The Impact of Automated Investment on Peer-to-Peer Lending:
Investment Behavior and Platform Efficiency

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ABSTRACT

In the face of fierce competition, many peer-to-peer (P2P) lending platforms have introduced automated investment tools to serve customers better. Based on a large sample of data from PPdai. com, the authors studied the impact of automated investment on lenders' investment behavior and platform performance. Using the propensity score matching (PSM) method, this article checks the differences of funding duration and loan performance with and without participation of automated investment tools in P2P lending. The empirical results show that automated investment in P2P lending can significantly weaken investors' herding behavior. The authors also found that automated investment prolongs the average funding duration of loans and undermines the platform efficiency. Furthermore, this study indicates that usage of automated investment does not affect the return on investment (ROI) in general.

KEYWORDS

Automated Investment, Funding Duration, Herding Effect, Loan Performance, Peer-to-Peer Lending

INTRODUCTION

Background and Motivation

As an emerging form of microfinance, online peer-to-peer (P2P) lending helps individual lenders and borrowers perform transactions directly on the Internet. Due to the existence of information asymmetry (Freedman & Jin, 2011; Massa & Simonov, 2006; Yum et al., 2012) and moral hazard (Arnott & Stiglitz, 1991; Pointner & Raunig, 2018) in P2P lending, many scholars are attracted to the study of P2P lending. There are two main streams of research. One explores how borrowers' information affects lenders' investment decisions. Borrowers' financial information has been confirmed to relate significantly to funding success (Herzenstein et al., 2008), and their credit ratings have a strong effect on interest rates (Klafft, 2008). Loan amount and interest rate have a negative impact on the funding success ratio (Puro et al., 2010, Zhang & Liu, 2012). Information such as loan description and borrower's picture can alleviate information asymmetry (Wang et al., 2019, Liang & He, 2020). The other research stream focuses on the behavior of lenders in P2P lending. Herding behavior has

been confirmed in P2P lending, as potential lenders are more likely to fund loans that have more prior lenders (Zhang & Liu, 2012, Herzenstein et al., 2011). The amount funded by prior lenders is also an important attribute valued by potential lenders (Lee & Lee, 2012; Liu et al., 2015). Lenders might bid in the latter stage of a loan period to minimize the opportunity cost of a failed loan (Ceyhan et al., 2011).

P2P lending platforms are facing fierce competition to attract lenders and provide better investment opportunities. Based on massive transaction data and sophisticated knowledge management methods (Roblek et al., 2014), P2P platforms are trying to lure and retain customers with innovative services. Nowadays, more and more P2P lending platforms (e.g., Prosper, LendingClub, and PPDai) are offering automated investment services to lenders. By using such an automated service, a lender can set his/her personal investment criteria including the borrower's credit rating, the loan's interest rate, and investment amount, and the automated investment tool will execute accordingly (Ceyhan et al., 2011). The automated investment tool can thus relieve some of the lender's burden of continuously looking for better investment projects, but the purpose of our study is to ascertain whether there are any other impacts. The authors want to find out how automated investment in P2P lending affects lender behavior, lender return on investment (ROI), and platform operation efficiency.

Focus Questions

Compared with manual investment, automated investment has many advantages. First, it can be online all the time and this feature enables real-time monitoring of P2P projects. Anthony and Jennings (2003) stated that an autonomous agent can help consumers to monitor and pick the auction in which to participate. Most platforms employed "all or nothing" mechanisms, which means that a P2P project will close once it reaches the requested amount. Therefore, successful participation in some hot P2P projects is one of the most important issues for investors. With automated investment, an investor will have more chance to identify preferred P2P projects on platforms than those without, due to the real-time monitoring. Second, the processing power of automated investment can significantly outperform humans in selecting projects and the speed of making decisions. Bui and Lee (1999) proposed that intelligent agents have tremendous potential in supporting multi process and objective decision tasks. This can save time and makes it easier to invest in popular funding projects. In addition, using the automated investment tool makes it possible to handle multiple P2P lending projects at the same time. Investors may have better returns, save more time, and the platform may have higher operation efficiency. With these advantages, however, the authors question how automated investment changes lender behavior and platform efficiency in P2P lending. This is the key research issue that the authors are going to focus on in this study.

Automated investment has been utilized in e-commerce for a long time. For example, on eBay buyers can set the maximum amount that they are willing to bid for an auction (Rogers et al., 2007). The proxy bidding system then automatically submits bids on their behalf, and the eBay protocol guarantees that the bidder who has entered the highest amount wins the item, but pays no more than the amount entered by the second highest bidder plus the minimum bid increment (Gregg & Walczak, 2003; Martin et al., 2009). Previous research has found that the proxy bidding agent can affect bidder behavior and auction process significantly. Cai et al. (2011) found the proxy auction performs better than the non-proxy auction in terms of the seller's expected revenue in an online auction. Kim et al. (2019) studied the efficiency of active-bidder (bid manually) and smart-bidder (bid by automated system) methods and found that the proxy bidding system helps consumers elevate their happiness in winning after the auction ends.

Another similar application of automated investment is high-frequency trading (HFT) in the stock market. O'Hara (2015) proposed that HFT is changing the market from human involvement to computer control, and the operating time scale has changed from minutes to microseconds. Her study indicates that HFT affects the strategies of traders and markets significantly. Menkveld (2016) showed that HFT reduces transaction costs substantially in the stock market. As a type of automated

trading characterized by high speeds and high frequency, previous studies have proven that HFT has a positive impact on traders' behavior and portfolio performance (Biais & Foucault, 2014; Angel et al., 2010; Cooper et al., 2016).

Similarly, the authors believe that the introduction of automated investment in P2P lending will bring changes to the whole market. However, this is not well studied in P2P lending. Previous studies are based on the assumption that all investments are made by real people, but this has changed with the introduction of automated investment. Therefore, this paper proposes that automated investment in P2P lending will have a significant impact on investors' behavior, platform efficiency, and ROI. The authors have studied the impact of automatic bidding on individual investors, market efficiency, and revenue, and the authors aim to answer the following three questions:

1. How will automated investment affect investment behavior?
2. How will automated investment affect ROI?
3. How will automated investment affect platform operation efficiency measured by average bidding duration?

Data and Results

The authors obtained a large dataset (26,034 completed P2P projects) from one of the largest P2P lending platforms in China, PPDai.com. By using the propensity score matching (PSM) method, the authors analyzed the impact of automated investment in P2P lending. Surprisingly, the results indicate that automated investment weakens investors' herding behavior, and it doesn't improve the platform operation efficiency that is measured by the average bidding duration, nor the ROI. These findings are quite different from previous ones in the fields of online auction and HFT.

Contributions

To the best of our knowledge, this study is the first to explore the impact of automated tools on investment behavior and platform performance in online P2P lending. Our findings not only provide insights into understanding the mechanism of automated investment, but also shed light on how to manage online crowdfunding platforms.

The rest of the paper is organized as follows. In Section 2, the authors provide a literature review, while Section 3 offers our hypothesis development. In Section 4, the authors present details of the data and descriptive statistic results, and in Section 5, the authors explore the impact of automated investment on investor behavior (especially the herding effect), bidding duration, and loan performance. Section 6 offers the robustness check, while conclusions, contributions, and future research are discussed in Section 7.

LITERATURE REVIEW

Information Cascade

In *The New Palgrave Dictionary of Economics*, Bikhchandani et al. (2008) define 'information cascade' and explain it with observational learning theory. An information cascade occurs when individuals make the same decision as those ahead of them after observing the previous investment instead of cautiously considering their own information and judgement. The possibility of using socially acquired information has been biologically proved, and when erroneous cascades are costly, individuals should only consider socially generated cues and not behavioral decisions (Giraldeau et al., 2002). These works provide psychological interpretation for the herding effect and a primary explanation for its negative effect.

Investment Behavior in P2P Lending

In P2P lending, many factors have been proved to have significant influence on investment behavior, such as interest rate (Puro et al., 2010), information offered by borrowers (Yan et al., 2018), and social relationships between borrowers and lenders (Lin et al., 2013; Liu et al., 2015; Hildebrand et al., 2017).

Herding is one of the significant phenomena in online P2P lending. As a social behavior, herding has been studied for a long time, with Devenow and Welch (1996) proposing that herding can be viewed from two pillars: non-rational and rational. The non-rational view centers on investor psychology, in which one follows another blindly and foregoes rational analysis. Rational herding centers on externalities, which means optimal decision-making is distorted by information difficulties. Raafat et al. (2009) define herding as a form of convergent social behavior that is the alignment of the thoughts or behaviors of individuals in a group (herd) through local interaction and without centralized coordination.

Zhang and Liu (2012) demonstrated the existence of rational herding in P2P lending markets using data from Prosper.com, while Lee and Lee (2012) found strong evidence of herding and its diminishing marginal effect as bidding advances. Chen and Lin (2014) discovered that irrational herding exists in the Chinese P2P lending market, and Ceyhan et al. (2011) found that herding behavior occurs during bidding, and the lenders' bids in most projects spike at similar time points. Vo and Phan (2017) proposed that investors under information asymmetry will seek collective wisdom to make reasonable investment decisions, which may lead to herding behavior. However, those studies focused on investments made only by human investors. With the participation of automated investment, how will the investor behavior change? This is still unknown.

Automated Tools and Their Impact

Previous studies have demonstrated that HFT can significantly affect the performance of the stock market. Naidu et al. (1994) compared stock trading before and after automation and found that automation increases trading volume, return volatility, and liquidity. Freund et al. (2000) found that stock trading automation improves operational efficiency but does not prompt significant changes in market efficiency. Angel et al. (2010) found computer-based automation helps fulfill investors' demands for better solutions, while Malinova et al. (2013) found that retail investors paid larger effective spreads in HFT. Cartlidge et al. (2012) revealed that slow-agent markets are more efficient than others. These studies provide a reliable basis for us to assume that automation tools will affect platform performance.

Veit et al. (2003) used simulations to demonstrate the superiority of automated bidding in online auction markets. Cai et al. (2011) found that proxy auctions perform better than non-proxy auctions in terms of the seller's expected revenue, while Kim et al. (2019) found that the proxy bidding system elevates bidder's happiness in winning.

Research on P2P platform performance is rather limited. Yan et al. (2018) used the number of investors to measure the P2P platform performance and found that credit records and capital of platform can affect the investors' trust. Serrano-Cinca and Gutiérrez-Nieto (2016) used internal rate of return to measure the expected profitability of investing in P2P loans.

A P2P lending platform serves as an intermediary between borrowers and lenders. For borrowers, the time for a project to be funded successfully (bidding duration) is a key factor in evaluating the performance of the lending platform. Lenders care about ROI, and a platform's main revenue comes from the transaction service fee. Faster fundraising, more transactions, and higher loan quality will attract more participants and bring more revenue to the platform. To understand automated investment's impact on P2P platform performance better, the authors use bidding duration as the metric in this study.

HYPOTHESIS DEVELOPMENT

In this paper, the authors mainly focus on the herding effect to study the change of investment behaviors with the participation of automated investment in P2P markets. Previous studies have revealed that the herding effect existed in online P2P lending before the introduction of automated investment. As the authors mentioned in our literature review, due to information asymmetry and a large number of non-professional investors, herding exists widely in P2P lending. Therefore, the authors use the herding effect to measure the impact of automatic bidding on investors' behavior.

Automated investment tools in the P2P market execute trading as specified, which is exempt from the interference caused by the herding of other individual investors. The automated investment agent can be regarded as the "most rational investor," since it will not be affected by the behavior of other investors. Due to the existence of herding in the P2P market, some investors will follow others to make bids blindly (Zhang & Liu, 2013; Lee & Lee, 2012). When a new P2P project is listed on the website, automated investments can increase the cumulative bid amount in a short time, which may lead to a higher probability of the herding effect. Considering this scenario, the authors make our first hypothesis (H1):

H1. Automated investment strengthens the herding effect in P2P lending.

In the field of online bidding and HFT, automated tools have been shown to improve platform performance significantly. Cooper et al. (2016) studied the data from NASDAQ and found that HFT enhances market liquidity by increasing the trade frequency and quantity of low frequency orders in the stock market. Biais and Foucault (2014) proposed that HFT in the stock market could enhance the efficiency of prices and play a positive role in the price discovery process. Kim et al. (2019) designed four experiments to compare active-bidder (manual) and smart-bidder (proxy bidding) methods, and found the online auction consumers rely heavily on proxy signals and that the proxy tools improved the bidding platform efficiency. If a new P2P project is listed on the site, automated investment agents will bid immediately if the project meets the criteria. Consequently, the speed of funding will be faster than the manual mode. The authors select the average bidding duration to represent the efficiency of the P2P lending market. Therefore, the authors propose our second hypothesis (H2):

H2. Automated investment shortens the average *bidding durations of P2P listings.*

Automated investment can result in faster investment decisions, but the tool might ignore important soft information. Netzer et al. (2016) found loan description plays an important role in predicting loan performance, while Dorfleitner et al. (2016) showed that description texts of borrowers have significant predictive capability in the probabilities of successful funding and default in P2P lending. Automated investment agents cannot take borrower's soft information and complex background into consideration. Therefore, automated investment may increase investment risk and deteriorate loan performance. The authors thus propose our third hypothesis (H3):

H3. Automated investment decreases the ROI.

METHODOLOGY

Research Instrument

The authors collected bidding data of loan projects launched on PPDai from May 2015 to Jan 2016. This dataset contains all bidding amounts and time information for nearly 500,000 P2P projects. However, it is challenging to collect repayment information because PPDai does not provide the data

Table 1. Descriptions of variables

Variables	Descriptions
AutoBid	The listing has automatic (if AutoBid=1) and non-automatic (if AutoBid=0) investments.
LAPF	Lag Accumulative Percentage Funded, which means the percentage of funds raised.
Rating	Credit rating of the listing, ranking from 6 to 1. It is evaluated and provided by the platform.
AMT	Borrowing amount of the listing.
P_Period	Payback period of the listing.
Age	Borrower's age, ranging from 18 to 60, provided in the dataset.
Gender	Borrower's gender, where 1 represents male and 0 female.
IR	Interest rate of a listing.
Bor_Cr	User's borrowing credit score, which is evaluated by the platform based on borrowers' credit records.
Lend_Cr	User's lending credit score, which is evaluated by the platform based on lenders' investment performance.
Cert	Certification provided by a borrower, which includes education qualification, household registration, and real name authentication. 1 represents that the borrower has uploaded at least one certification, while 0 means no certification is provided.
Max_T	Bidding duration of a listing measured by minute, which is the time a project takes to be fully funded.
Repay_S	Amount of repayment of a funded listing.
IR_S	Listed interest rate of a funded listing.
D_AMT	Default amount of a listing.
ROI	Return on investment.

of closed projects. Fortunately, PPDai uploaded a dataset on "kecsi.com" in 2018, which contains the repayment information of nearly 100,000 past P2P loans. The authors matched the original dataset with the repayment data using the loan IDs. Finally, the authors obtained 26,034 P2P loan projects with both bidding and repayment records. Variables are listed in Table 1.

Data

For a more comprehensive understanding of the data, the authors make summary statistics of the 26,034 listings, as shown in Table 2. In this dataset, the requested loan amount (*AMT*) ranges from 100 RMB to 500,000 RMB, with an average amount of 6,957.81 RMB. The average interest rate (*IR*) is 20.55%. *Rating* is the credit rating of the listing, which is evaluated by the platform, and the mean value is 3.04, which is between C-D rating. *Cert* indicates whether a listing has any certification, including ID card, education, or registered permanent residence. An average of 0.8529 means that 85% of the borrowers in the sample have completed at least one certification. *Bor_Cr* and *Lend_Cr* represent a user's borrowing-in credit score and lending-out credit score, respectively. In PPDai, users are allowed to borrow and lend money at the same time. The platform would evaluate the *Bor_Cr* and *Lend_Cr* according to the performance of a user as a borrower and investor, respectively. For example, a user often defaults on repayment as a borrower, but has lent a large amount of money as a lender at the same time. In such an instance, the user would have a low *Bor_Cr* and a high *Lend_Cr*.

Table 2. Summary statistics of paired listings

Variable	Obs	Mean	Std. Dev.	Minimum	Maximum
AMT	26034	6957.81	20991.95	100	500000
IR	26034	0.2055	0.0261	0.085	0.24
Rating	26034	3.4033	0.8952	1	6
P_Period	26034	9.6330	3.5028	2	24
Cert	26034	0.8529	0.3541	0	1
AutoBid	26034	0.3388	0.4733	0	1
Bor_Cr	26034	31.5314	12.9366	0	151
Lend_Cr	26034	83.1626	4411.5260	0	704203
Gender	26034	0.8184	0.3855	0	1
Age	26034	29.3953	14.0160	17	64
Max_T	26034	15.7722	42.0243	0	512
Repay_S	26034	6360.49	20644.57	0	500000
IR_S	26034	510.868	981.24	0	22323.54
D_AMT	26034	-237.632	2678.21	-24000	0
ROI	26034	0.0404	0.0932	-0.0844	0.1347

*Note:*The data for this table include a successfully paired sample of 26,034 listings posted on PPDai.com from May 2015 to Jan 2016.

To obtain a preliminary characterization of the *Rating* distribution, the authors analyzed the distribution of credit grades, categorized by whether the listing is automatically bid (*AutoBid*=1) or manually bid (*AutoBid*=0) upon. As shown in Table 3, there are almost no automated bids for P2P loan projects with credit rating 1 and 2. It can be inferred that an automated investment tool is mostly used with a high criteria of credit rating. These differences imply that if an automated tool is used, funds would not be invested into projects with lower credit. This increases bidding duration of listings with lower ratings.

Further, the authors analyzed the bidding duration of the projects in our dataset (see Figure 1 for distribution of bidding duration). Nearly 50% of the listings were successfully funded in an hour.

Table 3. Distribution of credit grade and bidding sort

Rating	Overall	AutoBid=0	AutoBid=1	Mean Difference
6	0.76%	1.00%	1.81%	0.81%
5	12.91%	6.07%	14.84%	8.77%
4	43.17%	25.87%	46.49%	20.62%
3	32.85%	46.51%	36.65%	-9.87%
2	9.04%	19.42%	0.19%	-19.23%
1	1.28%	1.13%	0.02%	-1.11%
Total	100.00%	100.00%	100.00%	
Number of Obs.	26034	17212	8822	

*Note:*The data for this table include a successfully paired sample of 26,034 listings posted on PPDai.com from May 2015 to Jan 2016.

Figure 1. Distribution of bidding duration
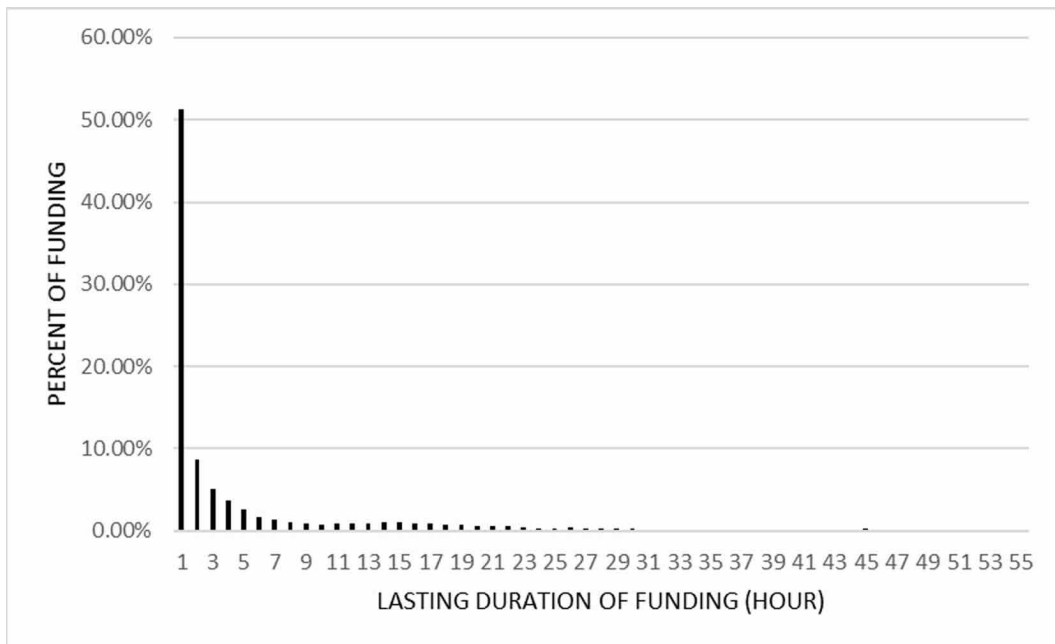
Thus, authors set the unit of the bidding period to one hour, which can help provide an optimal visual presentation of the data distribution.

Statistical Methods

With the repayment information of nearly 100,000 P2P loans on PPDai.com, the authors successfully matched the original dataset with the repayment data using loan IDs. Eventually, they obtained 26,034 P2P loan projects with both bidding and repayment records. Based on the data, the authors processed the variables and present them in Table 2. In later analysis, the authors performed OLS regression as a primary test of herding, then added new interaction terms to understand better the herding effect under automated investment. To find out the effect of automated investment on bidding duration and ROI, the authors employed the PSM method.

Validity

In the qualitative research part, the authors chose three dependent variables: herding behavior, bidding duration, and ROI. Herding behavior represents risk, bidding duration reflects the time cost, and ROI is the benefit. An investor pursues the largest benefit under the least time cost and smallest risk, which means that the three elements cover the most fundamental perspectives that an investor could experience during an investment. The authors applied OLS regression and the PSM method. The validity of these two methods have already been demonstrated. The herding behavior is represented by the ratio of the percentage funded manually and the lagged cumulative percentage that is funded, which shows the degree of herding effect influenced by the degree of bidding completion.

ANALYSIS AND RESULTS

Herding Behavior

The authors use OLS regression as a primary test of herding. The regression is composed of the percentage funded manually $y_{i,t}$, lagged cumulative percentage that is funded $Y_{i,t-1}$, and time-invariant listing attributes Z_t, as shown in Eq(1):

$$y_{i,t} = \alpha Y_{i,t-1} + \beta Z_i + \varepsilon_{i,t} \text{ Eq} \tag{1}$$

where t=1, 2, 3,,, T.

The listing attributes Z_t include the following variables: *Rating*, *AMT*, *P_Period*, *Age*, *Gender*, *Bor_Cr*, *Lend_Cr*, and *Cert*. In particular, *IR* and *Rating* are both set by the platform based on the information that borrowers provided and they are highly correlated. To avoid multi-collinearity, the authors only select *Rating* in our model.

Table 4 shows the OLS estimation with robust standard errors. In column (1), the effect of *Lag Accumulative Percent Funded* (LAPF) is positive and significant, which means that the closer the fund is to the requested amount, the more manual bids it can attract. The result provides strong evidence that there is a significant herding effect between the manual P2P investors. Additionally, several control variables have significant effects on y_{it}. *Rating* shows a positive and significant effect, which indicates P2P loans with higher credit have more manual biddings. The coefficient of *P_Period* is -0.00361, which indicates the expected payback period of P2P loans can affect funding negatively and manual investors are more willing to invest short-duration loans. The effect of *Cert* is also positive and significant, which means those P2P projects with borrowers' certifications are more likely to attract investors.

To understand better the herding effect under automated investment, the authors add a new interaction term *LAPF*Lautoamassratio* to the equation. *Lautoamassratio* is the lagged percentage of accumulated amount funded with automated investment with respect to the total amount funded. Meanwhile, the authors considered the fixed effect of the data based on the result of a Hausman test to establish Eq(2).

$$y_{i,t} = \alpha Y_{i,t-1} + Z_{it}\beta_2 + Y_{i,t-1} * Z_i\beta_3 + u_i + v_{i,t} \text{ Eq} \tag{2}$$

where $Y_{i,t-1}*Z_i$ denotes the interaction terms of the model and u_i denotes the coefficient of each loan in the fixed effect model.

The results of Eq(2) are reported in column (2) of Table 5. The coefficient of the interaction term *LAPF*Lautoamassratio* is negative and significant. As mentioned above, the impact of LAPF on $y_{i,t}$ (the percentage funded manually) reflects the herding effect among manual investors. In column (2), the impact of LAPF is positive while the interaction term *LAPF*Lautoamassratio* has a negative effect, which means a higher proportion of accumulative automated investment will lead to a lower proportion of manual bidding with respect to the total amount in the next period. The estimation result of Eq(2) suggests that, after the participation of automated investment, the herding effect in a P2P lending market becomes weaker than before. Thus, the data in column (2) do not support H1. For the results, there are two possible explanations: information cascade and the filtering effect of automated investment on P2P investors. In order to explain the facts, the authors provide a more detailed discussion in our Conclusion.

Table 4. Main Results of Herding

Variables	(1)	(2)	(3)	(4)
LAPF	0.0350***	0.180***		0.198***
	(0.00263)	(0.00473)		(0.0244)
Rating	0.0239***		0.0731***	
	(0.000941)		(0.00550)	
AMT	-4.30e-07***		-2.37e-06***	
	(8.40e-09)		(1.42e-07)	
P_Period	-0.00361***		0.00634***	
	(0.000218)		(0.00118)	
Age	0.00200***		0.00204	
	(0.000109)		(0.00129)	
Gender	0.0281***		0.176***	
	(0.00195)		(0.00999)	
Bor_Cr	-0.00195***		-0.00283***	
	(7.03e-05)		(0.000295)	
Lend_Cr	-4.81e-06***		1.35e-06***	
	(9.59e-07)		(1.78e-07)	
Cert	0.0623***		0.0923***	
	(0.00365)		(0.0113)	
LAPF *Lautoamassratio		-0.123***		-0.0915***
		(0.0129)		(0.0140)
LAPF*Rating				0.00616
				(0.00507)
LAPF*P_Period				0.000995
				(0.00107)
LAPF*Gender				0.00771
				(0.00851)
LAPF*AMT				-3.62e-07***
				(3.93e-08)
LAPF*Lend_Cr				1.98e-07
				(4.74e-06)
LAPF*Bor_Cr				-0.00330***
				(0.000304)
LAPF*Cert				0.0890***
				(0.0157)
Listing Fixed Effects	No	Yes	No	Yes
Observations	60,482	63,729	23,767	60,482
R^2	0.279	0.058	0.542	0.066
Adjusted R^2	0.279	0.0576	0.542	0.0663
Number of pid		11,672		10,876

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The dependent variable of column (1) ~ (4) is the percentage funded manually $y_{i,t}$.

Table 5. Matching estimates of the automated investment on Max_T and ROI

Variable	Sample	Treated	Controls	Difference	S.E.	T-Stat
Max_T	Unmatched	32.101	7.403	24.699	0.5285	46.73***
	ATT	32.102	7.2147	24.887	0.6996	35.57***
ROI	Unmatched	0.04903	0.04643	0.00259	0.00215	1.20
	ATT	0.04904	0.04976	-0.0007	0.00255	-0.28

Notes: This table presents the nearest-neighbor PSM estimates of the automated investment effect on *Max_T* and *ROI*. The number of matches to be searched M=3. *p<0.1; **p<0.05; ***p<0.01.

To test further if other listing attributes have the same weakening effect, the authors adjusted Eq(2) by adding the interaction terms between LAPF and other variables, which are significant in the former regression. Columns (3) and (4) of Table 4 present the new estimated main effects.

As shown in column (3), a larger proportion of manual funding is associated with a higher credit grade, a smaller amount requested, and certification. A smaller requested amount indicates a higher probability of funding success and less funding time. With the exceptions of *P_Period* and *Lend_Cr*, the coefficients of *Gender* and *Age* are consistent with the results of the regression, which are significant at the 10% level. Column (4) of Table 4 shows results based on whole periods of P2P loans. Some of the interaction terms have negative coefficients, showing the moderating effects. *LAPF* Lautoamassratio* and *LAPF* AMT* are negative and significant at the 1% level. This result not only verifies the correctness of the estimation coefficient in column (2), but also indicates that the higher borrowing amount will weaken the herding effect in the P2P market.

Bidding Duration and ROI

To ascertain the effect of automated investment on bidding duration and ROI, the authors employed the PSM method to match the loans that have automated investments with those that only received funds from manual investors. The covariates include *LAPF*, *Rating*, *AMT*, *P_Period*, *Age*, *Gender*, *IR*, *Bor_Cr*, *Lend_Cr*, and *Cert*.

The authors set the automated investment as "treatment." The control group includes loans funded by manual investment. Then, the authors estimated the treatment effect associated with the participation of automated investment using nearest-neighbor PSM. After, the authors estimated the following probability of being in the treatment group given the set of covariates discussed above, using a logistic regression shown in Eq(3).

$$\rho(x) = \Pr(D_i = 1 | X = x_i) \text{Eq} \tag{3}$$

where D_i is a dummy variable equal to 1 if automated investment participates in the funding, and X consists of all the covariates. Then, the authors estimated the average treatment effects on the treated (ATT) with Eq(4).

$$
\begin{aligned}
ATT &= E\left[Y_{1i} - Y_{0i} \mid D_i = 1\right] \\
&= E\{E\left[Y_{1i} - Y_{0i} \mid D_i = 1, P(X_i)\right]\} \qquad \text{Eq} \\
&= E\{E\left[Y_{1i} \mid D_i = 1, P(X_i)\right] - E\left[Y_{0i} \mid D_i = 0, P(X_i)\right]\}
\end{aligned}
\tag{4}
$$

In the aspect of bidding duration, the matching estimations of *Max_T* are shown in Table 5. For the automated-bidding group, the average bidding duration is 32.101 hours, whereas for the manual-bidding group it is 7.403 hours. The ATT of the matching estimates is 24.887, being significant at 1%, which means that there will be a 24.887 increase in the treated group compared with the non-treated group. The values of T-Stat in Table 5 reveal the fact that the participation of automated investment will significantly increase the average bidding duration of P2P loan projects. This result does not support H2.

The authors notice that 211 out of 26,034 listings were still in the payoff process when the data were collected. As such, the authors delete these loans and use PSM to estimate the ATT of ROI. However, as shown in Table 5, the value of T-Stat suggests that the matching estimation of ATT is not significant in ROI. There is no difference in this dependent variable between the two groups regarding the ROI of P2P loans.

Results

H1 is not supported, as the negative coefficients of interaction terms in the model indicate that the participation of automated investment weakens the herding effect in a P2P lending market significantly. Compared with the herding in the market without auto bidding, the weakening effect is considered to be an adjustment resulting from rationality (Zhang & Liu, 2013). Other variables such as credit rating and total amount requested also exhibit negative coefficients in the model, which also indicates the negative adjustment of the herding.

H2 is also not supported. The average bidding duration becomes longer with the participation of automated investment, as the PSM result shows. This is contrary to previous findings of efficiency improvement with automation in online auction and HFT. Due to the participation of automated investment tools, the herding effect is weakened, which means some investors will spend more time collecting relevant information and making decisions instead of following other investors blindly.

Further, H3 is also not supported. By comparing the loan performance with matched listings using PSM methods, the authors find there are no significant changes in ROI with the participation of automated investment. In the following robustness check, the authors employ a Cox Proportional Hazard Model using a sample with right censored data and find that the estimations are consistent. The results indicate that there is no significant relationship between the loan performance and automated investment.

ROBUSTNESS CHECK

Herding Effect Under Automated Investment

To testify the outcome, the authors first changed the variable *Lautoamassratio* to the dummy variable *AutoBid*. If *Lautoamassratio = 0* then *AutoBid* = 0, else *AutoBid = 1*. The authors reran the fixed effect model, and found the estimates are consistent with the results in Table 4. The results of this check are listed in Table 6.

Subsequently, the authors changed the time interval of the panel to check whether the herding effect under automated investment is consistent. The authors reconstructed the panel with a 30-minute interval based on the same set of samples. Table 7 shows the results of Eqs (1-2) at the half-hourly level. All the variables are significant, and their signs are the same as those in Table 4.

Bidding Duration

To check the result in Table 5 and further test the heterogeneity of matched samples, the authors categorized the samples according to their credit grades and total amount requested, and conducted PSM analysis. The authors estimate the ATT of *Max_T* in each category. The results of our robustness check are shown in Tables 8 and 9.

Table 6. Robustness check with different variables

Variables	(1)	(2)
LAPF	0.242***	0.206***
	(0.00992)	(0.0253)
LAPF*AutoBid	-0.105***	-0.0976***
	(0.0106)	(0.0110)
LAPF*Rating		0.0184***
		(0.00561)
LAPF*P_Period		0.00197*
		(0.00113)
LAPF*Gender		0.00648
		(0.00880)
LAPF*Capital		-3.42e-07***
		4.00e-08)
LAPF*Lend_Cr		7.63e-07
		(4.58e-06)
LAPF*Bor_Cr		-0.00350***
		(0.000325)
LAPF*Cert		0.0953***
LAPF*Rating		(0.0162)
Listing fixed effects	YES	YES
Observations	63,729	60,482
R^2	0.061	0.069
Number of pid	11,672	10,876
Adjusted R^2	0.0605	0.0686

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The robustness test provides the evidence that after the introduction of automated investment, the bidding duration of manual bidding is prolonged.

ROI

In this robustness test, the authors used the default rate of loans to replace the variable "ROI" to measure the loan performance. All of the listings in the sample have the corresponding loan performance records. A loan is defined as "defaulted" if it has been delinquent for 90 days or more. According to the definition, 7.34% of the loans had defaulted as of February 22, 2017.

To handle the projects that were still in the payoff period, the authors used a Cox Proportional Hazard (CPH) model to analyze the default rates. Table 10 presents the parameter estimates and associated hazard ratio. The hazard ratio of *Autocaprate* is not significant, consistent with the conclusion the authors draw in the PSM estimates.

Table 7. Half-hourly panel

Variables	(1)	(2)	(3)	(4)
LAPF	0.0228***	0.135***		0.212***
	(0.00192)	(0.00341)		(0.0178)
Rating	0.0163***		0.0632***	
	(0.000702)		(0.00538)	
AMT	-3.39e-07***		-2.17e-06***	
	(5.52e-09)		(1.35e-07)	
P_Period	-0.00247***		0.00404***	
	(0.000151)		(0.00117)	
Age	0.0227***		0.176***	
	(0.00143)		(0.00978)	
Gender	0.00159***		0.00203	
	(8.06e-05)		(0.00125)	
Bor_Cr	-0.00136***		-0.00282***	
	(4.95e-05)		(0.000290)	
Lend_Cr	-4.08e-06***		1.47e-06***	
	(9.58e-07)		(2.19e-07)	
Cert	0.0477***		0.0780***	
	(0.00280)		(0.0112)	
LAPF *Lautoamassratio		-0.118***		-0.0785***
		(0.00923)		(0.00938)
LAPF*Rating				-0.00630*
				(0.00340)
LAPF*P_Period				0.000273
				(0.000693)
LAPF*Gender				0.000262
				(0.00582)
LAPF*AMT				-2.35e-07***
				(2.40e-08)
LAPF*Lend_Cr				-1.03e-06
				(2.84e-06)
LAPF*Bor_Cr				-0.00238***
				(0.000216)
LAPF*Cert				0.0472***
				(0.0118)
Listing Fixed Effects	No	Yes	No	Yes
Observations	85,101	89,692	23,767	85,101
Adjusted R^2	0.243	0.0457	0.475	0.0537
Number of pid		13,388		12,477

Notes: *** p<0.01, ** p<0.05, * p<0.1

Table 8. Estimation of ATT categorized by credit grade and total amount requested

Rating	Rating=6		Rating=5		Rating=4	
	ATT	T-Stat	ATT	T-Stat	ATT	T-Stat
neighbor (3) radius	17.821	4.49***	10.904	10.18***	20.692	26.21***
	21.018	5.14***	10.362	9.79***	20.902	26.74***
Rating	**Rating=3**		**Rating=2**		**Rating=1**	
	ATT	T-Stat	ATT	T-Stat	ATT	T-Stat
neighbor (3) radius	40.765	31***	-10.167	-0.50***	-24.67	0
	42.386	32.75***	7.203	0.4	-	-
AMT	**0-1000**		**1000-5000**		**5000-10000**	
	ATT	T-Stat	ATT	T-Stat	ATT	T-Stat
neighbor (3) radius	1.651	2.28***	25.432	25.93***	29.873	29.47***
	1.508	2.29***	25.032	24.15***	29.58	28.71***
AMT	**10000-50000**		**50000-100000**		**100000-500000**	
	ATT	T-Stat	ATT	T-Stat	ATT	T-Stat
neighbor (3) radius	34.077	12.63***	14.427	1.65	30.545	2.60**
	33.88	12.82***	15.679	1.81***	31.467	2.73***

Notes: There is a deficiency of estimation at the category *Rating=1* because the sample size of this category is too small for the second matching method.

Table 9. PSM estimation of bidding duration and bidding density

Variables	Sample	Treated	Controls	Difference	S.E.	T-Stat
Funding Duration	Unmatched	401.465	366.192	35.273	10.493	3.36***
	ATT	401.511	159.47	245.041	111.73	2.19***
Bidding Density	Unmatched	1859.09	1409.98	449.1121	36.382	12.34***
	ATT	1859.06	1236.84	622.2131	238.88	2.60***

Notes: *** p<0.01, ** p<0.05, * p<0.1

DISCUSSION

None of the three hypotheses (H1, H2, H3) are supported, and the authors offer here some discussion on our results.

For H1:

The introduction of automated investment reduces the herding effect in P2P lending. Based on previous theories, the authors believe that information cascade and the filtering effect of automated investment on P2P investors are the main reasons.

Information cascade: Welch (1992) found that the information cascade among investors plays an important role in venture financing. Vismara (2016) studied the information cascade in equity crowdfunding and found that public profile increases the attractiveness of investors, while early

Table 10. Cox Proportional Hazard Model

Variables	Default	
	Estimate	Hazard Ratio
LAPF	-0.233***	0.8459***
	(0.0352)	
Rating	1.82e-06	1
	(1.48e-06)	
AMT	0.0900***	1.1303***
	(0.00764)	
P_Period	0.000893	1.0008
	(0.000872)	
Age	0.0361	1.0217
	(0.0693)	
Gender	-0.0152***	0.9913***
	(0.00298)	
Bor_Cr	-0.00204***	0.9977***
	(0.000786)	
Lend_Cr	-0.217***	0.8270**
	(0.0790)	
Autocaprate	0.178	1.0073
	(0.123)	
Numbers of Obs.	23,798	
-2 Log Likelihood	28114.694	

Notes: *** $p<0.01$, ** $p<0.05$, * $p<0.1$

investors in turn attracted later investors. However, automated investment affects the information cascade in the P2P lending market. The decision of automated investment is made entirely by machines. Later investors can realize that previous investments were made by a machine and as a result will not blindly follow. Therefore, automated investments may impact the behavior of other bidders in the P2P lending market.

The filtering effect of automated investment: When the automated tool is applied, a number of manual investors would choose to use the tool. The rest would be more rational, and less passive imitation would occur during bidding.

For H2:

The introduction of automated investment prolongs the average bidding duration of P2P loans. In general, automated tools would improve market efficiency. However, P2P loans with low credit rating were not chosen by the automated investment tool, as shown by the data. Loans with high credit ratings would get funded in less than an hour. Meanwhile, the bidding duration of a low-credit project is usually more than one day, and sometimes one month. Before the introduction of automated investment, irrational herding helped low-credit projects to get funded. Automated investment has

weakened this effect, which increases the time to successful bidding. Therefore, this result indicates that bidding duration becomes longer on average with automated investment.

For H3:

In terms of return, automated investment has no distinctive advantages over manual bidding. P2P loans with a high interest rate generally have high credit risks. However, there are some projects with a high interest rate and low repayment risk. To find these listings, one needs to go through the borrowers' soft information. However, at present, automated investment agents are unable to make investment decisions with reference to soft information. For example, a project has a low credit rating but the borrowers' description indicates that he or she has strong repayment ability. Therefore, it cannot be proved that automated investment has a better return than manual bidding.

CONCLUSION

In this paper, the authors used a large set of data from PPDai.com to investigate the impact of automated investment in the P2P lending market, and presented three hypotheses on the automated investment system in this market. The empirical results show that the participation of automated investment would significantly affect the behavior of investors, and the herding effect is weakened by automated investment. Furthermore, the authors found that the participation of the automated investment extends the average bidding duration of the loans on the P2P lending platform. This suggests that the application of automated investment in P2P lending reduces the platform transaction efficiency, which is the opposite of online auctions and high frequency stock trading. Further, the study indicates that automated investment on a P2P platform would prolong the bidding duration of loans, while there are no eminent changes discovered in loan performance on the ROI.

Practical Implications

This study reveals that platform efficiency is influenced by the application of automated investment tools. Therefore, the P2P platform owner can change the fund liquidity of the platform by adjusting the automated investment tool. In addition, to reduce risk and irrational herding behavior, online P2P platforms should recognize the importance of automated investment tools and update their function, which will further improve the platform's stability of operation and user satisfaction. Combined with a large amount of data and artificial intelligence technology of platform transactions, some P2P platforms' automated investment tools may develop their own investment logic, rather than simply acting as agents. Finally, for lenders on a P2P lending platform, this research can also help them make more rational investment decisions, thus reducing the risk of the herding effect within the market.

Limitations and Future Research

There are still some limitations in this study. First, this research only selected data samples from a lending platform that employs the "all or nothing" mechanism. In fact, there are also some different types of P2P lending mechanisms. For example, loan projects on prosper.com accept investment even when the requested amount is reached. And by analyzing those different mechanisms, it is possible for future research to find a market mechanism or rules for automated investment, under which either or both the average bidding durations and the ROI can get improved. Investors can have enough time to analyze loan projects, and the impact of automated investment may not be significant on such a platform. Second, the authors did not consider the impact of macroeconomic factors, such as policy, economic situation, and so on, and thus future research should consider these factors. Third, no explicit instructional strategy has been proposed for both the P2P platform and the user. Finding

projects that are more suitable for manual investors, like the "low credit rating and strong repayment ability" exception mentioned in our discussion of H3, is feasible for future research.

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