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Abstract

We explore individual lender behaviour on Renrendai.com, a leading Chinese peer-to-peer (P2P) crowdlending platform. Using a sample of roughly 5 million investor-loan-hour observations and applying a high-dimension fixed effect estimator, we establish evidence of herding behaviour: the investors in our sample tend to prefer assets that had attracted strong interest in previous periods. The herding behaviour relates to both the experience of the investor and the length of time of each investment session. The results show that herding happens mostly in the first or final hour of long sessions. Herding behaviour is further confirmed by estimates at the listing-hour data.

Keywords: FinTech; peer-to-peer; crowdlending; herding.
JEL Classification: G21, G40, G41.

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1 Introduction

With the growing use of the internet and telepresence, 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 that the borrower submit a listing with such information 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 they deem worthy. Funding requires no interaction with the borrower as in traditional financial lending arrangements.

The P2P platform innovation comes with advantages and disadvantages.[1] By eliminating layers of costly intermediation, P2P platforms permit participation of investors of any number and size to lend to a single borrower, enabling the supply of funds from multiple sources to cover the demand. Such platforms provide funding access to individuals and businesses who fail to satisfy conventional bank lending criteria. These platforms have simple and quick procedures that facilitate rapid lending decisions and arrange good 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 may itself 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 perfectly rational, maximizing their utility and unconfused by cognitive limitations or information processing errors.[2] However, it is also recognized that people behave irrationally, making bad decisions due to behavioural biases.[3] For instance, in the face of a non-trivial risk of loan default, investors may nevertheless skip due diligence and imitate the behaviour of others, i.e. herd, in the hope of achieving better returns. Such behaviour can be a rational strategy, of course, for an investor with the belief that those she is mimicking possess superior information.[4]

Do P2P investors also herd? Using US data, several researchers have established herding behaviour of P2P investors.[5] Without such behaviour, funds would likely be widely dispersed among available listings such that only a few applicants get funding. The majority would never

[1] See Agrawal et al. (2014), Morse (2015) and Yum et al. (2012) for further discussion.
[2] See, for instance, Fama (1991) and Markowitz (1952).
[3] See, for instance, Chuang and Lee (2006) and Malmendier et al. (2011) on overconfidence, Biais and Weber (2009) and Merkle (2017) on hindsight bias, Hoffmann and Post (2014) and Iqbal (2019) on attribution bias, 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.
[4] It is well documented that herding behaviour is greater during extreme market conditions as in, for instance, Chiang (2010), Galariotis (2015) and Bekiros (2017). Furthermore, Merli and Rogerz (2013) show that an individual investor with a poor past performance has a higher propensity to herd in the next quarter. Brown (2014) examines mutual fund managers herding behaviour with career concerns. Choi and Skiba (2015) consider herding behaviour of institutional investors.
[5] See Herzenstein et al., 2011, Zhang and Liu (2012, Lee and Lee (2012), Greiner 2013 and Liu et al. (2015).

receive funding, as a listing is funded only if it attracts sufficient lending.[6] Furthermore, given the large number of potential borrowers, lenders would incur high search costs if lenders were to evaluate each listing. In this study, we, too, examine herding behaviour on P2P platforms. Unlike the extant literature, our investigation directly focuses on data at the investor-loan-hour level rather than indirectly examining loan-based information.

To carry out our investigation, we explore the leading Chinese P2P loan platform, *Renrendai.com,* from which we extract over 5 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 focus on actual human bidding activities.[7] Using this dataset, we focus directly on investor behaviour to examine herding behaviour on *Renrendai.com*, and not indirectly by observing whether a listing that received funding in the previous round is filled by an investor or not.[8,9] Our investigation pays particular attention to whether bidding behaviour is affected by the length of session on the platform or the experience of the investor with the platform. Our models allow for both listing and investor fixed effects to control for unobserved heterogeneity across listings and peer influence among lenders.

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 actually making the bid 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 interested rate, as well as borrower specific information including borrower's credit grade, debt-to-income ratio and age. We follow each listing's progression for up to 60 hours. Lists that did not close within this time are assumed to never receive funding, as lists on *Renrendai.com* close much faster than 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*. Our main findings about investor behavior relate initially to time spent on the platform and investor experience with the platform. That is, we observe herding behaviour depends on the length

[6] See, for instance, Herzenstein et al. (2011) and Wang and Greiner (2011).

[7] It should be noted that *Renrendai.com* has offered an automated investment function since shortly after the platform opened.

[8] The standard model examines whether a listing that has been funded at time (*t-1*) has received further investment at time *t*. That is the standard approach examines listing activity. Instead, we examine investor behaviour directly for we have information on each investor and each listing open to investors.

[9] We also examine herding behavior based on listings for robustness purposes. This approach confirms our claims, but fails to yield the detail we obtain from data at the investor-loan-hour level.

[10] The average loan completion time on *Renrendai.com* is less than 5 hours, while an average loan on *Prosper.com* takes almost 8 days to complete (Wei and Lin, 2016).

of time an investor is active on the platform. Considering the dataset as a whole, herding behaviour is observed mainly amongst investors who are active on the site for an hour or less. This effect evaporates as investors spend more time on the platform. Moreover, experienced investors are more likely to display herding behaviour, and investors new to the platform tend not to herd.

Having established these insights into investor behaviour we scrutinize two additional issues. We first ask how first-hour herding behaviour relates to investor experience. Next, we examine 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.[11] Examination of these questions yields two key observations. First, only experienced investors who only spend a limited time on the platform (up to an hour) tend to herd but those investors who are inexperienced do not. Second, lenders with logged session lengths of four hours or more are most likely to herd in the first or last hour of the session.

Overall, our results provide several insights. Herding behaviour on P2P loan markets is evidently heavily associated with experience of the investors and the spell of investment activity per session. Although useful, listing-based data analysis does not yield the detail we obtain from investigating investor activities. For robustness purposes, we reconstruct a listing-based data and estimate the standard model implemented in the literature to 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 discussion of the key findings. Section 5 concludes.

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.[12] 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 about RMB

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

[12] Citation: *Lendit.com* http://blog.lendit.com/wp-content/uploads/2015/04/Lufax-white-paper-Chinese-P2P-Market.pdf, accessed 31 July 2019.

600 billion ($91 billion) in total outstanding loans as of July 2016.[13] 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 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 to 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, officials shut down several P2P platforms. 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.

Renrendai.com, established in October 2010, remains China's leading P2P platform. At the end of October 2018, it had about 1 million confirmed loans with a total lending amount of over $10 billion, and a total of about 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 successfully raising 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 on 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 settled to around 5. Panel D of Figure 1 shows that the number of new listings per hour is highest between 3am 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 requested (from RMB 3,000 to RMB 500,000). Each listing posted on the platform remains active for up to 168 hours. Most listings, however, are filled in less than five hours, and the standard deviation of completion of a listing is about 17 hours. Large variations in completion could be explained by the fact that the majority of

[13] Citation: Wind Information, https://www.wind.com.cn/en/ , accessed 27 January 2018.

loans are financed within the first several hours, but a small number of listings are never filled and remain on the platform until they expire.[14] To set up a listing, the borrower uploads a written statement that describes the purpose of the loan and provides information on his or her 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 to the platform by the potential borrower. The more evidence the borrow provides as to good creditworthiness, the higher the credit rating granted by the platform. Credit ratings are linked to personal identity, education, employment, salary, criminal records, housing estates, vehicle ownership, personal mobile and social media certification. Evidence of regular payment 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.[15] Once the amount of loan request is fully met, the loan is created and the listing is removed from consideration. 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 the potential lender, the downside of expiration of a listing that did not attract the full amount requested by a borrower is the opportunity cost of lost time.

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 collect all available information on loan listings and borrower characteristics for each completed application. 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 get a unique loan ID and obtain a sample that comprises over 5 million observations at the investor-listing-hour level. Each listing in the dataset comes with 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,

[14] This is the reason we track listings up to 60 hours.
[15] Although the average return is in the vicinity of 12%, lenders sometimes incur losses.

education level, marital status, home ownership and borrowing history on the platform. It should be noted that investors can also use an automatic bidding facility while manually bidding for listings. Because herding is a human behaviour, our examination only covers bids made by people, yet we control for the use of automatic bidding in our regressions. Variable definitions are provided in the Appendix.

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 about 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 in busy periods. The number of bidders on the platform at any average hour is 278 (in logs 5.58). The data contain information on bids carried out by the automatic bidding facility (about 6% of the data). Nevertheless, in interpreting these figures, one should keep in mind 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 (our models contain listing fixed effects in all possible specifications), it is useful to look at some basic statistics. The data provide us with about 111,000 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 slightly 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.[16] While it takes just over four hours on average to complete (fill) a listing, the standard deviation is around 17 hours. Note that listings receive an average of just over 23 bids in the first hour. This is substantial and hints at the mismatch between the number of borrowers and lenders in favour of lenders. This mismatch helps assure that borrowers' loan requests will be completed rather quickly and gives some idea about the dynamic environment of lending and borrowing on *Renrendai.com*.

Splitting the sample based on the average time investors spend on the platform, investors' experience on platform, and intensity of bidding provides us additional insights. Table 2 reports 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 platform up to one hour is RMB 74.08. This average investment per hour increases for investors who stay longer

[16] It should be noted that some borrowers carry no outstanding debt, i.e. their debt-to-income ratio is zero.

on the platform. A similar pattern is observed for the binary indicator of investing.[17] The number of hourly bids for listings is highest (around 12) when a bidder stays online 2–9 hours. The percentage 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 with the platform. Column 1 of panel A shows that investors with less than three months of experience with the platform invest the highest amount (RMB 159.60) on average, while their peers with more experience on the platform invest on average RMB 90–110. The average percentage of bids carried out by automatic bidding each hour stays around 5–7% in all four sub-samples, which is comparable to the statistic 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 give statistics for the first and last hour of the session, while the middle columns give the second and the penultimate hours. Looking at the columns, we see that the average invested amount peaks at 109.49 RMB 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 (log 5.27) and the lowest average percentage of bids carried out by automatic bidding (5%). The average percentage of unfunded amount varies from 63.81% to 73.51% throughout all spells. Also note that most 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 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 find out if investor j (a human bidder) invests in listing i based on the observation that other investors have invested in the same listing. In particular, 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. 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

[17] The binary indicator takes the value of 1 if investor j has a bid for listing i, zero otherwise.

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

where indices j, i, t indicate investor, listing and time, respectively. The dependent variable is the total (RMB) amount invested in listing i by investor j at time t. Alternatively, we construct an indicator which takes the value of 1 if investor j has bid for listing i or zero otherwise. In this model, the main variable of interest is the lagged total cumulative amount invested, $Total\ Amount$, in listing i. To argue in favour of herding behaviour on the platform, the coefficient (α) associated with the variable lagged $Total\ Amount$ should be positive and significant. This implies that bidder j observing that the other investors have lent listing i follows the crowd and invests in it. Equation (1) is estimated using a three-way high-dimension fixed effect estimator.[18,19]

We control for several other variables captured by the vector X_{it}. This vector includes the percentage of the amount requested, $\%Needed_{it-1}$, by listing i that is left unfunded at the end of time (t-1). We expect this variable to take a positive sign capturing the fact that investors submit smaller amounts to complete the loan request. The model contains the number of lagged-total bids, $TotalBids_{it-1}$ at time (*t-1*), and the number of bids to control for interest in a listing and the number of investors, *Log Bidders*, at time *t*. Given the platform offers investors use of an automatic bidding facility, we control for the effect of this type of investment behaviour and add *Lagged Percent Automatic Bidding.* Furthermore, we include an interaction term in the model between lag total amount, *Lag Total Amount*, and the percentage needed to fill the loan *Percentage Needed*, to capture payoff externalities. The model controls for investor and listing fixed effects, κ_j and μ_i, respectively.[20] Date fixed effects, denoted by τ_t, captures any macroeconomic policy changes. The error term is denoted by e_{it}.

[18] 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.
[19] 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.
[20] 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 the robustness section.

4 Results

4.1 Do individual investors herd?

Table 4 presents our initial set of results in search of herding behaviour on *Renrendai.com.* The first two columns present 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 1 if investor *j* bid for listing *i* at time *t*. The main variable that we focus on is *Lag Total Amount*, in listing *i* at time (*t-1*). We expect the coefficient associated with this variable to take 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 and day fixed effects.

Overall, the results provide support for 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 significant. Hence, we conclude that among the whole range of listings that are available, investors prefer those listings that received more funding in the previous hour: 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. *Lag Percentage Needed (%)* 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 *Lag Percent Automatic Bidding* is negative and highly significant at the 1% level in all columns. A negative coefficient for automatic bidding implies that the presence of machine bidding reduces the average funds that a human bidder would make. The automatic bidding facility simply spreads funds mechanistically across all available listings based on a set of criteria. Hence, the more it is used by investors, there will be less room for human investors to bid. Yet, this facility does not impact the herding behaviour of the investors; herding requires that human investors observe other investors and react accordingly. In fact, without human investors, there is a positive (though small) chance that funds could be distributed equally across all worthy borrowers and no listings are filled. The interaction between *Lag Total Amount* and *Lag Percentage Needed* is significant and negative suggesting that as the listing fills it will continue to attract new funds but at a slower rate. This finding makes sense. In this fast-moving market, investors seek for new opportunities as lists fill up and new listings are posted over the day to make sure that they will be able to bid a set amount on viable listings. As expected, *Log Bidders* plays a negative role in total bids.

4.2 The role of total logged session time on the platform

Does the number of hours each investor spend on the platform in a session make a difference on 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. However, most of the time investors spent an hour or less in a session. Table 5 considers the question of whether investors spending more time on the platform behave differently. Columns 1 to 6 present results for 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 twelve hours but more than nine hours and more than twelve hours. It should be noted that an investor who stays logged for several hours to the platform does not necessarily submit bids to lists that are available throughout session. Such investors generally bid several listings in the first hour or the last hour, while bidding intermittently during the remaining period that they are logged on to the platform.

When we examine Table 5, we find that *Lag Total Amount* is significant only for column (1). In the remaining columns, this variable never takes a significant coefficient. These results therefore suggest that herding is prevalent among those investors who are logged for up to one hour per session. If the investor stays for longer than an hour, we do not observe herding behavior. The results we present here should not be surprising as they confirm that investors substitute private information partially or completely with social information when they should make quick financial decisions. The heuristic of following others is a better use of one's time in an environment where private information is hard to come by. 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 as described in Table 4. For the rest of the columns, we see that although the signs associated with the variables are similar to what 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 of the investor on the platform. Columns (1) to (4) capture the behavior of those investors who have experience of less than 90 days (3 months), less than 180 days but greater than 90 days (between 3 to 6 months); less than 360 days but greater than 180 days (between 6 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 statistically not significant. However, for the remaining columns, lagged total effect takes 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 3 to 3.5 percentage points. These findings suggest that herding instincts may have evolved as a learning heuristic, enabling us to use social information about the potential value of the listing. It is also possible that individual investors start following the herd when they realize that there is "safety in numbers," doing as the others locks down a similar yield for all involved.

When we turn to examine the role of the control variables, we see in column 1 that none of them take 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. *Lag Percentage Needed* takes a positive coefficient, suggesting that funding of a listing slows as the loan approaches completion. *Automatic Bidding* takes a negative coefficient, implying that the presence of machine bidding reduces the average funds that a human bidder would make. The interaction between *Lag Total Amount* and *Lag Percentage Needed* is significant and negative, suggesting that as the listing is filled, it attracts new funds at a slower rate. As expected, *Log Bidders* plays a negative role in total bids.

4.4 Session length and investor behavior

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 as intensively at all times, thousands of investors stay logged onto the platform for multi-hour sessions. Indeed, these investors are generally most active during the first and the last hours of the session. The investor starts the session with several bids, goes several hours with no or few bids, then completes the session with several additional ones. This observation raises the question of whether investors who stay logged for long hours at the platform 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. We first examine separately the role of the first and the last hour in herding behaviour. We then examine the extent to which investors exhibit herding behaviour within the second and penultimate hours.

Table 7 presents the results. The first column of the table gives the first hour results, and column 4 gives the last hour results on a session. Columns 2 and 3, provide the results for the second and penultimate hours. The results are striking: lag total amount is positive and significant with similar magnitudes only for the first and the last hour of a long session. The stronger significance in the last hour may be due to increased activity before the session is completed. Thus, we conclude that investors who stay logged to the platform for long hours still herd, but only during the initial and final hours on the platform. During the second and penultimate hours, we observe no herding behaviour. In fact, during these hours, the extent of activity is rather low. It may be that when investors are not actively bidding, they spend their time examining listings and the activity of other investors.[21] The control variables are mostly significant and similar to what we reported for Table 6. For the middle two columns, significance of these coefficients drop.

4.5 Experience and the first-hour effect

Table 5 showed that investors who logged on for an hour or less tended to herd. We now examine the role of experience on herding behavior for investors who stay logged on for up to an hour on the platform.[22] In other words, do novices herd as much as experienced investors who have spent a year or more on the platform in sessions of one hour or less?

Table 8 provides the results. Column 1 shows the results for those investors who have up to three months of experience on the platform. Column 2 to 4 provide the respective results for more experienced investors (3-6 months, 6 months to a year and more than a year). Inspecting the coefficient of *Log Total Amount*, we see that it is significant and positive for all levels of experience. However, a closer inspection shows that herding behavior is more prominent for those investors with more than three months of experience. Note that the coefficient associated with lagged total amount in column 1, which captures the behavior of investors with more than three months of experience, is only significant at the 10% level and its impact is smaller than the remaining columns.[23] For investors with less than three months of experience, when *Lag Total Amount* invested increases by 1%, investment increases by 0.5 percentage points. However, for the more experienced investors, a 1% increase in *Lag Total Amount* leads to a 4 percentage-point increase in investment.

The effect and significance of control variables, especially those in columns 2 to 4, are similar to those reported in Table 6. *Lag Percentage Needed* takes a positive coefficient, suggesting that the amount of funds a listing receives slows as completion approaches. Automatic bidding takes a negative coefficient, implying that the presence of machine bidding reduces the average funds that a human bidder would make. The interaction between *Lag Total Amount* and *Lag Percentage Needed* is significant and negative, suggesting that listing continues to attract new funds at a slowing rate as it fills. As expected, *Log Bidders* plays a negative role in total bids. The control variables in Column (1), although they take the expected signs, have weaker statistical significance.

[21] Data do not allow us to examine this possibility.
[22] Table 2 shows that most of the investors who stay logged onto the platform for an hour or less. This gives us a set of more than 3.5 million observations. For longer sessions, we have fewer than 1 million observations.
[23] Note that the significance of the coefficient associated with *Lag Total Amount* is at the 1% level for the remaining columns.

4.6 Is there herding behaviour at the listing level?

We now report the results for our listing-level model. Unlike earlier research, we focus on hourly cumulative bids rather than daily cumulative bids because *Renrendai.com* is an extremely fast and dynamic platform.[24] Recall further that we strike out all unfunded lending at 60 hours, even if technically a listing can remain posted on the site for up to 168 hours. We begin our investigation by estimating the following naive model to seek evidence for sequential correlation:

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

where Bid_{it} denotes the amount of funding that list *i* receives at time *t* = 1, 2, ..., 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 α is significantly positive, we argue in favour of sequential correlation. Note that the difference between this model and model (1) is the investor dimension, as investor level information is now embedded in total bids of each listing.

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, $\%Needed_{it-1}$, the percentage of the amount requested by listing *i* that is left unfunded at the end of hour (*t – 1)*. To capture the possibility that lending concentrates on certain hours of the day, we include hour of the day, H_{it-1}, and day of the week, D_{it-1}, fixed effects. Vector Z_i, which captures the time-invariant listing characteristics, including *Amount Requested*, *Maturity*, a *Credit Risky* dummy, *Debt-to-Income Ratio* and a *Homeowner* dummy. The interest rate 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* in Z_i, to index the date the listing is posted on *Renrendai.com*. To capture the role of automatic bidding that some investors implement, we augment the model with lagged *Percent Automatic Bidding.* 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 investors' herding behaviour, because sequential correlation could be driven by a number of reasons including unobserved heterogeneity across lists, payoff externalities among lenders. It is possible to disentangle unobserved heterogeneity across lists by introducing listing fixed effects, μ_i, as characteristics of borrowers will not change over the duration of the loan. Also, to

[24] Looking solely at bids submitted by humans (i.e. dropping automatic bidding data), the average listing is filled in slightly less than 5 hours (4.94 hours).

capture payoff externalities, we introduce an interaction term *Lag Total Amount* x *Percentage Needed*$_{t-1}$ as an explanatory variable. These changes render the following model.

$$Bid_{it} = \vartheta + \alpha TotAmount_{it-1} + \delta TotalBids_{it-1} + X_{it}\beta_1 + Z_i\beta_2 + \mu_i + e_{it} \quad (3)$$

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 bring in listing and hour of day fixed effects into the model. Columns 2 and 4 bring in the role of automatic bidding into the model.

When we inspect the first two columns of the table, we see that the coefficient associated with *Lag Total Amount* is positive and significant at the 1% level. This finding suggests for the presence of sequential correlation. In the second column, notice 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 that this facility to add an extra amount 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. Yet automatic bidding clearly reduces the interest of investors for investment and reduces funding for listings. This result is also captured in our investor-level models.

Signs of coefficients associated with all the remaining variables in the first two columns are meaningful. *Lag Total Bids*, *Amount Requested*, *Interest Rate*, *Debt-to-Income Ratio* and *Log Bidders* all play a positive role in total bids for a listing. *Lag Percent Needed* takes a positive coefficient in all columns, suggesting that the filling of listings slows as the loan approaches completion. Maturity has a negative sign, indicating that investors prefer lending listings with shorter durations over those of longer duration. This is meaningful because there is substantial information asymmetry about 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 *Lag Total Amount* and *Lag Percentage Needed* is significant and negative suggesting that the listing attracts new funds at a slower rate as it fills. This makes sense. Given the speed of the action on *Renrendai.com*, investors must be quick in identifying opportunities for new listings are posted and older ones fill over the course of the day.

To examine herding behaviour of investors, we control for listing fixed effects. We do that in columns 3 and 4. The results across the two columns are similar. *Lag Total Amount* is still positive and significant, implying the presence for herding behaviour on *Renrendai.com*. Furthermore, this is not overturned by the presence of automated bidding, despite its negative and significant effect. Thus, the results provided in Table 9 validate the presence of herding behaviour on *Renrendai.com*.

5 Conclusion

It has been more than a decade that microloan markets have become part of our life 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 our investigation we focus on data from *Renrendai.com*, one of the largest microloan markets in China. This is a fast online-platform which also allows investors to subscribe 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. Yet, we also use listing level data to verify our findings. Examining the data from the perspective of investor activity, we provide significant evidence of herding behaviour. When we deepen our investigation, we show that herding behaviour is observed amongst investors who stay logged on to the platform for at most 1 hour in one session. Furthermore, we show that herding behaviour is more of a characteristic of experienced investors. While experienced investors tend to herd, investors who are new to the platform do not provide much evidence of herding behaviour. We then turn our attention to those who stay logged on to the platform for at least 4 hours in one session to scrutinize whether those investors herd during a particular period when they are logged on to the platform. It turns out that those who spend long hours (at least 4 hours) in one session are most active and herd during the first hour or the last hour of their session. Lastly, we focus on those investors who are logged to the platform for less than one hour and, in fact, show that mostly those investors with experience herd.

Overall, our investigation yields several new and important details that have not been discussed before. We show that herding is driven by experienced investors who complete their investments within an hour. Results from the listing approach that the extant literature has implemented lend support for our findings but they are far from providing the detail that we scrutinized from investor level data. Furthermore, contrary to one's perception, we show that automatic bidding facility reduces the amount that manual investors could channel towards available listings. Notwithstanding, there are several additional drawbacks of using the automatic bidding facility. In particular, borrowers who are worthy of the loan but ranked poorly by the platform will be automatically weeded out. Automatic bidding prevents human interaction and the possibility to extract and use incremental information about low ranked borrowers. Furthermore, because investors can instruct the platform about their personal risk return preferences before listings are filled, this may lead to some unwanted consequences as well. Risk is not observed yet is calculated based on borrower profiles while the return is observed. Risk calculations are formulaic and these formulas can be designed to achieve the goals of the platform (e.g. increase the number of borrowers or lenders, total amount funded). With time, composition of borrowers or lenders can change which could disrupt the functioning of the platforms. For instance, an increase in the composition of bad loans can cause a withdrawal of investors from the platform possibly triggering a collapse as well affecting the whole market. Hence, one needs to be careful as to what extent automatic bidding facility should be implemented for investment purposes on P2P markets.

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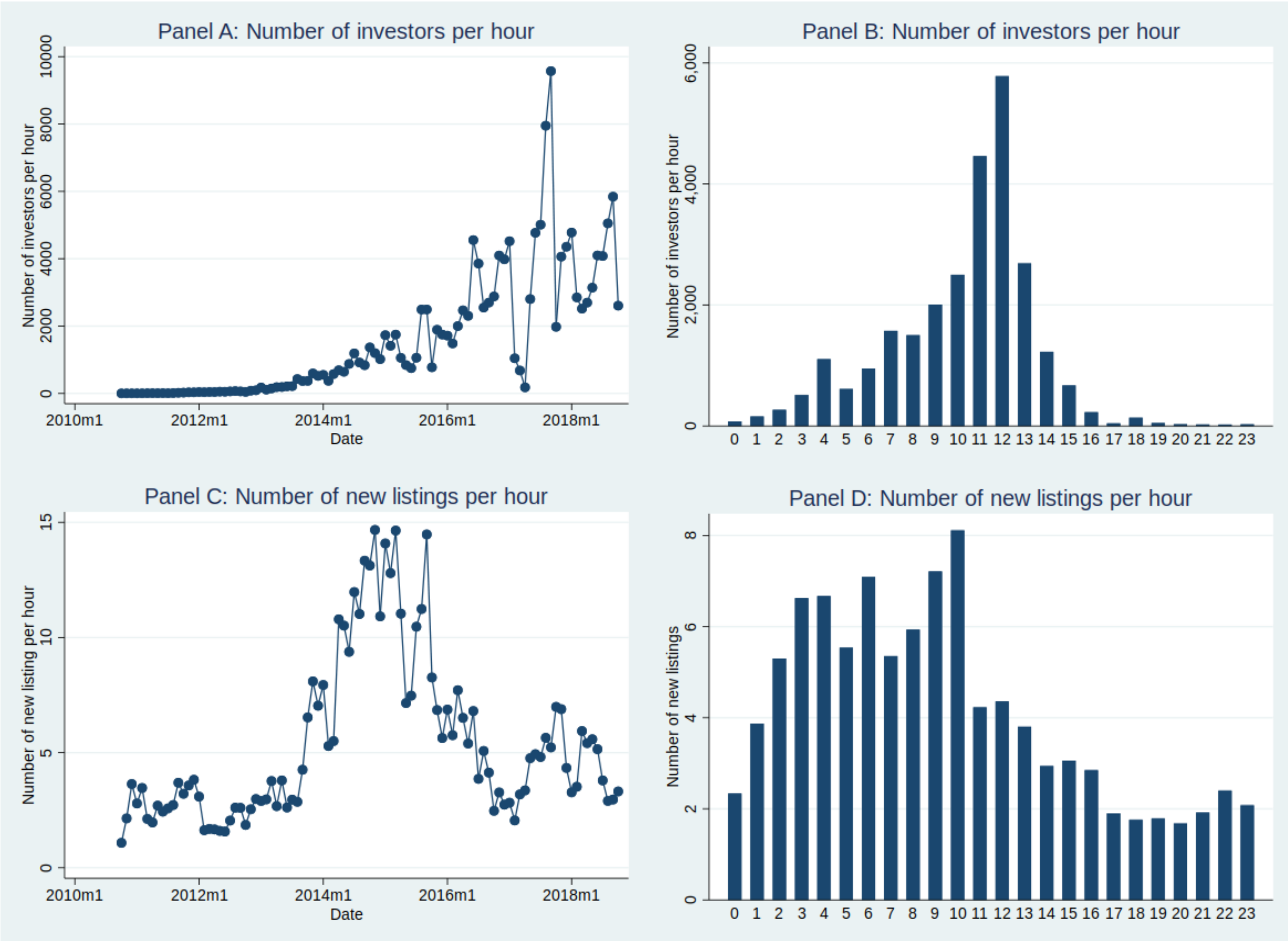
Figure and tables

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 (1)	Std. dev. (2)	P25 (3)	P50 (4)	P75 (5)
Invested amount	82.35	996.42	0.00	0.00	0.00
Invested=1	0.08	0.27	0.00	0.00	0.00
Hourly total bids	9.82	20.16	2.00	5.00	11.00
Percent needed	71.24	25.50	55.65	78.95	92.31
Log bidders	5.58	1.72	4.48	5.21	6.34
Hourly percent automatic bidding	0.06	0.21	0.00	0.00	0.00
Obs.	4,718,225				

Panel B: Loan-level data					
	Mean (1)	Std. dev. (2)	P25 (3)	P50 (4)	P75 (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 biddings (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. Percent Needed (%) represents the percentage of the amount requested that is left unfunded. Log Bidders represents the logarithm of number of bidders. *Hourly Percent Automatic Biddings* represents the percentage of automatic biddings each hour. *Loan Amount* represents the total amount of loan received. *Interest Rate (%)* represents annual percentage rate on the loan. *Maturity (Month)* 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 first hour of bidding period. Hourly Percentage Automatic Biddings represents the percentage of automatic biddings 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 (1)	Std. dev. (2).	Mean (3)	Std. dev. (4).	Mean (5)	Std. dev. (6)	Mean (7)	Std. dev. (8)	Mean (9)	Std. dev. (10)	Mean (11)	Std. dev. (12)
Invested amount	74.08	933.76	133.92	1462.71	94.68	1111.21	89.45	1018.65	102.31	946.81	107.77	1083.62
Invested=1	0.07	0.26	0.10	0.30	0.08	0.28	0.09	0.29	0.11	0.32	0.12	0.32
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
Percentage needed (%)	71.91	25.35	69.05	26.03	68.78	25.98	68.95	25.83	69.75	25.27	70.84	25.79
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 percent 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 time 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 hourly total number of bids from lenders for a loan request. *Percentage Needed (%)* represents the percentage of the amount requested that is left unfunded. *Log Bidders* represents the logarithm of number of bidders. *Hourly Percent Automatic Bidding* represents the percentage 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 (1)	Std. dev. (2)	Mean (3)	Std. dev. (4)	Mean (5)	Std. dev. (6)	Mean (7)	Std. dev. (8)
Invested amount	159.60	1862.50	106.91	1392.99	91.77	1230.18	111.34	1276.87
Invested = 1	0.09	0.28	0.08	0.27	0.07	0.25	0.08	0.27
Hourly total bids	8.95	20.69	10.49	18.87	9.43	18.32	10.30	20.77
Percentage needed (%)	71.78	25.45	68.57	26.30	71.74	25.68	70.67	25.64
Log bidders	6.89	1.53	6.94	1.43	7.01	1.42	6.85	1.49
Hourly percent 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 (1)	Std. dev. (2)	Mean (3)	Std. dev. (4)	Mean (5)	Std. dev. (6)	Mean (7)	Std. dev. (8)
Invested amount	87.41	953.95	91.29	750.09	86.84	847.39	109.49	1155.21
Invested=1	0.09	0.28	0.12	0.32	0.10	0.30	0.10	0.31
Hourly total bids	10.30	16.37	11.79	20.56	10.81	16.74	10.82	16.67
Percent needed (%)	63.81	27.10	66.05	26.77	73.51	25.50	71.39	24.44
Log bidders	5.27	1.49	5.54	1.43	5.87	1.45	5.63	1.78
Hourly percent 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. Percentage Needed (%) represents the percentage of the amount requested that is left unfunded. Log Bidders represents the logarithm of number of bidders. Hourly Percent 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)
Lag total amount	0.091***	0.088***	1.583***	1.566***
	(0.008)	(0.008)	(0.134)	(0.134)
Lag percentage needed (%)	0.008***	0.008***	0.138***	0.139***
	(0.001)	(0.001)	(0.014)	(0.014)
Lag total bids	0.001***	0.001***	0.012***	0.013***
	(0.000)	(0.000)	(0.003)	(0.003)
Lag percent automatic bidding	–0.023***	–0.025***	–0.505***	–0.524***
	(0.006)	(0.006)	(0.106)	(0.106)
Lag total amount x lag percentage needed (%)	–0.001***	–0.001***	–0.011***	–0.011***
	(0.000)	(0.000)	(0.001)	(0.001)
Log bidders	–0.008***	–0.009***	–0.152***	–0.148***
	(0.001)	(0.001)	(0.019)	(0.019)
Investor fixed effects	no	yes	no	yes
Obs.	4,728,299	4,718,225	4,728,299	4,718,225
R^2	0.136	0.176	0.144	0.180

Notes: This table shows the effects of the following variables. *Lag Total Amount* represents the total amount of loan received at time t–1. *Lag Percentage Needed (%)* represents the percentage of the amount requested that is left unfunded at the end of hour t–1. *Lag Total Bids* represents the total number of bids at time t–1. *Lag Percent Automatic Bidding* represents the percentage of automatic biddings at time t–1. *Log Bidders* 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 (1)	2–3 hours (2)	4–6 hours (3)	7–9 hours (4)	10–12 hours (5)	12+ hours (6)
Lag total amount	2.283***	–0.087	0.698	–0.005	0.898	0.666
	(0.172)	(0.542)	(0.486)	(0.499)	(0.630)	(0.575)
Lag percentage needed (%)	0.211***	–0.020	0.096*	0.045	0.096	0.071
	(0.018)	(0.054)	(0.049)	(0.050)	(0.062)	(0.055)
Lag total bids	0.034***	–0.037***	–0.006	–0.007	–0.013	–0.033**
	(0.003)	(0.012)	(0.009)	(0.009)	(0.014)	(0.015)
Lag percent automatic bidding	–0.538***	–1.268***	–0.080	0.134	–0.010	–1.173**
	(0.127)	(0.463)	(0.386)	(0.421)	(0.591)	(0.550)
Lag total amount x lag percentage needed (%)	–0.017***	0.004	–0.010**	–0.004	–0.011**	–0.008*
	(0.002)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Log bidders	–0.231***	0.065	0.311***	0.066	0.052	0.104
	(0.022)	(0.103)	(0.079)	(0.081)	(0.116)	(0.118)
Obs.	3,535,933	256,022	309,746	285,345	159,447	156,804
R^2	0.196	0.298	0.281	0.285	0.317	0.341

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. *Lag Total Amount* represents the total amount of loan received at time t–1. *Lag Percentage Needed (%)* represents the percentage of the amount requested that is left unfunded at the end of hour t–1. *Lag Total Bids* represents the total number of bids at time t–1. *Lag Percent Automatic Bidding* represents the percentage of automatic biddings at time t – 1. *Log Bidders* 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 (1)	90<X<180 days (2)	180<X<360 days (3)	360+ days (4)
Lag total amount	0.242	3.018***	3.013***	3.524***
	(0.218)	(0.404)	(0.368)	(0.290)
Lag percentage needed (%)	–0.007	0.315***	0.298***	0.355***
	(0.020)	(0.041)	(0.038)	(0.031)
Lag total bids	0.001	0.030***	0.009	0.018***
	(0.006)	(0.007)	(0.006)	(0.004)
Lag percent automatic bidding	–0.203	–0.634**	–0.260	–0.599***
	(0.241)	(0.323)	(0.205)	(0.169)
Lag total amount x lag percentage needed (%)	0.000	–0.030***	–0.027***	–0.028***
	(0.002)	(0.003)	(0.003)	(0.003)
Log bidders	–0.053	–0.160**	–0.063	–0.162***
	(0.057)	(0.076)	(0.048)	(0.024)
Obs.	1,291,306	452,464	872,915	2,085,201
R^2	0.263	0.277	0.230	0.161

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. *Lag Total Amount* represents the total amount of loan filled at time t–1. *Lag Percentage Needed (%)* represents the percentage of the amount still unfunded at the end of hour t–1. *Lag Total Bids* represents the total number of bids at time t–1. *Lag Percent Automatic Bidding* represents the percentage of automatic biddings at time t – 1. *Log Bidder*s 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 (1)	Second hour (2)	Penultimate hour (3)	Last hour (4)
Lag total amount	0.973*	–1.005	–0.460	1.116**
	(0.586)	(2.006)	(1.645)	(0.558)
Lag percentage needed (%)	0.128**	0.085	–0.045	0.101*
	(0.057)	(0.184)	(0.165)	(0.058)
Lag total bids	0.089***	–0.086	–0.079**	–0.022**
	(0.012)	(0.054)	(0.035)	(0.010)
Lag percent automatic bidding	0.512	–0.463	–0.337	0.371
	(0.586)	(1.876)	(1.195)	(0.403)
Lag total amount x lag percentage needed (%)	–0.016***	–0.016	0.001	–0.009*
	(0.005)	(0.016)	(0.014)	(0.005)
Log bidders	0.171	0.217	0.298	–0.471***
	(0.112)	(0.485)	(0.403)	(0.072)
Obs.	196,786	28,810	42,306	356,048
R^2	0.293	0.514	0.597	0.285

Notes: This table shows the effects of the following variables at different times on platform: (1) the first 1 hour, (2) the second hour, (3) the penultimate hour and (4) the last hour. *Lag Total Amount* represents the total amount of loan received at time t–1. *Lag Percentage Needed (%)* represents the percentage of the amount requested that is left unfunded at the end of hour t–1. *Lag Total Bids* represents the total number of bids at time t–1. *Lag Percent Automatic Bidding* represents the percentage of automatic bidding at time t–1. *Log Bidders* 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 (1)	90<X<180 days (2)	180<X<360 days (3)	360+ days (4)
Lag total amount	0.544*	4.254***	4.155***	3.961***
	(0.292)	(0.507)	(0.456)	(0.334)
Lag percentage needed (%)	–0.002	0.424***	0.423***	0.401***
	(0.028)	(0.052)	(0.048)	(0.036)
Lag total bids	0.043***	0.068***	0.040***	0.024***
	(0.007)	(0.009)	(0.007)	(0.005)
Lag percent automatic bidding	–0.346	–0.367	–0.221	–0.581***
	(0.306)	(0.389)	(0.247)	(0.202)
Lag total amount x lag percentage needed (%)	0.000	–0.038***	–0.037***	–0.031***
	(0.002)	(0.004)	(0.004)	(0.003)
Log bidders	–0.153**	–0.282***	–0.191***	–0.192***
	(0.069)	(0.089)	(0.055)	(0.027)
Obs.	964,788	320,587	657,826	1,574,833
R^2	0.304	0.315	0.249	0.174

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. *Lag Total Amount* represents the total amount of loan received at time t–1. *Lag Percentage Needed (%)* represents the percentage of the amount requested that is left unfunded at the end of hour t–1. *Lag Total Bids* represents the total number of bids at time t–1. *Lag Percent Automatic Bidding* represents the percentage of automatic bidding at time t–1. *Log Bidders* 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)
Lag total amount	0.321***	0.319***	0.176***	0.174***
	(0.009)	(0.010)	(0.021)	(0.021)
Lag percentage needed (%)	0.010***	0.010***	0.004***	0.004**
	(0.001)	(0.001)	(0.002)	(0.002)
Lag total bids	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 (%)	0.010***	0.011***		
	(0.000)	(0.000)		
Maturity	–0.017***	–0.017***		
	(0.000)	(0.000)		
Credit risky	0.001	–0.025***		
	(0.007)	(0.007)		
Debt-to-income ratio	0.010	–0.004		
	(0.009)	(0.009)		
Log bidders	1.233***	1.226***	1.280***	1.274***
	(0.002)	(0.002)	(0.004)	(0.004)
Lag total amount x lag percentage needed (%)	–0.001***	–0.001***	–0.001***	–0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Lag percent automatic bidding		–0.791***		–0.529***
		(0.017)		(0.026)
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. Lag Total Amount represents the total amount of loans received at time t – 1. Lag Percentage Needed (%) represents the percentage of the amount requested that remains unfunded at the end of hour t – 1. Lag Total Bids represents the total number of bids at time t – 1. Amount Requested represents loan amount on request. Interest Rate (%) represents annual percentage rate on the loan. C= Maturity (Month) represents current loan duration in months. *Credit Risky* (1=yes) means that the listing's credit grade is E or below, i.e. E, F or HR, and otherwise 0. *Debt-to-Income Ratio* represents the ratio of borrower's monthly gross income that goes to paying loans. *Log Bidders* represents the logarithm of number of bidders. *Lag Percent Automatic Bidding* represents the percentage of automatic biddings at time t – 1. *Significant at 10% level, ** significant at 5% level, and *** significant at 1% level. Robust standard errors are presented in parentheses.

Appendix

Table A1 Variable definitions

Variables	Definition
Hourly amount	Hourly total bidding amount for a loan request
Hourly total bids	Hourly total number of bids from lenders for a loan request
Hourly percentage of automatic bidding	Percentage of automatic bidding each hour
First Hour	Total bidding amount received within first hour of bidding period
Lag percentage needed	The percentage of the amount requested that is left unfunded at the end of hour t-1
Debt to income (%)	Ratio of borrower’s monthly gross income that goes to paying loans
Credit risky	1 means that the listing's credit grade is E and below, i.e. E, F and HR, else 0
Interest rate (%)	Annual percentage rate on the loan
Amount requested (RMB)	Loan amount on request
Maturity (month)	Current loan duration in months
Filling time	Bid completion time period for a loan request (in hours)

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