for borrower
amount_dd	Dummy variables for the money amount requested by borrower (1: ~1.5Million KRW, 2:2~2.5Million KRW, 3:3Million KRW ~)
Rankyn	Binary dummy variable that shows if the request is on the top 8 leaders' board at least one time(on the leaders' board =1, else =0)
bid_num i	The total number of participating bids for request i
Financedyn i	Binary dummy variable to get funded for request i
Performance i	Ternary variable that shows whether the loan of request i is in situations of default and loss(Not financed =-1, default=0, repayment=1)
avg_joinprice i	Average bid amount of money for request i
sd_joinprice i	Standard Deviation bid amount of money for request i
avg_interest i	Average interest rate of request i at the end of auction period
Autobid i	The number of bids that participated in request i automatically when certain conditions are met
Lendqna i	The number of Q&As for request i
Rankperiod i	The number of days when request i is on the leaders' board
Maxrank i	The maximum number of the rank of request i
Description of Panel Variables	
Rank it	Ranking of the requests i on a day t
Rankyn it (on the ranking chart =1, else =0)	Binary dummy variable that shows if the requests are on the top 8 ranking chart on a day t(on the leaders' board =1, else =0)
Bid_num it	Number of bids for the request i on a day t
Daily_Bid_Amount t (KRW)	The amount that lenders participate to bid for a day t (KRW)
Average_Bid_Amount (KRW)	Daily Bid Amount divided by Bid_num(KRW)
Total_money i (KRW)	Total sum of money the request i would get funded(KRW)
Funded i (yes =1, no =0)	Binary variable that shows if the total amount offered by lenders is bigger than the requested amount of request i (yes =1, no =0)
Loan Performance i (default=0, repayment=1)	Binary variable that shows whether the loan of request i is in situations of default and loss (default=0, timely repayment=1)

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