# Herding behaviour in P2P lending markets

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# Herding Behaviour in P2P Lending Markets

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**Abstract**

We explore lender behaviour on *Renrendai.com*, a leading Chinese peer-to-peer (P2P) crowdlending platform. Using a sample of around five million investor-loan-hour observations, and applying a high-dimensional fixed effect estimator, we confirm evidence of herding behaviour: the investors in our sample prefer assets that had attracted strong interest in previous periods. The herding behaviour relates to both the experience level of the investor and the length of time of an investment session on the platform. We also provide evidence of significant herding behaviour in the first hour of experienced investors' sessions. Our results are robust to the use of alternative specifications.

Keywords: FinTech; Peer-to-peer; crowdlending; herding; investor experience.

JEL Classification: G21, G40, G41

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## 1. Introduction

With the growing use of the internet and telepresence technology, anyone with access to a digital device can lend or raise money. A request to raise funds through an online peer-to-peer (P2P) platform only requires a minimal amount of information to be included when a borrower submits a listing, such as the amount of funds required, personal attributes and a narrative. On the other side of the transaction, crowdfunders use the P2P platform to support projects deemed to be worthy causes. Funding requires no interaction with the borrower, in contrast with traditional financial lending arrangements.

The P2P platform innovation comes with advantages and disadvantages.[1] By eliminating layers of costly intermediation, P2P platforms permit investors of any number and size to lend to a single borrower, enabling the supply of funds from multiple sources to cover the amount requested. These platforms involve swift, simple procedures that facilitate rapid lending decisions and provide attractive interest-rate deals for both borrowers and lenders. The downside is that lenders bear the direct risk of loss from a P2P loan default, without the remedies available to traditional lenders, not to mention the risk that the platform itself may collapse.

These developments in the financial services have increased the need to understand the lending behaviour of investors on digital platforms. Traditional finance theory assumes that economic agents are entirely rational, that they maximize their utility and that they cannot be confused by cognitive limitations or information processing errors (e.g., Markowitz, 1952; Fama, 1991). However, it is also recognized that individuals can behave irrationally, making bad decisions due to behavioural biases.[2] For instance, when faced with a non-trivial risk of loan default, investors may still skip due diligence and imitate the behaviour of others, i.e., herd, in the hope of achieving better returns. Such behaviour can, of course, be a rational strategy for an investor with the belief that those they are mimicking possess superior information.[3]

Do P2P investors also engage in herding behaviour? Using US data, several researchers have identified herding behaviour in P2P investors (e.g., Herzenstein et al., 2011; Zhang and Liu, 2012; Lee and Lee, 2012; Greiner, 2013; and Liu et al., 2015). Without the existence of such behaviour, it is likely that funds would be widely dispersed among available listings, such that only a few applicants would obtain funding. The majority would never receive any level of funding, as a listing is funded, only if it attracts sufficient lending (e.g., Herzenstein et al., 2011; Wang and Greiner, 2011).[4] Furthermore, given

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[1] See Yum et al. (2012), Agrawal et al. (2014), and Morse (2015) for further discussion.

[2] See, for instance, Chuang and Lee (2006) on overconfidence, Biais and Weber (2009) and Merkle (2017) on hindsight bias, Hoffmann and Post (2014) and Iqbal (2019) on attribution bias, Caglayan et al. (2020a) on inattention, Johnson and Tuckett (2017) on narrative fallacy, Chang et al. (2016) on cognitive dissonance and Barberis and Huang (2001) and Tom et al. (2007) on loss aversion.

3 It is well documented that herding behaviour is greater during extreme market conditions. Merli and Rogerz (2013) show that an individual investor with a poor past performance has a higher propensity to herd in the next quarter. Scharfstein and Stein (1990) model herding behaviour for investment decisions of managers.

[4] Herding in the context of P2P markets has stabilizing effects. However, there is also evidence that herding behaviour can cause extreme market volatility, stock market bubbles and misevaluation (e.g., Shiller et al., 1984;

the large number of potential borrowers, lenders would incur high search costs if they were to evaluate each listing.

In this study, we examine herding behaviour on P2P platforms and extend the herding literature into several new dimensions, by exploring the peculiarities of the data. First, we hypothesize the existence of herding in an environment without asymmetric elements. This peculiarity allows for the empirical testing of statistical herding models (e.g., Bannerjee, 1992; Bickchandani et al., 1992). Second, we model *decisions* at the crowd-lender level, while the previous research has depended on aggregate (across all investors at a time) measures.[5] Third, we control for both investor and listing fixed effects. This approach reduces the potential of any omitted variable bias by accounting for time invariant characteristics of lenders and borrowers.[6] Last, we construct measures of investor activity, as well as investor experience, on the platform, and explore crowd-lender level herding behaviour, taking these additional dimensions into consideration.

To carry out our investigation, we explore the leading Chinese P2P loan platform, *Renrendai.com*, from which we extract over five million investor-loan-hour observations. As herding behaviour is about human investors imitating other investors in an asymmetric information environment, we organize our data to investigate actual human bidding activities.[7] Using this dataset, we focus directly on investor behaviour to examine herding behaviour on *Renrendai.com*, as opposed to indirectly observing whether a listing that received funding in the previous round is filled by an investor or not.[8] Our investigation also pays particular attention to whether bidding behaviour is affected by the length of session on the platform or the level of experience an investor has with using the platform.

*Renrendai.com* provides detailed information, including borrowers' financial information and demographic indicators, to help lenders in their funding (bidding) decisions. For each bid, we have information on the amount funded, whether a human bidder is making the bid themselves, or using the automated bidding facility, the time stamp of the bid and the bidder ID. These are the key variables in our analysis. The listing information contains loan characteristics, including total amount requested, loan term, and interest rate, as well as borrower-specific information, such as borrower's credit grade, debt-to-income ratio and age. We follow each listing's progression for up to 60 hours, the maximum number of hours for a listing to be active at *Renrendai.com*, as of October 2018.[9] In fact, lists that did not close within this time do not receive further funding, as lists on *Renrendai.com* close significantly faster than

Nofsinger and Sias, 1999; Sias, 2004; Jegadeesh and Kim, 2010; Boyson, 2010; and Spyrou, 2013).

[5] The extant literature has studied herding behaviour using listing-based datasets, and scrutinized whether a listing funded at time (*t-1*) has received further investment at time *t*. By doing so, the literature has offered an indirect approach to testing for the presence of herding behaviour. Instead, we examine investor behaviour directly, as we observe each investor's bidding behaviour, as well as each listing that is available for bidding.

[6] Earlier studies could not control for investor heterogeneity, as they focused on listing-based data.

[7] *Renrendai.com* has offered an automated investment function, introduced shortly after the platform launched. We control for this facility in our investigation.

[8] We examined herding behaviour implementing the standard listing-data based models for robustness purposes.

[9] At the time of its launch, *Renrendai.com* did not set any time limits for listing.

lists on Western P2P platforms.[10] The data run from the inception of the platform in October 2010 to October 2018.

Our research provides evidence of herding behaviour among Chinese lenders on *Renrendai.com*. We initially show that investors' herding behaviour is related to the amount of time spent on the platform and their experience with the platform, an effect, to our knowledge, that has not previously been examined for peer-to-peer crowdfunding platforms. Furthermore, different from the earlier studies on online lending markets, we use the time stamp, indicating when an investor was logged on to the platform, to evaluate how long it took the investor to complete their bidding activities. Using this measure, we, then, examine whether the length of time an investor spends on the platform has any role in herding behaviour.[11] We show that herding behaviour is mainly observed amongst investors who are active on the site for an hour or less.[12]

Having established these insights into investor behaviour, we consider two additional issues. We first examine the interrelation between the level of experience and the first-hour bidding activities in the matter of investors' herding behaviour. We, next, investigate whether investors, who stay at least four hours on the platform in a session, show herding tendencies at any time during their spell on the platform.[13] Examination of these questions yields the following points: 1) only experienced investors (regardless of whether they are active on the platform for an hour or longer) are most likely to herd in the first hour of the session; 2) inexperienced investors do not exhibit herding behaviour.

Overall, our analysis provides several new insights. Herding behaviour on P2P loan markets is evidently associated with the experience level of investors and the spell of investment activity per session. We also argue that, although useful, listing-based analysis does not yield the level of detail we obtain from an investigation that uses investor-specific data. Nevertheless, for robustness purposes, we reconstruct a listing-based dataset and estimate the standard model implemented in the literature to further confirm our finding that investors on *Renrendai.com* herd.

The paper is structured as follows. Section 2 provides the background information on P2P lending in China and *Renredai.com*. Section 3 presents our empirical models and describes the data. Section 4 reports the key findings and discussion. Section 5 concludes.

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[10] The average loan completion time on *Renrendai.com* is less than five hours, while an average loan on *Prosper.com* can take up to eight days to complete (Wei and Lin, 2016).

[11] To the best of our knowledge, Gargano and Rossi (2018) is the only study which has examined the characteristics that lead certain investors to pay more attention to their investment portfolios, compared with others. They consider how investors allocate their attention and whether paying more attention would lead to better or worse investment decisions. They find that paying more attention to one's portfolio improves outcomes. The approach that we implemented in building our data are similar to theirs, in that they constructed their dataset by observing the time stamp for when an investor was logged into the brokerage account website, the web pages they browsed, and the time they spend on each web page. We thank a referee for highlighting this research.

[12] However, this effect evaporates as investors spend more time on the platform.

[13] Investors can have bidding sessions lasting several hours. Examining investor behaviour when an investor spends more than four hours on the platform allows us to examine and compare herding behaviour in the first, second, penultimate, and the final hour.

## 2. The P2P loan market in China and *Renrendai.com*

Peer-to-peer lending is the practice of lending money to individuals or businesses through online services that match lenders with borrowers. Zopa, the first P2P loan platform, was launched in the UK in February 2005. It was quickly followed by the Prosper and Lending Club in the US. China inaugurated its first P2P platform in 2007.[14] Since then, the industry in China has grown rapidly, despite the Internet financing regulations that were introduced in 2015. By the end of 2016, there were more than 2,000 providers operating in the market. The Chinese P2P market had around RMB 600 billion ($91 billion) in total outstanding loans, as of July 2016.[15] This phenomenal growth was driven by those with limited access to bank lending due to their credit histories, and by small individual investors seeking higher returns on their savings than was provided by bank savings accounts. Although expected annual returns fell from 20% to around 10–12% over the period 2014 to 2016, investors poured their funds into online platforms, financing consumers and small businesses in need of funds.

In the early years of P2P financing, platforms in China tended to attract low-quality borrowers, who caused investors to incur substantial losses and raised operational risks for platform hosts. In response, the government issued a regulatory guideline in July 2015, requiring that every online P2P lending platform had to register as an "information agency" firm with the authorities. Platforms were further required to move investor funds to third-party depository bank accounts, in order to certify ownership. After the policy intervention, several P2P platforms were shut down and some operators switched to other businesses. According to *wdzj.com*, a website that provides aggregate information on the state of P2P lending in China, the number of platforms engaged in normal operations dropped from 5,890 to 2,281 by early 2017. The decline in the number of platforms in China will apparently continue until only a handful of platforms are left to serve the whole market in the future.[16]

*Renrendai.com*, established in October 2010, remains China's leading P2P platform. At the end of October 2018, it had around one million confirmed loans with a total lending amount of over $10 billion, and a total of around 170,000 registered lenders to invest in loans. From its inception to the end of 2018, the platform has seen investor numbers soar and over 90,000 borrowers have successfully raised loans. As depicted in Panel A of Figure 1, the number of active investors has continuously increased between 2010 and 2018, and settled to over 5,000 per hour since mid-2016. Panel B of Figure 1 details the activity of the investors over a day. The data show that investors are most active around noon, while investor activity slows significantly between 4 pm and 4 am the next morning. Looking at borrowers, we find that the number of loans and the average principal loan amount has increased, largely due to a dramatic rise in new borrowers and higher lender activity. Panel C of Figure 1 provides visual evidence that the number of new listings per hour peaked between 2014 and 2016 at around 15 listings in an hour, which then

[14] Citation: *Lendit.com*, https://tinyurl.com/wbnz7zpv, accessed 08 February 2021.
[15] Citation: Wind Information, https://www.wind.com.cn/en/ , accessed 08 February 2021.
[16] The decline in the number of P2P platforms in China is mainly due to increasing supervision of the market by the regulatory authorities (Caglayan et al., 2020b; Hsu et al., 2020).

settled to around five. Panel D of Figure 1 shows that the number of new listings per hour is highest between 3 am and 10 am.

The mechanics of the *Renrendai.com* platform are straight-forward. A borrower seeks a loan by creating a listing that specifies the amount of funds to be requested (from RMB 3,000 to RMB 500,000), as well as an interest rate. Each listing posted on the platform remains active for up to 60 hours. Most listings, however, are filled in less than five hours, and the standard deviation of completion of a listing is around 17 hours. Significant variations in completion times could be explained by the fact that the majority of loans are financed within the first few hours, but a small number of listings are never filled and remain on the platform until they expire. To set up a listing, the borrower uploads a written statement that describes the purpose of the loan and provides information on their existing debt and current income.

The platform categorizes borrowers into eight credit grades, ranging from AA (top grade), A, B, C, D, F to HR (high risk). The credit ranking of the users is determined from the personal information provided to the platform by the potential borrower. The more evidence a borrower provides supporting their creditworthiness, the higher the credit rating granted by the platform. Credit ratings are linked to personal identity, education, employment, salary, criminal records, housing status, vehicle ownership, personal mobile and social media activity. Evidence of regular payments being made on earlier loans improves the user's credit rating, while a history of delayed payment or an earlier loan default garners a lower rating.

The platform provides lenders with relevant information on each prospective listing, provided by the borrowers. The investor can invest in one listing, or a set of listings to diversify the risk of default. Bidding can be done manually or through an automatic bidding facility, and information relating to previous bids (e.g., type of bidding, amount) is publicly available. Once the amount of loan requested is met in full, the loan is created, and the listing is removed from the platform. Subsequently, loan proceeds from all investors are credited into the borrower's bank account, from which repayments are automatically withdrawn on a monthly basis. When a listing expires without full funding, all lenders have their contributions refunded. For any potential lender, the downside of the expiration of a listing that did not attract the full amount requested by a borrower, is the opportunity cost of time lost for identifying alternative listings.

## 3. Empirical strategy

### *3.1 Data description*

Our data cover the period from October 2010 to October 2018. The dataset is constructed in two steps. Initially, we collected all available information on loan listings and borrower characteristics for each application, including unfunded ones. Second, we gathered investor-level data based on the time stamp for each bid and the amount invested in each listing at time *t.* Combining investor- and listing-level data, we produce a unique loan ID and obtain a sample that comprises over five million observations at the investor-listing-hour level. Each listing in the dataset includes the annual loan interest rate, loan amount, period of repayment, guarantee type and credit score issued by *Renrendai.com*, as well as borrower-specific characteristics such as age, income, location, occupation, employer information, education level, marital status, housing status and borrowing history on the platform. It should be noted that investors can also use an automatic bidding facility that the platform provides. Investors can allocate a certain amount of funds for this purpose while, at the same time, they continue investing manually.[17] As herding is a human behaviour, our examination only covers bids made by human bidders, yet we control for the use of automatic bidding in our regressions to address concerns that automatic bidding on listings may trigger the herding behaviour of a human bidder.[18]

Panel A of Table 1 presents the basic statistics on the dynamics of the key variables in our analysis. The average number of bids per hour is only around 9.82, with a substantial standard deviation of 20.16, implying that the number of bids is lower at certain times of the day, than it is during busy periods. The average number of bidders on the platform, at any hour, is 278 (in logs 5.58). The data contain information on bids submitted by the automatic bidding facility (around 0.06% of the data). Nevertheless, in interpreting these figures, it should be noted that both the number of investors and listings have increased over time, and that these figures are averages of data spanning eight years.

Panel B of Table 1 reports summary information for listing-level data. Even though we do not explicitly make use of these data items in our main investigation (our models contain listing fixed effects in all possible specifications), it is useful to consider certain basic statistics. The data provide us with around 111,200 listing observations. The loan amount requested varies from RMB 3,000 ($429) to RMB 500,000 ($69,900), with an average of RMB 50,500 ($7,060). The average interest rate is 12.25% and the average maturity is just over 22 months. 21% of the listings are considered to be high-risk (HR) investments, as estimated by the platform's own credit score system. Although the average debt-to-income ratio is almost 28%, the standard deviation is 36%, suggesting that the debt-to-income ratios of borrowers vary substantially.[19] While it takes just over four hours, on average, to fill a listing, the standard deviation is around 17 hours.

When we split the sample based on the average time investors spend on the platform, investors' experience using the platform, and the intensity of bidding, we are provided with additional insights. Table 2 reports the means and standard deviations for six sub-samples, based on average time spent on the platform. The average amount invested by a lender, among investors who stay logged onto the

[17] Overall, only 0.06% of the data are due to the use of the automatic bidding facility in our estimation sample.
[18] D'Acunto et al. (2020) has shown that automatic bidding ('robo-advising') can have unintended consequences, such as avoidance of gender or culturally based discrimination, while at the same time yielding better returns. Also see D'Acunto and Rossi (2020), who discusses the theoretical and empirical aspects of the design and impact of robo-advisors' investment choices and the allocation of financial resources between spending and saving. In our setting, automatic bidding would not produce falsely interpreted herding behaviour, as its size is small and borrower requests could not be fulfilled by this facility all at the same time. We thank a referee for highlighting these recent studies.
[19] It should be noted that some borrowers carry no outstanding debt, i.e., their debt-to-income ratio is zero.

platform up to one hour, is RMB 58.80. This average investment per hour increases for investors who remain on the platform for longer. A similar pattern is observed for the binary indicator of investing, equal to one, if an investor *i* bids for listing *j* and zero otherwise. The number of hourly bids for listings is highest (around 12) when a bidder stays online for 2–9 hours. The remaining share needed to fill a listing, and the extent of automatic bidding per hour across columns, are similar.

Panel A of Table 3 reports the summary statistics when the investor has less than three months, between three and six months, between six and twelve months, and more than a year of experience using the platform. Column (1) of Panel A shows that investors with less than three months of experience using the platform invest the highest amount (RMB 140.60), on average, while their peers with more experience on the platform invest, on average, RMB 80–110. The average percentage of bids submitted by automatic bidding each hour stays at around 0.05–0.07% in all four sub-samples, which is comparable to the statistic observed for the full sample. The average values of hourly total bids are similar across all groups. Panel B of Table 3 examines data for investors who spend at least four hours on the platform per session. Columns (1) and (4) provide statistics for the first and last hour of the session, while the middle columns provide the second and the penultimate hours. Looking at the columns, we see that the average amount invested peaks at RMB 94.16 in the final hour of the session. The first hour of the session has the lowest average number of bids per hour (10 bids), the lowest average number of bidders (in logs 5.27) and the lowest average percentage of bids carried out by automatic bidding (0.05%). The average percentage of the amount unfunded varies from 69% to 72% throughout all spells. Note, also, that the majority of the activity takes place during the first and the last hours of the session.

### *3.2 Econometric modelling*

This section presents the main empirical model that we implement to examine the presence of herding behaviour on *Renrendai.com*. The model scrutinizes the behaviour of active *human bidders* at any point in time, and seeks to establish if investor *j* (a human bidder) invests in listing *i* based on the observation that other investors have funded the same listing.[20] As an example, suppose we observe that bidder *j* at hour *t* has made a bid on listing *i*. Based on this observation, we implicitly assume that bidder *j* was active during this particular time.[21] Furthermore, we know which listings were available for investors at any point. Availability of information on these aspects (investor *j*, listing, *i*, and time, *t*) allows us to create a unique investor-listing-hour level dataset, covering all activities on the platform. We then construct a high-dimension, three-way fixed effect model to examine the data of the following form:

$$Bid_{jit} = \vartheta + \alpha Total\ Amount_{it-1} + \delta TotalBids_{it-1} + X_{it}\beta_1 + \kappa_j + \mu_i + \tau_t + e_{it}\ , \qquad (1)$$

[20] See Banerjee (1992), Bikhchandani et al. (1992) or Graham, (1999) for theoretical background of our empirical modelling.

[21] It is also possible that a bidder who is present on the platform may not bid. Our data do not allow us to identify these cases.

where indices *j*, *i*, *t* indicate investor, listing and time, respectively. The dependent variable, $Bid_{jit}$, is the sum of all bids (RMB) *manually* invested in listing *i* by investor *j* at time *t*. Additionally, we construct an indicator, which takes the value of one, if investor *j* has bid for listing *i* or zero otherwise. In Equation (1), the main variable of interest is the lagged total cumulative amount invested, $Total\ Amount_{it-1}$, in listing *i*. We should recall that this variable aggregates the amount bid for *listing i* for both *automated and manual bids*, and the dependent variable captures the manual bid amount made by investor *j* for listing *i*, so that we can examine the herding behaviour of the human bidders. To argue in favour of the existence of herding behaviour on the platform, the coefficient ($\alpha$), associated with the variable $Total\ Amount_{it-1}$ should be positive and significant. This implies that human bidder *j*, upon observing that other investors have lent to listing *i*, follows the crowd and also invests in it. Equation (1) is estimated using a three-way high-dimension fixed effect estimator.[22,23]

We control for several other variables captured by the vector $X_{it}$. This vector includes the lagged share of the amount requested, $ShareNeeded_{it-1}$, by listing *i* that is left unfunded at the end of time (*t-1*). We expect this variable to exhibit a positive sign, capturing the fact that investors submit smaller amounts to complete the loan request. The model contains the lagged total number of bids, $Total\ Bids_{it-1}$, at time *(t-1)* to control for interest in a listing, and the number of investors, $Log\ Bidders_t$, at time *t*. Given that the platform offers investors the use of an automatic bidding facility, we control for the effect of this type of investment behaviour and add $Share\ Automatic\ Bidding_{it-1}$. Furthermore, we include an interaction term in the model between lagged total amount, $Total\ Amount_{it-1}$, and the lagged share needed, $Share\ Needed_{it-1}$, to fill the loan so as to capture the risk of not being funded.[24] To address the possibility that lending becomes concentrated at certain hours of the day, we include hour of the day, $H_t$, fixed effects. The model controls for investor and listing fixed effects, $\kappa_j$ and $\mu_i$, respectively.[25] Date fixed effects, denoted by $\tau_t$, capture any macroeconomic policy changes. The error term is denoted by $e_{it}$.

## 4. Results

### *4.1 Do individual Renrendai investors herd?*

Table 4 presents our initial set of results seeking to identify herding behaviour on *Renrendai.com.* The first two columns present the results when the dependent variable is the (RMB) amount invested by investor *j* for listing *i* at time *t*. The latter two columns are obtained when the dependent variable is an indicator variable set equal to one, if investor *j* bids for listing *i* at time *t*. The main variable that we focus

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[22] The specification with a binary dependent variable and listing fixed effects only is also estimated using a panel data logit estimator and yields qualitatively similar results.
[23] Our regression results report robust standard errors, but we have also experimented with clustering standard errors by listing id and investor id. These results are quantitatively similar.
[24] Zhang and Liu (2012) argue that that investors also assess the risk of loan materialization, based on remaining percentage left, and the herding effect is enhanced by the payoff externality if the interaction term is positive.
[25] Given that we have listing- and investor-level fixed effects, we cannot use loan-level attributes in this model. Instead, we do so when examining listing-level data in Section 4.6 for robustness purposes.

on is the lagged total amount bid, $Total\ Amount_{it-1}$, in listing *i* at time (*t-1*). We expect the coefficient associated with this variable to exhibit a positive sign. Also note that we introduce investor level fixed effects in Columns (2) and (4), while they are not included in Columns (1) and (3). All specifications include listing, hour of the day and date fixed effects.

Overall, the results provide support for the herding behaviour of investors on *Renrendai.com*. Regardless of the availability of listing level fixed effects and the type of dependent variable, the coefficient, associated with lagged total amount invested in listing $i$, is positive and highly significant. Hence, we conclude that, among the whole range of listings that are available, investors prefer those listings that have received more funding in the previous hour, leading to the following claim: investors in *Renrendai.com* herd.

When we examine the coefficients associated with the control variables, we see that the effects associated with all remaining variables are meaningful. $Share\ Needed_{t-1}$ takes a positive coefficient in all columns, suggesting that the amount of funds a listing receives slows down as the loan approaches completion. That is, investors bid less as listings are filled. The impact of *Share Automatic Bidding*$_{t-1}$ is not significant in any of the columns. Hence, if a listing attracts both manual and automatic bidding, the impact of automatic bidding is not significant enough to affect human investor behaviour.[26] As expected, *Log Bidders*$_t$ play a negative role as an increase in number of investors on platform in previous period reduce investment opportunities in current period. Finally, the interaction between *Total Amount*$_{t-1}$ and *Share Needed*$_{t-1}$ is significant and negative, suggesting that, as the listing fills, it will continue to attract new funds, but at a slower rate. This evidence is not in line with Zhang and Liu (2012), who document positive payoff externalities. The difference could be explained by specific aspects of the Renrendai platform, in which loan materialization risks are low.

### *4.2 The role of total logged session time on the platform*

Does the number of hours each investor spends on the platform in a session affect herding behaviour? The descriptive statistics (Table 2) for investors show that an investor can stay logged onto the platform for more than 12 hours per session. Table 5 considers whether investors spending more time on the platform behave differently from those who spend less time on the platform. Columns (1) to (6) present the results for the herding behaviour of those investors who stay logged on to the platform up to one hour, less than three hours but more than one hour, less than six hours but more than three hours, less than nine hours but more than six hours, less than 12 hours but more than nine hours and more than 12 hours. It should be noted that an investor who stays logged for several hours to the platform does not necessarily submit bids to listings that are available throughout the session. Such investors generally bid to several listings in the first hour or the last hour, while bidding intermittently during the remaining

[26] Recall that the share of automatic bidding is too small relatively (0.06% in the data) to affect human bidders' behaviour. Hence, a uniform spread of funds through automatic bidding would not cause herding behaviour.

period that they are logged on to the platform.

When we examine Table 5, we find that *Total Amount*$_{t-1}$ is significant only for Column (1). In the remaining columns, this variable never exhibits a significant coefficient. These results, therefore, suggest that herding is prevalent among those investors who are logged in for up to one hour per session. If the investor stays for longer than an hour, we do not observe herding behaviour. The results we present here should be expected, as they confirm that investors substitute private information, partially or completely, with social information, when it is necessary that they make rapid financial decisions. The heuristic of following others is a more effective use of one's time. This is particularly relevant in an environment where private information on all loans may be impossible to acquire or to process quickly in a fast-moving platform, such as *Renrendai.com.* This is in addition to the fact that the mixture of private and public information available is sub-optimal (e.g., Trueman, 1994; Chen and Jiang, 2006; Hollie et al., 2017). Consequently, as the processing of all information relating to all loans would take longer than the time that the listings will remain available, investors resort to copying what others are doing. Under this strategy of convenience, one goes with the flow and mimics the behaviour of others. The remaining variables in Column (1) of the table play a similar role to that described in Table 4. For the rest of the columns, we see that, although the signs associated with the variables are similar to those we reported in Table 4, they have weak significance or none at all.

### *4.3 The role of experience on the platform*

Table 6 presents our results when we split the data in relation to the experience level of the investor on the platform. Columns (1) to (4) capture the behaviour of those investors who have experience of less than 90 days (three months), less than 180 days but greater than 90 days (between three to six months); less than 360 days but greater than 180 days (between six to 12 months) and greater than 360 days (more than one year). Interestingly, in Column (1), although the coefficient of lagged total effect is positive, it is not statistically significant. However, for the remaining columns, lagged total effect exhibits a positive and highly significant (at the 1% level) coefficient. Furthermore, the size of the coefficient across all three columns are of similar magnitude: a one percent increase in lagged total amount invested in a listing, on average, increases funding by 2.4 to 2.6 percentage points. These findings suggest that herding instincts may have evolved as a learning heuristic, enabling investors to use social information about the potential value of a listing.

It is also possible that individual investors begin following the herd when they realize that there is "safety in numbers", doing as the others do in order to secure a similar yield for all involved. Several other explanations are suggested for the herding, or anti-herding behaviour, of sophisticated investors or analysts, including the presence of asymmetric information, complexity, information processing, reputation, and compensation schemes. Hirshleifer and Teoh (2003) suggest that analysts follow their peers because they mistrust the available information and ignore their private information signals. This explanation applies to investor behaviour in fast-moving P2P platforms, where listings complete very quickly as they must make rapid decisions.

When we turn to examine the role of the control variables, we see in Column (1) that only a few exhibit a significant coefficient, although their signs are as expected. Yet, in the rest of the table, the coefficients are significant and assume the signs as shown in Table 5. *Share Needed*$_{t-1}$ exhibits a positive coefficient, suggesting that the funding rate of a listing slows as the loan approaches completion. The interaction between *Total Amount*$_{t-1}$ and *Share Needed*$_{t-1}$ is significant and negative, suggesting that, as the listing is filled, it attracts new funds at a slower rate.

### *4.4 Session length and investor behaviour*

Table 5 showed that investors are more likely to herd if they are logged onto the platform for an hour or less. Although they may not be investing intensively throughout the entire period, thousands of investors stay logged onto the platform for multi-hour sessions. Such investors are generally most active during the first and last hours of the session. The investor starts the session with several bids, goes several hours making no or few bids, then completes the session with several additional ones. This observation raises the question of whether investors who stay logged onto the platform for long hours also herd. To investigate this possibility, we focus on the behaviour of those investors that stay logged onto the platform for at least four hours. Table 7 presents the results on the herding behaviour of investors during the first, second, penultimate and last hour of their session.

The first column of Table 7 presents the first hour results, and Column (4) presents the last hour results from a session. Columns (2) and (3) provide the results for the second and penultimate hours. The results are striking, as the lagged total amount is positive and significant with similar magnitudes, only for the first hour of a long session. During the second, penultimate and last hours, we observe no herding behaviour. In fact, during these hours, the level of activity is relatively low. It may be that, when investors are not actively bidding, they are spending their time examining listings and the activity of other investors.[27] The control variables are mostly significant and similar to what we reported for Table 6. For Columns (2)-(4), the significance of these coefficients drops.

### *4.5 Experience and the first-hour effect*

Table 7 showed that investors who logged on for an hour or less tended to herd. We now examine the role of experience level on herding behaviour for investors who stay logged on for up to an hour on the platform. In other words, do novices herd as much as experienced investors, who have spent more than three months on the platform in sessions of one hour or less?

Column (1) of Table 8 shows the results for those investors who have up to three months of experience on the platform. Columns (2)-(4) provide the respective results for more experienced investors (three-six months, six months to a year, and more than a year). Inspecting the coefficient of

[27] Unfortunately, our data do not allow us to examine this possibility.

*Total Amount*$_{t-1}$, we see that it is positive for all levels of experience. However, a closer inspection shows that herding behaviour is more prominent in those investors with more than three months of experience. Specifically, the coefficient associated with lagged total amount in Column (1), which captures the behaviour of investors with more than three months of experience, is not significant and its impact is smaller than the remaining columns. For investors with between three to six months of experience, when lagged *Total Amount* invested increases by 1%, investment increases by 4.1 percentage points. As investors gain further experience, their reaction to *Total Amount*$_{t-1}$ declines slightly, while still remaining positive and highly significant. For investors with 180-360 days of experience on the platform, a 1% increase in *Total Amount*$_{t-1}$ leads to a 3.3 percentage-point increase in investment; for those investors who have more than a year of experience on the platform, a similar increase in lagged *Total Amount* leads to a 2.7 percentage-point increase in investment.

The effect and significance of control variables, especially those in Columns (2) to (4), are similar to our results reported in Table 6. *Share Needed*$_{t-1}$ exhibits a positive coefficient, suggesting that the rate of funding a listing receives slows as the listing completion approaches. The interaction between *Total Amount*$_{t-1}$ and *Share Needed*$_{t-1}$ is significant and negative, suggesting that a listing continues to attract new funds at a slowing rate as it fills. As in previous results, *Log Bidders*$_t$ plays a negative role which can be explained by reduction in funding opportunities in current period when number of investors in previous period increases. Although they exhibit the anticipated signs, the control variables in Column (1) have weaker statistical significance.

### *4.6 Does herding behaviour exist at the listing level?*

For the purposes of robustness and comparison, we reorganize our data and estimate the standard model that has been previously implemented in the extant literature for listing-based datasets. Unlike earlier research, here we focus on hourly cumulative bids, rather than on daily cumulative bids, due to the fact that *Renrendai.com* is an extremely fast-moving and dynamic platform.[28] We begin our investigation by estimating the following naive model to seek evidence for sequential correlation:

$$Bid_{it} = \vartheta + \alpha Total\ Amount_{it-1} + \delta TotalBids_{it-1} + X_{it}\beta_1 + Z_i\beta_2 + e_{it}\ , \tag{2}$$

where $Bid_{it}$ denotes the amount of funding that *list i* receives at time $t = 1, 2, \ldots, 60$. In our model, to test for the prevalence of sequential correlation, we include $Total\ Amount_{it-1}$ to measure the lagged total cumulative funding a list has received in the previous hour. If coefficient $\alpha$ is significantly positive, we argue in favour of sequential correlation. Note that the difference between this model and model (1) is the investor dimension; the investor level detail that we have examined earlier is now embedded in the bids associated with each listing.

[28] Looking solely at bids submitted by humans (i.e., dropping automatic bidding data), the average listing is filled in just under than five hours (4.94 hours).

The model contains the number of lagged-total bids, $TotalBids_{it-1}$, as well as several time-varying and time-invariant listing attributes, denoted by vectors $X_{it}$ and $Z_i$. The former vector includes, $Share\ Needed_{it-1}$, the share of the amount requested by listing *i* that is left unfunded at the end of hour $(t-1)$. To capture the possibility that lending is more concentrated at certain hours of the day, we include hour of the day, $H_t$, and day of the week, $D_t$, fixed effects. Vector $Z_i$, which captures the time-invariant listing characteristics, including *Amount Requested$_i$*, *Maturity$_i$*, a *Credit Risky$_i$* dummy, *Debt-to-Income Ratio$_i$* and a *Homeowner$_i$* dummy. The interest rate that a lender would have earned, had the list filled at the end of day $(t-1)$, is captured by $IntRate_{it-1}$. We also include *Start Day$_i$* in $Z_i$, to index the date the listing is posted on *Renrendai.com*. To control for the role of automatic bidding, we augment the model with lagged $Share\ Automatic\ Bidding_{it-1}$. The error term is denoted by $e_{it}$.

Although Model (2) allows us to detect sequential correlation in the data, its presence does not suggest the existence of herding behaviour of investors. This is because sequential correlation could occur for a number of reasons, including unobserved heterogeneity across lists or payoff externalities among lenders. It is possible to disentangle unobserved heterogeneity across lists by introducing listing fixed effects, $\mu_i$, as the characteristics of borrowers will not change over the duration of the loan. Additionally, in order to capture payoff externalities, we introduce an interaction term $Total\ Amount \times Share\ Needed_{i,t-1}$ as an explanatory variable.[29] These changes render the following model.

$$Bid_{it} = \vartheta + \alpha Total\ Amount_{it-1} + \delta TotalBids_{it-1} + X_{it}\beta_1 + Z_i\beta_2 + \mu_i + e_{it} \tag{3}$$

The results are given in Table 9. The first two columns of the table display the sequential correlation results. The last two columns present the results for herding behaviour, as we include listing and hour of day fixed effects into the model. Columns (2) and (4) incorporate the role of automatic bidding within the model.

When we inspect the first two columns of the table, we see that the coefficient associated with *Total Amount$_{t-1}$* is positive and significant at the 1% level. This finding suggests the presence of sequential correlation. In the second column, note that the sign of automatic bidding is negative, implying that the presence of the automatic bidding facility reduces (rather than increases) the average amount of funds channelled to listings. Under normal circumstances, one would expect this facility to increase the funding to the average loan listing, as the facility is not used by all investors and automation would spread the available funds across all borrowers equally, based on rule-based criteria. This observation for listing based models is possibly an outcome of the fact that the heterogenous behaviour of investors is not fully accounted for.[30] Hence, we argue that one should observe the results from listing based models with caution, and avoid using it to design policy rules for results from similar models, which may be biased, due to model specification errors.

[29] See Zhang and Liu (2012) and Gao et al. (2020) for a detailed discussion of payoff externalities in crowdlending.
[30] Recall that we have not observed a significant role for automatic bidding in investor-level models.

Signs of coefficients associated with all the remaining variables in the first two columns are meaningful. *Total Bids*$_{t-1}$, *Amount Requested*$_t$, *Interest Rate*$_t$, *Debt-to-Income Ratio*$_t$ and *Log Bidders*$_t$ all play a positive role in amount invested into listing *i*. *Share Needed*$_{t-1}$ exhibits a positive coefficient in all columns, suggesting that the filling rate of listings slows as the loan approaches completion. *Maturity*$_t$ has a negative sign, indicating that investors prefer lending to listings with shorter durations, over those of longer durations. This is meaningful, because there is substantial information asymmetry relating to the borrowers on a P2P lending platform. Risk plays a negative role when automatic bidding is introduced in the model, as one would expect. The interaction between *Total Amount*$_{t-1}$ and *Share Needed*$_{t-1}$ is significant and negative, suggesting that the listing attracts new funds at a slower rate as it fills. This is in line with our expectations. Given the speed of the actions taken on *Renrendai.com*, investors must be quick to identify opportunities as new listings are being posted and older ones are filled over the course of the day.

To examine the herding behaviour of investors, we control for listing fixed effects. We do this in Columns (3) and (4). The results across the two columns are similar. *Total Amount*$_{t-1}$ is still positive and significant, implying the presence of herding behaviour on *Renrendai.com*. Furthermore, this is not affected by the presence of automated bidding, despite its negative and significant effect on the invested amount. Thus, the results provided in Table 9 validate the presence of herding behaviour on *Renrendai.com.*

### *4.7 Listing Specificities and Herding*

In this subsection, we explore some of the key specificities of the listings that are on the low and high end of the spectrum for herding behaviour. This investigation reveals some of the drivers of herding. Table 10 reports loan level descriptive statistics across different quartiles for the average cumulative amount invested; our key independent variable. Top quartile (Q4) corresponds to those listings with the largest degree of herding. In contrast, the bottom quartile (Q1) contains the listings that have a lower degree of herding. There are some interesting observations. More popular listings spend much less time on the platform compared to the least popular listings, and their term to maturity is almost two to three times longer than the terms of those listings in the bottom quartile. We also find that the crowd is more likely to follow listings, which are deemed to be less risky and that offer lower interest rates. Hence, it emerges that, for investors, rather than focusing on the expected return, the overall quality and the term of a listing tend to be important. Another driver of herding relates to the costs of reviewing applications and making the right decision under uncertainty. Earlier, Figure 1 Panel D documented that the average number of new listings per hour is staggered around the clock. Given the limited time each investor has, our results suggest that the experienced investors would follow the crowd to minimize the reviewing costs and decision uncertainty, when confronted with several opportunities which disappear quickly.

Although the evidence we provide in our paper is correlational, we would like to indicate that there is extensive literature on herding, or anti-herding, behaviour of sophisticated investors and financial analysists (e.g., Clement, 1999; DeBondt and Forbes, 1999; Wermers, 1999; Hirshleifer and Teoh, 2003; Jegadeesh and Kim, 2010). This line of research has suggested several reasons for herding (or anti-herding) behaviour, including the role of asymmetric information, complexity, information processing, reputation, compensation schemes. We expect that theoretical aspects on the role of experience and the length of time per session will soon be developed, given the strong empirical results we have obtained from *Renrendai.com*.

Another potential question that needs to be considered is the effect of omitted variables. In our examination, compared to the earlier literature on herding on P2P platforms, we have made a significant step towards overcoming such problems, by accounting for listing, investor, day of week and time of the day heterogeneities. Overall, our adjustments offer a partial solution to the omitted variable problem, as we cannot exclude the possibility that there may be other time-invariant individual factors (for instance, changes in investor education/financial literacy) that could potentially affect the association between the variables. Due to data limitations, these possibilities cannot be explored, yet future studies should consider all sources of data to avoid the potential problems of model specification.

## 5. Conclusion

Microloan markets have been a part of our life for over a decade, offering loans to consumers who previously had little or no access to financial markets. Herding behaviour is expected to support the effective operation of these markets, as otherwise scarce resources would be dispersed widely and only a small number of listings would be funded in full. In our investigation we focus on data from *Renrendai.com*, one of the largest microloan markets in China. This is a fast-moving, online platform, which also allows investors to subscribe to the platform's automatic bidding facility, in addition to the manual bidding facility.

Different from the earlier research, we base our investigation on investor level data, and focus on the herding behaviour of human investors while accounting for the impact of automatic bidding. Examining the data from the perspective of investor activity, we provide significant evidence of herding behaviour. We show that herding behaviour is more prevalent in experienced investors. When we deepen our investigation, we provide evidence that herding behaviour is observed in the first hour bidding process of experienced investors, regardless of whether investors stay logged on to the platform for short periods of time (up to one hour) or longer. We argue that the heuristic of following others is sensible on a fast-moving platform, such as *Renrendai.com*, where private information on all loans may be impossible to acquire, or to process quickly while high quality listings are rapidly filled. For comparison and robustness purposes, we also utilize the listing-based approach as implemented by the extant literature. This approach lends support to our findings relating to the prevalence of herding behaviour, however, it does not provide the extent of detail that we were able to analyse using investor level data.

Our modelling approach unveils a number of new and important details that were previously omitted from the literature. We show that herding behaviour is driven by experienced investors who complete their investments within an hour. This finding is new and relevant for markets/platforms where the reaction time for processing information is limited, due to the completion speed of available investment opportunities. We also provide evidence that the automatic bidding facility does not have a significant effect on investors' lending, as well as herding, behaviour. This additional result is interesting on its own, given the expanding literature on 'robo-advisor' and how it relates to investment and the spending behaviour of individuals (e.g., D'Acunto et al., 2019, D'Acunto and Rossi, 2020). Overall, given the findings reported in our study, we argue that one should observe the results from listing based models with caution, as they do not account for the heterogenous behaviour of investors fully and may be biased due to model specification error.

While providing new evidence on the behavioural aspects of crowdlenders from China, our analysis sets a number of research areas for future exploration. We believe that it would be interesting to use our proposed empirical approach to data on different platforms, to establish whether the results on experience level and time spent on the platform are generalizable. Second, surveys could be designed to examine the activities of P2P investors on crowdlending platforms. In particular, survey data on investors' activities on different platforms would allow researchers to explore the substitutability of crowdlending platforms. This information could provide insights into whether herding behaviour is observable across multiplatform environments.

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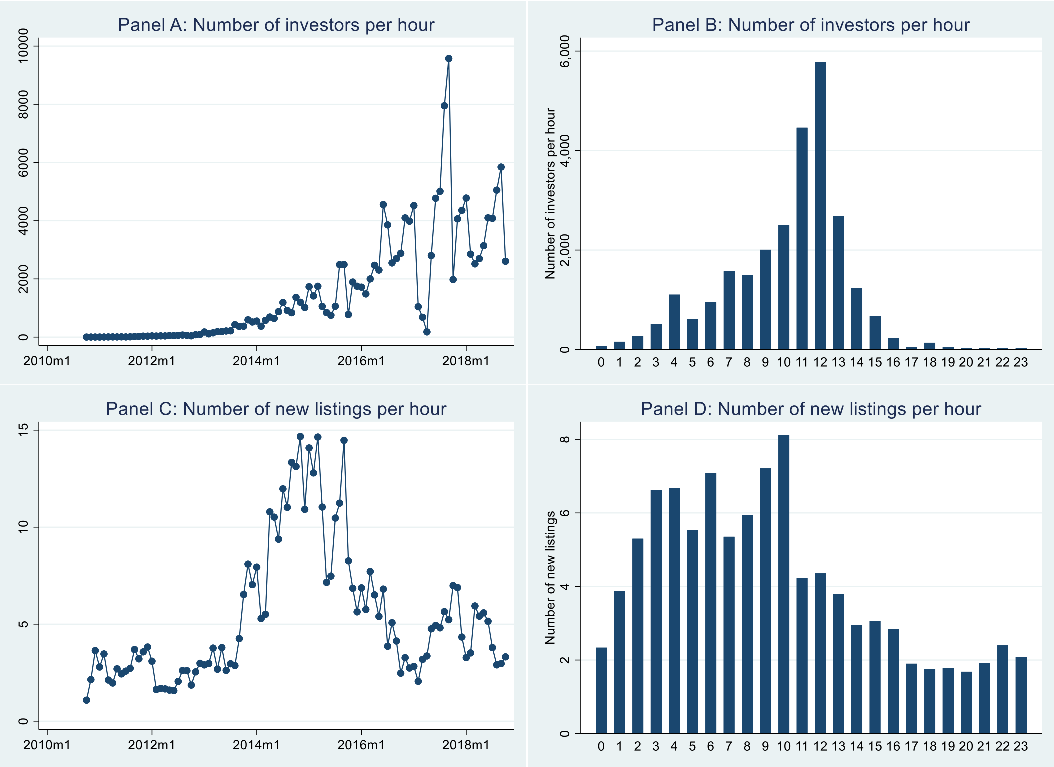
**Figure 1.** Number of investors and number of new listings per hour.




Notes: Panel A represents the number of investors per hour from 2010 to 2018. Panel B shows the number of investors per hour of day (starting at midnight). Panel C reports the number of new listings per hour over the period from 2010 to 2018. Panel D represents the number of new listings per hour of day (starting at midnight).

**Table 1. Summary statistics for all bidding**

| Panel A: Investor-hour-level data | | | | | |
|---|---|---|---|---|---|
| | Mean | Std. dev. | P25 | P50 | P75 |
| | (1) | (2) | (3) | (4) | (5) |
| *Invested Amount* | 66.25 | 946.40 | 0.00 | 0.00 | 0.00 |
| *Invested=1* | 0.06 | 0.23 | 0.00 | 0.00 | 0.00 |
| *Hourly Total Bids* | 9.82 | 20.16 | 2.00 | 5.00 | 11.00 |
| *Share Needed* | 0.71 | 0.26 | 0.56 | 0.79 | 0.92 |
| *Log Bidders* | 5.58 | 1.72 | 4.48 | 5.21 | 6.34 |
| *Hourly Percentage Automatic Bidding (%)* | 0.06 | 0.21 | 0.00 | 0.00 | 0.00 |
| Obs. | 4,718,225 | | | | |

| Panel B: Loan-level data | | | | | |
|---|---|---|---|---|---|
| | Mean | Std. dev. | P25 | P50 | P75 |
| | (1) | (2) | (3) | (4) | (5) |
| *Loan Amount* | 50500.53 | 43939.90 | 16000.00 | 43800.00 | 75100.00 |
| *Interest Rate (%)* | 12.25 | 2.61 | 10.80 | 12.00 | 13.00 |
| *Maturity (Months)* | 22.16 | 12.32 | 12.00 | 24.00 | 36.00 |
| *Credit Risky (1=yes)* | 0.21 | 0.41 | 0.00 | 0.00 | 0.00 |
| *Debt-to-Income Ratio* | 0.28 | 0.36 | 0.11 | 0.19 | 0.35 |
| *Time on Market* | 4.19 | 17.18 | 0.00 | 0.00 | 1.00 |
| *Hourly Percentage Automatic Bidding (First Hour) (%)* | 0.04 | 0.17 | 0.00 | 0.00 | 0.00 |
| *Number of Bids (First Hour)* | 23.62 | 28.34 | 8.00 | 18.00 | 31.00 |
| Obs. | 111,234 | | | | |

Notes: This table shows the Mean (1), Standard deviation (2), and quartiles (3)-(5) of the following variables. *Invested amount* represents the amount of money invested. *Invested* is a dummy variable which equals 1, if the listing is invested and 0 otherwise. *Hourly Total Bids* represents hourly total number of bids from lenders for a loan request. *Share Needed* represents the share of the amount requested that is left unfunded. *Log Bidders* represents the logarithm of number of bidders. *Hourly Percentage Automatic Bidding (%)* represents the percentage of automatic bidding each hour. *Loan Amount* represents the total amount of loan received. *Interest Rate (%)* represents annual percentage rate on the loan. *Maturity (Months)* represents current loan duration in months. *Credit Risky (1=yes)* means that the listing's credit grade is E and below, i.e., E, F and HR, else =0. *Time on Market* represents total time spent on market. *Number of Bids (First Hour)* represents the total bids within the first hour of bidding period. *Hourly Percentage Automatic Bidding (First Hour) (%)* represents the percentage of automatic bidding in the first hour. *Debt-to-Income Ratio* is debt to income ratio.

**Table 2. Summary statistics of time sub-samples: results for time spent on platform (number of hours on same day)**

| | 1 hour | | 2-3 hours | | 4-6 hours | | 7-9 hours | | 10-12 hours | | 12+ hours | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| *Invested Amount* | 58.80 | 879.49 | 115.20 | 1425.60 | 73.97 | 1044.72 | 73.70 | 995.18 | 86.07 | 921.49 | 86.14 | 1033.96 |
| *Invested=1* | 0.05 | 0.22 | 0.07 | 0.25 | 0.06 | 0.24 | 0.07 | 0.25 | 0.08 | 0.28 | 0.08 | 0.27 |
| *Hourly Total Bids* | 9.28 | 20.56 | 12.38 | 20.85 | 12.16 | 18.83 | 11.95 | 18.44 | 10.26 | 17.28 | 8.13 | 14.34 |
| *Share Needed* | 0.72 | 0.25 | 0.69 | 0.26 | 0.68 | 0.26 | 0.69 | 0.26 | 0.70 | 0.25 | 0.70 | 0.26 |
| *Log Bidders* | 5.57 | 1.75 | 5.78 | 1.62 | 5.71 | 1.63 | 5.65 | 1.65 | 5.45 | 1.64 | 5.28 | 1.58 |
| *Hourly Percentage Automatic Bidding (%)* | 0.05 | 0.20 | 0.09 | 0.25 | 0.08 | 0.23 | 0.07 | 0.22 | 0.06 | 0.22 | 0.06 | 0.22 |
| Obs. | 3,535,933 | | 256,022 | | 309,746 | | 285,345 | | 159,447 | | 156,804 | |

Notes: This table shows the Mean (1), Standard deviation (2) of the following variables in six-hour sub-samples. *Invested Amount* represents the amount of money invested. *Invested* is a dummy variable which equals 1, if the listing is invested and 0 otherwise. *Hourly Total Bids* represents the hourly total number of bids from lenders for a loan request. *Share Needed* represents the share of the amount requested that is left unfunded. *Log Bidders* represents the logarithm of number of bidders. *Hourly Percentage Automatic Bidding (%)* represents the share of automatic bids submitted each hour.

**Table 3. Summary statistics by experience on the platform and timing of bidding**

| **Panel A:** Experience in days (X) on the platform | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | <90 | | 90<X<180 | | 180<X<360 | | 360+ | |
| | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Invested Amount* | 140.60 | 1828.62 | 98.92 | 1382.32 | 81.84 | 1209.14 | 103.02 | 1258.90 |
| *Invested = 1* | 0.07 | 0.25 | 0.07 | 0.25 | 0.05 | 0.22 | 0.06 | 0.24 |
| *Hourly Total Bids* | 8.95 | 20.69 | 10.49 | 18.87 | 9.43 | 18.32 | 10.30 | 20.77 |
| *Share Needed* | 0.72 | 0.25 | 0.69 | 0.26 | 0.72 | 0.25 | 0.71 | 0.26 |
| *Log Bidders* | 6.89 | 1.53 | 6.94 | 1.43 | 7.01 | 1.42 | 6.85 | 1.49 |
| *Hourly Percentage Automatic Bidding (%)* | 0.05 | 0.19 | 0.07 | 0.22 | 0.07 | 0.23 | 0.05 | 0.20 |
| Obs. | 1,307,558 | | 460,616 | | 888,714 | | 2,162,529 | |

| **Panel B:** Timing of bidding | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | First Hour | | Second Hour | | Penultimate Hour | | Last Hour | |
| | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Invested Amount* | 78.46 | 936.20 | 61.35 | 682.60 | 55.34 | 795.38 | 94.16 | 1122.53 |
| *Invested=1* | 0.08 | 0.26 | 0.06 | 0.24 | 0.04 | 0.20 | 0.08 | 0.28 |
| *Hourly Total Bids* | 10.30 | 16.37 | 11.79 | 20.56 | 10.81 | 16.74 | 10.82 | 16.67 |
| *Share Needed* | 0.64 | 0.27 | 0.66 | 0.27 | 0.74 | 0.26 | 0.71 | 0.24 |
| *Log Bidders* | 5.27 | 1.49 | 5.54 | 1.43 | 5.87 | 1.45 | 5.63 | 1.78 |
| *Hourly Percentage Automatic Bidding (%)* | 0.05 | 0.20 | 0.07 | 0.22 | 0.08 | 0.23 | 0.07 | 0.23 |
| Obs. | 196,786 | | 28,810 | | 42,306 | | 356,048 | |

Notes: This table shows the Mean (1), Standard deviation (2) of the following variables. *Invested Amount* represents the amount of money invested. *Invested* is a dummy variable which equals 1, if the listing is invested and 0 otherwise. *Hourly Total Bids* represents hourly total number of bids from lenders for a loan request. *Share Needed* represents the share of the amount requested that is left unfunded. *Log Bidders* represents the logarithm of number of bidders. *Hourly Percentage Automatic Bidding (%)* represents the percentage of automatic bids submitted each hour.

**Table 4. Do investors herd?**

| | Log (Amount) | | Invested=1 Dummy | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Total Amount$_{t-1}$* | 0.061*** | 0.061*** | 1.023*** | 1.039*** |
| | (0.021) | (0.020) | (0.377) | (0.360) |
| *Share Needed$_{t-1}$* | 0.510** | 0.519*** | 7.898** | 8.344** |
| | (0.209) | (0.201) | (3.804) | (3.641) |
| *Total Bids$_{t-1}$* | 0.002** | 0.002** | 0.028** | 0.029** |
| | (0.001) | (0.001) | (0.014) | (0.014) |
| *Share Automatic Bidding$_{t-1}$* | 0.564 | 0.058 | 6.570 | -1.701 |
| | (1.526) | (1.430) | (27.357) | (25.417) |
| *Total Amount$_{t-1}$* × *Share Needed$_{t-1}$* | -0.043** | -0.045** | -0.693** | -0.747** |
| | (0.019) | (0.018) | (0.346) | (0.332) |
| *Log Bidders$_t$* | -0.015*** | -0.014*** | -0.272*** | -0.241*** |
| | (0.003) | (0.003) | (0.057) | (0.054) |
| *Investor fixed effects* | no | yes | no | yes |
| Obs. | 4,728,299 | 4,718,225 | 4,728,299 | 4,718,225 |
| $R^2$ | 0.153 | 0.188 | 0.167 | 0.201 |

Notes: The dependent variable in Columns (1) and (2) is the sum of all bids invested in listing *i* by investor *j* at time *t*. In Columns (3) and (4) we construct an indicator which takes the value of 1, if investor *j* has bid for listing *i* or zero otherwise. *Total Amount$_{t-1}$* represents the total amount of listing *i* received from all investors at time *t–1*. *Share Needed $_{t-1}$* represents the share of the amount requested that is left unfunded at the end of hour *t–1*. *Total Bids $_{t-1}$* represents the total number of bids at time *t–1*. *Share Automatic Bidding$_{t-1}$* represents the share of automatic bidding at time *t–1*. *Log Bidders$_t$* represents the logarithm of number of bidders. Coefficient in Columns (3) and (4) are multiplied by 100 for presentation purposes. * = significant at 10% level, ** = significant at 5% level, and *** = significant at 1% level. Robust standard errors are presented in parentheses.

**Table 5. Results for time spent on platform (hours daily)**

| | 1 hour | 2-3 hours | 4-6 hours | 7-9 hours | 10-12 hours | 12+ hours |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Total Amount*$_{t-1}$ | 1.633*** | -0.240 | 0.357 | 0.352 | 1.120 | 0.666 |
| | (0.454) | (0.607) | (0.596) | (0.608) | (0.681) | (0.681) |
| *Share Needed*$_{t-1}$ | 14.820*** | -5.379 | 5.008 | 4.771 | 10.184 | 6.197 |
| | (4.637) | (6.093) | (6.183) | (6.075) | (6.706) | (6.907) |
| *Total Bids*$_{t-1}$ | 0.036** | -0.014 | 0.040** | 0.027 | 0.026 | 0.044* |
| | (0.014) | (0.020) | (0.019) | (0.020) | (0.022) | (0.025) |
| *Share Automatic Bidding*$_{t-1}$ | -18.047 | -47.350 | 18.444 | 9.307 | 63.587 | -56.709 |
| | (27.674) | (43.121) | (37.702) | (41.303) | (54.739) | (61.812) |
| *Total Amount*$_{t-1}$ × *Share Needed*$_{t-1}$ | -1.239*** | 0.514 | -0.636 | -0.478 | -1.227** | -0.849 |
| | (0.416) | (0.529) | (0.540) | (0.537) | (0.605) | (0.618) |
| *Log Bidders*$_t$ | -0.294*** | 0.085 | 0.210** | -0.052 | -0.195 | -0.245 |
| | (0.056) | (0.114) | (0.092) | (0.099) | (0.138) | (0.154) |
| Obs. | 3,535,933 | 256,022 | 309,746 | 285,345 | 159,447 | 156,804 |
| $R^2$ | 0.227 | 0.292 | 0.267 | 0.270 | 0.297 | 0.32 |

Notes: This table shows the effects of the following variables, based on the number of hours on spent on the platform on a given day: (1) 1 hour, (2) 2-3 hours, (3) 4-6 hours, (4) 7-9 hours, (5) 10-12 hours and (6) more than 12 hours. The dependent variable is an indicator which takes the value of 1 if investor *j* has bid for listing *i* or zero otherwise. *Total Amount* $_{t-1}$ represents the total amount of listing *i* received from all investors at time *t–1*. *Share Needed* $_{t-1}$ represents the percentage of the amount requested that is left unfunded at the end of hour *t–1*. *Total Bids*$_{t-1}$ represents the total number of bids at time *t–1*. *Share Automatic Bidding*$_{t-1}$ represents the share of automatic bidding at time *t–1*. *Log Bidders*$_t$ represents the logarithm of number of bidders. For presentation purposes all coefficients are multiplied by 100. * = significant at 10% level, ** = significant at 5% level, and *** = significant at 1% level. Robust standard errors are presented in parentheses.

**Table 6. X days of experience on the platform with less than 1 hour per session**

| | <90 days | 90<X<180 days | 180<X<360 days | 360+ days |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Total Amount*$_{t-1}$ | 0.237 | 2.680*** | 2.384*** | 2.401*** |
| | (0.340) | (0.656) | (0.715) | (0.751) |
| *Share Needed*$_{t-1}$ | -2.127 | 26.669*** | 23.024*** | 24.229*** |
| | (3.206) | (6.698) | (7.570) | (8.027) |
| *Total Bids*$_{t-1}$ | 0.025 | 0.059*** | 0.030* | 0.026* |
| | (0.017) | (0.022) | (0.018) | (0.015) |
| *Share Automatic Bidding*$_{t-1}$ | 11.197 | -3.294 | 14.338 | -19.973 |
| | (35.816) | (41.309) | (30.042) | (28.004) |
| *Total Amount*$_{t-1}$ × *Share Needed*$_{t-1}$ | 0.068 | -2.622*** | -2.161*** | -1.925*** |
| | (0.304) | (0.614) | (0.671) | (0.694) |
| *Log Bidders*$_t$ | -0.317*** | -0.211* | -0.113* | -0.207*** |
| | (0.093) | (0.112) | (0.068) | (0.062) |
| Obs. | 1,291,306 | 452,464 | 872,915 | 2,085,201 |
| $R^2$ | 0.297 | 0.300 | 0.258 | 0.179 |

Notes: This table shows the effects of the following variables for investors with X days of experience on the platform: (1) less than 90 days, (2) 90-180 days, (3) 180-360 days and (4) more than 360 days. The dependent variable is an indicator which takes the value of 1, if investor *j* has bid for listing *i* or zero otherwise. *Total Amount*$_{t-1}$ represents the total amount of listing *i* received from all investors at time *t–1*. *Share Needed* $_{t-1}$ represents the share of the amount still unfunded at the end of hour *t–1*. *Total Bids* $_{t-1}$ represents the total number of bids at time *t–1*. *Share Automatic Bidding* $_{t-1}$ represents the share of automatic bidding at time *t–1*. *Log Bidders*$_t$ represents the logarithm of number of bidders. For presentation purposes all coefficients are multiplied by 100. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Robust standard errors are presented in parentheses.

**Table 7. Results for daily session with at least four hours spent on platform**

| | First hour | Second Hour | Penultimate Hour | Last hour |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Total Amount*$_{t-1}$ | 1.314* | 0.864 | 0.410 | 0.541 |
| | (0.737) | (1.759) | (1.799) | (0.767) |
| *Share Needed*$_{t-1}$ | 16.240** | 17.869 | 0.678 | 4.666 |
| | (7.254) | (16.726) | (18.359) | (7.867) |
| *Total Bids*$_{t-1}$ | 0.111*** | -0.089 | -0.063 | 0.002 |
| | (0.029) | (0.068) | (0.047) | (0.022) |
| *Share Automatic Bidding*$_{t-1}$ | -16.802 | 71.039 | -4.472 | 57.565 |
| | (52.525) | (127.569) | (108.342) | (50.972) |
| *Total Amount*$_{t-1}$ × *Share Needed*$_{t-1}$ | -1.776*** | -2.831* | -0.487 | -0.474 |
| | (0.648) | (1.456) | (1.611) | (0.692) |
| *Log Bidders*$_t$ | 0.130 | -0.303 | 0.022 | -0.502*** |
| | (0.143) | (0.369) | (0.409) | (0.113) |
| Obs. | 196,786 | 28,810 | 42,306 | 356,048 |
| $R^2$ | 0.292 | 0.430 | 0.531 | 0.274 |

Notes: This table shows the effects of the following variables at different times on platform: (1) the first one hour, (2) the second hour, (3) the penultimate hour and (4) the last hour. The dependent variable is an indicator which takes the value of 1, if investor *j* has bid for listing *i* or zero otherwise *Total Amount*$_{t-1}$ represents the total amount of listing *i* received from all investors at time *t–1*. *Share Needed*$_{t-1}$ represents the share of the amount requested that is left unfunded at the end of hour *t–1*. *Total Bids*$_{t-1}$ represents the total number of bids at time *t–1*. *Share Automatic Bidding*$_{t-1}$ represents the share of automatic bidding at time *t–1*. *Log Bidders*$_t$ represents the logarithm of number of bidders. For presentation purposes all coefficients are multiplied by 100. *Significant at 10% level; **Significant at 5% level; ***Significant at 1% level. Robust standard errors are presented in parentheses.

**Table 8. Results for experience on platform of investors that spend one hour or less per daily session**

| | <90 days | 90<X<180 days | 180<X<360 days | 360+ days |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Total Amount$_{t-1}$* | 0.293 | 4.101*** | 3.269*** | 2.761*** |
| | (0.219) | (0.454) | (0.366) | (0.288) |
| *Share Needed$_{t-1}$* | -2.632 | 40.750*** | 33.081*** | 28.162*** |
| | (2.119) | (4.651) | (3.873) | (3.088) |
| *Total Bids$_{t-1}$* | 0.042*** | 0.066*** | 0.040*** | 0.029*** |
| | (0.006) | (0.008) | (0.006) | (0.004) |
| *Share Automatic Bidding$_{t-1}$* | -21.420 | 8.230 | 8.641 | -34.883** |
| | (22.912) | (34.840) | (19.833) | (17.455) |
| *Total Amount$_{t-1}$* × *Share Needed$_{t-1}$* | 0.144 | -3.746*** | -2.986*** | -2.218*** |
| | (0.182) | (0.388) | (0.326) | (0.260) |
| *Log Bidders$_t$* | -0.325*** | -0.308*** | -0.217*** | -0.236*** |
| | (0.052) | (0.080) | (0.044) | (0.023) |
| Obs. | 964,788 | 320,587 | 657,826 | 1,574,833 |
| $R^2$ | 0.373 | 0.343 | 0.287 | 0.197 |

Notes: This table shows the effects of the following variables at different number of days of experience on platform: (1) less than 90 days, (2) 90-180 days, (3) 180-360 days and (4) more than 360 days. The dependent variable is an indicator which takes the value of 1, if investor *j* has bid for listing *i* or zero otherwise. *Total Amount$_{t-1}$* represents the total amount of listing *i* received from all investors at time *t–1*. *Share Needed$_{t-1}$* represents the percentage of the amount requested that is left unfunded at the end of hour *t–1*. *Total Bids$_{t-1}$* represents the total number of bids at time *t–1*. *Share Automatic Bidding$_{t-1}$* represents the percentage of automatic bidding at time *t–1*. *Log Bidders$_t$* represents the logarithm of number of bidders. For presentation purposes all coefficients are multiplied by 100. * = significant at 10% level. ** = significant at 5% level. *** = significant at 1% level. Robust standard errors are presented in parentheses.

**Table 9. Results for sequential correlation and herding**

| | Sequential | | Listing FE | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Total Amount$_{t-1}$* | 0.321*** | 0.319*** | 0.176*** | 0.174*** |
| | (0.009) | (0.010) | (0.021) | (0.021) |
| *Share Needed$_{t-1}$* | 1.030*** | 0.985*** | 0.444*** | 0.390** |
| | (0.072) | (0.074) | (0.157) | (0.157) |
| *Total Bids$_{t-1}$* | 0.003*** | 0.005*** | 0.003*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| *Amount Requested* | 0.167*** | 0.175*** | | |
| | (0.006) | (0.006) | | |
| *Interest Rate$_t$ (%)* | 0.010*** | 0.011*** | | |
| | (0.000) | (0.000) | | |
| *Maturity$_t$ (Months)* | -0.017*** | -0.017*** | | |
| | (0.000) | (0.000) | | |
| *Credit Risky$_t$* | 0.001 | -0.025*** | | |
| | (0.007) | (0.007) | | |
| *Debt-to-Income Ratio$_t$* | 0.010 | -0.004 | | |
| | (0.009) | (0.009) | | |
| *Log Bidders$_t$* | 1.233*** | 1.226*** | 1.280*** | 1.274*** |
| | (0.002) | (0.002) | (0.004) | (0.004) |
| *Total Amount$_{t-1}$ × Share Needed$_{t-1}$* | -0.139*** | -0.131*** | -0.056*** | -0.047*** |
| | (0.007) | (0.008) | (0.016) | (0.016) |
| *Share Automatic Bidding$_{t-1}$* | | -79.117*** | | -52.914*** |
| | | (1.723) | | (2.631) |
| *Hour-of-day fixed effects* | Yes | Yes | Yes | Yes |
| *Hour-of-listing fixed effects* | Yes | Yes | Yes | Yes |
| Obs. | 463,787 | 463,787 | 466,293 | 466,293 |
| $R^2$ | 0.849 | 0.850 | 0.704 | 0.705 |

Notes: This table shows Sequential Correlation in Columns (1) and (2) and fixed effects in Columns (3) and (4) for the following variables. The dependent variable is amount invested by all investors for listing *i* at time *t*. *Total Amount$_{t-1}$* represents the total amount of loans received from all investors at time *t – 1*. *Share Needed$_{t-1}$* represents the share of the amount requested that remains unfunded at the end of time *t–1*. *Total Bids$_{t-1}$* represents the total number of bids at time *t–1*. *Amount Requested$_t$* represents loan amount on request. *Interest Rate$_t$ (%)* represents annual percentage rate on the loan. *Maturity$_t$ (Months*) represents current loan duration in months. *Credit Risky$_t$* is 1 if the listing's credit grade is E or below, i.e., E, F or HR, and otherwise 0. *Debt-to-Income Ratio$_t$* represents the ratio of borrower's monthly gross income that goes to paying loans. *Log Bidders$_t$* represents the logarithm of number of bidders. *Share Automatic Bidding$_{t-1}$* represents the share of automatic bidding at time *t–1*. *Significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Robust standard errors are presented in parentheses.

**Table 10. Descriptive statistics of loan characteristics for cumulative total amount.**

| | Q1 | | Q2 | | Q3 | | Q4 | |
|---|---|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | mean | sd | mean | sd |
| *Interest Rate (%)* | 14.06 | 4.06 | 11.68 | 1.61 | 11.65 | 1.35 | 11.61 | 1.38 |
| *Maturity (Months)* | 10.28 | 8.39 | 21.00 | 10.33 | 27.74 | 10.19 | 29.69 | 9.79 |
| *Credit Risky (1=yes)* | 0.59 | 0.49 | 0.20 | 0.40 | 0.04 | 0.19 | 0.01 | 0.12 |
| *Debt-to-Income Ratio* | 0.20 | 0.20 | 0.26 | 0.32 | 0.28 | 0.34 | 0.36 | 0.48 |
| *Time on Market* | 12.29 | 31.29 | 2.06 | 7.02 | 1.40 | 5.74 | 1.01 | 5.53 |

*Interest Rate (%)* represents annual percentage rate on the loan. *Maturity (Months)* represents current loan duration in months. *Credit Risky* is 1 if the listing's credit grade is E and below, i.e., E, F and HR, and 0 otherwise. *Time on Market* represents total time spent on market. *Debt-to-Income Ratio* represents the ratio of borrower's monthly gross income that goes to paying loans. Q1-Q4 are quartiles of average per hour cumulative total amount invested.