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Herding in Multi-winner Auctions

Research-in-Progress

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Abstract

Herding behavior is widely observed in auctions. There are rational reasons for herding but herding can also be counterproductive. We found evidence of herding behavior and sub-optimal outcome in a multi-winner auction setting. This study adds to the knowledge of herding by looking at herding in an auction setting where there is extra incentive to herd (multi-winner auction). Our findings reconfirm evidence in previous research about strategic usage of herding that diminishes after certain threshold; in addition, our findings indicate sub-optimal outcomes of herding behavior which include unjustified risk-return ratio, low ROI, wasted investment opportunities, and underutilized resource.

Keywords: Herding, information cascades, P2P lending, online auction, E-business
Introduction

Information technologies have made online auctions a convenient and economic way for doing business. On one hand, online auctions are characterized by their openness and sequential choice setting where everyone can see what choices everyone else ahead of them has made. On the other hand, online marketplaces are characterized by anonymity and uncertainty. Buyers commonly have to make purchase decisions without accurate or reliable information about the sellers and their products. A commonly employed strategy is following the choices others have made (Duan, Gu, and Whinston 2009; Huang and Chen 2006; Simonsohn and Ariely 2008). Such herding behavior can be rational in situations characterized by information asymmetry such as in an electronic marketplace (Duan et al. 2009). However, if buyers overly rely on the behaviors of other buyers and disregard important signals from the seller and product, herding can lead to inferior purchase decisions (Dholakia and Soltysinski 2001; Dholakia, Basuroy, and Soltysinski 2002; Simonsohn and Ariely 2008).

P2P lending websites create an online platform to connect lenders who have money to invest and borrowers who need to borrow money. P2P lending auctions are unique in that in most cases multiple lenders are needed to finance one loan. Previous research finds evidence of herding behavior in P2P lending to be strategic and diminishing after a certain point (Herzenstein, Dholakia, and Andrews 2010). We report preliminary analysis of herding behavior in P2P lending with respect to listing options and timing. Our study provides evidence of herding behavior in P2P lending that might lead to low ROI, high risk-return ratio, and under-utilized lender money resource.

Theoretical Background

Herding in Multi-winner Auctions

It is difficult to precisely define herding. Devenow and Welch (1996) pointed out that in its most general form, herding could be defined as behavior patterns that are correlated across individuals, but such behavior patterns could be due to correlated information arrival in independently acting individuals. The type of herding behavior that is most interesting to researchers and widely studied in stock trading and online auctions (e.g., Simonsohn and Ariely 2008) is caused by informational cascades. Informational cascades occur “when it is optimal for an individual, having observed the actions of those ahead of him, to follow the behavior of the preceding individual without regard to his own information” (Bikhchandani, Hirshleifer, and Welch 1992, p.994). Banerjee (1992) defines herding behavior as “everyone doing what everyone else is doing, even when their private information suggests doing something quite different.” It is interesting to look at why people follow others and ignore what their private information suggests, and the consequences of this behavior. Our study examines this herding behavior in the context of P2P lending.

On a P2P lending Web site, borrowers post loan request listings (auctions) with the amount of money requested and the interest rate for the loan. Interested lenders bid on particular listings with the amount of money they are willing to offer individually, often much less than the amount requested. If the total amount offered by lenders exceeds the amount requested on the listing, lenders start to bid down the interest rate the borrower has to pay. All lenders winning the auction earn the same interest rate decided at the end of the auction. A listing only proceeds to loan creation if the requested amount is fully funded. As P2P lenders often bid only a small amount (as small as $25) on each listing to lower overall portfolio risk, in most cases, multiple lenders are needed for each listing to be fully funded. Although such can happen that one lender funds the entire loan, these cases are rare. For the sake of discussion, we disregard the rare cases where a single lender funds the entire loan as they are not of interest here. The facts that individually lenders only buy a proportion of the listing and that a listing has to be fully funded otherwise there will be no winner of the auction requests that multiple bidders have to win the auction together, we call this “multi-winner” auction. This distinct property of P2P lending auctions has unique implications on herding behavior in that on top of everything else, bidders are motivated to herd to improve the chance of winning as a group. We look at causes for herding next.

Reasons for Herding

It is easy to observe what peers are doing on e-Commerce marketplaces. For instance, people can watch how prices and the number of bids change as they happen at real-time at eBay auctions. Likewise, P2P lending marketplaces
Herding in P2P Lending - Rational or Irrational Behavior?

make it very easy to see what other lenders have decided about particular listings. For instance, on Prosper (a major U.S. based P2P lending marketplace), bidding status is clearly displayed on each loan listing. The number of bids, the percentage of the requested amount that has been accounted for, and the time left before the listing expires are all available at a glance of the top section of each listing. In addition, all lenders who placed bids are listed including the bid amount and interest rate offered.

Herding behavior has been associated with search cost (Lin, Tsai, and Sun 2010). When the uncertainty about returns and risks are high, to lower search cost, investors are motivated to follow other investors’ choices, with the assumption that the observed choices are based on relevant information processing. Lenders incur search cost when looking for attractive investment options and comparing listings on various aspects. Due to the reach of Internet markets, the number of borrowers and listings on P2P lending marketplaces are overwhelming. Choosing among similar listings based on interest rate, information of individual borrowers’ credit and social capital, and the reasons they borrow can be very time consuming and difficult. Under this situation, following what other lenders have chosen is a very practical approach.

Lenders incur opportunity cost when the money invested is lost on defaulted loans (type I), or when the money is locked in the listing awaiting the auction to end earning no interest (type II). Type II opportunity cost is inevitable but it gets compensated from the interest earned in the future if a loan is created. If no loan is created (the listing is not fully funded), then the opportunity cost gets no compensation at all. Therefore, lenders want to bid on listings that have a good chance to get fully funded. When everything else is the same, listings that are closer to getting fully funded are more attractive than listings that are less close to getting fully funded. Consequently, we expect to see bidding activities increase with the percentage funded of a listing. Timewise, we expect to see bidding activities increase toward the end of an auction on timed auctions (i.e., auctions that have a fixed auction length and won’t close as soon as the listing amount is fulfilled), as the waiting time is shorter and hence less type II opportunity cost.

Consequences of Herding

Herding is a widely employed practical strategy, it may help reduce search cost and opportunity cost. It has been shown theoretically and empirically that herding can be counterproductive when observers follow choices that have already lost their advantage, such as a low starting price on eBay. For instance, buyers on eBay may end up paying higher prices or having a smaller chance to win an auction at the same price level (Simonsohn and Ariely, 2008). In the context of P2P lending, Herzenstein et al. (2010) finds that in contrast to eBay buyers, P2P lenders benefit from herding by strategically herding over listings with more bids up to the point where they get fully funded. Our preliminary investigation of P2P lending auctions revealed some possible negative consequences of herding such as less than optimal risk-return ratio, wasted investment opportunity, and wasted resource of lender money. We also found increased herding behavior toward the end of P2P auctions, which calls for further investigation for its implications on P2P lending practice.

Preliminary Investigation of Herding Behavior in a P2P Lending Marketplace

Our preliminary investigation of P2P lending auctions provided the following results. One, there is evidence of herding in multi-winner auctions. Two, herding might have led to sub-optimal decisions that are costly for lenders, borrowers, and the P2P lending marketplace.

We used publicly available data on Prosper (www.prosper.com) from 2/13/2007 to 10/15/2008. This time span was chosen because Prosper changed their credit grade categories on 2/12/2007, and suspended their lending activities in October 2008 in order to register with the Securities and Exchange Commission (SEC) and did not reopen until 9 months later. The chosen time frame provides over one and half years of data for analysis of lender behavior when the practice on the marketplace is stable and consistent.

Evidence of Herding

Biding Concentration

We found bidding concentrate with respect to listing options and timing. A lot of fully funded listings were over-funded - bids total higher than requested amount. Over the time frame from 2/13/2007 to 10/15/2008, 78% of the 21,337 listings that were fully funded received funds exceeding the requested amount, 50% received funding as high as 80% over the requested amount, some listings received funds over 200%. If listings that automatically closed
after getting 100% funding are left out, these numbers get even higher. Figure 1 shows that for listings that were open for the entire auction time 4% received 100% funding, which means 96% was overfunded.

![Figure 1. Percentage Funded of Fully Funded Listings](image1)

While many listings received over funding, a large amount of listings did not receive much attention at all. Over the same time period, 146,844 listings did not receive enough funding and expired. As illustrated in Figure 2, over 80% of expired listings received less than 10% of the requested amount. It looks like if a listing did not receive enough bids to look promising to begin with, then it would not receive much attention afterwards and probably would simply go expired.

![Figure 2. Percentage Funded of Expired Listings](image2)

Bidding also concentrated with respect to timing - listings received most of bids at the beginning and end of the auction. We draw a second sample from Prosper’s data. We extracted all bids placed in May 2008 on listings that are either completed or expired (i.e., stayed open till the end of the auction), from those we removed all bids from the states of TX, AE, and AE because these states had maximum borrower interest rate state caps that could skew our results. This resulted in 6,934 listings and 275,273 bids from 5,775 unique members.
In the time frame of our analysis, auction duration was seven days. Figure 3 depicts bidding activity by each hour of the auction duration. The figure shows a bipolar trend, peaking at the beginning and the end of the auctions. This implies that lenders favor bidding at the beginning and the end of an auction, and remain dormant in the time between. This could indicate herding behavior and sniping as observed in other auction marketplaces such as eBay. Although bids are not placed during the last minutes of an auction like on eBay, we can see a substantial increase in bids placed in the last five hours. There could be two reasons for this behavior. First, lenders want to make sure that a listing gets fully funded and that their money is not locked into a listing for very long, supporting our arguments above. Second, lenders want to observe the behavior of others as an indicator for listing quality, supporting our arguments for informational cascades.

Figure 3. Average Number of Bids Per Listing by Hour For Funded and Un-funded Listings

Predicting the Likelihood of Getting another Bid

The evidence above does not rule out the possibility that the concentrations on listings and auction time were due to lenders choosing to bid on attractive listings independently rather than following others. Therefore, we estimated hierarchical logit regression models to predict the likelihood of another bid on the listing at three different stages, when a listing is funded for no more than 10%, between 10 and 100%, and over 100%, and compared the explanatory power of the independent variables. We chose two groups of independent variables based on previous P2P lending research (Kumar 2007; Berger and Gleisner 2009; Everett 2008; Greiner and Wang, forthcoming; and Herzenstein et al. 2010). The first group of independent variables represents listing and borrower characteristics. The second group has one variable - the natural logarithm of the number of bids placed on the listing.

Figure 4 presents the regression models. The first two rows report the adjusted R-squares of the regression models. When listings are funded for 10% or less (Model 1), listing and borrower characteristics explain 36.3% of the variation in the likelihood of another bid. Adding the logarithm of the number of current bids bared changes the explanatory power, a 1% increase. When listings are funded for over 10% and less than 100% (Model 2), the hierarchical regression shows that the explanatory power increases noticeably by adding the number of current bids into the model. In other words, comparing to Model 1, the number of bids received is much more important in predicting the likelihood of another bid in Model 2. This means that when a listing is funded to a certain degree (in this case between 10% and 100%), lenders base their bidding decisions more on bids received and less on listing and borrower characteristics. After listings are fully funded (Model 3), the additional explanatory power of number of bids received drops. The same pattern can be seen in the variable coefficients (last row in the figure). The coefficient of the number of bids received increases from Model 1 (.424) to Model 2 (.975), indicating that the number of bids
received becomes a more important predictor after the listing has received certain amount of funding. When the listing is fully funded (Model 3), the coefficient becomes negative, a likely indication that lenders try not to compete on interest rate.

<table>
<thead>
<tr>
<th>Adj. R² - Borrower Credit Data and Listings Characteristics</th>
<th>Model 1 (Listing is less than 10% Funded)</th>
<th>Model 2 (Listing between 10% and 100% Funded)</th>
<th>Model 3 (Listing is more than 100% Funded)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adj. R² - Including Number of Bids</td>
<td>36.3%</td>
<td>10.4%</td>
<td>5.4%</td>
</tr>
<tr>
<td>Credit Grade</td>
<td>.980 ***</td>
<td>.264 ***</td>
<td>.509 ***</td>
</tr>
<tr>
<td>Is Borrower Home Owner</td>
<td>-.110 *</td>
<td>-.170 **</td>
<td>-.016 n.s.</td>
</tr>
<tr>
<td>Debt to Income Ratio</td>
<td>-.003 ***</td>
<td>-.003 ***</td>
<td>-.006 ***</td>
</tr>
<tr>
<td>Starting Interest Rate</td>
<td>.050 ***</td>
<td>-.025 ***</td>
<td>.056 ***</td>
</tr>
<tr>
<td>Amount Requested</td>
<td>.000 ***</td>
<td>.000 ***</td>
<td>.000 ***</td>
</tr>
<tr>
<td>Current Delinquencies</td>
<td>-.091 ***</td>
<td>-.108 ***</td>
<td>-.164 ***</td>
</tr>
<tr>
<td>Group Rating</td>
<td>.168 ***</td>
<td>.086 **</td>
<td>.031 n.s.</td>
</tr>
<tr>
<td>Number of Endorsements</td>
<td>-.007 n.s.</td>
<td>-.030 **</td>
<td>.011 n.s.</td>
</tr>
<tr>
<td>Length of Listing Description</td>
<td>.000 ***</td>
<td>.000 ***</td>
<td>.000 n.s.</td>
</tr>
<tr>
<td>Availability of Image</td>
<td>.217 ***</td>
<td>.243 ***</td>
<td>.312 ***</td>
</tr>
<tr>
<td>Number of Bids on Listing (Log)</td>
<td>.424 ***</td>
<td>.975 ***</td>
<td>-.873 ***</td>
</tr>
</tbody>
</table>

***p<.001, **p<.01, *p<.05, n.s. = not significant

Figure 4. Hierarchical Regressions for the Likelihood of another Bid

The combination of the increase in explanatory power of the number of bids received and the decrease in listing and borrower characteristics provides strong evidence that the bidding concentration on listings is not due to individual lenders making independent decisions based on the listings; rather, it indicates that lenders look at how many others have already “voted” for a particular listing and then cast their votes accordingly, that is, at least until the listing gets fully funded. This result reconfirms the findings in Herzenstein et al. (2010) that the likelihood of attracting another bid increases with the number of bids received until a listing gets fully funded, after which it starts to decrease with the number of bids received. By controlling listing and borrower characteristics, this result provides strong evidence that the herding behavior is due to following others rather than coming to independent decisions based on private information.

Influences of Herding

The high concentration of bidding on certain listing options, while ignoring others, invariably led to a large sum of lender money being outbid. Over the same time frame, over $140 million worth of loans were generated, even more lender money (over $145 million) was outbid and loan requests (over $149 million) not funded (expired, cancelled, or withdrawn). Bids on expired listings counted for only $62,886,437, much less than outbid lender money. Outbid lender money is costly for all participants of P2P lending. For lenders, it results in unrecovered opportunity cost that includes wasted time and potential returns on loans that the lenders could win; for borrowers, it is a wasted resource that could generate more loans; and for the marketplace, it represents reduced revenue as a marketplace makes money on funded loans. The reasons behind this highly concentrated bidding behavior call for further investigation. From the lenders’ point of view, this may be rational decision - to fund only those that have a chance to get funded.
based on the number of bids the listings already received; or to get a good ROI if the listing offers an attractive interest rate. On the other hand, blindly following others may lead to sub-optimal decisions for lenders.

Interest rate is a measure of return on investment, hence an indicator of the quality of lender decisions. Good investment decisions should be justified by risk-return ratios. Table 1 shows that in the time frame of this analysis, for all listings that remained open after getting fully funded, interest rates were bid down in all credit categories - on average final interest rates on the loans are lower than starting interest rates offered by borrowers on the listings. What is interesting is that the interest rates for some higher risk listings (the D, E, and HR categories, with HR stands for “high risk”) are as low as 1% (see column “Lowest Final Interest Rate), much lower than the “Average Final Interest Rate” for less risky listings (the A, AA, and B categories). A look at the distribution of the interest rates for different credit categories shows that the interest rates for the high risk loans (the HR category) are widely spread, some much lower than the group average (Figure 5). Why do some high risk listings get funded at relatively low interest rates? Is it related to the observed herding behavior? These questions remain to be answered by future research.

### Table 1. Starting and Final Interest Rates by Credit Grade

<table>
<thead>
<tr>
<th>Credit Grade</th>
<th>Number of Listings</th>
<th>Average Starting Interest Rate</th>
<th>Average Final Interest Rate</th>
<th>Lowest Final Interest Rate</th>
<th>Highest Final Interest Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>AA</td>
<td>2290</td>
<td>12.9%</td>
<td>9.6%</td>
<td>4.3%</td>
<td>25.0%</td>
</tr>
<tr>
<td>A</td>
<td>2079</td>
<td>16.1%</td>
<td>12.3%</td>
<td>5.0%</td>
<td>35.0%</td>
</tr>
<tr>
<td>B</td>
<td>2618</td>
<td>19.8%</td>
<td>15.1%</td>
<td>4.0%</td>
<td>32.0%</td>
</tr>
<tr>
<td>C</td>
<td>2850</td>
<td>22.6%</td>
<td>17.2%</td>
<td>3.0%</td>
<td>35.0%</td>
</tr>
<tr>
<td>D</td>
<td>2379</td>
<td>25.9%</td>
<td>20.1%</td>
<td>1.0%</td>
<td>36.0%</td>
</tr>
<tr>
<td>E</td>
<td>1100</td>
<td>30.0%</td>
<td>25.3%</td>
<td>1.0%</td>
<td>36.0%</td>
</tr>
<tr>
<td>HR</td>
<td>1019</td>
<td>25.9%</td>
<td>26.0%</td>
<td>6.5%</td>
<td>35.0%</td>
</tr>
</tbody>
</table>


Counterproductive herding behavior could also be indicated if interest rates are bid down to below an average (assuming that lenders would compete until a risk-return balance is reached and that the average interest rate could be regarded as a measure of this risk-return balance). When looking at how much lenders bid down listing interest rates, we found the following: interest rates of 7,085 completed listings out of 7,755 were bid down; 44% of these listings started above the average interest rate of their corresponding credit grade category, and were downbid to below the average; 17% started below their corresponding average interest rate and were further downbid (on average they were downbid by 2.3%); 39% started above their corresponding average interest rate and were downbid but not to as low as below the average interest rate. If a listing is downbid, it can indicate rational behavior
as long as the interest rate is not bid down to below the average interest rate; but as soon as a listing is downbid to below this average, then non-rational behavior is indicated.

**Conclusion and Future Research Questions**

In summary, we found strong evidence of herding behavior in P2P lending marketplaces. When listings have been funded to a certain level, lenders start to follow in without paying much attention to the characteristics of the listing and borrower. Some listings were funded way over 100%, which led to outbid lender money and in some cases, interest rate being bid down significantly. For many listings that failed to attract enough bids to begin with, they may very likely go unnoticed and end up expired. Although there are strong reasons to herd in a multi-winner auction such as in a P2P lending setting, herding may still lead to negative consequences which include sub-optimal investment decisions, wasted investment opportunities, and unutilized resources.

This preliminary investigation also leads to other questions about herding in P2P lending:

- Why do some listings receive so much attention from lenders and other listings go completely unfunded?
- If lenders tend to bid on listings that already received many bids, how do listings get funded in the first place? Is there some threshold listings have to take?
- When is herding rational and when does it become non-rational and counterproductive for buyers?
- What factors (antecedents) lead to non-rational herding?

**References**


