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Attributes and Impacts of Learning from Prior Lenders in Peer-to-peer Lending

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Abstract: Learning from others is a facet of human nature. In peer-to-peer lending, potential lenders who are interested in the loan, but have not yet funded it, observe and learn from the behavior of prior lenders who have funded the loan. It is unclear, however, whether potential lenders learn from the prior lenders' attributes other than the observed bidding behavior. Using data from PPDai.com, the study finds that potential lenders consider the prior lender's risk preference, investment experience, and historical investment performance when making investment decisions. Specifically, potential lenders are more likely to fund loans that have more female or older prior lenders. The potential lenders' decisions are positively affected by the proportion of prior lenders with long account duration, high investment success ratio, low bad debt ratio, and high money-weighted rate of return.

Keywords: Peer-to-peer (P2P) lending; Information asymmetry; Investment decision; Observational learning; Prior lenders

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1. Introduction

As an important component of Internet financing, peer-to-peer (P2P) lending can effectively address the financing needs of individuals as well as small and micro-enterprises. Individual borrowers can seek microloans supported by anonymous lenders via online P2P lending platforms [1]. The information asymmetry in P2P lending is even more complex than that in the traditional financial market [2–4]. Moreover, P2P lenders face a moral dilemma in that borrowers might only provide partial information in their favor [5]. Mutual anonymity between lenders and borrowers in P2P lending makes it difficult for lenders to recoup their investments if the loan defaults [6]. For these reasons, P2P lenders tend to search for more than the basic publicized information when making investment decisions.

The information asymmetry and moral dilemma in P2P lending create an ideal situation for observational learning, in which individual behavior changes due to observing the environment and other participants [7–9]. Information asymmetry allows some investors to keep private information unknown to other investors [3]. Investors can speculate on the private information held by others by observing the others' behavior accordingly.

In P2P lending, prior lenders are defined as investors who have funded the loan, while potential lenders are those interested in the loan but have not yet funded it. Empirical studies have confirmed the existence of herding in P2P lending, showing that potential lenders observe prior lenders' bidding decisions to determine whether to bid [10–11]. Whether potential lenders learn from prior lenders' attributes other than investment behaviors has not yet been reported. Given this research gap, this study investigates what attributes of the prior lenders are influential, and how these attributes affect potential lenders.

In the P2P lending setting, the herding behavior of lenders occurs as a result of observational learning. Rational observational learners focus on the behavior of prior lenders, as well as the logic for these behaviors [11]. The lenders' observational learning constitutes an effective approach to reducing investment risk [2]. Potential investors can discern loan situations and make their investment decisions by observing and learning the attributes of prior investors' attributes other than their known behavior. Such attributes will be referred to as beyond behavior in the paper.

The website PPDai.com publishes individual information about prior lenders and their historical investment performance in loan projects. Potential lenders can check not only the borrower's information but also the attributes of all prior lenders on the platform, which allows potential lenders to learn from the attributes of prior lenders. This study developed a logit model to regress the impact of prior lender attributes on the potential lenders' lending decisions and explore how the observational learning of information beyond behavior works. The study finds that the prior lender's gender, age, account duration, number of historical bids, investment success ratio, bad debt ratio, and money-weighted rate of return are significantly related to the lending decisions of potential lenders. The conclusions suggest that potential lenders can optimize their portfolios by observing and analyzing the decisions and attributes of prior lenders. These findings are an important complement to research on observational learning in online microloan markets.

2. Research hypotheses

To examine the impact of prior lender attributes on potential lenders' behaviors in P2P lending, this study first classifies the attributes into four categories, which are prior lender risk preference attributes, prior lender investment experience attributes, prior lender investment performance attributes, and prior lender authentication attributes as shown in **Figure 1**.

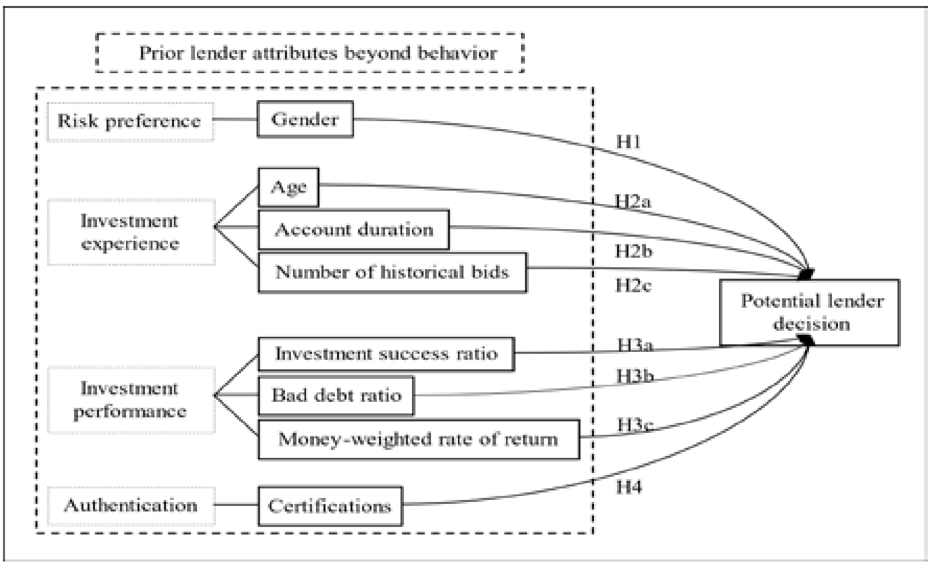

Figure 1. Conceptual model of prior lender attributes and potential lender decision

2.1. Gender differences in risk aversion

Previous research suggests that there are gender differences in attitudes toward the risk of investment decisions [12]. Women are more risk-averse than men, and women tend to avoid high-risk loans [13]. Moreover, scholars have found that men are more overconfident than women under uncertainty [14]. Overconfident investors typically make poor decisions about fund trading, resulting in poor performance [15]. Hence, the study supposed Hypothesis 1 as follows.

Hypothesis 1: A potential lender is more likely to bid on a listing with a higher proportion of female prior lenders.

2.2. Age, account duration, and number of historical bids

Older and more experienced investors exhibit weaker behavioral biases [16]. Young investors are inexperienced in experimental asset markets, and they make investment decisions rashly and impulsively [17]. In this regard, the study sets the median age of all investors in the sample as the dividing line between older and younger and assumed in Hypothesis 2a. The investors' long-term accumulation of experience develops their ability to assess project risks and identify high-risk borrowers [2]. Inexperienced investors are less capable of assessing investment opportunities [18]. Studies have found that P2P lenders can aggregate over peer viewpoints to improve lending efficiency [19]. Lenders' experience and ability to identify risks grow with the accumulation of bidding experience. Hence, Hypothesis 2b and Hypothesis 2c were proposed.

Hypothesis 2a: A potential lender is more likely to bid on a listing with a higher proportion of older prior lenders.

Hypothesis 2b: The higher the proportion of prior lenders who have longer account duration, the more likely it is that potential lenders invest.

Hypothesis 2c: The larger the number of historical bids of prior lenders, the more likely it is that potential lenders invest.

2.3. Investment success ratio, bad debt ratio, and money-weighted rate of return

When investing in online platforms, financial returns are based on the success of the loan project, and investors tend to fund loans that are more likely to succeed. If a project fails to attract enough funds, although the funds will be returned to investors, the resource costs of preparing bids will not be recovered [20]. Lenders with high investment success ratios are more likely to identify and select good listings from many similar loan projects. As previously mentioned, borrowers have a low cost to default, while lenders have difficulties recouping their investments in defaulted loans [6]. The prior lenders' bad debt ratio can be used to assess their poor historical investment performance, including their ability to identify potential defaults. In online trading platforms, investors can obtain better returns by following the trading behaviors of better-performing traders [21]. This study uses the money-weighted rate of return as another metric of investment performance. The following three hypotheses are proposed accordingly.

Hypothesis 3a: The higher the proportion of lenders with a high investment success ratio among prior lenders, the more likely it is that potential lenders invest.

Hypothesis 3b: The higher the proportion of lenders with a high bad debt ratio among prior lenders, the less likely it is that potential lenders invest.

Hypothesis 3c: The higher the proportion of the high money-weighted rate of return lenders among prior lenders, the more likely it is that potential lenders invest.

2.4. Certifications

Certifications are information verified and published through the P2P platform, such as identification, diploma, and phone number. In P2P lending, borrower listings with more certifications attract more bids [10]. Borrowers who submit certification information related to education increase their likelihood of funding success [22]. Certifications can reduce information asymmetry and predict the credibility of borrowers. Similarly, lenders can provide certification information on the platform, which may reflect their status, knowledge, and social capital. This leads to the following hypothesis.

Hypothesis 4: The proportion of prior lenders who provide certifications has a significant positive effect on the potential lenders' investment behavior.

3. Data and Methodology

3.1. Data

Sample data from PPdai.com was obtained to test the hypotheses. As of December 2016, the number of registered users in PPdai was 32.61 million, and its annual turnover reached 19.878 billion RMB [23]. Transaction data from January 1, 2014 to December 31, 2014 period was collected as the initial sample. Listings with amounts less than 10,000 RMB and failed listings were excluded. The bidding duration is divided into hour units, and hourly bidding records are collected. The final cumulative bidding reaches a total of 29,746 biddings, and the record information is listed in **Table 1**.

Table 1. Variable description

Category	Variable	Description
Bidding information	$Tamount_{i,t}$	The amount of funding that listing *j* receives in hour *t* (*t=2...T*).
	$Lamount_{i,t-1}$	The cumulative amount of funding that listing *i* has received by the end of hour *t-1* (*t=2...T*).
	$Lbids_{i,t-1}$	The cumulative number of bids that listing *i* has received by the end of hour *t-1* (*t=2...T*).
	$Lpercent_{i,t-1}$	The percentage of the amount requested by listing *i* at the end of hour *t-1* (*t=2...T*).
Identity information	$Lgender_{i,t-1}$	The cumulative percentage of female lenders in listing *i* by the end of hour *t-1* (*t=2...T*).
	$Lage_{i,t-1}$	The cumulative percentage of older lenders in listing *i* by the end of hour *t-1*. The median age of lenders is 32 in the sample, so any lender over 32 years old is considered to be an older lender (*t=2...T*).
Bidding experience information	$\mathrm{LAD}_{i,t-1}$	The cumulative percentage of longer account duration from lenders that listing *i* has received by the end of hour *t-1* (*t=2…T*). In the sample, the median of account duration is 303 days. Therefore, any lender registered 303 days before 2014/12/31 is labeled a longer account duration.
	$\mathrm{LNHB}_{i,t-1}$	The cumulative percentage of lenders with a larger number of historical bids in listing *i* by the end of hour *t-1* (*t=2…T*). In the sample, the median number of bids is 392; therefore, any lender who has bid more than 392 times is considered to be a lender with a larger number of historical bids.
Bidding performance information	$\mathrm{LISR}_{i,t-1}$	The cumulative percentage of high investment success ratio lenders in listing *i* by the end of hour *t-1* (*t=2…T*). In the sample, the median bid success ratio of lenders is 0.85; therefore, lenders are considered to have a high bidding success ratio if their success ratio is over 0.85.
	$\mathrm{LBDR}_{i,t-1}$	The cumulative percentage of high bad debt ratio lenders in listing *i* by the end of hour *t-1* (*t=2…T*). In the sample, the median bad debt ratio of lenders is 0.06, so lenders are considered to be lenders with high bad debt ratios if their bad bidding debt rate is over 0.06.
Risk preference information	$\mathrm{LMRR}_{i,t-1}$	The cumulative percentage of high money-weighted rate of return lenders that listing *i* has received by the end of hour *t-1* (*t=2…T*). In the sample, the median money-weighted rate of return is 0.16, so lenders are considered to be the high money-weighted rate of return lenders if their money-weighted rate of return is over 0.16.

Table 1 (Continued)

Category	Variable	Description
Certification information	$LCT_{i,t-1}$	The cumulative percentage of certified lenders that listing *i* has received by the end of hour *t-1* (*t=2…T*). Prior lenders who provide at least one piece of certification information are certified lenders.
Control variable	$Control_i$	Includes variables such as listing characteristics (credit rating, amount, duration, interest, and description length); borrower characteristics (success bid times, failed bid times, age, gender, occupation, registration date, certifications, material score).

Note: *T* refers to the total time spent in getting a loan fully funded (unit: hour)

3.2. Research model

A logit model is conducted to explore the impact of prior lender attributes on potential lender decisions, formulated as **Equation 1**. The specific variables are defined in **Table 1**, and the borrower characteristics and listing characteristics are placed into the model as control variables.

$$Tamount_{i,t} = \beta_0 + \beta_1 Lamount_{i,t-1} + \beta_2 Lbids_{i,t-1} + \beta_3 Lpercent_{i,t-1} + \beta_4 Lgender_{i,t-1} + \beta_5 Lage_{i,t-1} + \beta_6 LAD_{i,t-1} + \beta_7 LNHB_{i,t-1} + \beta_8 LISR_{i,t-1} + \beta_9 LBDR_{i,t-1} + \beta_{10} LMRR_{i,t-1} + \beta_{11} LCT_{i,t-1} + \gamma Control_i + e_{it} \quad (1)$$

4. Results

4.1. Descriptive analysis

Table 2 shows that the average bid amount per hour is 3,304.35 RMB for all bidding records. For bidding records of every hour, the cumulative amount of funding is 22,138.12 RMB, and the cumulative number of bids is 111.53. On average, female lenders only accounted for 20% of bids for the hourly bidding records, while the proportion of lenders aged over 32 (the median lender age) in loans is 65%. For all bidding records, the lenders with higher investment success ratios over the median of 0.85 accounts for an average of 61%.

Table 2. Descriptive statistics of variables

Variables	Mean	Maximum	Minimum	Std. Dev.
Tamount	3304.35	224692	0	7736.49
Lamount	22138.12	479811	50	39063.83
Lbids	111.53	1693	1	177.47
Lpercent	0.47	1	0.0007	0.29
Lgender	0.20	1	0	0.14
Lage	0.65	1	0	0.14
LAD	0.58	1	0	0.23
LNHB	0.55	1	0	0.21
LISR	0.61	1	0	0.22
LBDR	0.50	1	0	0.22
LMRR	0.41	1	0	0.25
LCT	0.29	1	0	0.15

4.2. Empirical results

In Model 1 of **Table 3**, the impact of the bid amount, number of bids, and funding ratio on the potential lenders' investment behavior are examined. In Model 2, prior lender attributes are added to explore their influence on potential lender investment behavior. Finally, an interaction item of LBDR×LNHB is added in Model 3. The regression results of these models are shown in **Table 3**.

In Model 2 of **Table 3**, the coefficient of *Lgender* (β_4 = 0.402, P < 0.01) is significantly positive, showing that the higher the proportion of females in the prior lenders, the more likely potential lenders are to invest. Therefore, Hypothesis 1 is confirmed. The significant positive relationship between the proportion of the prior lenders' age and the subsequent funding amount (β_5 = 0.567, P < 0.01) is predictably demonstrated in Model 2, which supports Hypothesis 2a. Regarding the effect of experience, the coefficient of LAD (β_6 = 1.266, P < 0.01) on *Ln(Tamount)* is significantly positive and Hypothesis 2b is confirmed. The study also finds a statistically significant positive relationship between LISR and subsequent funding amount (β_8 = 0.620, P < 0.01), supporting Hypothesis 3a. The higher the proportion of high investment success ratio lenders among the prior lenders, the more likely potential lenders are to invest. The coefficient of LBDR (β_9 = -0.228, P < 0.05) shows that the higher the proportion of high bad debt ratio lenders among the prior lenders, the less likely it is that potential lenders will invest. Thus, the evidence supports Hypotheses 3a and 3b. The coefficient of LMRR (β_{10} = 0.665, P < 0.01) reveals that the higher the proportion of the high money-weighted rate of return lenders among the prior lenders, the more likely it is that potential lenders will invest, so Hypothesis 3c is supported. The coefficient of LCT (β_{11} = 0.141, P > 0.10) is insignificant, which shows that the prior lender's certification information has no significant effect on the potential lender's investment behavior, so Hypothesis 4 is not supported. The coefficient of LBDR × LNHB (β_{12} = 1.845, P < 0.01) is significantly positive, indicating that when LBDR is unchanged, the higher the proportion of lenders with more bids among the prior lenders, the more likely potential lenders are to invest. Thus, this study finds evidence to support Hypothesis 2c.

4.3. Robustness testing

To further test the robustness of the results, *Ln(Tbids)*, the number of lenders in hour *t* is used as the dependent variable. The test results are shown in Models 4–6 of **Table 3**. The correlation between the independent variables and the dependent variable is still significant.

Table 3. Impact of prior lender information on potential lenders

Variable	Dependent variable: *Ln(Tamount)*			Dependent variable: *Ln(Tbids)*		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Ln(Lamount)	0.884***	0.858***	0.849***	0.157***	0.149***	0.147***
	(21.346)	(20.697)	(20.479)	(8.948)	(8.497)	(8.348)
Ln(Lbids)	0.276***	0.229***	0.205***	0.368***	0.336***	0.329***
	(7.821)	(6.185)	(5.524)	(24.577)	(21.367)	(20.865)
Lpercent	-1.895***	-1.789***	-1.740***	-1.007***	-0.956***	-0.943***
	(-16.319)	(-15.357)	(-14.927)	(-20.430)	(-19.347)	(-19.046)
Lgender		0.402***	0.458***		0.258***	0.274***
		(3.224)	(3.666)		(4.878)	(5.164)
Lage		0.567***	0.512***		0.318***	0.303***
		(4.743)	(4.282)		(6.280)	(5.969)
LRD		1.266***	1.139***		0.530***	0.495***
		(11.677)	(10.375)		(11.527)	(10.616)

Table 3 (Continued)

Variable	Dependent variable: *Ln(Tamount)*			Dependent variable: *Ln(Tbids)*		
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
LNHB		-0.837***	-1.737***		-0.352***	-0.604***
		(-7.728)	(-10.450)		(-7.664)	(-8.558)
LISR		0.620***	0.516***		0.150***	0.121***
		(6.031)	(4.971)		(3.447)	(2.753)
LBDR		-0.228**	-1.176***		-0.004	-0.269***
		(-2.189)	(-6.969)		(-0.085)	(-3.754)
LMRR		0.665***	0.600***		0.120**	0.087*
		(5.388)	(4.897)		(2.323)	(1.667)
LCT		0.141	0.200		-0.071	-0.054
		(1.150)	(1.634)		(-1.368)	(-1.046)
LNHB × LBDR			1.845***			0.516***
			(7.135)			(4.700)
Constant	-2.037***	-2.902***	-2.350***	-3.314***	-3.734***	-3.580***
	(-4.893)	(-6.504)	(-5.192)	(-18.759)	(-19.720)	(-18.632)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.230	0.236	0.237	0.334	0.339	0.340
Obs.	29746	29746	29746	29746	29746	29746
Loans	8846	8846	8846	8846	8846	8846

Note: Asymptotic t-values are in parentheses. *** ,**, and *represents significant at 1% ,5%and 10% level in a two-tailed test, respectively.

5. Discussion and conclusion

Previous research on online P2P lending has shown that lenders show typical features of herding behavior. However, little attention has been paid to how prior lender attributes beyond behavior affect the potential lenders' investment decisions. Using data from PPDai.com, this study finds that potential lenders consider the prior lender's risk preference, investment experience, and historical investment performance when making investment decisions. Specifically, potential lenders are more likely to fund loans that have more female or older prior lenders. The potential lenders' decisions are positively affected by the proportion of prior lenders with long account duration, high investment success ratio, low bad debt ratio, and high money-weighted rate of return. This paper provides new insights into the mechanisms of how potential lenders learn from prior lender attributes and enriches theoretical research about lender behavior in the P2P lending market.

Disclosure statement

The author declares no conflict of interest.

References

[1] Lin M, Prabhala NR, Viswanathan S, 2013, Judging Borrowers by the Company they Keep: Friendship Networks and Information Asymmetry in Online Peer-to-peer Lending. Management Science, 59(1): 17–35.

[2] Freedman SM, Jin GZ, 2011, Learning by Doing with Asymmetric Information: Evidence from Prosper.com. National Bureau of Economic Research, No. 16855.

[3] Massa M, Simonov A, 2006, Hedging, Familiarity and Portfolio Choice. The Review of Financial Studies, 19(2): 633–685.

[4] Yum H, Lee B, Chae M, 2012, From the Wisdom of Crowds to My Own Judgment in Microfinance through Online Peer-to-peer Lending Platforms. Electronic Commerce Research and Applications, 11(5): 469–483.

[5] Pointner W, Raunig B, 2018, A Primer on Peer-to-peer Lending: Immediate Financial Intermediation in Practice. Monetary Policy & the Economy, 3(18): 36–51.

[6] Herzenstein M, Dholakia UM, Andrews RL, 2011, Strategic Herding Behavior in Peer-to-peer Loan Auctions. Journal of Interactive Marketing, 25(1): 27–36.

[7] Banerjee AV, 1992, A Simple Model of Herd Behavior. The Quarterly Journal of Economics, 107(3): 797–817.

[8] Plavnick JB, Hume KA, 2014, Observational Learning by Individuals with Autism: A Review of Teaching Strategies. Autism, 18(4): 458–466.

[9] Van GT, Paas F, Marcus N, et al., 2009, The Mirror Neuron System and Observational Learning: Implications for the Effectiveness of Dynamic Visualizations. Educational Psychology Review, 21(1): 21–30.

[10] Lee E, Lee B, 2012, Herding Behavior in Online P2P Lending: An Empirical Investigation. Electronic Commerce Research and Applications, 11(5): 495–503.

[11] Zhang J, Liu P, 2012, Rational Herding in Microloan Markets. Management Science, 58(5): 892–912.

[12] Croson R, Gneezy U, 2009, Gender Differences in Preferences. Journal of Economic Literature, 47(2): 448–474.

[13] Holt CA, Laury SK, 2002, Risk Aversion and Incentive Effects. The American Economic Review, 92(5): 1644–1655.

[14] Healy A, Pate J, 2011, Can Teams Help to Close the Gender Competition Gap? The Economic Journal, 121(555): 1192–1204.

[15] Bailey W, Kumar A, Ng D, 2011, Behavioral Biases of Mutual Fund Investors. Journal of Financial Economics, 102(1): 1–27.

[16] Korniotis GM, Kumar A, 2011, Do Older Investors Make Better Investment Decisions? The Review of Economics and Statistics, 93(1): 244–265.

[17] Nagel S, Greenwood RM, 2009, Inexperienced Investors and Bubbles. Journal of Financial Economics, 93(2): 239–258.

[18] Ahlers GKC, Cumming D, Günther C, et al., 2015, Signaling in Equity Crowdfunding. Entrepreneurship Theory and Practice, 39(4): 955–980.

[19] Iyer R, Khwaja AI, Luttmer EF, et al., 2015, Screening Peers Softly: Inferring the Quality of Small Borrowers. Management Science, 62(6): 1554–1577.

[20] Riggins FJ, Weber DM, 2017, Information Asymmetries and Identification Bias in P2P Social Microlending. Information Technology for Development, 23(1): 107–126.

[21] Dorfleitner G, Fischer L, Lung C, et al., 2018, To follow or not to follow: An Empirical Analysis of the Returns of Actors on Social Trading Platforms. The Quarterly Review of Economics and Finance, 2018(70): 160–171.

[22] Han JT, Chen Q, Liu JG, et al., 2018, The Persuasion of Borrowers' Voluntary Information in Peer-to-peer Lending: An Empirical Study based on Elaboration Likelihood Model. Computers in Human Behavior, 2018(78): 200–214.

[23] PPdai, 2016, 2016 Performance Report of PPdai, viewed August 24, 2022, http://www.ppdai.com/event/2016annals.html