Information Asymmetry and Strategic Early Bidding in Peer-to-Peer Lending

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Abstract

We study how investors in peer-to-peer (P2P) lending utilize their information advantage to bid strategically. As documented in the auction literature, better-informed bidders may withhold bidding until the last moment (i.e., "sniping") to avoid competition. We argue that, since collective effort from investors is required in P2P lending, informed investors are facing a tradeoff between the funding probability of loan requests and the anticipated return of their investment when deciding the timing of bidding. Using a unique dataset from Prosper.com, we document the phenomenon of an early bidding (or "squatting") strategy. We show that "good" loans attract more early bids than "bad" loans. Most importantly, "good" loans with a low ex-ante probability of funding success attract more early bids from better-informed investors. Those early bids would benefit not only the borrowers but also uninformed investors. Our findings provide important implications for managing the information asymmetry and strategic behaviors among investors on peer-to-peer lending platforms.

Keywords: Peer-to-peer lending, Online auctions, Information asymmetry, Sniping, Squatting

1. Introduction

Peer-to-peer lending (hereafter, P2P lending) has been a global phenomenon in recent years, and its growth attracts significant interests from institutional and individual investors around the world.[1] Despite its prominence in the "FinTech" (financial technologies) era, investing on P2P lending platforms is risky because of the high default rate of unsecured personal loans funded on such platforms. For example, statistics suggest that the default rate was typically above 10% in the early years of P2P lending (Renton 2012). On the other hand, the potential rate of return can be much higher than that of other investments if P2P loans are repaid. Several estimates report consistently that the risk-adjusted average return from P2P loans is around 10%, which is higher than the return from other major investments such as stocks, bonds, and real estate (Galland 2017, Fast Invest 2017). Investors of P2P loans are thus in great need of information about borrowers' ability to repay. P2P platforms typically collect and report detailed credit information and other related information to solve the issue (Lin, Prabhala, and Viswanathan 2013, Morse 2015, Iyer, Khwaja, Luttmer, and Shue 2016, Freedman and Jin 2017).

An alternative way for P2P investors to obtain more information is to learn from other investors who may have information advantages (Zhang and Liu 2012). For example, some investors may have private information about borrowers' backgrounds or can evaluate the potential of the associated projects (Lin and Viswanathan 2015, Freedman and Jin 2017). If informed investors are willing to fund a loan request,[2] other investors are naturally more willing to follow. This type of information spillover from informed investors to uninformed investors, however, will introduce more competition

[1] Morgan Stanley research estimated that the global P2P lending market may reach $290 billion worth of loans with an annual growth rate of more than 50% between 2014 and 2020 (Morgan Stanley 2015). U.S., China, and the U.K. are the three largest markets.

[2] P2P lending platforms allow borrowers to post their requests of personal loans on the website. The posts are often called "listings," "loans requests," or simply "projects." To fix terms, we use "loan requests" and "projects" interchangeably in the paper. If a loan request is funded, we name it a "loan" or a "personal loan."

to fund P2P loans and thus may reduce the anticipated return for informed investors when a project is funded through the auction mechanism.[3] The increased number of bidders can push down the interest rate and therefore reduce the surplus that informed investors can extract from their information advantages. In such case, as the literature has documented, informed investors have the incentive to withhold the information and only provide funds at the last moment (i.e., "sniping"), which under certain conditions is an equilibrium strategy in auctions (Roth and Ockenfels 2002, Bajari and Hortaçsu 2003, Ockenfels and Roth 2006). The consequence is that quality borrowers may have to pay at a higher interest rate and, in some cases, do not receive sufficient funds.

In this paper, we argue that P2P lending is different from standard auctions focused on in the literature. In those eBay-type auctions, bidders compete for the exclusive ownership of a product. For P2P lending, successful funding typically requires collective effort—the aggregation of money—from multiple investors. If uninformed investors cannot learn from informed investors, the chance that the loan request will eventually fail increases, generating a type of payoff externality in the sense of Katz and Shapiro (1985). This is because most platforms require that the aggregate fund has to reach a pre-specified amount; otherwise, the effort of fundraising will fail (Burtch, Hong, and Liu 2018). Even without such a rule, the chance that borrowers have to default may increase merely because of the lack of sufficient funding for their projects. Therefore, for a high-quality project that has a relatively low ex-ante probability of being sufficiently funded, informed investors face a tradeoff between helping the project to be successfully funded and the return from the investment when they decide the timing of the lending decisions. This can lead to a new type of bidding strategy at equilibrium: as informed investors need uninformed investors to "co-invest" to make sure that the loan request succeeds, they might choose to commit to lending early on, i.e., "squatting" (Ely and Hossain 2009), and help

[3] Many P2P lending platforms use auctions as their primary funding mechanism. Examples are Monestro, Sofi, Thincats, and Flender. Fu, Huang, and Singh (2019) argues that the "crowd-based" auction mechanism (using the "wisdom of the crowd" to identify interest rates) has certain advantages over other pricing mechanisms that rely on algorithms.

generate the information spillover. This is the focus of our study.

To study this phenomenon, we first develop a stylized theoretical model to demonstrate that, first, when information asymmetry exists among investors and the probability of being successfully funded is low, squatting is common in the funding process. Moreover, the model predicts that squatting is more common in high-quality projects (i.e., with lower default probability) than in otherwise "bad" projects. Most importantly, our model demonstrates that when there exists asymmetric information among investors, squatting can be an equilibrium strategy of investment in high-quality projects that have a relatively lower ex-ante probability of getting sufficiently funded on P2P platforms. Sniping, on the other hand, is an equilibrium strategy for investing in high-quality projects with relatively high ex-ante success probability.

We then use data from Prosper.com to test the hypotheses. First open to the public in 2006, Prosper is the first and one of the largest P2P lending platforms in the U.S. (in terms of transaction volume). The dataset, which we obtain from Prosper's data portal, provides a unique opportunity to test our model predictions. For each loan request, in addition to an extensive set of credit variables about the borrower (at the time of funding) and characteristics about the specific project, the dataset contains all bids submitted during the funding process. For each bid, we know the amount of dollars that the investor committed, the timestamp when the bid was submitted, and the investor's Prosper identity. On top of the information about the funding process, we also obtain all loans' final payment status. Successfully funded projects will turn into a fully amortized personal loan with a typical maturity of three years (or 36 monthly installments). For all the personal loans funded on Prosper during our study period, we know whether a loan was paid in full eventually.

Consistent with the hypothesis, we *first* find evidence in the data that squatting exists in Prosper investors' bidding strategy. Specifically, we find that on average, more than 10% of investors submitted their bids in the first 5% funding duration. As we discussed above and formally develop in the model, by squatting, investors face a tradeoff between increasing the probability of having a loan request funded and the return from the investment. We test this assumption and find supporting evidence in the data as well. Specifically, our results suggest that the fraction of investors in the first 5% funding time is positively correlated with the funding success probability and negatively correlated with the final interest rate at which a loan will be repaid. *Second*, also consistent with the model prediction, we show that investors are more likely to bid early in "good" loans that were eventually paid off.

In order to test our main hypothesis that predicts that informed investors bid early in good loans with a low ex-ante funding probability, we use in-group investors[4] as a proxy for informed investors and use the credit grade Prosper assigns to each particular loan request (mostly based on the borrower's credit score) as a proxy for the ex-ante funding probability. We show that, first, compared with out-group investors, good loans attract a larger proportion of in-group investors who participate in a loan request, suggesting that these investors likely have information advantages about the potential risk of a loan request from the borrower who belongs to the same group. Second, we find that the funding probability declines monotonically in Prosper credit grades. In particular, no more than 5% of the loan requests in the lowest category, HR grade, were successfully funded. Based on these observations, we run a regression analysis and find that in-group investors are more likely to bid early in the funding of good loans that belong to the HR grade. Our empirical findings are thus consistent with the predictions of the stylized model.

We examine an alternative explanation that the phenomenon is only driven by altruism from in-group investors. We argue that, although in-group investors may intend to help out borrowers who belong to the same group, the result that, relative to other similar loan requests, they are more likely to bid early for good projects with low ex-ante funding probability is due to the economic reason. We

[4] More details about the group feature on Prosper will be provided in the section of research context, but as a quick note, borrowers and investors can form groups on the platform based on, e.g., geography (from the same city) and alumni relationships. Most notably, a Prosper user—a borrower or an investor—can join at most one group.

also fail to find evidence that in-group investors are more likely to help out for projects that have not yet received full funding towards the end of the funding process. Finally, we also show how our empirical findings are robust under different specifications.

Our results have several implications for P2P lending. First, the squatting behavior we identify in our empirical findings benefits uninformed investors. This is an important implication because most of the investors on P2P platforms are retail investors who are not endowed with much private information or not as experienced as their institutional counterparts (Lin, Sias, and Wei 2019). Our findings also imply that the squatting behavior benefits borrowers on P2P platforms, who otherwise may not be able to raise funds from such platforms. Being a typical Internet-enabled two-sided market, the participation of not only investors but also borrowers is vital for the long-term viability of P2P platforms. Last but not least, our results have implications for how P2P lending platforms may manage the information asymmetry and strategic behaviors of investors.

The rest of the paper is organized as below. We summarize several strands of related literature and highlight our contributions in the next section. Section 3 introduces P2P lending and our specific research context—Prosper.com, and then presents the dataset we obtain from Prosper. We develop the theoretical model in Section 4 and discuss the hypotheses generated from the model. Then, Section 5 reports our empirical findings, including direct tests of the three research hypotheses, tests of a vital model assumption, results that exclude an alternative explanation, and robustness checks. The last section concludes.

2. Literature and Contributions

Our study naturally relates to the literature on P2P lending.[5] A set of previous papers in this

[5] Morse (2015) provides a thorough review of the literature on P2P lending. We only summarize the most related papers that help clarify our contributions to the extensive literature. In addition to the papers summarized in the main text, a broad set of recent papers study various aspects of P2P lending such as the role of identity claim in loan narratives (Herzenstein, Sonenshein, and Dholakia 2011), discrimination (Pope and Sydnor 2011), borrower appearance (Duarte,

literature have explored the mitigation of information asymmetry that can lead to adverse selection and moral hazard, with a variety of mechanisms including signaling, reputation, and "soft" information (e.g., Kawai, Onishi, and Uetake (2014), Iyer, Khwaja, Luttmer, and Shue (2016), Xin (2018) among others). These papers focus on the asymmetry in information between borrowers and investors. In particular, also using data from Prosper, Kawai, Onishi, and Uetake (2014) estimates that 16% of the loss in total surplus can be attributed to adverse selection and that signaling recovers as much as 95% of the loss. Using the same dataset, Xin (2018) further separates the welfare loss and estimates that 22% of the loss is due to adverse selection and moral hazard accounts for the balance. We add to this stream of literature by studying information asymmetry on the investor side of the market and show, both theoretically and empirically, that investors strategically utilize information advantages in the funding process. We show that the squatting strategy can create information spillover to uninformed investors and thus alleviate the problems caused by information asymmetry.

Another strand in the P2P lending literature focuses on the impact of social networks (or social groups) on funding outcomes and transaction efficiency (Lin, Prabhala, and Viswanathan 2013, Freedman and Jin 2017, Hildebrand, Puri, and Rocholl 2017). This literature documents how borrowers with social ties have a higher chance of being funded and pay at lower interest rates conditional on being funded (Lin, Prabhala, and Viswanathan 2013, Freedman and Jin 2017). Hildebrand, Puri, and Rocholl (2017) further demonstrates that these "socialized" loans (in their case, loans with the endorsement of group leaders), however, have higher default rates. We borrow from the literature to investigate the strategic squatting behaviors of in-group investors who may have information advantages (see, for example, Lin, Prabhala, and Viswanathan (2013)). Compared with the existing studies that primarily focus on the impact on funding and repayment outcomes, our study

Siegel, and Young 2012), home bias (Lin and Viswanathan 2016), market mechanisms (Wei and Lin 2017), sophisticated investors versus noise traders in P2P markets (Lin, Sias, and Wei 2019), and the impact of P2P lending on local financial markets (Wang and Overby 2017, Alyakoob, Rahman, and Wei 2019).

extends our understanding of the role of social ties to their impact in the funding process by relying on our detailed investment level data. In addition, our results provide a potential mechanism underlying the findings in the previous studies—in-group investors' strategic bidding.

Our study also adds to the literature on Internet auctions, which has documented the phenomenon of sniping in particular and offers a variety of explanations both theoretical and empirical.[6] For example, Roth and Ockenfels (2002) shows that late bidding is an equilibrium strategy that softens the competition conditional on the "hard ending" auction rule. Ockenfels and Roth (2006) argues that late bidding is the best response of sophisticated bidders to the existence of naïve bidders. Bajari and Hortaçsu (2003) shows that last-minute bidding occurs in models of online auctions with a common value. More recent studies started exploring the opposite of sniping—early bidding or "squatting." In a study closely related to this paper, Ely and Hossain (2009) conduct a field experiment on eBay and show that the squatting strategy may deter the entry of rival bidders because it signals competition. In another study, Groenwegen (2017) uses bid-level data from eBay and finds inconclusive results about the benefit of squatting in auctions. We differ from their studies in a fundamental way, as P2P lending auctions require collective effort from multiple investors to fund the loan requests. Our findings suggest that the squatting strategy from informed investors benefits borrowers and uninformed investors. Overall, we contribute to this literature by documenting the existence of squatting in Prosper auctions and, more importantly, by providing a potential mechanism to underlie the phenomenon.

Last but not least, squatting behavior is related to the information spillover from informed investors to uninformed investors. The literature on herding has documented the information spillover in various settings (Nofsinger and Sias 1999, Simonsohn and Ariely 2008, Duan, Gu, and

[6] Bajari and Hortaçsu (2004) reviews the extensive literature on Internet auctions and summarize the explanations of sniping offered in the literature.

Whinston 2009). Herzenstein, Dholakia, and Andrews (2011) and Zhang and Liu (2012) study herding and observational learning in P2P lending. In particular, Zhang and Liu (2012) documents rational herding in the Prosper marketplace but does not formally test whether informed investors strategically utilize their information advantage. Our model builds upon the rational herding behavior, i.e., uninformed investors follow informed investors as the best response when the market is at equilibrium. We extend the literature by explaining why, in some cases, early informed investor bidding is an optimal decision.

3. Research Context and Data

3.1. Peer-to-Peer Lending and Prosper.com

P2P lending is an Internet-based financing channel through which consumer borrowers seek funds to meet financial needs such as debt consolidation and home improvement. By getting rid of financial intermediaries (e.g., banks), institutional or retail investors can directly fund these unsecured personal loans. Lending Club and Prosper are the two largest P2P platforms in the U.S. and have facilitated the funding of over $26 billion in personal loan issuance by 2017.[7] P2P lending is also a global phenomenon with the U.S., China, and the U.K. as the three largest markets. Morgan Stanley Research estimated that global P2P lending can reach $290 billion worth of loans by the year 2020 (Morgan Stanley 2015).

During our study period from November 2005 to October 2008,[8] Prosper applied a reverse Dutch auction as its funding mechanism and was often considered the "eBay for P2P lending" (see Chen,

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[7] More statistics about P2P lending in the U.S. by the end of the year 2017 can be found at https://www.forbes.com/sites/oliviergarret/2017/01/29/the-4-best-p2p-lending-platforms-for-investors-in-2017-detailed-analysis/#79c0513752ab.

[8] After October 2008, Prosper voluntarily shut down its primary website to work with the U.S. Securities and Exchange Commission (SEC) on formal registration. Prosper made several changes to its funding rules and requirements after reopening in July 2009. The most notable change is to increase the minimum credit score from 600 to 640. In contrast, there was no major policy change during our study period.

Ghosh, and Lambert (2014) and Wei and Lin (2017) for more details about Prosper auctions). A typical auction begins with the borrower posting a crowdfunding project on Prosper's website. In the loan request, the borrower chooses an amount (between $1,000 and $25,000), the term (or the maturity of typically 12, 36, or 60 months), and a maximum interest rate at which s/he is willing to pay (capped at 35%). In addition to the basic loan characteristics, some credit information about the borrower is also displayed on the project page. Some of the information is self-reported, such as monthly income and employment status, while other information is obtained by the platform from a credit report bureau along with the borrower's current FICO score.[9] Prosper, based on the borrower's credit score, assigns one of seven grades, AA, A, B, C, D, E, or HR for the loan. AA projects are the least risky (with highest credit scores). HR refers to "high risk" and is considered the riskiest category (with lowest credit scores). All credit information mentioned above is available to all Prosper investors.

Potential investors can submit bids during the period the auction process is open. A typical auction lasts for 7 or 14 days. Investors can submit bids at any time when the auction is open. In their bids, investors must choose an amount between $25 and the total amount requested by the borrower. A bid should specify an interest rate, which cannot be higher than the borrower's reserve interest rate and is considered the lowest interest rate at which the investor is willing to lend the associated amount. Winners of an auction are the investors who bid the lowest interest rates, with the aggregate amount supplied by these winners to cover the amount specified by the borrower. After the auction process ends, the interest rate at which the borrower repays the loan will be the lowest interest rate submitted by the losing bidders.[10] Then, the crowdfunding project will become a fully amortized personal loan

[9] Instead of the exact credit score at the time the borrower posts the project, Prosper displays a 20-point range to protect the borrowers from identity theft.

[10] As a specific example, suppose the target amount of a loan is $1,000 and the maximum acceptable interest rate (prespecified by the borrower) is 25%. Further suppose there are three investors A, B, and C (note, in our data, the average number of bidders is much larger than three). Each submits one bid as follows: A bids $300 at 20%; B bids $600 at 18%; and C bids $400 at 16%. Then, investors B and C will be the winners who fund the loan at the contract interest rate 20%. The total funding pledged by B and C add up to the target amount. Investor A will be excluded from the loan.

(unsecured, however, by any personal assets). Investors' yield equals the contract interest rate (at which the borrower repays) minus a 1% to 5% fee charged by the platform. The yield is the same for all investors although they may bid different interest rates in the auction process.

The success of funding typically requires collective commitments from many investors. For example, in our sample, the average dollar amount that an investor commits is about \$80, which is notably below the required amount pre-specified by the borrower—with an average of \$7,600. Thus, the number of investors needed for a loan request to be funded is large: the average number of investors for funded loans in our sample is 141. If a loan request does not reach the pre-specified total amount, it will fail. As such, the borrower cannot receive any funds, and the committed investors cannot enjoy the promised return.

Prosper borrowers and investors can form groups on the platform. A wide range of groups appeared on the platform. For example, there were many alumni groups that borrowers and investors who attended the same college/university could join. There were also geography-based groups that individuals from the same state/city/community formed. A Prosper member, borrower or investor, can join at most one group on the platform. When a group member posts a loan request, the group leader and other group members can submit bids alongside a notable "endorsement" (e.g., see Freedman and Jin (2017) for a more complete description of the group feature and its evolution over time). Investors from the same group as the borrower arguably have advantages over other investors in terms of information about the borrower's credit worthiness. The reasons are mainly twofold. First, being in the same group suggests that these investors have common experience/interests/background with the borrower so that they are naturally endowed with more information about the borrower's default risk. For example, being graduated from the same college, in-group investors arguably know more about borrowers than out-group investors. Similarly, in-group investors get information advantages because of geographic proximity (Lin and Viswanathan 2015). Second, group members also interact with each other outside the platform (Freedman and Jin 2017). In particular, in-group investors can gather more credit information from the borrower by emails, interviews, or even on-site visits (Renton 2011).

3.2. Data, Samples, and Summary Statistics

We obtained the data from Prosper's data portal. Our sample contains all personal loan requests posted between the platform's inception in 2005 and October 2008. For each loan request, we observe the characteristics of the borrower and the associated loan that are publicly posted and known by potential investors. A separate data file records all winning and losing bids. We observe all bids submitted during the auction process. This allows us to construct the measure for squatting, e.g., the fraction of investors in the first 5% of funding duration, for in-group investors and out-group investors separately.

For each funded loan, we observe the final contract interest rate, which may be lower than the initial interest rate preset by the borrower. The funded amount of dollars is the same as the requested amount.[11] We also observe the final payment outcome, as the loans in our sample have all matured by 2017. We define a loan being "good" if it is eventually paid off and being "bad" if it defaults.[12]

Table 1 reports the summary statistics of all variables used in our analysis. Panel A summarizes the variables for all posted projects. Our sample includes 107,778 projects in total. The maximum interest rate that a borrower can preset caps at 35%, and the borrower can request a loan between \$1,000 and \$25,000. About 28% of the projects were initiated by a group borrower. Among all projects, 21,211 (roughly 20%) were successfully funded and transformed to fully amortized loans. The median interest rate at which these loans were funded is 15.42%, and half of these loans were funded with

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[11] Prosper later allowed for partial funding in which some loans can be funded if they receive at least 70% of the requested amount in response to a similar rule by Lending Club.

[12] Investors do not necessarily lose all their investment if a loan defaults, because most defaulted borrowers stopped making payments after a few payment cycles. To simplify analysis, we focus on whether a loan is fully paid off or defaulted at some time.

more than $5,000 (see Panel B). Overall, compared with all requests (both funded and unfunded projects), funded loans had lower interest rates, smaller amounts of funds requested, higher fractions of homeownership, higher fractions of group loans, and, more importantly, higher fractions of investors during the first 5% funding duration. Panel C further summarizes the group loans. Relative to all funded loans, group loans have slightly higher interest rates, even smaller amounts of dollars requested, and slightly worse credit profiles, such as smaller fractions of homeownership and full-time employment. These group loans also attracted smaller fractions of investors in the first 5% funding time. The loans have a slightly higher default rate than all loans (63.1% of group loans were repaid in full versus 67.6% of all loans).

[Insert Table 1 about here.]

Table 2 reports the summary statistics of funded loans categorized by credit grade. Panel A summarizes all funded loans, and Panel B presents the means of the variables for group loans. It is easy to see that credit grades are a good indicator of loan payment outcomes. More than 80% of AA loans were paid off in full. In sharp contrast, only 40% of HR grade loans were paid in full. Loans across credit grades also differ in characteristics. Most notably, the interest rate borrowers preset increases with the level of risk. The average interest rate of HR loans more than doubles that of AA loans, while the average amount of HR loans is only about 20% of the average amount of AA loans.

[Insert Table 2 about here.]

4. A Stylized Model of "Crowd" Lending

In this section, we present a stylized model to show how on P2P lending platforms investors with asymmetric information strategically interact with one another. The model considers two types of investors: "informed" investors ($\theta = 1$) who have private information about the borrower's creditworthiness and "uninformed" investors ($\theta = 0$) who only have access to the public information.

All crowdfunding projects require a collective effort from investors, as no single investor can offer the funding that the projects require. The funding is conducted through a Dutch auction mechanism, as adopted by Prosper.com. If the aggregate fund that investors commit at the end does not reach the amount requested by the borrower, the project will fail, and investors will have zero return. The model focuses on the decision of when to bid from both types of investors and abstracts from the decisions on what interest rate they bid and the amount of loans they commit.

There are two types of crowdfunding projects, represented by the probability that the project will be successfully funded as "high" (i.e. H-type) or "low" (i.e. L-type). The categorization will be defined below. A borrower chooses the maximum interest rate, R, that she is willing to pay. Conditional on being funded, the probability of default during the repayment period measures the risk of the loan. Let $p = \{p^H, p^L\}$ be the average default rates of the two types of projects.[13] With only public information, the default rates represent the fraction of similar loans that have defaulted in the past. We assume the average default rate p of a loan to be the public information.

An investor is "informed" if she has private information about the loan's riskiness or the borrower's creditworthiness. The private information comes from various resources. For example, an alumni investor may have more information about the borrower when they were both in school. If the project is a good loan, the informed investor expects the default rate to be lower than the average default rate, namely $E[p^k|\theta = 1] \equiv p_G^k < p^k$, where $k = \{H, L\}$ and the subscript "G" represents a good loan. Likewise, for a bad loan the investor expects the default rate to be higher, i.e., $E[p^k|\theta = 1] \equiv p_B^k > p^k$. We assume that, if the loan is bad, the expected return is negative even when the interest rate is at the maximum level R. That is, $\left(1 - p_B^k\right) \cdot (1 + R) - 1 < 0$. For a good loan, the return at interest rate level R is positive, i.e. $\left(1 - p_G^k\right) \cdot (1 + R) - 1 > 0$. For uninformed investors,

[13] Typically, the default rate of a crowdfunding project with high success probability will be lower than that with low success probability, i.e. $p^H < p^L$.

their belief for either type of loan is $E[p^k|\theta = 0] = p^k$.

We assume that informed and uninformed investors arrive simultaneously as a crowdfunding project starts. An informed investor chooses to bid ($b_{in} = 1$) or not to bid ($b_{in} = 0$). If she decides to bid, she also chooses to bid early ($e_{in} = 1$) or to bid late ($e_{in} = 0$). An uninformed investor makes similar decisions, i.e., $b_{un} = 1$ or 0 and $e_{un} = 1$ or 0. If the uninformed investor bids late, she will observe the informed investor's decision if $e_{in} = 1$, and based on that update her belief of the loan's risk, which is represented by $E[p^k|\theta = 0, e_{in}]$.[14] As such, there is an information spillover from the informed to the uninformed investor.

When making bidding decisions, the informed investor is aware that her decision may affect the uninformed investor's bidding decision. She faces a tradeoff that is formalized as the following: let $r(b_{in}, b_{un})$ be the actual interest rate the borrower has to pay, which is a function of the investors' bid decisions. By default, $r(b_{in}, b_{un}) \leq R$, the maximum interest rate set by the borrower. We assume that $r(b_{in} = 1, b_{un} = 1) < r(b_{in} = 1, b_{un} = 0)$. This captures the fact that Prosper uses auctions as the pricing mechanism. As such, the return for the informed investor will be lower if the uninformed investor enters to compete. Let $P^k(b_{in}, b_{un})$, where $k = \{H, L\}$, be the probability that the crowdfunding project will be successfully funded, which again is a function of the investors' bid decisions. We assume that $P^k(b_{in} = 1, b_{un} = 1) > P^k(b_{in} = 1, b_{un} = 0)$ and $P^k(b_{in} = 0, b_{un} = 1) > P^k(b_{in} = 0, b_{un} = 0)$. That is, the uninformed investor's decision to bid will increase the success probability. Conditional on b_{in} and b_{un}, we assume that the success probability of H-type loans weakly dominates that of L-type loans. For the simplicity of the analysis, we assume that if both investors bid, all loans will have 100% success rate, i.e. $P^H(b_{in} = 1, b_{un} = 1) = P^L(b_{in} = 1, b_{un} = 1) = 1$. If the informed investor bids, but the uninformed does not, H-type loans will still be successfully funded

[14] Observing $e_{in} = 1$, the uninformed investor knows that $b_{in} = 1$. If $e_{in} = 0$, however, b_{in} can be either 0 or 1. The investor will make an inference based on the equilibrium condition which we will discuss below.

but L-type loans will not. That is, $P^H(b_{in}=1, b_{un}=0)=1$ and $P^L(b_{in}=1, b_{un}=0)=0$.[15] Given that on P2P platforms the proportion of uninformed investors is typically much larger than that of informed investors, we assume that $P^H(b_{in}=0, b_{un}=1)=P^L(b_{in}=0, b_{un}=1)=1$.[16]

Conditional on b_{in} and b_{un}, for a project $j=\{G,B\}$ (i.e. good or bad loan) that belongs to type $k=\{H,L\}$, the expected rate of return for an informed investor can be written as

$$E\left[\text{Rate of return}_j|\theta=1\right]=P^k(b_{in},b_{un})\cdot\left\{\left(1-p_j^k\right)\cdot[1+r(b_{in},b_{un})]-1\right\}\cdot\{b_{in}=1\} \qquad (1)$$

It is post-multiplied by the indicator function $\{b_{in}=1\}$ since otherwise the return for the investor will be zero.

For an uninformed investor, the expected rate of return depends on the informed investor's decision e_{in}. If the informed investor bids early, i.e. $e_{in}=1$ (and $b_{in}=1$), it can be written as

$$\begin{aligned} E\left[\text{Rate of return}_j|\theta=0,e_{in}=1\right]&=P^k(b_{in}=1,b_{un}) \\ &\cdot\left\{\left(1-E[p^k|\theta=0,e_{in}=1]\right)\cdot[1+r(b_{in}=1,b_{un})]-1\right\}\cdot\{b_{un}=1\} \end{aligned} \qquad (2)$$

Note that the expected default probability p^k is updated based on the information $e_{in}=1$. If $e_{in}=0$, b_{in} can be either 0 or 1. The uninformed investor will form an expectation of b_{in} based on the equilibrium strategy that the informed investor will use, which is in the subsection below.

4.1. Equilibrium Bidding Strategies

For the objective of this study, we focus on L-type loans first. Below is the proposition that describes the equilibrium strategies of both types of investors.

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[15] The difference between H- and L-type loans can be due to the borrower's credit rating or the loan's credit grade given by the platform. Higher credit ratings or grades will attract more investors and thus have a higher success probability.

[16] Our analysis results are valid if the probabilities are continuous, as long as $P^H(b_{in}=1,b_{un}=0)>P^L(b_{in}=1,b_{un}=0)$. We focus the analysis on the probability that the crowdfunding project is sufficiently funded, because otherwise the committed investors cannot enjoy the return at Prosper.com. On other P2P platforms, a borrower may still borrow even if the project is only partially funded. The return for committed investors will not be zero. The default rate, however, may be higher in such case, and, therefore, the cost for the informed investor will become higher. Our analysis results will still be valid.

Proposition. *The equilibrium bidding strategies of investors for* L*-type loans are the following: for a good loan, the informed investor's strategy is* $b_{in} = 1$ *and* $e_{in} = 1$ *(i.e. "squatting"), and the uninformed investor strategy is* $b_{un} = 1$ *and* $e_{un} = 0$*; for a bad loan, the informed investor's strategy is* $b_{in} = 0$*, and the uninformed investor will also follow, i.e.* $b_{un} = 0$.

Intuition of the proof: First assume that the uninformed investor uses a bidding strategy as follows: she will bid late (i.e. $e_{un} = 0$) and will bid only if the informed investor bids early (i.e. $e_{in} = 1$). We will show that this is an equilibrium strategy.

If the loan is a bad loan, given the assumption that $(1 - p_B^L) \cdot (1 + R) - 1 < 0$, the informed investor will not invest, and thus $b_{in} = 0$.

If the loan is a good loan, the decision e_{in} depends on the tradeoff between helping the crowdfunding project to be successful and intensifying the competition from the uninformed investor. If $e_{in} = 0$, the uninformed investor will not bid in the late stage. Since we assume the loan request will fail if only the informed investor bids (i.e. $P^L(b_{in} = 1, b_{un} = 0) = 0$), the return of the investor will be zero. If $e_{in} = 1$, the uninformed investor will follow by $b_{un} = 1$, and thus the interest rate $r(b_{in} = 1, b_{un} = 1)$ will be lower than the maximum interest rate R. Suppose $(1 - p_G^L) \cdot [1 + r(b_{in} = 1, b_{un} = 1)] - 1 > 0$, i.e. the expected return for investors is positive when both types of investors bid (and thus the interest rate $r(b_{in} = 1, b_{un} = 1)$ is lower than R). The optimal strategy for the informed investor is $e_{in} = 1$, i.e., squatting.

It is easy to see that, under the auction mechanism, $(1 - p_G^L) \cdot [1 + r(b_{in} = 1, b_{un} = 1)] - 1$ has to be positive. This is because otherwise investors will incur an expected loss. No one therefore will bid an interest rate lower than this level.

Given that $e_{in} = 0$ if the loan is bad and $e_{in} = 1$ otherwise, it is easy to see that the uninformed investor's optimal strategy is to bid only if the informed investor bids early (i.e. $e_{in} = 1$). Furthermore, if the investor bids early, she will not be able to observe the informed investor's decision. It is also easy to see that the strategy $e_{un} = 0$ dominates the strategy $e_{un} = 1$.

For the completeness of the analysis, we now turn to H-type loans. If the loan is bad, given the assumption that $(1 - p_B^H) \cdot (1 + R) - 1 < 0$, the informed investor will not invest, and thus $b_{in} = 0$.

Suppose the loan is good. If the informed investor's strategy is $e_{in} = 0$, the uninformed investor cannot update her belief based on the decision (since she cannot differentiate $e_{in} = 0$ from $b_{in} = 0$), her expected return rate conditional on bidding thus is $\{(1 - p_G^H) \cdot [1 + r(b_{in} = 1, b_{un} = 1)] - 1\} \cdot \text{Prob}(G|H) + \{(1 - p_B^H) \cdot [1 + r(b_{in} = 0, b_{un} = 1)] - 1\} \cdot \left(1 - \text{Prob}(G|H)\right)$, where $\text{Prob}(G|H)$ is the ex-ante belief of the uninformed investor that an H-type loan is a good loan. If the expected return rate is negative, $b_{un} = 0$. Since we assume the H-type projects will be fully funded even if only the informed investor bids, the return for the informed investor will be higher when $b_{un} = 0$. Therefore, the investor's optimal strategy is $e_{in} = 0$. If the uninformed investor's expected return rate is positive, $b_{un} = 1$ even when $e_{in} = 0$. In this case, however, it does not matter to the informed investor whether e_{in} is 0 or 1. Therefore, $e_{in} = 0$ (i.e. "sniping") is a dominatant strategy for H-type loans for the informed investor.

The predictions derived from the model have important implications on the information spillover among investors and on welfare. For crowdfunding projects with a low probability of being successfully funded (L-type), the model predicts that informed investors will bid early for good ones. This information is valuable for uninformed investors so that they can differentiate good projects from bad projects. It helps solve the information asymmetry problem and thus increases the uninformed investors' expected profit. The information spillover is also important for creditworthy borrowers because otherwise their projects may not be sufficiently funded. As more good projects are funded, it will benefit P2P platforms, since attracting investors to invest and creditworthy borrowers to borrow is important for the business. In contrast, sniping will reduce the extent of information spillover; however, as sniping is for the H-type, it does not significantly impact the probability that a crowdfunding project can be sufficiently funded. The model also has policy implications. The incentive for informed investors to bid early comes from the probability that projects will fail. For P2P platforms, it may benefit borrowers and investors by setting a rule to let some projects fail (e.g. when there are not enough investors). This is especially important when the information asymmetry is a serious problem on the platform.

4.2. Hypotheses

The stylized model makes several strong assumptions. In reality, investors can bid any time throughout the lending process. They may have heterogeneous beliefs regarding the default rate of a loan and the probability that the loan request will be successfully funded. Furthermore, there may be non-strategic investors whose bidding decisions may not be rational. Still, the model generates several hypotheses about squatting behaviors that we can test using data from Prosper. First, when information asymmetry exists among investors and the probability of being successfully funded is low for many projects (which is true for Prosper, since only 20% of projects were funded. See Panel A of Table 1), the model suggests that early bidding is a common phenomenon. Moreover, since informed investors only bid early for projects with low default risk, the model predicts that squatting is more common for good projects than for bad projects. Finally, the model predicts that informed investors will bid early for good projects only if they have lower ex-ante success probability. Therefore, the following hypotheses can be developed from the stylized model and tested from data:

Hypothesis 1. *Squatting is common in Prosper auctions;*

Hypothesis 2. *"Good" projects attract more early bidders than "bad" projects;*

Hypothesis 3. *"Good" projects with low ex-ante funding probability attract more informed investors to bid early.*

5. Empirical Analysis

We test in this section the hypotheses generated from the theoretical model. We note that, due to the data limitation, we are unable to use randomized experiments or advanced econometric techniques that exploit exogenous data variations to establish the causality argument. Although we have controlled for all observables in data, the regression analyses in this section are descriptive in nature. Our goal of the empirical analysis is to investigate whether the correlational relationships between early bidding behaviors and other key variables (i.e. good projects, informed investors, and ex-ante funding probabilities) are consistent with the theory predictions.

As a quick roadmap, we start with testing an important model assumption that there exists a tradeoff between funding probability and interest rates. We then show evidence supporting Hypothesis 1 and Hypothesis 2. Section 5.3 presents the main test results. We first present evidence that in-group investors are more informed and that HR projects have low ex-ante funding probability. Based on these, we formally test Hypothesis 3. We also examine an alternative explanation for our main finding. The last section, Section 5.4, reports some robustness checks.

5.1. Tradeoff between Funding Probability and Interest Rates

Our model predicts that early bidding is common in Prosper auctions (as in Hypothesis 1). An important assumption is that informed investors face a tradeoff by taking the squatting strategy, that is, the tradeoff between increasing the funding probability (from encouraging uninformed investors to participate) and decreasing the interest rate at which the loan is funded (from competition). Before formally detecting the prevalence of early bidding, we start with testing this tradeoff. Specifically, we ask if there is such a tradeoff between two funding outcomes: (1) being funded or not and (2) the interest rate? We conduct regression-adjusted analyses to answer this question. Our main regression equation can be written:

$$Y_i = \beta_0 + \beta_1 \cdot \text{Frac\_investors\_early5\%}_i + \tau X_i + \varepsilon_i, \quad (3)$$

where Y_i is the dependent variable. We run two sets of regressions based on this specification. First, we run logit regressions with the dependent variable indicating that a project is successfully funded. Conditional on projects that are funded, we run the second set of regressions. We construct a normalized contract interest rate for each funded loan, which equals the contract interest rate divided by the maximum interest rate preset by the borrower, as the dependent variable. For example, if a loan request is funded at 18% with a maximum acceptable interest rate 20%, the normalized contract interest rate will be 0.9. We then run OLS regressions using the specification as Equation (3). Since projects have different maximum acceptable interest rates, the normalized interest rate can better capture how competition leads to a lower return for investors.

The key independent variable is *Frac_investors_early5%*, which is the fraction of investors who submit bids during the first 5% funding duration (among all investors participating in the current loan request).[17] For other control variables in X_i, we use three different specifications. Specification (1) only includes an intercept. Specification (2) further incorporates some loan and borrower characteristics, including the borrower's credit grade (fixed effects) and the amount of dollars requested. Following the literature, we also include the maximum interest rate in the funding probability regression. In the final specification, we also include homeowner status, full-time employment status, and the state she lives in (fixed effects).

Table 3 reports the marginal effects from logit regressions of the funding indicator on *Frac_investors_early5%* and control variables. The positive coefficients of *Frac_investors_early5%* suggest that the funding probability increases with the fraction of investors who enter early in an auction. This

[17] For consistency and easy comparison of our findings, we use the first 5% funding time in general as our definition of early funding duration. We run robustness checks to ensure that the results are consistent by using 1% or 10% as our definition of early funding.

is consistent throughout the three specifications. To understand the magnitude of the impact of early bidding, we calculate the funding probability of a loan request assuming it has the average fraction of early bidders and average X_i, based on the logit specification, then recalculate the funding probability assuming the fraction of early bidders increases by 10%. The result suggests that the funding probability will increases by 0.16% if the fraction of early 5% investors increases by 10%.

[Insert Table 3 about here.]

For other results, the negative coefficients of credit grade dummies suggest that the funding probability is lower in all other grades relative to AA loans and decreases with credit grades (from A to HR). Controlling for credit grade, the higher the borrower's preset interest rate, the higher the funding probability will be. The requested dollar amount is, in contrast, negatively correlated with the funding probability. Homeownership is also negatively correlated, while the full-time employment status does not have a statistically significant impact on funding probability controlling for credit grades.

Table 4 presents the results from OLS regressions of the normalized contract interest rate on the fraction of bidders in the first 5% funding duration and other variables. The coefficients for *Frac_investors_early5%* are significantly negative in all three specifications. The result in the full specification (3) implies that a 10% increase in the fraction of investors in the first 5% funding duration decreases the normalized contract interest rate by 0.8%. The average normalized contract interest rate in our sample is 0.818. Thus, the estimate suggests that increasing the fraction of investors in the early 5% funding duration by 10% will decrease the normalized rate to 0.81 (= 0.818 – 0.008).

[Insert Table 4 about here.]

For other estimation results, the amount of dollars requested is positively correlated with the normalized interest rate. In other words, investors have to fund a project with a larger amount of dollars at a higher interest rate. Not surprisingly, both homeownership and full-time job status are negatively correlated with the interest rate.

Overall, the results suggest that by squatting, investors may face a tradeoff between funding probability and potential profits acquired, although more bidders who enter early always benefit the borrower with higher funding probabilities and lower interest rates. Therefore, "rational" investors will potentially seek a balance between the benefit and cost by strategically squatting. We next detect whether early bidding is common in Prosper auctions (per Hypothesis 1).

5.2. Early Bidding and Good Loans

Figure 1 depicts a (discrete) distribution of bids by the submission time. Specifically, we normalize the funding duration to be between 0 (starting time) and 1 (ending time). For each loan and each 5% bin of the funding duration, we calculate the fraction of investors who entered during the corresponding period (relative to all participating investors in the current auction). Then, we compute the average fraction across all funded loans in each 5% bin and draw the means in Figure 1. The figure clearly demonstrates the prevalence of squatting in Prosper auctions, as the bar for the first 5% funding duration is notably higher than other bars in the early durations (such as 10%, 15%). On average, more than 10% of bidders in a Prosper auction entered during the first 5% bin, while for all 5% bins between 10% funding time and 80% funding time, the fractions of entering bidders are smaller than 5%. The last few 5% bins have a significantly larger fractions of bidders entering—namely "sniping," that are well documented in online auctions (see Roth and Ockenfels (2002) for more examples).

[Insert Figure 1 about here.]

Hypothesis 2 further predicts that good projects, or loan requests with lower default risk, attract more early investors than bad (high default risk) projects. To operationalize the tests, we use the ex-post payment outcomes as a proxy for the ex-ante default risk. Specifically, we define a loan being "good" if it was eventually paid off by the borrower and being "bad" if the borrower defaulted (or was charged off) at some time. Assuming that lenders are rational in making the investment decision without systematic errors (e.g. some loans systematically have a higher default risk, but the risk is continuously ignored by investors), the difference between the proxy we use and the expected risk can be treated as a random measurement error. In such a case our estimates are consistent without systematic bias.

We test Hypothesis 2 by first presenting some model free evidence, as shown in Figure 2. It is similar to Figure 1, but we separate the sample into paid (or good) loans and defaulted (or bad) loans. The figure shows that, first, the squatting phenomenon exists for not only good but also bad loans. Since the prior expectations of the risk for the same loan are heterogeneous, some investors may consider a loan that eventually defaults as a good project and thus choose to bid early. Overall, however, more investors tend to enter early in good loans than in bad loans. Quantitatively, for good loans, the average fraction of investors in the first 5% funding duration is about 11.8%, significantly higher than the average fraction among bad loans, which is about 7.8%. This result is consistent with the prediction of Hypothesis 2.

[Insert Figure 2 about here.]

We formally test Hypothesis 2 by running a set of regressions. The regression equation is:

$$\text{Frac\_investors\_early5\%}_i = \beta_0 + \beta_1 \cdot 1(\text{"Good" loan})_i + \tau X_i + \varepsilon_i. \tag{4}$$

The dependent variable is the fraction of investors in the first 5% funding duration. The coefficient of interest is β_1 that captures whether and by how much a good project attracts more early bidders than a bad project. We control for borrower and loan characteristics in X_i. The results are in column (1) of Table 5. Consistent with the hypothesis and the model-free evidence in Figure 2, the estimate suggests that good projects indeed attract more investors in the first 5% funding duration. Among all loan requests, the average fraction of early bidders is about 0.53% higher in good projects than in bad projects. Note that we have controlled for the credit grade of each loan in the regression. This is important since, as Table 2 shows, a higher-grade project attracts more early bidding and is also more likely to be fully repaid. Estimation results show loan requests with lower credit grades (e.g., E and HR loans) attract fewer early bidders than the requests with higher credit grades. In addition, the maximum interest rate set by the borrower is negatively correlated with the fraction of early bidders. Similarly, the asking amount is also negatively correlated. We also find that a borrower attracts more early investors if she has a fulltime job and is not a homeowner.

[Insert Table 5 about here.]

5.3. Do Informed Investors Bid Early for Good Loans with Low Funding Probability?

As stated in Hypothesis 3, our model predicts explicitly that informed investors will strategically utilize their advantages in information and bid early in good loans with lower expected funding probability. We formally test this hypothesis in this section. We use groups formed on the platform as a proxy for whether an investor is informed or not. The reasons that in-group investors are likely to be informed are discussed in Section 3. A formal test of this assumption is in section 5.3.1. We also use the credit grade Prosper assigns to a loan request as the proxy for the ex-ante funding probability. We present evidence to support this assumption in Section 5.3.2.

5.3.1. Are In-Group Investors Better Informed?

We first test whether in-group investors are indeed better informed than out-group investors. We define an investor being "in-group" if she was in the same group as the borrower at the time the loan request was posted. We define "out-group" investors if these investors are not in the same group as the borrower. Our main regression equation is:

$$Y_i = \beta_0 + \beta_1 \cdot 1(\text{"Good" loan})_i + \tau X_i + \varepsilon_i. \tag{5}$$

We run two separate regressions for in-group and out-group investors. In the first regression, we study how the good loan status is associated with the proportion of in-group investors who participated.

The proportion of in-group investors equals the number of in-group investors in a loan divided by the total number of investors who had joined the same group by the end of the loan's funding process. For example, if a group has in total 100 investors joined by the end of a project's auction process, and 2 out of 100 participated in the current auction, the in-group investor proportion for this specific loan will be 0.02.[18] In the second regression, we calculate the same proportion for out-group investors (= the number of out-group investors in a loan / the total number of all investors who were not in the same group by the end of the auction process) as the dependent variable. We include the same set of control variables as in regressions of Equation (3). We only focus on group loans here because there are no in-group investors for loan requests initiated by an out-group borrower.

We report the coefficient estimates in Panel A in Table 6. Notably, the good loan indicator is more positively associated with the proportion of in-group investors (column (1)) than with the proportion of out-group investors (column (2)): good loans have on average 0.77% more in-group investors than bad loans; in contrast, the difference in out-group investors between good and bad loans is roughly 0.06%. To put these figures in perspective, the average proportion of in-group investors in group loans is about 2.85%, and the average proportion for out-group investors is 0.49%. For in-group investors, the difference between good and bad loans is therefore more than 27% of the average proportion (=0.77 / 2.85). A similar calculation for out-group investors shows that the difference is only about 12% of the average proportion (=0.06 / 0.49).

[Insert Table 6 about here.]

We use another method of comparison by calculating a "normalized" effect of being a good project. Specifically, we first calculate the fitted values, $\widehat{Y_i}$, based on the regressions. Then, for each observation, we compute the normalized effects $\widehat{\beta_1}/\widehat{Y_i}$ (as in Equation (4)). Hence, this "normalized"

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[18] Note that this is the proportion of investors throughout the auction process, which is different from the proportion of investors who bid in the early stage of the auction process we study later.

marginal effect captures, for each group loan, the predicted marginal effect of being a good loan that is scaled by the predicted proportion of in-group or out-group investors. Panel B of Table 6 presents the 25th, 50th (median), and 75th percentile of the normalized effect distributions from the two regressions reported in Panel A. It shows that the percentiles from the *Proportion_in-group_investors* regression are all greater than those from the *Proportion_out-group_investors* regression. Overall, the evidence suggests that in-group investors possess information advantages over other investors. Therefore, it is reasonable to use the in-group indicator as a proxy of information advantage in the test (of Hypothesis 3).

5.3.2. Are Credit Grades a Good Proxy for Ex-Ante Funding Probability?

We use the credit grades Prosper assigned to each project as a proxy of the ex-ante funding probability. This is public information available to all investors before they make bidding decisions. The credit grade is typically displayed in the most prominent section when investors check for the detailed information of a loan request. We depict in Figure 3 the fractions of loans funded across credit grades. It shows that the fraction is monotonically decreasing from the highest AA to the lowest HR grade. Numerically, more than 35% AA projects in our sample were successfully funded, while in sharp contrast, only about 5% of HR projects were funded. That is, the success rate of the best loans was more than seven times the success rate of the worst loans. Therefore, in our regressions reported in the next section, we use the grade HR indicator as the proxy for low ex-ante funding probability. We check the robustness of using this proxy in Section 5.5.

[Insert Figure 3 about here.]

5.3.3. Strategic Early Bidding by In-Group Investors

We first present the model-free evidence shown in Figure 4. We focus on HR loans that are used as the proxy for low ex-ante funding probability. We compare the fractions of in-group investors who bid in each 5% bin throughout the funding duration of good loans (namely, paid HR loans) and bad loans (defaulted). Hypothesis 3 states that more in-group investors will bid early for good loans, which is supported by the figure. For example, the fraction of in-group investors in the first 5% funding duration is roughly 9.3% for good loans, almost double the fraction for bad loans (about 5%).

[Insert Figure 4 about here.]

As a more formal test, in the regression analysis, we only focus on group loans because there are no in-group investors for other loans. The main specification of testing Hypothesis 3 is as follows,

$$\begin{aligned} Y_i = \beta_0 &+ \beta_1 \cdot 1(\text{"Good" loan})_i \cdot 1(\text{Credit grade HR})_i \cdot 1(\text{In-group})_i \\ &+ \beta_2 \cdot 1(\text{"Good" loan})_i \cdot 1(\text{Credit grade HR})_i \\ &+ \beta_3 \cdot 1(\text{"Good" loan})_i + \beta_4 \cdot 1(\text{In-group})_i + \tau X_i + \varepsilon_i \end{aligned} \tag{6}$$

For each loan, we calculate both the fraction of in-group investors and out-group investors in the early 5% funding duration. Therefore, each loan corresponds to two observations in this regression. The coefficient of the three-way interaction term, β_1, measures whether and by how much more in-group investors enter early in good loans with lower ex-ante funding probability.

The second column in Table 5 reports the results. The positive estimate of β_1, the coefficient of the three-way interaction term, suggests that relative to out-group investors, in-group investors are more likely to bid early for good projects with a lower ex-ante funding probability (i.e., the HR loans). The estimate therefore lends support to Hypothesis 3. In contrast, the significantly negative estimate for the interaction of good projects and HR grade (β_2) suggests that out-group investors are unlikely to bid early. The positive coefficient of the good loan indicator (β_3 in Equation (6)) suggests that more investors tend to enter early in good loans than in bad loans, consistent with Hypothesis 2. Other estimates are similar to that in the first column of the table.

5.3.4. An Alternative Explanation

The empirical evidence suggests that in-group investors, being more informed investors, utilize their information advantage and bid early for strategic reasons. One may argue that the phenomenon can be driven by an alternative explanation: in-group investors bid early out of altruism. Being in the same group, in-group investors may feel obliged to help out borrowers who belong to the same group, especially when the funding probability of these projects is low; therefore, they will choose to bid early.

Note that the evidence presented in this section does not rule out that in-group investors may bid for altruistic reasons. Indeed, the proportion of in-group investors who bid for in-group loan requests is 2.85%, far higher than the proportion of out-group investors (0.49%). This could indicate the existence of the helping intention among in-group investors. Our empirical results show that, relative to out-group investors, they are more likely to bid early for good projects with low ex-ante funding probability. We argue that this behavior is driven by the interest of in-group investors to maximize the return of their investment. To support this argument, we re-run regression (6) by including $1(\text{"Good" loan})_i \cdot 1(\text{In-group})_i$ and $1(\text{Credit grade HR})_i \cdot 1(\text{In-group})_i$ as additional controls. The estimation results are reported in Column (3) of Table 5.

Estimated coefficients for variables included in Column (2) remain qualitatively the same. In particular, the coefficient for the three-way interaction term is significantly positive (with an even larger magnitude). What is interesting is that the coefficient for $1(\text{"Good" loan})_i \cdot 1(\text{In-group})_i$ is significantly negative. This result suggests that, in comparison with out-group investors, in-group investors do not bid early to help good loans, although they are more likely to bid for these projects because of their information advantages (see Table 6).[19] In addition, the coefficient for

[19] A seemingly counter-intuitive result is that the coefficient for $1(\text{"Good" loan})_i \cdot 1(\text{Credit grade HR})_i$ becomes significantly negative, suggesting out-group investors are more likely to bid late for those projects. We believe the negative coefficient is due to the following. As in-group investors bid early for these good projects, less informed out-group investors are likely to follow (i.e. herding) and bid late. Consequently, the proportion of early bids among out-group investors will appear smaller.

$1\left(\text{Credit grade HR}\right)_i \cdot 1\left(\text{In-group}\right)_i$ is statistically insignificant. This is inconsistent with the argument that in-group investors bid early to help projects with a low ex-ante probability.

As more indirect evidence to support our argument, if in-group investors want to help good projects that have lower ex-ante funding probability, we would expect that they are also more likely to bid for those projects that still have not received sufficient funds toward the end of the auction process. We test this argument by running regressions based on the following equation:

$$Y_i = \beta_0 + \beta_1 \cdot 1(\text{"Good" loan})_i \cdot 1(\text{Unfunded by 95\%})_i + \beta_2 \cdot 1(\text{Unfunded by 95\%})_i \\ + \beta_3 \cdot 1(\text{"Good" loan})_i + \tau X_i + \varepsilon_i. \tag{7}$$

We run separate regressions for in-group and out-group investors. The dependent variables are the fraction of in-group investors in the last 5% funding time and a similar fraction for out-group investors. We construct a new dummy, $1(\text{Unfunded by 95\%})_i$, to indicate that a project has not received full funding by the 95% funding time. We control for the same set of covariates as in our other regressions. Table 7 presents the estimation results. The first row shows that the coefficient of interest is not significant in the in-group regression, meaning that in-group investors do not bid more in good projects that have not received full funding by 95% funding time. Out-group investors do not increase bids either (as shown in column (2) of Table 7). The results again cast doubt on the argument that our finding is driven by altruism from in-group investors.

[Insert Table 7 about here.]

5.4. Robustness Checks

We report two sets of robustness checks in this section. First, in our empirical analyses we treat bidding in the first 5% in a funding duration as early bidding. One may worry that this definition of "being early" is arbitrary. We repeat all regressions in Table 5 but use the first 1% and the first 10%, separately, to calculate the fraction of "early" bidders. Regression results are reported in Tables 8 and 9. The results are qualitatively consistent in the 10% specification as in Table 8. In the 1% specification, the coefficient of the three-way interaction term, β_1, is positive but not statistically significant. The lack of significance is due to the lack of observations. For many projects, the number of bids in the first 1% funding duration is zero. Specifically, only 5.89% of group loans had at least one bid from in-group investors in the first 1% funding time. Overall, the results suggest that our findings are robust to the specification of early bidding.

[Insert Tables 8 and 9 about here.]

Another potential concern of our main specification is only using the HR grade to proxy for low funding probability. Table 10 reports the results from a specification in which we use either E grade or HR grade as the proxy for low ex-ante funding probability. Table 11 presents the results from further including credit grade D to indicate low funding probability. The results are qualitatively the same as the results in Table 5, suggesting the robustness of our findings under different specifications.

[Insert Tables 10 and 11 about here.]

6. Concluding Remarks

We study how informed investors in P2P lending strategically utilize their information advantage by bidding early. The auction literature has well documented that informed investors have the incentive to withhold the information and bid until the last moment, i.e., "sniping." We, however, argue that collective effort from investors is required in P2P lending. The sniping strategy therefore has a potential cost for informed investors. We demonstrate both theoretically and empirically that bidding early, or "squatting," can be an equilibrium strategy for informed investors under some conditions. Using detailed project-level and bid-level data from Prosper.com, our empirical findings lend support to the predictions. Specifically, we find that, first, squatting is common in Prosper auctions. Second, good projects are more likely to attract early investors than bad projects. Most importantly, our results suggest that informed investors bid early in the funding process for good projects that have relatively lower ex-ante funding probability.

We make several important contributions to various strands of literature. First, to the best of our knowledge, we are the first to explore the information asymmetry on the investor side of P2P lending. In contrast, the literature on P2P lending has been focusing on the asymmetry between borrowers and investors. Second, our study adds to the economics literature on "sniping" behavior in online auctions by providing empirical evidence of the "squatting" strategy in P2P lending and demonstrates a potential underlying mechanism driving this strategy. Our work also extends our understanding of the role of social networks in online platforms by uncovering how in-group investors utilize their information advantage. Last but not least, we also contribute to the literature on herding in online markets by revealing a potential reason that generates the information spillover from informed investors to uninformed investors.

Our study has several managerial implications. First, our results suggest that squatting behaviors in Prosper auctions benefit not only uninformed investors but also borrowers who otherwise may not be able to raise sufficient funding from P2P lending platforms. Our results also have implications for how P2P lending platforms may manage information asymmetry and the strategic behaviors of investors. For example, both Prosper and Lending Club (the two leading P2P platforms in the U.S.) adopted a new rule that allows for "partial funding," under which a project may be funded as long as it collects 60% or 70% of the funding requested by the borrower. Our study suggests that partial funding may reduce the incentive of early bidding, and thus may reduce the information spillover. This may lead to unintended negative consequences for both lenders and borrowers on P2P lending platforms.

Figures and Tables:

Figure 1. Distribution of Bidders by Bid Timing—All Loans

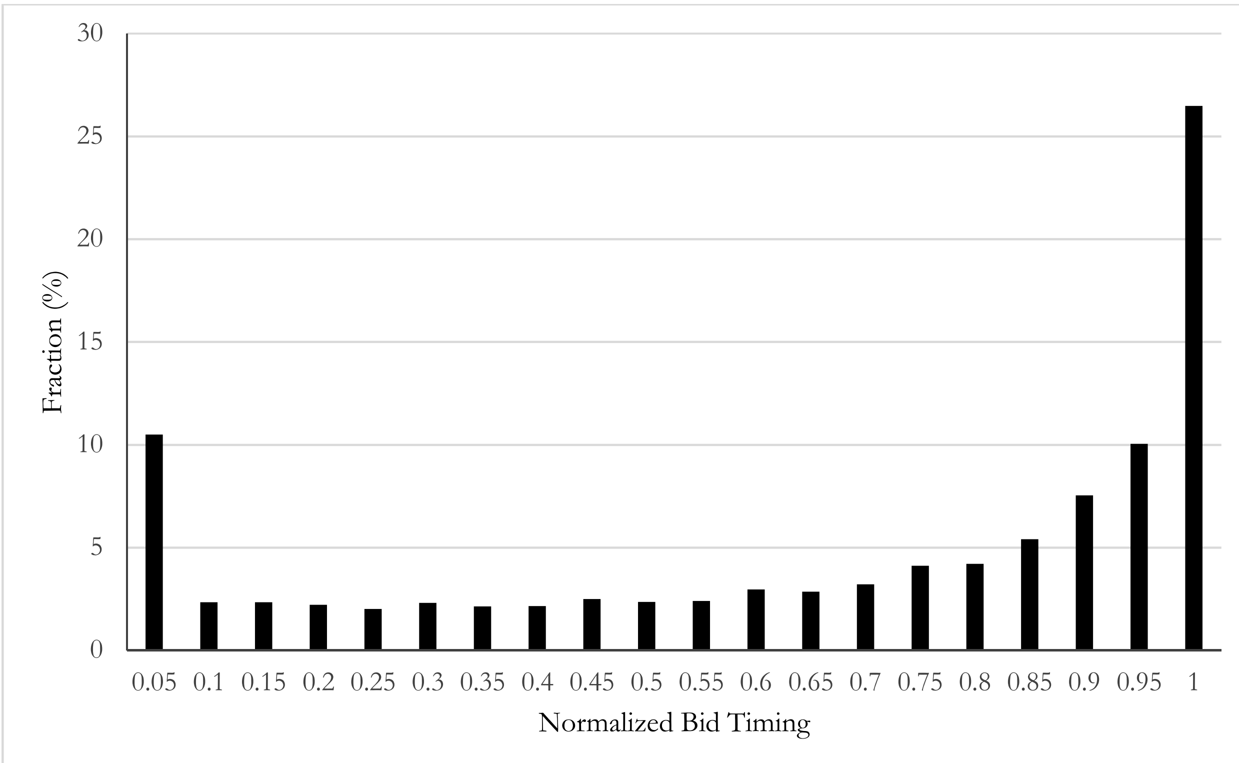

Figure 2. Distributions of Bidders by Bid Timing—Paid versus Defaulted Loans

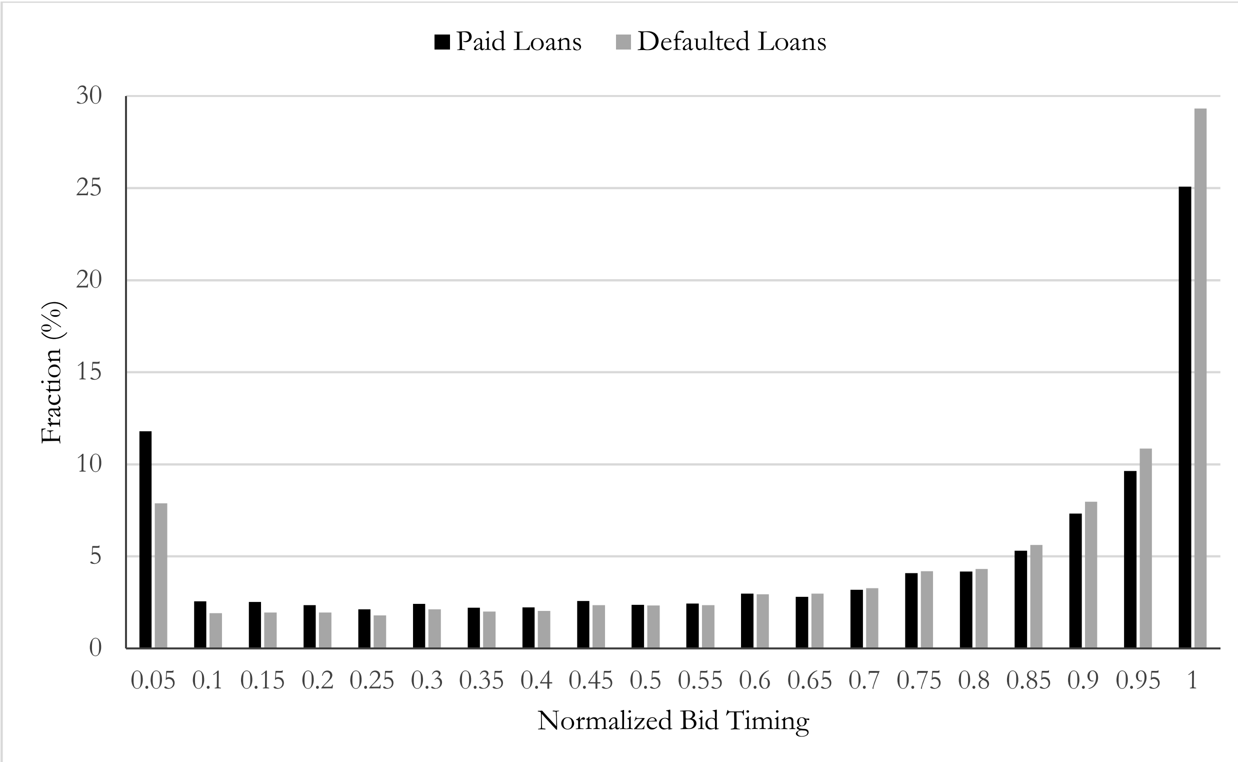

Figure 3. The Proportion of Loan Requests Successfully Funded by Credit Grade

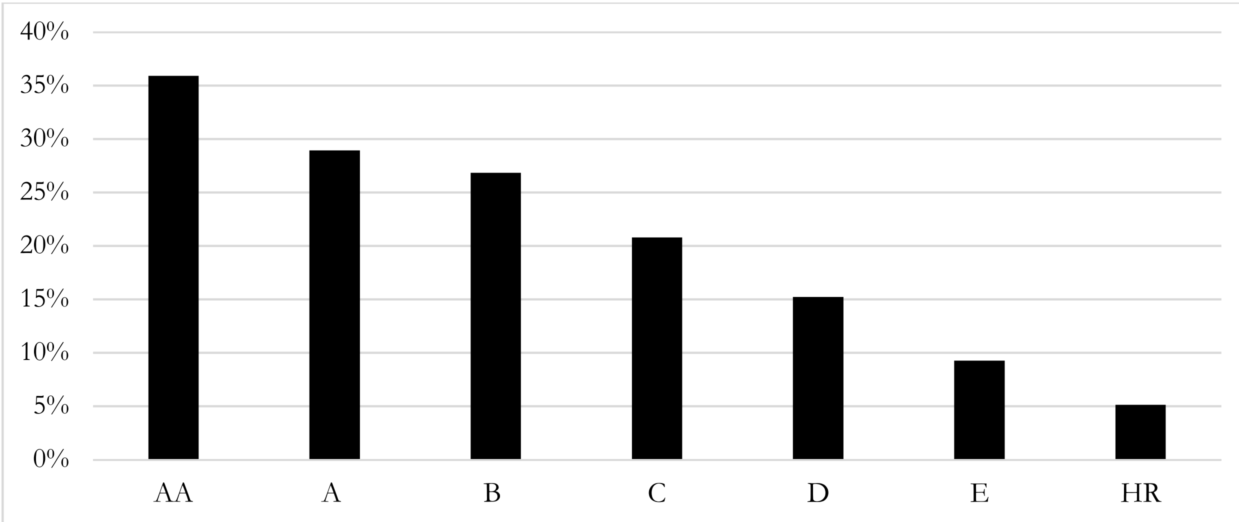

Figure 4. Distributions of In-Group Bidders by Bid Timing—Paid versus Defaulted HR Loans

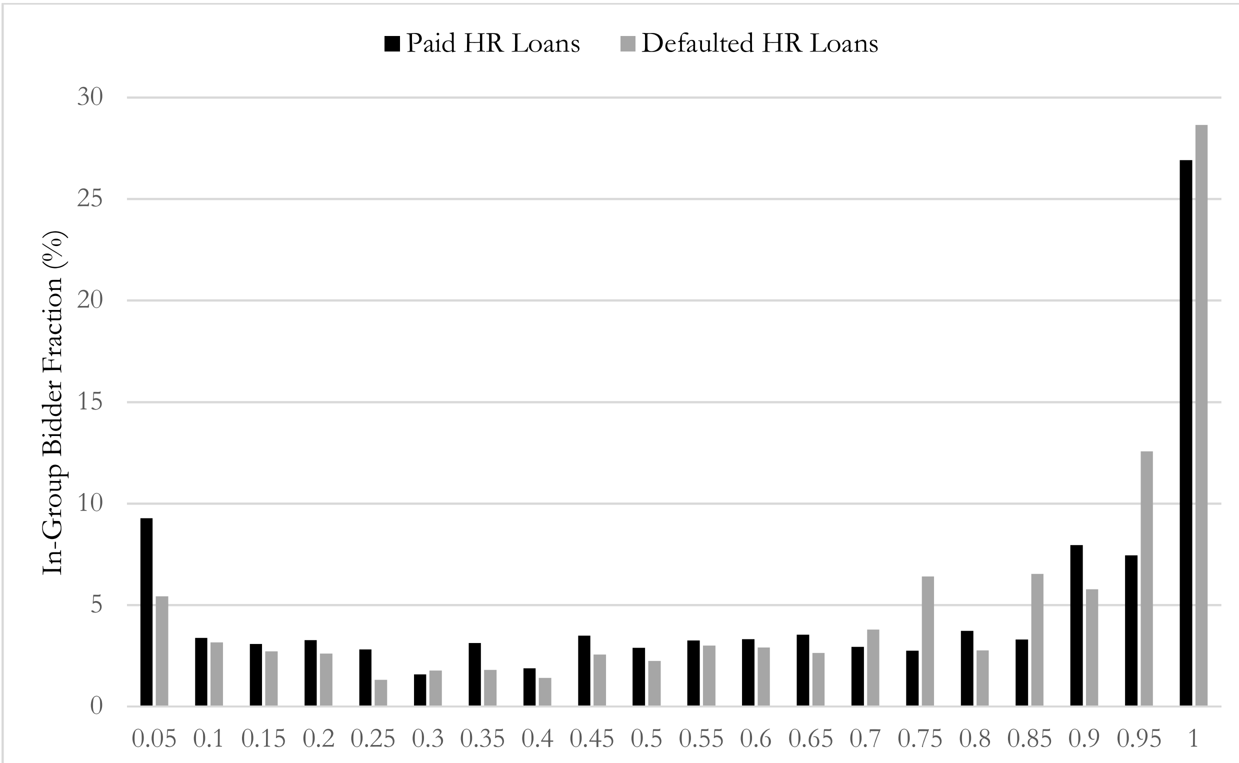

Table 1. Summary Statistics

This table reports the summary statistics of the sample used in our empirical analysis. The variable definitions can be found in Table A1 in the appendix.

	Min	Median	Max	Mean	s.d.	N
Panel A: All loan requests						
Total number of investors	1	3	399	32.8559	71.9489	107,778
Average bid amount	50	62.6597	469.2483	79.6710	56.4418	107,778
Amount requested (in $1,000)	1	5	25	7.6415	6.4743	107,778
Borrower maximum rate	0.0831	0.2100	0.3500	0.2182	0.0870	107,778
Homeowner status	0	0	1	0.3925	0.4883	107,778
Fulltime job status	0	1	1	0.6979	0.4592	107,778
1(Group loan)	0	0	1	0.2768	0.4474	107,778
1(Listing funded)	0	0	1	0.1970	0.3978	107,778
Frac_investors_early5%	0	0	1	0.0981	0.2074	107,778
Panel B: All loans						
Total number of investors	4	106	565	141.1181	119.3784	21,211
Average bid amount	56.62469	83.6300	568.8006	96.6292	63.3213	21,211
Amount requested (in $1,000)	1	5	25	6.5504	5.7035	21,211
Borrower maximum rate	0.0831	0.1950	0.3500	0.2061	0.0766	21,211
Contract interest rate	0.0612	0.1542	0.3500	0.1669	0.0674	21,211
Normalized Contract Rate	0.4329	0.8333	1	0.8184	0.1398	21,211
1("Good" loan)	0	1	1	0.6761	0.4680	21,211
Homeowner status	0	0	1	0.4568	0.4981	21,211
Fulltime job status	0	1	1	0.6929	0.4613	21,211
1(Group loan)	0	0	1	0.3732	0.4837	21,211
Frac_investors_early5%	0	0.0588	0.9528	0.1335	0.1907	21,211
Panel C: Group loans only						
Total number of investors	3	98	517	130.3532	109.9574	7,917
Average bid amount	59.7265	91.6931	603.2272	106.4659	69.3796	7,917
Amount requested (in $1,000)	1	5	25	6.5595	5.6875	7,917
Borrower maximum rate	0.0831	0.2000	0.3500	0.2087	0.0704	7,917
Contract interest rate	0.0679	0.1694	0.3495	0.1744	0.0629	7,917
Normalized Contract Rate	0.4673	0.8582	1	0.8428	0.1309	7,917
1("Good" loan)	0	1	1	0.6316	0.4824	7,917
Homeowner status	0	0	1	0.4055	0.4910	7,917
Fulltime job status	0	1	1	0.5385	0.4986	7,917
Frac_investors_early5%	0	0.0525	0.7816	0.1049	0.1413	7,917
Proportion_in-group_investors	0	0	1	0.0285	0.0926	7,191
Proportion_out-group_investors	0	0.0029	0.1944	0.0049	0.0078	7,917

Table 2. Summary Statistics by Credit Grade

Credit grades	Total number of investors	Average bid amount	Amount requested (in $1,000)	1("Good" loan)	Borrower maximum rate	Homeowner status	Fulltime job status	Frac_investors _early5%	N
Panel A: All funded personal loans									
AA	198.3634	92.4123	9.0369	0.8577	0.1236	0.7470	0.6812	0.2114	3,134
A	202.8695	91.3590	9.3319	0.7681	0.1542	0.5493	0.7115	0.1472	2,842
B	185.4251	85.7971	8.2717	0.6921	0.1893	0.5247	0.7098	0.1343	3,667
C	129.5328	86.1823	6.0261	0.6652	0.2152	0.4797	0.7434	0.1450	4,259
D	103.7604	93.3646	4.8169	0.6355	0.2468	0.2818	0.7193	0.1190	3,602
E	62.6773	126.7843	3.1885	0.5481	0.2851	0.2561	0.6159	0.0604	1,859
HR	41.9605	161.0451	2.4413	0.4275	0.2794	0.1786	0.5601	0.0480	1,848
All loans	141.1181	96.6292	6.5504	0.6761	0.2061	0.4568	0.6929	0.1335	21,211
Panel B: All funded group loans									
AA	171.2972	112.8341	8.8462	0.8866	0.1187	0.7078	0.5050	0.2039	794
A	194.242	100.3408	9.8353	0.7789	0.1466	0.5221	0.5356	0.1288	814
B	186.9745	98.0364	9.2038	0.6962	0.1771	0.5055	0.5493	0.1128	1,096
C	150.6358	95.3906	7.3736	0.6417	0.2033	0.4881	0.5940	0.1049	1,510
D	119.8844	101.4120	5.8702	0.6265	0.2339	0.2912	0.6061	0.0931	1,470
E	73.2362	112.7654	3.6941	0.5219	0.2682	0.2604	0.4859	0.0693	1,029
HR	45.9801	139.7197	2.6292	0.3920	0.2648	0.1960	0.4452	0.0591	1,204
All group loans	130.3532	106.4659	6.5595	0.6316	0.2087	0.4055	0.5385	0.1049	7,917

Table 3. Early Bidding and Success Probability of Loan Requests

This table reports the logit regressions of the listing success dummy on the proportion of early bidders and other loan characteristics. All variables except for dummy/categorical variables are winsorized at 1% and 99% levels. We exclude projects that were withdrawn or cancelled. The main independent variable, *Frac_investors_early5%*, measures the fraction of investors who bid in the first 5% of a listing's duration (= number of investors in early 5% / total number of investors who bid in the listing). Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are in parentheses.

	(1)	(2)	(3)
	1(Listing funded)	1(Listing funded)	1(Listing funded)
Frac_investors_early5%	0.8940***	0.7400***	0.7070***
	(0.0325)	(0.0413)	(0.0421)
Borrower maximum rate		4.0000***	3.5050***
		(0.120)	(0.1310)
Amount requested (in $1,000)		-0.1320***	-0.1350***
		(0.0017)	(0.0018)
Homeowner status			-0.1290***
			(0.0190)
Fulltime job status			-0.0215
			(0.0194)
1(Credit grade A)		-0.5910***	-0.5980***
		(0.0398)	(0.0406)
1(Credit grade B)		-1.0470***	-1.0590***
		(0.0378)	(0.0387)
1(Credit grade C)		-1.9350***	-1.9610***
		(0.0380)	(0.0390)
1(Credit grade D)		-2.7450***	-2.8060***
		(0.0404)	(0.0421)
1(Credit grade E)		-3.6300***	-3.7420***
		(0.0452)	(0.0471)
1(Credit grade HR)		-4.4060***	-4.5250***
		(0.0449)	(0.0473)
Constant	-1.5030***	1.0430***	1.3950**
	(0.0086)	(0.0386)	(0.6000)
Borrower State FEs	No	No	Yes
Observations	107,778	107,778	107,778
Pseudo R-squared	0.0066	0.1992	0.2124

Table 4. Early Bidding and Interest Rates

This table reports the coefficients from regressions of a normalized interest rate on the proportion of early bidders and other loan characteristics for funded loans only. All variables except for dummy/categorical variables are winsorized at 1% and 99% levels. We exclude projects that were withdrawn or cancelled. The normalized contract interest rate is the contract interest rate divided by the borrower's preset maximum acceptable interest rate. The main independent variable, *Frac_investors_early5%*, measures the fraction of investors who bid in the first 5% of a listing's duration (= number of investors in early 5% / total number of investors who bid in the listing). Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are in parentheses.

	(1) Normalized Contract Interest Rate	(2) Normalized Contract Interest Rate	(3) Normalized Contract Interest Rate
Frac_investors_early5%	-0.1140***	-0.0816***	-0.0800***
	(0.0050)	(0.0051)	(0.0051)
Amount requested (in $1,000)		0.0007***	0.0011***
		(0.0002)	(0.0002)
Homeowner status			-0.0057***
			(0.0020)
Fulltime job status			-0.0289***
			(0.0021)
1(Credit grade A)		0.0084**	0.0077**
		(0.0035)	(0.0035)
1(Credit grade B)		0.0084**	0.0096***
		(0.0033)	(0.0033)
1(Credit grade C)		0.0039	0.0074**
		(0.0033)	(0.0033)
1(Credit grade D)		0.0225***	0.0268***
		(0.0035)	(0.0036)
1(Credit grade E)		0.0677***	0.0716***
		(0.0042)	(0.0043)
1(Credit grade HR)		0.0922***	0.0928***
		(0.0043)	(0.0044)
Constant	0.8340***	0.8030***	0.7950***
	(0.0012)	(0.0032)	(0.0671)
Borrower state FEs	No	No	Yes
Observations	21,211	21,211	21,211
R-squared	0.0240	0.0600	0.0840

Table 5. Investors' Strategic Early Bidding

This table reports the coefficients from regressions of the fraction of investors in the first 5% of lending duration on default status, indicator for credit grade HR, default status, interaction terms among the three variables, and other loan characteristics. The dependent variable in model (1) is *Frac_investors_early5%* (see Table 3 for definition). Model (2) calculates a similar quantity for in-group investors and out-group investors separately. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are in parentheses.

	Frac_investors_ early5% (all projects) (1)	Frac_investors_ early5% (in- and out-group) (2)	Frac_investors_ early5% (in- and out-group) (3)
1("Good" loan) × 1(Credit Grade HR) × 1(In-group)		0.0439***	0.0455***
		(0.0117)	(0.0159)
1("Good" loan) × 1(Credit Grade HR)		-0.0203**	-0.0212*
		(0.0097)	(0.0110)
1("Good" loan)	0.0053*	0.0097***	0.0232***
	(0.0028)	(0.0034)	(0.0046)
1(In-group)		-0.0502***	-0.0338***
		(0.0028)	(0.0053)
1("Good" loan) × 1(In-group)			-0.0284***
			(0.0064)
1(Credit Grade HR) × 1(In-group)			0.0105
			(0.0105)
Borrower maximum rate	-0.4980***	-0.1690***	-0.1700***
	(0.0238)	(0.0312)	(0.0312)
Amount requested	-0.0048***	-0.0018***	-0.0018***
	(0.0238)	(0.0003)	(0.0003)
Homeowner status	-0.0142***	-0.0109***	-0.0108***
	(0.0028)	(0.0031)	(0.0031)
Fulltime job status	0.0177***	0.0052*	0.0053*
	(0.0028)	(0.0029)	(0.0029)
1(Credit grade A)	-0.0496***	-0.0483***	-0.0483***
	(0.0048)	(0.0062)	(0.0062)
1(Credit grade B)	-0.0511***	-0.0510***	-0.0509***
	(0.0047)	(0.0061)	(0.0061)
1(Credit grade C)	-0.0403***	-0.0632***	-0.0631***
	(0.0050)	(0.0061)	(0.0061)
1(Credit grade D)	-0.0592***	-0.0670***	-0.0670***
	(0.0057)	(0.0068)	(0.0068)
1(Credit grade E)	-0.1020***	-0.0804***	-0.0803***
	(0.0070)	(0.0079)	(0.0079)
1(Credit grade HR)	-0.1180***	-0.0858***	-0.0907***
	(0.0072)	(0.0089)	(0.0102)
Constant	0.2870***	0.1870***	0.1800***
	(0.0902)	(0.0645)	(0.0645)
Borrower State FEs	Yes	Yes	Yes
Observations	21,211	15,108	15,108
R-squared	0.1110	0.0720	0.0740

Table 6. Are In-Group Investors Better Informed?

Panel A reports the coefficients from regressions of normalized investor proportions on the indicator of a loan being paid off and other loan characteristics. The dependent variable, *Proportion_in-group_investors*, measures the proportion of in-group investors who participated in the current loan (= number of in-group investors in a loan / total number of in-group investors by the end of the current loan). The other dependent variable, *Proportion_out-group_investors*, calculates a similar proportion for out-group investors. The main independent variable, 1("Good" loan), is 1 if the loan is fully paid off and 0 if it defaults. Panel B compares the coefficients of 1("Good" loan) in the two regressions in Panel A. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are in parentheses.

Panel A: Regression Coefficients

	Proportion_in-group_investors	Proportion_out-group_investors
	(1)	(2)
1("Good" loan)	0.0077***	0.0006***
	(0.0019)	(0.0001)
Borrower maximum rate	-0.0504***	-0.0078***
	(0.0192)	(0.0011)
Amount requested	0.0016***	0.0004***
	(0.0002)	(0.0000)
Homeowner status	-0.0040**	-0.0007***
	(0.0019)	(0.0001)
Fulltime job status	0.0058***	-0.0042***
	(0.0018)	(0.0001)
1(Credit grade A)	-0.0023	-0.0000
	(0.0038)	(0.0002)
1(Credit grade B)	-0.0042	-0.0001
	(0.0037)	(0.0002)
1(Credit grade C)	-0.0026	-0.0003
	(0.0038)	(0.0002)
1(Credit grade D)	0.0035	-0.0006***
	(0.0042)	(0.0002)
1(Credit grade E)	0.0096**	-0.0011***
	(0.0049)	(0.0003)
1(Credit grade HR)	0.0142***	-0.0020***
	(0.0049)	(0.0003)
Constant	-0.0064	0.0049**
	(0.0418)	(0.0022)
Borrower state FEs	Yes	Yes
Observations	7,191	7,917
R-squared	0.0760	0.4000

Panel B: Comparing the Coefficients of 1("Good" loan) in the Regressions in Panel A

	p25	p50	p75
Proportion_in-group_investors	0.2390	0.3100	0.4230
Proportion_out-group_investors	0.0740	0.1130	0.2000

Table 7. Alternative Explanation: Do Investors Bid out of Altruistic Reasons?

This table reports the coefficients from regressions of the fraction of in-group/out-group investors in the last 5% funding duration on the indicator of a loan being paid off, an indicator of a loan not having received full funding by 95% time, the interaction term of the two indicators, and other loan characteristics. The dependent variable, *Frac_in-group_investors_Last5%*, measures the fraction of in-group investors who participated in the current loan in the final 5% of lending duration (= the number of in-group investors in the last 5% of lending duration in a loan / the total number of in-group investors by the end of the auction process). The other dependent variable, *Frac_out-group_investors_Last5%*, calculates a similar fraction for out-group investors. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are in parentheses.

	Frac_in-group_investors_Last5%	Frac_out-group_investors_Last5%
	(1)	(2)
1(“Good” loan)	-0.0007	0.0000
× 1(Unfunded by 95)	(0.0009)	(0.0000)
1(Unfunded by 95)	-0.0004	0.0000
	(0.0007)	(0.0000)
1(“Good” loan)	0.0009**	0.0001***
	(0.0004)	(0.0000)
Borrower maximum rate	0.0006	-0.0011***
	(0.0040)	(0.0003)
Amount requested	0.0004***	0.0001***
	(0.0000)	(0.0000)
Homeowner status	-0.0007*	-0.0000**
	(0.0004)	(0.0000)
Fulltime job status	0.0014***	-0.0007***
	(0.0004)	(0.0000)
1(Credit grade A)	0.0009	0.0002***
	(0.00079)	(0.0000)
1(Credit grade B)	0.0012	0.0004***
	(0.0008)	(0.0000)
1(Credit grade C)	0.0020***	0.0004***
	(0.0008)	(0.0000)
1(Credit grade D)	0.0031***	0.0004***
	(0.0009)	(0.0000)
1(Credit grade E)	0.0033***	0.0004***
	(0.0010)	(0.0000)
1(Credit grade HR)	0.0044***	0.0003***
	(0.0010)	(0.0000)
Constant	-0.0053	0.0003
	(0.0086)	(0.0005)
Borrower state FEs	Yes	Yes
Observations	7,191	7,917
R-squared	0.0350	0.3410

Table 8. Robustness: The First 1% Funding Duration

This table reports coefficients from regressions that are similar to those in Table 5 with dependent variables the fraction of investors who bid in the first 1% of listing duration. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are in parentheses.

	Frac_investors_ Early1% (all projects) (1)	Frac_investors_ Early1% (in- and out-group) (2)	Frac_investors_ Early1% (in- and out-group) (3)
1(“Good” loan) × 1(Credit Grade HR) × 1(In-group)		0.0232**	0.0455***
		(0.0091)	(0.0159)
1(“Good” loan) × 1(Credit Grade HR)		-0.0127*	-0.0212*
		(0.0076)	(0.0110)
1(“Good” loan)	0.0031	0.0054**	0.0232***
	(0.0025)	(0.0026)	(0.0046)
1(In-group)		-0.0443***	-0.0338***
		(0.0022)	(0.0053)
1(“Good” loan) × 1(In-group)			-0.0284***
			(0.0064)
1(Credit Grade HR) × 1(In-group)			0.0105
			(0.0105)
Borrower maximum rate	-0.4010***	-0.1450***	-0.1700***
	(0.0207)	(0.0243)	(0.0312)
Amount requested	-0.0043***	-0.0017***	-0.0018***
	(0.0002)	(0.0002)	(0.0003)
Homeowner status	-0.0115***	-0.0065***	-0.0108***
	(0.0024)	(0.0024)	(0.0031)
Fulltime job status	0.0203***	0.0064***	0.0053*
	(0.0024)	(0.0022)	(0.0029)
1(Credit grade A)	-0.0427***	-0.0347***	-0.0483***
	(0.0042)	(0.0048)	(0.0062)
1(Credit grade B)	-0.0427***	-0.0316***	-0.0509***
	(0.0041)	(0.0047)	(0.0061)
1(Credit grade C)	-0.0316***	-0.0377***	-0.0631***
	(0.0043)	(0.0047)	(0.0061)
1(Credit grade D)	-0.0486***	-0.0438***	-0.0670***
	(0.0049)	(0.0053)	(0.0068)
1(Credit grade E)	-0.0842***	-0.0504***	-0.0803***
	(0.0061)	(0.0061)	(0.0079)
1(Credit grade HR)	-0.0968***	-0.0565***	-0.0907***
	(0.0062)	(0.0069)	(0.0102)
Constant	0.2460***	0.1540***	0.1800***
	(0.0785)	(0.0503)	(0.0645)
Borrower State FEs	Yes	Yes	Yes
Observations	21,211	15,108	15,108
R-squared	0.1010	0.0680	0.0740

Table 9. Robustness: The First 10% Funding Duration

This table reports coefficients from regressions that are similar to those in Table 7 with dependent variables the fraction of investors who bid in the first 10% of listing duration. Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are in parentheses.

	Frac_investors_ Early10% (all projects) (1)	Frac_investors_ Early10% (in- and out-group) (2)	Frac_investors_ Early10% (in- and out-group) (3)
1("Good" loan) × 1(Credit Grade HR) × 1(In-group)		0.0548***	0.0587***
		(0.0134)	(0.0182)
1("Good" loan) × 1(Credit Grade HR)		-0.0223**	-0.0242*
		(0.0112)	(0.0126)
1("Good" loan)	0.0072**	0.0115***	0.0292***
	(0.0030)	(0.0039)	(0.0052)
1(In-group)		-0.0559***	-0.0344***
		(0.0032)	(0.0060)
1("Good" loan) × 1(In-group)			-0.0372***
			(0.0073)
1(Credit Grade HR) × 1(In-group)			0.0119
			(0.0120)
Borrower maximum rate	-0.5590***	-0.1900***	-0.1910***
	(0.0255)	(0.0356)	(0.0356)
Amount requested	-0.0052***	-0.0015***	-0.0015***
	(0.0003)	(0.0003)	(0.0003)
Homeowner status	-0.0160***	-0.0123***	-0.0122***
	(0.0029)	(0.0035)	(0.0035)
Fulltime job status	0.0155***	0.0043	0.0044
	(0.0030)	(0.0033)	(0.0033)
1(Credit grade A)	-0.0529***	-0.0541***	-0.0541***
	(0.0051)	(0.0071)	(0.0071)
1(Credit grade B)	-0.0571***	-0.0608***	-0.0607***
	(0.0051)	(0.0069)	(0.0069)
1(Credit grade C)	-0.0459***	-0.0716***	-0.0716***
	(0.0053)	(0.0070)	(0.0070)
1(Credit grade D)	-0.0670***	-0.0777***	-0.0777***
	(0.0061)	(0.0077)	(0.0077)
1(Credit grade E)	-0.1140***	-0.0938***	-0.0936***
	(0.0076)	(0.0090)	(0.0090)
1(Credit grade HR)	-0.1340***	-0.1040***	-0.1090***
	(0.0077)	(0.0102)	(0.0117)
Constant	0.3280***	0.2130***	0.2050***
	(0.0967)	(0.0737)	(0.0737)
Borrower State FEs	Yes	Yes	Yes
Observations	21,211	15,108	15,108
R-squared	0.1190	0.0710	0.0730

Table 10. Robustness: Credit Grades E and HR

This table reports coefficients from regressions similar to those in Table 7, in which we include credit grades E and HR to indicate a loan being "risky." Statistical significance at the 10%, 5%, and 1% levels are denoted by *, **, and ***, respectively. Standard errors are in parentheses.

	Frac_investors_ early5% (all projects) (1)	Frac_investors_ early5% (in- and out-group) (2)	Frac_investors_ early5% (in- and out-group) (3)
1("Good" loan) × 1(Credit Grade E or HR) × 1(In-group)		0.0302***	0.0270**
		(0.0083)	(0.0127)
1("Good" loan) × 1(Credit Grade E or HR)		-0.0173**	-0.0160*
		(0.0075)	(0.0088)
1("Good" loan)	0.0053*	0.0111***	0.0241***
	(0.0028)	(0.0038)	(0.0051)
1(In-group)		-0.0514***	-0.0386***
		(0.0029)	(0.0059)
1("Good" loan) × 1(In-group)			-0.0274***
			(0.0071)
1(Credit Grade E or HR) × 1(In-group)			0.0178*
			(0.0092)
Borrower maximum rate	-0.4980***	-0.1690***	-0.1700***
	(0.0238)	(0.0312)	(0.0312)
Amount requested	-0.0048***	-0.0017***	-0.0018***
	(0.0238)	(0.0002)	(0.0002)
Homeowner status	-0.0142***	-0.0107***	-0.0106***
	(0.0028)	(0.0031)	(0.0030)
Fulltime job status	0.0177***	0.0052*	0.0053*
	(0.0028)	(0.0029)	(0.0029)
1(Credit grade A)	-0.0496***	-0.0481***	-0.0481***
	(0.0048)	(0.0062)	(0.0062)
1(Credit grade B)	-0.0511***	-0.0507***	-0.0506***
	(0.0047)	(0.0060)	(0.0060)
1(Credit grade C)	-0.0403***	-0.0628***	-0.0627***
	(0.0050)	(0.0061)	(0.0061)
1(Credit grade D)	-0.0592***	-0.0665***	-0.0665***
	(0.0057)	(0.0068)	(0.0068)
1(Credit grade E)	-0.1020***		
	(0.0070)		
1(Credit grade HR)	-0.1180***		
	(0.0072)		
1(Credit grade E or HR)		-0.0810***	
		(0.0085)	
Constant	0.2870***	0.1850***	0.1810***
	(0.0902)	(0.0646)	(0.0645)
Borrower State FEs	Yes	Yes	Yes
Observations	21,211	15,108	15,108
R-squared	0.1110	0.0720	0.0740

Table 11. Robustness: Credit Grades D, E, and HR

This table reports coefficients from regressions similar to those in Table 7, in which we include credit grades D, E, and HR to indicate a loan being "risky." Statistical significance at the 10%, 5%. and 1% levels are denoted by *, **, and ***, respectively. Standard errors are in parentheses.

	Frac_investors_ early5% (all projects) (1)	Frac_investors_ early5% (in- and out-group) (2)	Frac_investors_ early5% (in- and out-group) (3)
1("Good" loan) × 1(Credit Grade D, E or HR) × 1(In-group)		0.0206***	0.0273**
		(0.0064)	(0.0117)
1("Good" loan) × 1(Credit Grade D, E or HR)		-0.0060	-0.0092
		(0.0068)	(0.0082)
1("Good" loan)	0.0053*	0.0093**	0.0252***
	(0.0028)	(0.0046)	(0.0061)
1(In-group)		-0.0525***	-0.0393***
		(0.0031)	(0.0072)
1("Good" loan) × 1(In-group)			-0.0333***
			(0.0085)
1(Credit Grade D, E or HR) × 1(In-group)			0.0134
			(0.0093)
Borrower maximum rate	-0.4980***	-0.1980***	-0.1990***
	(0.0238)	(0.0302)	(0.0302)
Amount requested	-0.0048***	-0.0016***	-0.0016***
	(0.0238)	(0.0002)	(0.0002)
Homeowner status	-0.0142***	-0.0106***	-0.0105***
	(0.0028)	(0.0031)	(0.0039)
Fulltime job status	0.0177***	0.0064**	0.0064**
	(0.0028)	(0.0028)	(0.0028)
1(Credit grade A)	-0.0496***	-0.0477***	-0.0477***
	(0.0048)	(0.0062)	(0.0062)
1(Credit grade B)	-0.0511***	-0.0496***	-0.0495***
	(0.0047)	(0.0060)	(0.0060)
1(Credit grade C)	-0.0403***	-0.0606***	-0.0606***
	(0.0050)	(0.0061)	(0.0061)
1(Credit grade D)	-0.0592***		
	(0.0057)		
1(Credit grade E)	-0.1020***		
	(0.0070)		
1(Credit grade HR)	-0.1180***		
	(0.0072)		
1(Credit grade D, E or HR)		-0.0738***	-0.0801***
		(0.0081)	(0.0093)
Constant	0.2870***	0.1920***	0.1880***
	(0.0902)	(0.0647)	(0.0646)
Borrower State FEs	Yes	Yes	Yes
Observations	21,211	15,108	15,108
R-squared	0.1110	0.0710	0.0740

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Online Appendix

Table A1. Definition of Variables

Variable	Definition
Total number of investors	The total number of investors for each project/ loan.
Average bid amount	The average bid amount by investors for each project/loan.
Borrower maximum rate	The maximum interest rate a borrower presets at the beginning of an auction representing the maximum acceptable interest rate.
Amount requested (in $1,000)	The amount that a borrower requests to borrow in the project.
Credit grades	Credit Grade of the borrower at the time the project was created. A categorical variable that takes the value of one of seven letter grades.
Homeowner status	A dummy variable equals one if the borrower is a verified homeowner at the time the project is created and zero otherwise.
Fulltime job status	A dummy variable equals one if the borrower is a verified full-time worker at the time the project is created and zero otherwise.
1("Good" loan)	A dummy variable equals one if a loan is paid and zero otherwise.
1(In-group)	A dummy variable equals one if an observation corresponds to in-group investors, e.g., the fraction of in-group investors in the first 5% of lending duration
1(Project funded)	A dummy variable equals one if the project runs to completion and funded and zero otherwise.
1(Unfunded by 95)	A dummy variable equals one if a project has not been fully funded at the 95% of funding duration.
Normalized Contract Interest Rate	Calculated as the contract interest rate (Borrower Rate) divided by the borrower maximum rate.
Proportion_in-group_investors	Calculated as the total number of in-group investors that bid in the project divided by the total number of in-group investors available by the end of the project.
Proportion_out-group_investors	Calculated as the total number of out-group investors that bid in the project divided by the total number of out-group investors available by the end of the project.
Proportion_in-group_investors_Last5%	Calculated as the number of in-group investors in the final 5% of lending duration in a project over the total number of in-group investors by the end of the auction process.
Proportion_out-group_investors_Last5%	Calculated as the number of out-group investors in the final 5% of lending duration in a project over the total number of out-group investors by the end of the auction process.
Frac_investors_early1%	Calculated as the number of investors who bid during the first 1% of a project's duration over the total number of investors for the project.
Frac_investors_early5%	Calculated as the number of investors who bid during the first 5% of a project's duration over the total number of investors for the project.
Frac_investors_early10%	Calculated as the number of investors who bid during the first 10% of a project's duration over the total number of investors for the project.