HERDING BEHAVIOR IN ONLINE P2P LENDING: AN EMPIRICAL INVESTIGATION

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Abstract

We study lenders' behavior in the peer-to-peer (P2P) lending market, where individuals bid on unsecured microloans requested by other individual borrowers. Online P2P exchanges are growing, but lenders in this market are not professional investors. In addition, lenders have to take big risks because loans in P2P lending are granted without collateral. While the P2P lending market shares some characteristics of the online markets with herding behavior, it also has characteristics that may discourage it. This study empirically investigates herding behavior in the P2P lending market where seemingly conflicting conditions and features of herding are present. Using a large sample of daily data from one of the largest P2P lending platforms in Korea, we find strong evidence of herding and its diminishing marginal effect as bidding advances. We employ a multinomial logit market-share model where relevant variables verified by prior studies on P2P lending are controlled.

Keywords: P2P lending, herding, social networks, reverse auction

1 INTRODUCTION

Peer-to-peer (P2P) lending is a certain breed of financial transaction that occurs directly between individuals without the intermediation of a traditional financial institution.[1] It has a short history, but has rapidly grown in recent years. The first online P2P lending company was Zopa (http://www.zopa.com), launched in 2005 in the United Kingdom. In the United States, Prosper (http://www.prosper.com/) was the first P2P lending firm, and opened to the public in February 2006. It is now the largest P2P lending platform, with over a million members and over $219 million in personal loans funded as of February 2011. P2P online exchanges are growing in the United States and United Kingdom as an alternative platform to traditional saving and investment (Slavin 2007). Harvard Business Review reports that every major bank will have its own P2P lending network within five years, and that P2P lending will be among the most important financial service innovations in the coming decade (Sviokla 2009).

This new phenomenon has garnered significant attention from researchers. Many of them focus on social networks in P2P lending (Lin et al. 2009; Herrero-Lopez 2009; Freedman et al. 2008). In the P2P lending market, transaction costs are reduced by eliminating expensive intermediaries, but information asymmetry problems become more severe than in traditional markets. This is because most individual lenders in online P2P lending lack financial expertise, and the lending experience takes place in a pseudonymous online environment (Klafft 2008). In this situation, social networks between individuals mitigate adverse selection and lead to better outcomes in all aspects of the lending process (Lin et al. 2009). Social networks on Prosper reveal some soft information about borrower risk, and therefore have the potential to compensate for the lack of hard information (Freedman et al. 2008). Besides social networks, borrowers' characteristics, including demographic characteristics, financial strength, and effort prior to making a request, are regarded as determinants of funding success in P2P lending (Herzenstein et al. 2008).

Despite of those new experimental mechanism designs and system features, the risk of information asymmetry lenders face may not be erased easily. It has been studied that players exhibit herding behaviors in online commerce when they face risk of uncertainty such as information asymmetry. Herding behavior describes many social and economic situations in which an individual's decision-making is highly influenced by the decisions of others (Duan et al. 2009). Therefore, it has been theoretically linked to many economic areas such as investment recommendations (Scharfstein & Stein 1990), price behavior of initial public offerings (IPOs) (Welch 1992), fads and customs (Bikhchandani et al. 1992), and delegated portfolio management (Maug & Naik 1995).

Duan et al. (2009) present that herding behavior could be especially prominent on the Internet for two reasons. The first is information overload. There is an excessive amount of information on the Web, so online users have difficulty understanding and using all the information (Brynjolfsson & Smith 2000). Doing what others do could be an efficient and rational way to make decisions in this circumstance. The second reason is that people can easily observe others' choices on the Internet. Most online e-commerce websites provide a way to sort their products in the order of previous sales performance. When a customer clicks on a book in one of the largest online bookstores, Amazon.com, he or she will not only obtain information about that book, but also see other items that previous customers bought with the particular book.

According to Herzenstein et al. (2008), there is a considerable difference between the number of lenders bidding on funded loan listings and the number of lenders bidding on unfunded loan listings. The average of the former is 62.6, while the average of the latter is only 1.6. What makes such significant difference? Is it the outcome of rational judgement of investors or inflated by herding

[1] http://en.wikipedia.org/wiki/P2p_lending

behaviors? Investigating herding behavior in P2P lending market is the main objective of this study. Since P2P lending platforms are online, it is obvious that they satisfy the aforementioned conditions for herd behaviors that Duan et al. (2009) identify.

When the lenders decide whether to invest their money in a loan request, they can verify the number of lenders who have already participated. If investors are influenced by the decisions of other investors (Devenow & Welch 1996), this number is a kind of signal for lenders. In other words, an auction that already has many bidders may be more attractive to lenders considering investment. We speculate that herding behaviors are more prolific in this market due to the possibility of adverse selection and the limited institutional knowledge mentioned above when lenders face unknown borrowers over the Internet. We empirically examine lenders' herding behaviors in the P2P lending market.

What makes this study interesting is two folds. First, we question whether herding behaviors exist in the P2P lending market because some characteristics of this market are distinctly different from those online markets where herding behaviors are observed. Herd behavior refers to people who do what others are doing instead of using their own information (Banerjee 1992). In other words, players take herding strategy because he or she believes that others are better informed than he or she. For example, herding behavior in the stock market is led by so-called experts (analysts). Many other cases of herding behaviors show that buyers rely on information gathered by other buyers of experience goods. Prior consumers already experienced goods and services, therefore, potential buyers believe that those experienced in prior to them have better information. Thus, they flock to popular goods or bands. However, online P2P lending does not seem to have such obvious source of the better information. Most of peers in P2P lending are not professional investors. In addition, auctions are not experienced goods when they are invested in. This is because it will take much longer time until the true information is revealed by loan default or payments on time. Therefore, these circumstances make us begin to doubt of the existence of herding in the P2P lending market where no clear superior information source is identified. In other words, is herding behavior triggered by the blind trust on the collective intelligence in online market? Secondly, we have so-called nano data from one P2P lending company that enables us to investigate the dynamics of herding behavior, which have not been explored fully to the best of our knowledge.

The rest of the paper is organized as follows. Section 2 presents the related theoretical and empirical literature on P2P lending and herding behavior. Section 3 shows our research hypotheses with logical reasoning, and section 4 describes the data. In section 5, we develop and analyze the empirical model and discuss the results. We conclude the paper by mentioning limitations and future research in section 6.

2 LITERATURE REVIEW

Since the primary characteristics of online P2P lending are disintermediation and reliance on existing social networks[2], many of previous studies address roles and impact of social networks on P2P lending. Lin et al. (2009) found that social networks, especially their relational aspects, lead to better outcomes, including a higher likelihood of a loan being funded, a lower risk of default, and lower interest rates, using data from Prosper. Their study suggested that social networks as a new source of soft information can mitigate the problem of adverse selection, which is particularly severe in online P2P lending. According to Herrero-Lopez (2009), affiliation with Trusted Groups on Prosper doubles the probability of getting a loan request successfully funded. Freedman and Jin (2008) also suggested that social networks on P2P lending sites help alleviate information problems, but also found evidence against this argument. They revealed that the return gap between group and non-group loans is closing over time. In addition, Weiss et al. (2010) found that although the screening of potential borrowers by

[2] http://en.wikipedia.org/wiki/P2P_lending

groups can help mitigate adverse selection, groups could have a negative impact on a borrower's probability of receiving the requested funds. Lenders who are not in the group might be discouraged from lending to a group member due to the group's focus on certain special interests. Other determinants of success in online P2P lending have also been studied. Borrower attributes such as demographic characteristics, financial strength, and effort prior to making the request affect the likelihood of funding success (Herzenstein et al. 2008). Loan decision variables such as loan amount, interest rate offered, and duration of loan listing mediate between borrower characteristics and the likelihood of funding success (Herzenstein et al. 2008). Iyer et al. (2009) found that the credit score given to borrowers by Prosper is indeed related to underlying creditworthiness and predicts the likelihood of default.

On the other hand, herding behavior has been theoretically and empirically explored in a variety of different fields. Graham (1999) studied herding among investment newsletters by developing and empirically testing a model that examines the incentives investment advisors face when deciding whether to herd. Pritsker and Kodres (1995) detected herd behavior by analyzing daily trading data on futures contracts. Devenow and Welch (1996) and Bikhchandani and Sharma (2001) created overviews of many papers on the economics of herding in financial markets.

Decision makers in many cases of IT adoptions also herd. Kauffman and Li (2003) found that corporate decision makers in IT adoption invest in what was chosen by earlier adopters. Duan et al. (2009) empirically investigated informational cascades, which is one of the major mechanisms for herd behavior in the software downloading market. They controlled other factors that affect online users' adoption decisions, and identified informational cascades. Their findings show that the download ranking of software products highly influences online users' choice of product. Herding on eBay has been studied by Simonsohn and Ariely (2007). They found that online bidders prefer auctions with more existing bids, even though they are non-diagnostic of quality, which means that non-rational herding occurs on eBay.

Analysis on herding in the online P2P lending market is in the initial stage. Krumme and Herrero (2009) presented simulations of different scenarios of herding behavior and reciprocity in an attempt to explain the observed bidding patterns of lenders. Herzenstein et al. (2010) defined herding behavior in online P2P lending as a greater likelihood of bidding in auctions with more existing bids. They used data from Prosper to empirically test herding behavior and employed logit models with a binary dependent variable. Wang and Greiner (2010) suggested that herding behavior in online P2P lending might lead to low return on investment (ROI), high risk-return ratio, and under-utilized lender money resources. Complementing these studies, we empirically explore herding behavior in the online P2P lending market using a multinomial logit market-share model. We differentiate our study through a completely dissimilar model and dataset.

3 DEVELOPMENT OF HYPOTHESES

3.1 Research Context

This empirical study is conducted in the context of auctions on Popfunding (http://www.popfunding.com). Popfunding is one of the biggest P2P lending platforms in South Korea. It opened in June 2007, and as of February 28, 2011, it had 55,060 members and 12,927 requested loans, of which 1,099 loans had been successfully funded[3].

[3] We retrieved information on the number of members and loans from the Popfunding administrator. The 12,927 requested loans included 163 ongoing auctions and 4,556 withdrawn auctions. A withdrawn auction refers to an auction in which the borrower has quit before the end of the auction.

Popfunding has a similar lending process and reverse auction mechanism to other P2P lending sites, such as Prosper and Zopa. First, a borrower requests a loan with a requested amount and duration; maximum interest rate; and borrower's profile, including age, gender, and occupation. The borrower also posts a detailed description of the purpose of the loan and a plan for repayment, and emotionally appeals to lenders by explaining his or her urgent situation. To prove their creditworthiness and authenticity, borrowers can submit personal certificates, including identification, credit report, address, job, income, and tax information to the Popfunding platform operator[4]. Once a loan request is listed on the site, it becomes an auction on which Popfunding lenders can place bids. Also, Popfunding provides a Q&A board for each loan request where lenders can make direct requests to borrowers for additional information. Through the board, lenders can interact extensively with borrowers, and the interaction between them is visible to everyone on the lending site. Lenders are not only able to obtain information, but also form connections with the borrowers. Based on the collected information and borrower's description, lenders decide whether to lend to the borrower and if so, how much money and what interest rate they wish to offer. When the total bid amount by lenders exceeds the amount requested by the borrower, the lenders with the lowest interest rates win the auction and are granted a stake in the loan. If a loan fails to attract a sufficient number of lenders, the loan is automatically cancelled by the system after the auction duration expires.

The overall mechanism of Popfunding is similar to those of Prosper and Zopa, but there is an important difference between them. The main target customers of Popfunding are non-bankable borrowers whose credit scores are below the threshold of traditional financial institutions. In other words, Popfunding is trying to utilize its P2P lending platform for micro-financing. Therefore, their clients on the borrowing side are mostly desperate ones who often are lured to black financial markets while the three largest P2P lending sites (Prosper, Zopa, and LendingClub) report that only approximately 20% of their loans are for small businesses (Farrell 2008). Because of their desperate situation, borrowers are willing to submit and reveal much of personal information. This fact provides a fertile ground for possible herding behavior. Credit scores provides very little information to lenders because their scores are all bad with very little variance in this market and they have to rely on soft information while lenders in Popfunding face much bigger risk of adverse selection than those in other frequently mentioned sites.

Visitors to the Popfunding site are able to view and bid on auctions. As of March 1, 2011, there were 163 auctions posted by borrowers on the site. If a lender clicks on an auction, he or she can obtain the information mentioned above. In addition, Popfunding provides the status of each auction, allowing lenders to view participation rates[5] calculated by Prosper. Lenders can sort auctions by participation rate.

In summary, Popfunding lenders can gather information by analyzing the characteristic features of auctions and observing previous bidders' choices. We investigate the herding behavior of lenders using Popfunding data[6].

3.2 Research Hypotheses

When an individual has to make a decision, he or she gets the information from two sources. The first is based on one's own knowledge about and analysis of the subject, and the other is derived from an observation of decisions made by others. If the individual is very knowledgeable and an expert in the

[4] Lenders who visit Popfunding can only confirm the existence of these certificates. Popfunding does not make public the contents of the documents. Partial information may be disclosed if a funded borrower delays payment for more than 10 days.

[5] Suppose that there is an auction in which the borrower requests KRW 2 million. If KRW 0.5 million is already invested in the auction, the participation rate of the auction is 25%. Lenders can also check the number of people investing in the auction. In Prosper, people are able to verify the identities of investors, but Popfunding does not disclose such information.

[6] We omit screen shots of the Popfunding site because the site is only available in Korean. It is very similar to other P2P lending sites such as Prosper and Zopa.

subject, his or her decision will hardly be influenced by others. If this is not the case, predecessors' decisions will critically affect a decision maker. In other words, an individual will follow the decision making of others regardless of privately obtained information if he or she is unsure of his or her own knowledge. This is known as herding.

In Popfunding, when a lender chooses an auction to bid on, he or she analyzes the auction's own characteristics and, at the same time, observes the investment choices of others by checking the participation rate. Most Popfunding lenders are not professional investors. As we mentioned earlier, most borrowers have a low credit grade, which is assigned based on objective information. In this circumstance, it is difficult for a lender to have confidence in his or her ability to distinguish good auctions from bad ones. Therefore, we expect lenders to be exposed to herding behavior which will reply on the participation rate of an auction in this case. This is because the participation rate directly represents predecessors' decisions.

Potential bidders may try to predict a request's likelihood of being fully funded based on its current level of participation. Table 1 presents the final participation rate of auctions after the duration expired which were conducted from June 15, 2009 to July 21, 2010.

Final Participation Rate (%)	Number of Auctions	Portion
0~10	1094	0.489
11~20	260	0.116
21~30	147	0.066
31~40	82	0.037
41~50	51	0.023
51~60	37	0.016
61~70	31	0.014
71~80	26	0.012
81~90	22	0.010
91~100	17	0.007
Over 100	469	0.210
Total	2236	1.000

Table 1. Distribution of Ultimate Participation Rate

Assuming that this distribution is typical in this market, the estimated statistical probability of being funded of an auction with less than the current 10% participation rate at the given moment of time is less than 21% since only 469 bids out of 2,236 are ultimately funded. On the other hand, if the current participation standing is beyond 80%, its probability improves to about 0.923 since 469 bids are fully funded out of 508[7] bids beyond 80% participation level.

Hence, it can be easily shown that the probability of being fully funded increase as the current participation rate advances. Bidders will have more incentive to participate in auctions with higher participation rate, that is, herding. We therefore suggest the following hypothesis.

H1: An auction with a higher participation rate attracts more bids[8].

Now, we turn our attention to net increase of the probability of full funding as the level of participation advances. As calculated above, if an auction has less than 10% of participation, its estimated probability of full funding is 21%, but if it advances to the next level of more than 20%, then the estimate improves to 41% since 469 auctions were successful out of 1,142 auctions beyond

[7] 508 = 22 + 17 + 469
[8] Bids are measured by two values. One is the number of lenders who bid on the auction. The other is bid amount. This also applies to other hypotheses. There is a high correlation between these two variables, but we would like to confirm whether there is any difference.

20% of participation. Let's assume that an auction's participation levels up from 80% to 90%, then its success probability improves from 92.3%[9] to 96.5%[10]. Hence, the net increase of loan success probability is about 20% (from 21% to 41%) when the participation level changes from 10% to 20%. However, that is only 4.2% (from 92.3% to 96.5%) when the participation moves from 80% to 90%. This is because the uncertainty level of being fully funded when an auction has very little participation is very high but that with higher participation evaporates quickly. This implies the following hypothesis.

H2: There is a diminishing marginal effect of the participation rate.

Bidders will weigh the quality of an auction not only by the participation rate but also by the speed of fulfilling the participation rate. It is not difficult to speculate that any auction attracting bids in the shorter time will be estimated as more attractive one to crowds than other auctions taking much longer time to fulfill the same participation. In other words, an auction with a 20% participation rate in the first day has a higher chance of being fully funded, but an auction with the same participation rate of 20% in the last day of its duration would most likely fail. We therefore propose the following hypothesis.

H3: Participation rate being equal, a newer auction attracts more bids.

To prove herding behavior on Popfunding, other factors that influence lenders' decision making should be controlled for. Petersen (2004) classified these factors into hard and soft information. Hard information is quantifiable, verifiable, and easily transmittable, while soft information is fuzzier and harder-to-quantify. Lin et al. (2009) suggested that social networks in P2P lending act as a new source of soft information. They mentioned the positive effects of social networks on the funding success of borrowers. For Popfunding lenders, the number of postings on the Q&A board, which is automatically generated when a borrower posts a loan request, is interpreted as soft information in the form of activity in the social network. Also, the borrowers' attributes affect the likelihood of funding success (Herzenstein et al. 2008). In our study, this factor is controlled by the number of verified certificates submitted by a borrower to Popfunding. It is regarded as hard information about the loan request. We predict that this soft information and hard information will also have a positive effect on Popfunding loans, resulting in the following hypotheses.

H4: An auction with more postings on the Q&A board attracts more bids.

H5: An auction with more verified certification attracts more bids.

According to Herzenstein et al. (2008), the starting interest rate influences loan funding success. When people invest, they consider the payback period. No matter how high the interest rate, the attractiveness of an investment is diminished with a long payback period. The shortest payback period is 3 months and the longest is 24 months. Considering the starting interest rate and payback period, we propose the following hypotheses.

H6: An auction with a higher starting interest rate attracts more bids.

H7: An auction with a shorter payback period attracts more bids.

We also consider a borrower's loan request history on Popfunding as a factor that influences lenders. As previously mentioned, most Popfunding borrowers are non-bankable, which means that Popfunding has a feature of microfinance. Schreiner (1999) found that first-time borrowers are riskier than second-time borrowers in traditional microfinance. Therefore, Popfunding lenders may be able to retrieve some information from a borrower's history[11]. If a borrower applied for a loan through Popfunding, successfully got the loan, and paid back the loan, the borrower would have a good

[9] 469/(22 + 17 + 469) = 0.923
[10] 469/(17 + 469) = 0.965
[11] Many borrowers have a past history with Popfunding. See Table 4.

reputation and credibility on Popfunding. However, a borrower who has several failed auctions can hardly take out a loan through Popfunding unless there is evidence of circumstantial change. We therefore suggest the following hypotheses.

H8: An auction posted by a borrower with a history of more successfully funded auctions[12] attracts more bids.

H9: An auction posted by a borrower with a history of fewer failed auctions attracts more bids.

An overview of the suggested hypotheses is presented in Table 2.

Index	Hypothesis
H1	An auction with a higher participation rate attracts more bids.
H2	There is a diminishing marginal effect of the participation rate.
H3	Participation rate being equal, a newer auction attracts more bids.
H4	An auction with more postings on the Q&A board attracts more bids.
H5	An auction with more verified certification attracts more bids.
H6	An auction with a higher starting interest rate attracts more bids.
H7	An auction with a shorter payback period attracts more bids
H8	An auction posted by a borrower with a history of more successfully funded auctions attracts more bids.
H9	An auction posted by a borrower with a history of fewer failed auctions attracts more bids.

Table 2. Hypotheses

4 DATA

4.1 Data Collection

We used Popfunding's daily data from June 15, 2009 to July 31, 2010 for this study. There are a total of 14,279 data items, including 2,236 auctions. Participation rate varies every time lenders bid on the auction, and age that refers to the number of days passed from the open date, increases by one each day even for the same auction. We set the unit of analysis as daily data to treat each day as different data. In our study, the Popfunding site is a marketplace, and auctions that lenders can invest in are considered goods in the market.

4.2 Key Variables and Descriptive Statistics

The key dependent variable in this empirical study is lender's choice. We measure lender's choice using two values. One is the number of bidders who invest in an auction, and the other is the total amount of money invested in an auction. There is a very high correlation between these two values[13]. However, there may be some different factors between small investors and big investors and, if so, these two dependent variables would reveal the difference. We use market share instead of the absolute number of bidders or the absolute value of the amount, because this automatically removes invisible influences, including weekend and holiday effects. Thus, our two dependent variables are the daily market share of the number of bidders, and the daily market share of bid amounts for each auction. To help readers understand this better, we provide an example. On June 1, 2010, the total amount of money invested in all Popfunding auctions active on that day was KRW 7,421,000. Among

[12] There are no borrowers who received a loan through Popfunding, did not repay the loan, and requested a loan again. Thus, the number of past auctions that were successfully funded is equal to the number of auctions successfully paid.
[13] The correlation value is 0.92. See Table 5.

these, the auction with index B100525-5 attracted KRW 195,000. Thus, the market share of bid amounts for this auction was 0.026[14].

The independent variables include predecessors' choice and auction information available on Popfunding. The predecessors' choice is represented by participation rate, which is calculated and provided by Popfunding. This variable enables us to investigate lenders' herding behavior in the P2P lending market. Auction information includes loan decision variables such as starting interest rate and payback period. It also contains the number of postings on the Q&A board as soft information, and includes hard information such as the number of verified certificates submitted by a borrower, and the history of borrowers. Key variables are summarized in Table 3. Tables 4 and 5 represent the descriptive statistics of key variables and the correlation matrix between variables, respectively.

Variable	Description
$DailyShare\_Bidders_{it}$	Daily market share of the number of bidders in auction i, which opened t days ago
$DailyShare\_Money_{it}$	Daily market share of bid money in auction i, which opened t days ago
$ParticipationRate_{it}$	Participation rate of auction i when it opened t days ago
Age_{it}	Number of days that auction i has been listed up to time t
$NumOfQnA_{it}$	Cumulative total number of postings on the Q&A board of auction i up to time t
$NumOfCertificats_{it}$	Number of verified certificates submitted by the borrower of auction i
$InterestRate_{it}$	Maximum interest rate of auction I suggested by the borrower (%)
$PaybackPeriod_{it}$	Suggested duration for repayment of auction i by the borrower (months)
$PastSuc_{it}$	Number of past auctions successfully funded by the borrower who posted auction i
$PastFail_{it}$	Number of past failed auctions by the borrower who posted auction i

Table 3. Description of Key Variables[15]

Variable	N	Mean	Median	S.D.	Min.	Max.
$DailyShare\_Bidders_{it}$	14279	0.0289	0.0104	0.0535	0.0011	0.6943
$DailyShare\_Money_{it}$	14279	0.0289	0.0073	0.0613	0.000064	0.6902
$ParticipationRate_{it}$	14279	11.2966	4	18.9206	0	348
Age_{it}	14279	5.9037	5	4.0721	1	16
$NumOfQnA_{it}$	14279	8.4180	5	10.7185	0	121
$NumOfCertificats_{it}$	14279	1.4069	0	2.2711	0	7
$InterestRate_{it}$	14279	29.7299	30	1.9851	3	30
$PaybackPeriod_{it}$	14279	14.5876	12	5.6471	3	24
$PastSuc_{it}$	14279	0.2437	0	0.6799	0	7
$PastFail_{it}$	14279	2.7945	2	3.0787	0	37

Table 4. Descriptive Statistics of Key Variables

[14] 195,000/7,421,000 = 0.026

[15] $NumOfCertificates_{it}$, $InterestRate_{it}$, $RequestAmount_{it}$, and $PaybackPeriod_{it}$ are actually time-invariant.

Variable	1	2	3	4	5	6	7	8	9	10
1. $DailyShare\_Bidder_{it}$	1									
2. $DailyShare\_Money_{it}$	0.92	1								
3. $ParticipationRate_{it}$	0.65	0.59	1							
4. Age_{it}	0.19	0.21	0.37	1						
5. $NumOfQnA_{it}$	0.44	0.44	0.50	0.37	1					
6. $NumOfCertificates_{it}$	0.16	0.16	0.14	0.05	0.20	1				
7. $InterestRate_{it}$	0.05	0.03	0.05	0.03	0.04	0.11	1			
8. $PaybackPeriod_{it}$	-0.07	-0.03	-0.16	0.03	0.07	0.13	-0.08	1		
9. $PastSuc_{it}$	0.18	0.19	0.12	-0.01	0.10	0.05	0.04	0.16	1	
10. $PastFail_{it}$	0.04	0.04	0.07	0.02	0.05	-0.02	0.09	-0.12	0.22	1

Table 5. Correlation Matrix of Key Variables

5 EMPIRICAL METHODOLOGY AND RESULTS

5.1 The Empirical Model

The objective of our study is to analyze lenders' herding behavior in online P2P lending. To test our hypotheses, we employ the multinomial logit (MNL) market-share model. This model has been extensively applied in various fields to explain consumer choice among multiple discrete alternatives. Since it can deal with market response over time (Cooper 1993), it is appropriate for our circumstance. According to the MNL market-share model, the market share of the *i*-th product in a market of *I* products at time *t* is defined as follows:

$$S_{it} = \frac{A_{it}}{\sum_{i=1}^{I} A_{it}} \qquad (1)$$

where A_{it} represents the "attractiveness" of the product. The model specifies attractiveness as:

$$A_{it} = \exp(\alpha_i + \sum_{k=1}^{K} \beta_k X_{ikt} + \varepsilon_{it}) \qquad (2)$$

where α_t is a parameter for the intrinsic value of the *i*-th product and X_{ikt} represents the *k*-th exploratory variable that may influence users' decisions, and ε_{it} is the error term. Substituting equation (2) into equation (1), we derive the following:

$$S_{it} = \frac{\exp(\alpha_i + \sum_{k=1}^{K} \beta_k X_{ikt} + \varepsilon_{it})_{it}}{\sum_{i=1}^{I} \exp(\alpha_i + \sum_{k=1}^{K} \beta_k X_{ikt} + \varepsilon_{it})} \qquad (3)$$

Since the MNL market-share model is originally nonlinear, we need to do the log-centering transformation in order to estimate the parameters using linear regression techniques (Cooper 1993). Taking logarithms on both sides of equation (3), we find:

$$\ln(S_{it}) = \alpha_i + \sum_{k=1}^{K} \beta_k X_{ikt} + \varepsilon_{it} - \ln \sum_{j=1}^{I} \{\exp(\alpha_j + \sum_{k=1}^{K} \beta_k X_{jkt} + \varepsilon_{jt})\} \qquad (4)$$

If we sum equation (4) over *i* and divide it by *I*, we find:

$$\ln(\tilde{S}_t) = \bar{\alpha} + \sum_{k=1}^{K} \beta_k \bar{X}_{kt} + \bar{\varepsilon}_t - \ln \sum_{j=1}^{I} \{\exp(\alpha_j + \sum_{k=1}^{K} \beta_k X_{jkt} + \varepsilon_{jt})\} \qquad (5)$$

where $\tilde{S}_t$ is the geometric mean of S_{it}, and $\bar{\alpha}$, $\bar{X}_{kt}$, and $\bar{\varepsilon}_t$ are the arithmetic means of α_t, X_{ikt}, and ε_{it}, respectively. Subtracting equation (5) from equation (4), we find:

$$\ln(\frac{S_{it}}{\tilde{S}_t}) = (\alpha_i - \overline{\alpha}) + \sum_{k=1}^{K} \beta_k (X_{ikt} - \overline{X}_{kt}) + (\varepsilon_{it} - \overline{\varepsilon}_t) \tag{6}$$

Setting $\alpha_i' = (\alpha_i - \overline{\alpha})$ and considering that $\overline{\varepsilon}_t$ can be captured by time-fixed effects α_t, we reach the following reduced form:

$$\ln(\frac{S_{it}}{\tilde{S}_t}) = \alpha_i' + \alpha_t + \sum_{k=1}^{K} \beta_k (X_{ikt} - \overline{X}_{kt}) + \varepsilon_{it} \tag{7}$$

Since α_i' denotes auction-specific fixed effects, and α_t denotes time-related variables, or time-fixed effects, equation (7) leads to a typical panel data regression model. Our panel data consist of daily observations of auctions and their information on Popfunding. The auction-specific fixed effects capture the idiosyncratic and time-constant unobserved characteristics, which controls for intrinsic auction characteristics. The time-fixed effects capture any influence on market share due to timing differences.

To use the equation in our context, a market is defined. Since auctions on Popfunding have similar features and compete to be chosen, it is natural to consider Popfunding as a single market. In this market, the individual lender's choice is not observed, but lenders' choices can be collectively measured by the daily market share. Thus, the daily market share of auction *i* at time *t* is captured as follows:

$$DailyShare\_Bidder_{it} = \frac{NumOfBidder_{it}}{\sum_{i=1}^{I} NumOfBidder_{it}} \tag{8}$$

$$DailyShare\_Money_{it} = \frac{BidAmount_{it}}{\sum_{i=1}^{I} BidAmount_{it}} \tag{9}$$

where $NumOfBidder_{it}$ is the number of bidders who invest in auction *i* at time *t* and $BidAmount_{it}$ is the total bid amount invested in auction *i* at time *t*. These two dependent variables are S_{it} in equations (1) through (7).

To test H1, we include the variable $ParticipationRate_{it-1}$, which represents the previous day's participation rate of auction i that opened t days ago. Suppose that a borrower makes a loan auction requesting KRW 1 million today. The rate of participation of the auction today is 0. If the total amount of money that the auction attracts today is KRW 200,000, then the participation rate of the auction tomorrow is 0.2. The coefficient of this variable represents the jump in the number of bidders or the bid amount that the auction experiences. We also include as a variable the square term of $ParticipationRate_{it-1}$ ($ParticipationRateSQ_{it-1}$). H2 indicates that the number of bidders and the amount of bid money are increasing and concave functions of the participation rate. The participation rate increases for an auction with a lower rate (e.g., increasing from 10% to 20%), leading to a steeper rise in the number of bidders and bid amounts than for an auction with a higher rate (e.g., increasing from 80% to 90%). The coefficient of the quadratic term is therefore expected to be negative. To test H3, we add the interaction terms of $ParticipationRate_{it-1}$ and Age_{it} (*ParticipationRate*Age*). The coefficient of the interaction term represents how the impact of the rate of participation of an auction is moderated by the number of days that the auction has been listed up to the particular day. If the auction fails to be fully funded, the loan request auction is automatically canceled by the system. Thus, the age of the auction, which is the number of days that the auction has been listed up to that day, is meaningful for lenders. Suppose there are two auctions with the same participation, say 20%, today. One of the auctions opened yesterday, and the other opened 10 days ago. Since the former has a higher chance of being fully funded than the latter, the newer auction will be more attractive for lenders who are considering investments in the P2P lending market. Therefore, the coefficient of the interaction term is expected to be negative.

To test H4 through H9, we include variables $NumOfQnA_{it}$, $NumOfCertificates_{it}$, $InterestRate_{it}$, $PaybackPeriod_{it}$, $PastSuc_{it}$, and $PastFail_{it}$.

According to our hypotheses mentioned above, the expected signs of independent variables are summarized in Table 6.

Variable	Expected Sign	Variable	Expected Sign
ParticipationRate	+	*InterestRate*	+
ParticipationRateSQ	-	*PaybackPeriod*	-
(ParticipationRate)(Age)*	-	*PastSuc*	+
NumOfQnA	+	*PastFail*	-
NumOfCertificates	+		

Table 6. Expected Sign of Independent Variables

5.2 Results

As mentioned earlier, we have one dependent variables with two measurements: the daily market share of bidders and daily market share of bid amounts. Table 7 represents the results with the former as a dependent variable, and Table 8 represents results with the latter.

	Coefficient	S.D.	t-statistic
1: *ParticipationRate*	4.4463	0.1103	40.3227***
2: *ParticipationRateSQ*	-1.2951	0.0532	-24.3566***
3: *(ParticipationRate)*(Age)*	-0.0370	0.0084	-4.4089***
4: *NumOfQnA*	0.0208	0.0008	26.6500***
5: *NumOfCertificates*	0.0796	0.0036	21.9715***
6: *PaybackPeriod*	-0.0055	0.0013	-4.2783***
7: *InterestRate*	0.0077	0.0033	2.3030**
8: *PastSuc*	0.2616	0.0102	25.6068***
9: *PastFail*	-0.0042	0.0022	-1.9053*
N = 14,279, R^2 = 0.5157, adjusted R^2 = 0.5154			

Table 7. Results with daily market share of bidders as dependent variable[16]

	Coefficient	S.D.	t-statistic
1: *ParticipationRate*	5.3813	0.2092	25.7201***
2: *ParticipationRateSQ*	-1.1723	0.1009	-17.0827***
3: *(ParticipationRate)*(Age)*	-0.0319	0.0159	-1.9990**
4: *NumOfQnA*	0.0370	0.0015	25.0013***

[16] *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively. This also applies to Table 8.

5: *NumOfCertificates*	0.1654	0.0069	24.0426***
6: *PaybackPeriod*	-0.0146	0.0024	-5.9507***
7: *InterestRate*	0.0299	0.0063	4.7108***
8: *PastSuc*	0.4256	0.0194	21.9579***
9: *PastFail*	-0.0016	0.0042	-0.3687
N = 14,279, R^2 = 0.3794, adjusted R^2 = 0.3790			

Table 8. Results with daily market share of bid amounts as dependent variable

According to Tables 7 and 8, all hypotheses are accepted except H9-2. Lenders in the P2P lending market tend to herd, and there is a diminishing marginal effect of the herding behavior. Both soft information and hard information are also important factors for lenders. With regards to H9-2, it can be interpreted as follows. When lenders decide whether or not to invest, and how much money to invest, the failure history of a borrower is not an important factor. This may be because the borrower is better prepared for a loan request after past failures.

6 CONCLUSION

We studied P2P lending, through which individuals make unsecured loans to other individuals without the intervention of financial intermediaries. In particular, we provided a systematic analysis of lenders' herding behavior in the online P2P lending market through empirical investigation, and found strong evidence of herding behavior. We also presented the diminishing marginal effect of the herding behavior.

Although this research sheds light on lenders' herding behavior, it has some limitations. First, the participation rate goes up in real time when a lender invests in an auction. However, we measured it by the value of participation rate until the previous day. This would not be a problem in the early days of an auction, but results may be less precise for the last day. The bidders are highly attracted during the last day when an auction becomes fully funded, as we have shown in Figure 1. In this case, our measure of participation rate is not accurate. In addition, we did not take into account the content of descriptions written by the borrowers about their situations. Most Popfunding borrowers are non-bankable, which means that they are financially desperate. According to a survey conducted by Popfunding, lenders gain an emotional benefit from helping the poor by investing in their auctions. To test this emotional impact, content analysis is required.

According to Bikhchandani et al. (1992), the primary mechanisms for herd behavior are informational cascades, sanctions on deviants, positive payoff externalities, and conformity preference. It would be interesting to examine the main mechanism that induces herd behavior in online P2P lending.

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