# The Geography of Bidder Behavior in Peer-to-Peer Lending Markets*

Garrett T. Senney

*The Ohio State University, Department of Economics*

Original Draft: November 10, 2014
Current Draft: November 3, 2015

**Abstract.** *Theory predicts that investors and borrowers will tend to locate relatively close to each other due to the cost of information gathering and monitoring. However, new online platforms could overcome the traditional geographical constraints on investing. Recent empirical work, across many types of crowdfunding, has found mixed results. In this paper, using transaction data from a peer-to-peer lending site, I find that local bidders tend to bid earlier, both chronologically and relatively to other bidders in the auction, and bid larger amounts than nonlocal bidders. Additionally, local bidders are more informed in the sense that they are better able to evaluate the underlying risk of borrowers. This is demonstrated by the fact that local bidders bid significantly higher interest rates on loans that ex-post default and lower rates on loans that ex-post pay back in full. Lastly, I develop a simple model of social learning with heterogeneous agents that provides testable predictions. My results are consistent with this model; a listing with more early local bidding activity will attract more bidders, leading to a higher probability of funding and a lower final interest rate, if funded. This work suggests that the behavioral differences between local and nonlocal bidders are driven mostly by informational frictions and not merely preferences. Local bidders are better informed because they have easier and cheaper access to information, and this asymmetry contributes to explaining why geographic-based frictions are still present and relevant in online lending markets.*

**Keywords:** Geography, Peer-to-Peer Lending, Informational Frictions.

**JEL Classification:** D82, D83, L10, L86.

## 1. Introduction

It is an established fact that most of the inefficiencies in the credit market are due to the existence of asymmetric information between lenders and borrowers (Stiglitz and Weiss, 1981; Dell'Ariccia and Marquez, 2004). However, the modern financial ecosystem is

*Special thanks to Jason Blevins, Maryam Saeedi, and Stephen Cosslett for their assistance and guidance, Xiang Hui and Robert Munk for their comments and encouragements, and Efraim Berkovich for providing the data.

evolving rapidly, as innovations and technological advancements are radically altering the delivery of financial services worldwide. Increasingly, through use of the internet, people have been able to interact with each other more intensively (sharing more information) and extensively (cheaper to develop larger networks). Utilizing these new online connections and crowdfunding websites, individuals are starting to find new ways to address and overcome the asymmetry in the credit market. In this paper, I explore the information problem that has traditionally plagued the credit market and evaluate the effectiveness of online peer-to-peer lending to address it. Peer-to-peer (henceforth P2P) lending is a mechanism for individuals to lend directly to other individuals without using a bank as an intermediary. This arrangement creates the possibility that borrowers can obtain loans at lower interest rates than they would get on a credit card or a normal loan without collateral. Individual lenders get the opportunity to invest in short-duration assets with higher rates of return than would be available on certificates of deposit, bonds, or money market accounts, all due to the cost savings arising from removing the intermediary.

P2P lending has been heralded as an online tool that has the potential to level the playing field in the credit market by providing access to financing to more people in a more approachable way. A potential blend of altruism and the allure of higher yields has attracted investors to lending money online, especially in the aftermath of the 2008 financial crisis, where interest rates and banks' willingness to lend have hit historic lows. Additionally, a survey performed by Zopa.com (a British P2P site) reports that, although most P2P loans are unsecured, borrowers feel a greater responsibility to repay a loan that has been created by individual people instead of a loan from a bank (Cortese, 2014). Compared to traditional banks, online lenders enjoy the advantage that online marketplaces currently face fewer regulatory constraints, albeit the Security Exchange Commission and the Treasury Department are deeply interested their activities. Moreover, P2P sites are structured to facilitate faster transfers of capital to the borrowers, and are operated by internet-based companies, which have lower overhead costs than companies with physical locations. Therefore, these companies operate more profitably in a market traditionally viewed as fairly risky with low margins (Cowley, 2015). P2P lending, along with other forms of crowdfunding, has established itself as an emerging alternative source of financing for startups and people with particularly limited access to traditional means of financing.[1]

Using data from an American P2P lending site, I examine whether the internet has improved the efficiency of the credit market by loosening the geographic constraints on investing. Evidence for this potential reduction in the informational difference between local and nonlocal lenders should be observable in their bidding behavior. If the two types

[1] Belleflamme, Lambert, and Schwienbacher (2010); Schwienbacher and Larralde (2010); Mollick (2014).

of lenders bid the same way when faced with similar investing options, the internet will have removed the geographic frictions. However, if local and nonlocal lenders behave differently, this might be explained –as pointed out in the empirical literature –by one of two possible channels: asymmetric information or preference. My analysis shows that lenders indeed behave differently based on geography and, while a local preference exists, informational differences seem to be a major driver for this behavior.

Most of the scholarly work on P2P lending has focused on the determinants of a listing being funded and the determinants of the final interest rates. The consensus is that soft factors like demographic and network effects matter; however, they are second order in importance,[2] after hard factors, like the verified financial information of income, debt, and credit score.[3] Because P2P lending is still in its infancy, its full potential as an alternative or supplement to the traditional banking industry is still an open empirical question.

Extensive theoretical work on early investing and capital ventures predicts initial investors will tend to be located relatively close to the borrowers they invest in.[4] This result is because the cost of gathering and processing information, as well as monitoring, are generally thought to increase as the distance between lender and borrower grows. Most of the empirical evidence supports these findings.[5] Explicitly, recent research on angel investing and large-scale acquisition reports that most investors are located within a half day of travel of the entrepreneur that they funding.[6] The predicted informational asymmetry between potential local and nonlocal investors may derive from the informational opacity of startups and small firms. Potential investors collect a sizeable amount of information before deciding to invest and at what rate. The geographic proximity of local bidders facilitates cheaper and easier access to this information. Anderson and van Wincoop (2004) find that informational frictions associated with geography, including search costs, communication barriers, and contracting costs, contribute to reducing transactional efficiency when parties are physically separated from each other.

In addition to more standard channels of financing, small to medium-sized firms also rely on relationship-based lending to obtain funds. Relationship lending is when a financial institution uses a sustained relationship across multiple interactions with the potential borrower in addition to normal financial information they regularly gather in order to process a loan request. Many studies of relationship lending find that the physical distance

[2] Herzenstein, Andrews, Dholakia, and Lyandres (2008); Berger and Gleisner (2009); Pope and Sydnor (2011); Ravina (2012); Duarte, Siegel, and Young (2012); Lin, Prabhala, and Viswanathan (2013).

[3] Klafft (2008b,a); Iyer, Khwaja, Luttmer, and Shue (2009); Weiss, Pelger, and Horsch (2010).

[4] Arthur (1986, 1988, 1990); David and Rosenbloom (1990); Krugman (1991a,b).

[5] Tribus (1970); Florida and Kennedy (1988); Florida and Smith (1988); Martin, Sunley, and Turner (2002); Mason and Harrison (2002); Powell, Koput, Bowie, and Smith-Doerr (2002); Zook (2002); Mason (2007).

[6] Sohl (1999); Sorenson and Stuart (2001); Wong, Bhatia, and Freeman (2009).

between the banks and the borrowers has increased significantly, implying that banks from farther away are able to develop the needed relationship with the borrower that historically only local banks would have.[7] However, other studies find no discernable change in the distance between lenders and borrowers.[8] Elyasiani and Goldberg (2004) suggest that the observed mixed results are most likely caused by the fact that the technological developments that mitigate geographic-based frictions have only been adopted by a small share of banks engaging in relationship lending. As the adoption and use of these new tools become more widespread, it is thought that location should become a less important factor in obtaining financing.

The informal capital markets, alternative sources of financing outside of the traditional mainstream credit market, have not to date been the focus of much scholarly analysis. However, it is generally accepted, as noted by Harrison, Mason, and Robson (2010), that they comprise a series of potentially overlapping local markets rather than one fully integrated national market. With the internet and e-commerce being omnipresent, it is important to examine whether this shift in the commercial paradigm coupled with new online tools has been strong enough to alter or even invalidate the theoretical predictions of the effects that geography has on investing. Recent empirical work has shown that the internet has the potential to allow individuals and firms to overcome many traditional barriers that have fettered offline markets by mitigating some geographic frictions.[9] Other research on online transactions finds that online platforms might reduce some, but not all, of the distance-related frictions.[10]

Although technology makes it easier and cheaper for individuals to gather and process information about market conditions, it is unclear if informational frictions like search costs persist in the online marketplace. I examine the ongoing empirical question of whether the internet is improving the efficiency of the online credit market. My analysis centers on how geography affects bidder behavior in P2P lending markets by focusing on the issue of whether the new P2P lending sites can loosen the geographic constraints on investing. More explicitly, I ask relative to nonlocal bidders: (1) do local bidders bid different amounts, (2) do local bidders evaluate and price the risk of the listings differently, and (3) do local bidders tend to bid at different times during the auction. Additionally, if distance-related frictions do exist, (4) does the difference in behavior arise from informational asymmetry or simply a preference on the part of local bidders, and lastly, (5) how does the presence

[7] Cyrnak and Hannan (2000); Wolken and Rohde (2000); Petersen and Rajan (2002).

[8] Degryse and Ongena (2003); Brevoort and Hannan (2003).

[9] Ratchford, Pan, and Shankar (2003); Brynjolfsson, Hu, and Rahman (2009); Goldfarb and Tucker (2011); Lendle, Olarreaga, Schropp, and Vézina (2013).

[10] Blum and Goldfarb (2006); Hortaçsu, Martínez-Jerez, and Douglas (2009); Agrawal, Catalini, and Goldfarb (2011); Lin and Viswanathan (2014).

of local bidders in the market affect other bidders' decisions to enter and their behavior after entering.

Using bid and listing level transaction data from lending auctions on Prosper.com, I estimate that local bidders tend to bid earlier and larger amounts than nonlocal bidders. Furthermore, local bidders also seem better able to evaluate the riskiness of loan requests. They tend to ex-ante bid larger interest rates when the loan ex-post defaults and less when the loan ex-post pays back in full. Reconciling theory and previous empirical work, I conclude from my results that there exists a local preference in the demand for loans, but local bidders' interest rate bids demonstrate support for the informational-based explanation of the observed behavioral differences between bidders.

## 2. Overview of Peer-to-Peer Lending

Crowdfunding, which P2P is a part of, is a process through which an individual or firm attempts to obtain financing by soliciting for usually small contributions from a large number of online investors. These new financing platforms are the result of a social movement that arose in reaction to the emergence of new technologies that are enabling new and cheaper ways of forming social networks (Adams and Ramos, 2010). The crowdfunding market has quickly grown from its creation in the early 2000's and is predicted to reach $34.4 billion globally in 2015 (Massolution.com, 2015). The movement has bifurcated into donation and financial (debt/equity) based sites both geared towards different market segments. The first American online platform to facilitate debt transactions launched in late 2005. The two current largest domestic players, Lending Club and Prosper, control about 98% of the American P2P credit market and, combined, issued almost $5 billion in loans in 2014 (NSR Invest, 2015). In this paper I will focus on the P2P lending site Prosper.com, which has been called the eBay of loans.[11]

Prosper provides unsecured, 36-month, fixed-rate personal loans ranging from $1,000 to $25,000. Borrowers and lenders must be legal U.S. residents with a valid domestic address and bank account. The members' true identities, addresses, and other contact information are never publicly disclosed by the site. For privacy, the borrower is prohibited from releasing that information to bidders. However, the borrower's state of residence is displayed on the listing.

Borrowers create a listing requesting a loan for a specified amount and a maximum interest rate they are willing to accept (borrower's max rate). They set the duration

[11] The market description in this section refers to market conditions and mechanisms that were in place when the data was collected. Some policy and regulation changes have since occurred, making the current market slightly different.

of the listing (up to 14 days), specify the category of use (Debt Consolidation, Home Improvement, Business, etc.), write a brief description, and, optionally, include an image of themselves. Each listing displays financial information about the borrower including debt-to-income ratio, income, occupation, employment status, credit grade (40-point bands of the borrower's Experian credit score), total credit lines open, number of credit inquiries in the last six months, current delinquencies, and home ownership status. Prosper posts aggregate historical data on the default and interest rates grouped by credit grade.

After some institutional and legal restructuring in 2008, Prosper started to collaborate with a national bank, who became the legal originator for all Prosper loans. This arrangement makes it possible for the site to utilize a 1978 Supreme Court decision allowing all Prosper borrowers to avoid their individual state's usury law and face a uniform fixed legal maximum borrower rate of 36%.

Lenders (bidders) search through the listings for loan requests that they want to bid on (Figure 1). The funding mechanism is a descending uniform price auction. Lenders' bids are made up of two components: amount of bid ($50 minimum) and the lowest interest rate that they are willing to accept. The bidding process is proxy bidding, similar to that on eBay. Each bid is considered independent, so a lender may bid multiple times with potentially different interest rates. These price-quantity pairs form the supply curve of available funds for this loan request. The auction is partially open; lenders always see the number of bids and the quantity of money pledged of each bid. The interest rate submitted by the lenders is only shown for losing bids; accordingly, before the loan is fully funded, bidders only see the borrower's maximum rate.

Successfully submitted bids cannot be rescinded. Given that this platform is a collection of individualized markets for each individual loan, each market clears when the amount of pledged funds is at least as large as the requested amount, with the interest rate determined by the auction. In the case of ties, bids placed earlier take precedence over later bids. When the auction closes, the bids are sorted by bid interest rate. The bids with the lowest rates are bundled until the total loan amount has been reached and are then combined into a single loan. Each winning bidder receive the same interest rate, which is determined by the marginal losing or last winning bid, depending on the auction. Winning bids are either fully or partially participating in the loan; a partially participating bid means that the lender is allocated a smaller share of loan than his or her quantity bid. If the loan request is not fully funded by the listing's close date, the listing is closed and dismissed; no partial funding is allowed. Successful loan requests get further review by the site to initiate the needed legal documentation for the loan to be originated. A borrower who defaults on his or her Prosper loan is barred from using the site again.

## 3. Data

This paper uses publicly released data containing all loan requests, with their accompanying bids, using the open auction format posted by borrowers with FICO credit scores greater than or equal to 560 that were active from January to October 2008. Prior to late 2008, any legal resident of the United States could be a lender on the site and legal residents of every state, except South Dakota, could be borrowers. During the period in my sample, 42,657 loan requests and 2,022,910 bids were posted. A total of 9,624 listings and 1,688,531 bids were for listings that were fully funded. The publicly available characteristics of the borrowers are: debt-to-income ratio (henceforth DIR, the variable is top coded at 10.1), credit grade, homeowner status, whether the borrower is in a Prosper group, and state of residence.

Klafft (2008b) confirm that the rules that apply in the traditional banking system apply to P2P lending as well; credit grade and the DIR are the two most important hard financial variables in determining the financial outcomes. The site provides members the ability to join groups that are designed to develop and foster a community of lenders and borrowers akin to what occurs in relationship lending, contract enforcement via reputation, and peer effects. Agrawal et al. (2011) and Lin et al. (2013) find that social connections seem to reduce market frictions. Therefore, I collect data on these on-site social networks. In the loan-level analysis, the In Group variable indicates whether a borrower is in a Prosper group; and in the bid-level analysis, the In Group variable indicate whether that particular bidder is in the borrower's specific Prosper group.

In addition to the variables collected directly from Prosper, I construct two variables –Total Competition and Credit Grade Competition –to measure the competition that each listing faces. The competition measures are the number of current listings that are active for at least one full day at the same time that the particular listing is also active. Total Competition is the number of total listings, regardless of credit grade, while Credit Grade Competition is the number of listings from the same credit grade. At the bid level, I recreate the auction to determine the current standing interest rate, money pledged, and bid count that exist in the auction at the exact moment that each bidder bids on a particular listing. This process allows me to observe the current state of the listing as each bidder sees it before he or she bids.

Table 1 shows the summary statistics of the borrower's characteristics for all listings. The maximum listing request amount is $25,000, but most listings request significantly less (around $6,000–9,000). Intuitively, the mean request amount increases as the credit grade improves as more credit-worthy borrowers have the ability to support larger loans. Although borrowers can select the duration of their listing (3–14 days), around 80% of

listings are active for one week. The borrower's max rate is the reservation price for the auction and, as one would expect, it tends to increase as the credit grade worsens. However, across all credit grades, over 22% of borrowers select max rates greater than or equal to 35%. Table 2 displays that breakdown of the listings and completed loans by credit grade; over half of all of the listing requests are in the bottom credit grades. However, the simple funding rate decreases strictly monotonically as the credit grade worsens.

I also collect data on the ex-post loan outcomes, paid back or defaulted, for the listings that are actually originated. However, I do not observe when in the cycle a borrower defaulted or how much of the loan's principle was paid back, but only the discrete outcomes of default or not. The loan outcome data comes from a different Prosper data release, which contains only outcomes of the loans that were settled by early September 2011. Out of the 9,624 completed listings in my sample, I am able to match 9,099 of them to their final outcomes in 2011. The last column of Table 2 displays the simple default rate by credit grade for this sample. As one would expect, the default rate has a clear positive trend as the credit grade worsens. The top half of Table 3 presents the frequency distribution of the different categories of use by credit grade. Regardless of credit grade, the three most commonly chosen categories are debt consolidation, business, and personal. The bottom half of Table 3 displays the completion rate of loan requests by credit grade and category of use. While the Other category is the fourth most common request type, it has the highest simple completion rate across all credit grades. It is well established that business loan requests have noticeably more difficulty being fully funded on P2P lending sites than other types of crowdfunding, especially for lower credit grades (Lin and Viswanathan, 2014).[12] The sizeable share of listings that are business loan requests across all credit grade is a contributing factor in explaining the rather low completion rate for the bottom credit grades.

Table 4 presents the descriptive statistics of the bid amounts and bid interest rates, grouped by credit grade. The median bid amount, regardless of credit grade, is the minimum bid ($50). This result is in-line with previous Prosper research that most bidders tend to diversify across listings by only pledging small amounts in any one particular listing. The mean bid amount is non-monotonic across credit grades. Bidders in the better credit grades tend to be bid larger amounts, but bidding in E listings has the largest mean. However, when bid amount is viewed as a share of the loan request amount, the mean and median become significantly closer to being monotonically increasing as the credit grade worsens. This is a function of the loan request amounts generally becoming smaller as the credit grade worsens. One immediate question that might arise, given the

[12] In a recent industry survey, it was found that 22% of all funds obtained by startups from crowdfunding sites came via debt-based platforms (Massolution.com, 2013).

size of an individual bid, is why a lender would invest in this unsecured market. It has been observed that most lenders commit to invest around $50–100 across dozens of loans. Aggregated, a portfolio of an individual lender on a P2P lending site resembles a new asset class, different from the traditional ones. If diversified correctly, they can offer lenders returns that do not directly follow the motions of stocks and bonds (Lieber, 2011).

The nature of the auction mechanism does not allow me to observe the bid interest rates for winning bids. Similarly to how eBay operates, the interest rate and amount of a bid are displayed for losing bids, while only bid amount is shown for winning bids. The current standing interest rate is also shown, which is either the borrower's max rate or interest rate of the first losing bid. The final interest rate sets an upper bound on what the actually bid interest rates may be for the winning bids. Unless otherwise noted, following Bajari and Hortaçsu (2003) and the rest of the literature, I assume that winning bids equal the final interest rate. Not surprisingly, the mean and median bid interest rate increase as the credit grade worsens. Additionally, the amount of variation in bid interest appears to increase as the credit grade worsens (the correlation between credit grade and standard deviation is 0.833).

## 4. Empirical Analysis

Although existing theory states that distance between investors and borrowers is important, recent empirical work has been inconclusive on this issue. Intuitively, since the internet makes it cheaper and easier to connect and share information with more people, online platforms could reduce informational frictions and improve the efficiency of the credit market. Additionally, several features of this market make the presence of geography-related frictions less plausible: loans are unsecured, lenders have no legal recourse against borrowers who default, and lenders agree to never contact delinquent borrowers. These constraints minimize the ability of lenders to individually monitor and enforce the contract. Therefore, physical proximity should be less important online as compared to offline lending. Moreover, given this is an online market, participants have to possess at least a minimum level of computer competency. Therefore, it is highly probable that these bidders have the ability to research general local conditions like population, demographics, median household income, unemployment rate, and housing starts.

Considering the above, it has yet to be determined if there exist a meaningful difference in lender behavior based on geography. If the differences are driven strictly by information, then these P2P lending sites might be able to eliminate these geographic frictions, and the behavior of local and nonlocal bidders should be observationally equivalent. However, if there are differences between behavior based upon the location of the bidder relative to

the borrower, it might be caused by two different mechanisms. One channel, as predicted by theory, is an informational asymmetry story where distance-related frictions still matter. The other channel is a preference story: local bidders are not any better informed than nonlocal bidders, but they simply prefer local projects.

Given that I do not observe information about the market participants' offline activity or connections, one immediate concern that needs to be addressed is whether my definition of local is picking up borrowers' friends and family simply using the site as a way to formalize their loans. While friends and family would be better informed about the borrower's characteristics, it is unlikely that they be motivated by profits. If friends and families are a major part of the local bidding, it is reasonable that they will join the site around the time that borrower creates his or her listing. It is unlikely to imagine that a majority of the borrowers creating listings will have friends and family who are previously active on Prosper. Table 5 presents some descriptive statistics on the amount of previous bidding and length of time on the site of the bidders at the time of their first local bid. The median local bidder has been active on the site for over 124 days and has submitted 15 previous bids by the time that they place their first local bid. Additionally, the average bidder has been active for over 210 days and has placed about 50 bids before he submits his first local bid. Furthermore, less than 2% of bidders place their very first bid on a local project and less than 8% of local bids are placed during the first three days after the bidder joins the site. This suggests that it is highly unlikely that a major part of local bidding is coming from friends and family.

I start this analysis by documenting the fact that local bidders do behave differently than nonlocal bidders in the P2P lending market under study. The evidence I find that strongly suggests that information-based frictions are still a major contributor to the observed behavioral differences between local and nonlocal bidders. Thus, I develop a simple model of social learning to motivate these empirical observations and to assist in explaining how local bidders' actions can transmit their private information about the underlying quality of borrowers to nonlocal bidders, who are less informed. This social learning will act like a signal, making a listing with more local bidders more attractive to other bidders.

All regressions include Borrower and Bidder State (where applicable), Credit Grade, Category of use, Quarter, Month, and Day of the Week fixed effects.[13] The variable Loan Amount is measured in thousands of dollars, Borrower Max Rate and Current Rate are measured in percentage points (1=1%), and Total Competition and Credit Grade Competition are measured in a single listing.

[13] I also explicitly control for observable borrower state characteristics in place of the borrower state FE and found no noticeable difference in the results.

### *4.1. Local Bidders Bid Larger Amounts*

The left half of Table 6 displays the mean, median, and $75^{th}$ percentile of bid amounts by local status. The median bid is the minimum allowable amount of \$50. However, the average and $75^{th}$ percentile local bid amounts are around \$10 dollar larger than the nonlocal bids; these differences are significant at the 1% level. Knowing that local bidders have a larger demand for local loans suggests that bidders behave differently based on locality, but tells nothing about the channel that is driving this behavior. To examine this, I restrict my focus to listings that become loans and their outcome is known. Bids are divided into sub-samples based on the loans' ex-post outcome (default or paid back). The results are qualitatively the same as when the listings are not divided by ex-post outcome. There is no meaningful difference between the summary statistics of local bid amounts if the loan ex-post defaults or pays back; additionally, local bidders still bid more money on average than their nonlocal counterparts. This behavior suggest that there exists a local premium driven by a preference for local loans.

To formally test the question of whether local bidders bid larger amounts than nonlocal bidders, I run a Tobit regression of log bid amount with left censoring at $\log(\$50)$ while including an indicator for local bidder. Standard errors are clustered at the bidder level to control for any unobserved correlation between the bidding activity of the same bidder. Table 7 shows the results; I find that even after controlling for all the observable listing characteristics, local bidders bid roughly 7% larger amounts than nonlocal bidders. This effect is of the similar magnitude to the increase in bid amount that occurs if bidder and borrower are in the same Prosper group, and is roughly equivalent to the current standing interest rate in the auction being 5.3 percentage points higher. This result is consistent with the findings of local preference in other online markets (Hortaçsu et al., 2009; Lin and Viswanathan, 2014). It is worth noting that *Pseudo* $R^2$ is a rather low value (0.159). This is not surprising given that I only have information about bidders' behavior on the site, and not on the bidders themselves. It is well documented that demographic characteristics like age, educational attainment, marital status, gender, race, and risk tolerance all affect asset holdings.[14] More information about the heterogeneity of bidders would likely improve the fit of this regression.

### *4.2. Local Bidders Evaluate the Probability of Default Better than Nonlocal Bidders*

If local bidders are merely acting altruistically towards individuals living in their area, then local bidders should bid lower interest rates, regardless of the borrower's quality, than their nonlocal counterparts. However, if local bidders are actually more informed about

[14] Kreinin (1959); Baker and Haslem (1974); Figner and Weber (2011).

the underlying riskiness of the borrower and the general market conditions, they should be better able to evaluate the risk of the listing. For example, if there are two listings that look identical to nonlocal bidders, but one is riskier than another, local bidders should bid larger interest rates on the listing with the hidden extra riskiness. To examine this, I restrict my focus to listings that became loans and their outcomes are known. These bids are divided based on the loans' ex-post outcome. I further focus on only losing bids where I know the actual bid interest rate. Table 8 presents the mean, median, and $75^{th}$ percentile of bid interest rate for losing bids by credit grade, local status, and loan outcome. For loans that ex-post default, local bidders tend to submit ex-ante larger interest rates for all credit grades. For loans that ex-post pay back in full, the opposite result is seen, with local bidders tending to bid lower ex-ante interest rates. These two observations strongly suggest that local bidders seem to more accurately price the underlying risk of the listings than nonlocal bidders.

To formally evaluate this claim, I perform two tests on the distributions of bid interest rates by locality: (1) a $t$-test on whether the difference between the distributions' means is significantly different from zero, and (2) a two-sample Mann-Whitney $U$-test (Wilcoxon rank-sum test), which is a nonparametric rank-sum test to determine if one sample stochastically dominates the other sample. The top half of Table 9 presents the $t$-statistics and the p-values for testing the differences between the means, $(\mu_{Nonlocal} - \mu_{Local})$, by ex-post loan outcome. For loans that default, the differences are negative and significant for all credit grades; the difference for credit grade C is significant at the 10%, while the rest are significant at the 5% level. For loans that pay back, the differences are all positive. These differences in means are significant at the 5% or smaller level for all credit grades except A and B. To further explore the difference between the local and nonlocal bid interest rate distributions, the bottom half of Table 9 displays the $U$-statistics and p-values from the one-sided two-sample Mann-Whitney U-tests. The testing procedure can be interpreted as comparing the medians of the two samples. The results are for a one-sided test to determine if one of the distributions of bid interest rates, by credit grade, stochastically dominates the other. Given the large sample size, the test statistics are approximately normal.[15]

For loans that eventually default, the null hypothesis is that values drawn from the nonlocal distribution tend to be larger than or equal to values drawn from the local distribution (the nonlocal distribution stochastically dominates or is equal in distribution to the local distribution). The $U$-statistics for this one-side test are negative for all credit grades. Given that all the p-values are less than 0.02, I can reject the null in favor of the

[15]For further reference see Wilcoxon (1945); Mann and Whitney (1947); Hettmansperger and McKean (1998); Lehmann and D'Abrera (2006).

alternative hypothesis (i.e., the local distribution stochastically dominates the nonlocal distribution). Values drawn from the local distribution tend to be larger than values drawn from the nonlocal distribution. Additionally, for loans that pay back ex-post, the null hypothesis is that the local distribution stochastically dominates or is equal in distribution to the nonlocal distribution. I find that the $U$-statistics are positive for all credit grade and the p-values are less than 0.05 for all credit grades except B and E. However, the difference for E listings is significant at the 10% level. Accordingly, I reject the null in favor of the alternative (i.e., that the values drawn from the local distribution tend to be smaller than the values drawn from the nonlocal distribution) for most of the credit grades. To put these results into context, local bidders' bid interest rates seem to better reflect the true revealed riskiness of a local listing.[16]

To further examine this difference in the bid interest rates, I run a Type II Tobit regression with left censoring at each listing's winning interest rate, since that is the smallest rate that I observe for each listing. The standard errors are clustered at the bidder level. The regression contains indicators for local bidder interacted credit grade, an indicator for if the loan defaulted, and the local bidder indicator interacted with credit grade and the default dummy. The results displayed in Table 10 are consistent with the previous results, showing that local bidders act differentially based on ex-post loan outcomes. The coefficients on the local indicator interacted with credit grade are all negative and significant at the 5% level. The magnitude of the difference between local and nonlocal bids for loans that do not default varies significantly across credit grades; B listings have the lowest differential at 0.032 percentage points while E listings have the largest at 0.907 percentage points. The reduction that local bidders give to loans that pay back ex-post in their ax-ante bids, generally increases as the credit grade worsens. The correlation between credit grade and the rate reduction is -0.702. This implies that local bidders are more willing to accept a lower rate from ex-ante potentially riskier borrowers who ex-post turn out to be lower risk than their financial information indicates. This result makes sense in the context that the better information possessed by the local bidders should have the biggest effect on the listing in the worst credit grades, since these listings have the most potential space for a difference between true risk and perceived risk.

The coefficients for the local indicator interacted with credit grades and default are all positive and significant. The net effect of being local on the submitted bid interest rate is positive if the loan ex-post defaults. The premium that local bidders give to loans that ex-post default, relative to nonlocal bidders, ranges from 0.056 to 0.28 percentage points. The pattern across credit grades is less clear here than for the reduction seen for loans that

[16] I also ran two-sample Kolmogorov-Smirnov distributional equality tests; the results are consistent with the findings of the Wilcoxon-Mann-Whitney test presented here.

do not default. E listings generally get the smallest premium followed very closely by A, B, and D listings but these differences are all less than 0.1 percentage points. However, the local premium is significantly larger for AA and C listings. The total effect of this local behavior on the final outcome for the borrower depends on many factors, but reducing the final interest rate by 1% would lower the total loan payment made by the borrower by a few hundred dollars. Given that there exists a preference for local projects, the total effect of this behavior would be significant when aggregated across a lender's portfolio. This differential bidder behavior supports the idea that local bidders seem better able to evaluate a listing's underlying risk than nonlocal bidders, with the obvious rationale being that local bidders are relatively more informed. Theory predicts that this informational symmetry arises from the fact that the cost of becoming more informed about the market conditions and quality of local borrowers is significantly cheaper for local bidders due to their proximity. This result supports the idea that informational frictions are a main driver in explaining the behavioral difference between local and nonlocal bidders.

### *4.3. Local Bidders Bid Earlier*

If local bidders are better informed about the quality of listings posted by local borrowers, they should be more willing to bid earlier in the auction when the only information that has been revealed is the original public information and their private signal. Additionally, if nonlocal bidders are learning from local bids, then local bidders should be bidding earlier in the auction so that nonlocal bidders have time to react and process this newly revealed information before they bid. The right part of Table 6 shows the $25^{th}$ percentile, mean, and median of bid times. Bid times are normalized so that zero is the beginning and one is the end of the auction. The data shows that local bidders tend to bid earlier during the auction than nonlocal bidders. To put these normalized time differences into perspective, a vast majority of the listings are active for seven days, so 0.00595 is roughly equal to a single hour. Consequently, the average local bid is placed a little more than 2.5 hours and the $25^{th}$ percentile local bid is placed about 5.5 hours earlier than its nonlocal counterparts.

To formally test if local bidders do bid significantly earlier than nonlocal bidders, I perform a two-sample Mann-Whitney test on bid times. The p-value for test is 0.000, implying that the distribution of bid times for local bidders tends to be significantly smaller than the distribution of bid times for nonlocal bidders.[17] To further illustrate that local bidders bid earlier more often, Figure 2 plots the cumulative distribution functions of the bid time distribution by local status. The nonlocal bid time distribution first

[17] A two-sample Kolmogorov-Smirnov distributional equality test is consistent with the findings of the Mann-Whitney test presented here.

order stochastically dominates the local bid time distribution. The distance between the cumulative distribution function's decreases rather sharply towards the end of the auction, which can be accounted for by the sniping effect that has been observed in other online auctions with a similar structure.[18] There is generally a good amount of bidding activity at the end of the auction, since people are bidding to capture extra benefit awhile trying to avoid bidding wars and bid chasing from the other bidders. End-of-auction bidding is a common practice for both local and nonlocal bidders on Prosper as well.

One might be concerned that it is not just timing that matters in determining if a bid is actually early or not; therefore, Table 11 displays the summary statistics for the number of bids placed and money pledged in a listing immediately before a bidder bids by local status. As can be clearly seen, local bidders bid earlier in an auction not just chronologically. Local bidders have demonstrated that they are more comfortable bidding in periods where limited information is being revealed by other bidders.

I have documented that local bidders tend to bid earlier and larger amounts, on average, than nonlocal bidders. Additionally, local bidders bid different interest rates from nonlocal bidders depending on the ex-post outcome of the loan. This empirical evidence strongly suggest that while altruism might play a part, the dominant channel explaining this observed behavior is that local bidders are better informed than other bidders, which fits well with theory. This asymmetric information based on physical geography creates a situation where social learning can occur as local bidders, through their bidding behavior, reveal their private information to nonlocal bidders. As a listing accumulates bids, a general sense of quality is signaled that may lead to rational herding behavior in crowdfunding markets, (Agrawal et al., 2011; Zhang and Lui, 2012; Burtch, Ghose, and Wattal, 2013). Given these results, I develop a simple information-based social learning model to explain and predict how better informed local bidders reveal their private information to nonlocal bidders through their actions. The model produces the testable hypothesis that listings with more early local bidders will attract more bidders to the listing.

## 5. Motivating Model

The central proposition of this paper is that local bidders are more informed about local listings than nonlocal bidders. Thus, local bidders are better able to correctly evaluate the underlying risk in the listing when they bid. Being better informed allows local bidders to be more comfortable bidding earlier, acting mostly on their own private information.

[18] Bajari and Hortaçsu (2003); Ariely and Simonson (2003); Ariely, Ockenfels, and Roth (2005); Ockenfels and Roth (2006).

Similar to Sorensen (2006) and Smith and Sørensen (2008), local bidders' actions serve as signals of their private information. As pointed out by Devenow and Welch (1996), social learning involves an informational externality where bidders may gain useful information from observing previous bidders' decisions. Due to the existing informational asymmetry, nonlocal bidders can learn from observing the actions of others, particularly local bidders. This behavior leads to listings that have more early local bidding to have more revealed private information available and thus attract more bidding activity.

To provide some theoretical context and motivation for my analysis, I abstract away from the auction environment on Prosper and develop a simple social learning model with heterogeneous agents in the spirit of Banerjee (1992) and Bikhchandani, Hirshleifer, and Welch (1992). There is a population of $N$ identical risk neutral bidders, with vNM utility, who are maximizing their expected utility of monetary payoff from investing.[19] The heterogeneity comes from the existence of two different types of bidders: local and nonlocal. An $L$ share of the bidders are local, who are better informed, and a $(1 - L)$ share are nonlocal.[20] Each bidder is presented with the same collection of listings indexed by $i \in [0, 1]$. The monetary return from investing in the $i$th listings is $z(i) \in \mathbf{R}$, which is the same for all bidders. Assume that only one unique listing, $i^*$, will yield strictly positive returns, while all other listings produce returns of zero, $z(j) = 0$ for all $j \neq i^*$. This assumption can be interpreted as there existing a single listing which has excess returns that are strictly greater than those of all other listings. Therefore, the optimal ex-post outcome for all bidders is to invest in that listing. Although in Prosper bidders decide how much money to pledge in a particular listing, for simplicity, each bidder's decision is restricted to simply choosing which listing to invest in.[21]

At start of the game, all bidders have the same ex-ante uniform priors about which listing will pay positive returns. However, some bidders have an idea of which listing is the likely candidate for $i^*$. Formally, with probability $\alpha \in (0, 1)$, bidder $i$ will receive a noisy signal, $S_i \in [0, 1]$, about which listing to invest in. The signal need not be true, and will be false with some positive probability. Local bidders are assumed to be more informed than nonlocal bidders, so their signals will be more informative. The signal of a local bidder is correct with probability $\beta \in (0.5, 1)$, and with probability $(1 - \beta)$ the signal is strictly noise drawn randomly from $U[0, 1]$. The signal structure for nonlocal bidders is the same as of local bidders, except it is less informative. Formally, a nonlocal signal is

[19] If bidders' risk tolerances are identical, risk preference has no effect on the outcome of the game

[20] Smith and Sørensen (2000) also study herding with heterogeneous agents, but the types vary along preferences, not the information quality.

[21] It is possible that a bidder's demand level for a particular listing may be a transmission channel for information about his or her private signal. The median bid, regardless of local status, is \$50; thus most bids contain no additional information.

correct with probability $\gamma \in (0.5, 1)$, with $\beta > \gamma$.

Bidders do not ex-ante know the local status of the preceding bidders. If their behavior does not reveal their status, the current bidder will assume that the preceding bidder is as informed as the average bidder in the population, $\theta = L\beta + (1 - L)\gamma$. To ensure that this game is solvable in a general setting without a complicated dependence on the primitives of model in addition to the observed history, I impose some mild structure on how much more informed a local bidder is than a nonlocal one.[22] Given that the local bidders are better informed, they are more resistent to being persuaded away from their own private signals, but can be if a sufficient number of other bidders act in unison. Bidders move sequentially in a fixed order, a bidder cannot decide to delay his decision, which is exogenously set randomly before the game begins. Each bidder's information set includes only the actions of the preceding bidders, their own local status, and potentially their own private information if they receive a signal.

The timing of the game is as follows. An individual bidder observes the history, potentially receives a private signal, and then computes via Bayes' rule his private belief about which listing is most likely to have positive returns. The bidder then chooses to invest in that listing. The rest of the game proceeds in this way, with each new bidder using the observed history and their own signal, if he has one, to make his choice. Due to the symmetry between bidders, some actions, after a particular history, will reveal that a preceding bidder must be local. This revealing behavior occurs when a bidder chooses to act in a way that only a local bidder with a signal would act given the decisions made by the preceding bidders. I refer to these bidders as revealed local bidders. All following bidders will rationally update their beliefs when optimizing to account for this fact. After all the bidders have chosen a listings, all the uncertainty is resolved and one listing pays out its return to those that invested in it.

Rationality and the structure of the game is common knowledge to all bidders. Consequently, each bidder's decision rule is based solely on the history and his signal. When indifferent, bidders use the three classical tie-breaking assumptions in Banerjee (1992): (A) If a bidder has no signal and everyone else before her has chosen the zero listing, then she will always choose the zero listing, (B) if a bidder is indifferent between following her own signal or someone else's choice, she always follows her own signal, and (C) if a bidder is indifferent between following more than one other bidders' choices, she will always choose the listing with the largest index. Assumption (A) can be thought of making the zero listing the default for a bidder that is completely uninformed. Assumption (B) follows from the idea that when in doubt, bidders will trust their own information, and

[22] See the appendix for the condition.

Assumption (C) is just purely a tie-breaking rule.[23]

Because each bidder's payoff function is independent from the subsequent choices, there are no dynamic strategic elements in this game. Implying that the game can be solved by forward induction; the uniqueness of the solution is automatically guaranteed. It is obvious that the decisions made by bidders will dependent on whether they receive a signal and their local status. Formally solving the unique Bayesian Nash equilibrium for this game is outside the scope of this paper; however, I will brief explain the optimal decisions for the first three bidders. This example will summarize the basic intuition of this model to motivate why early local bidding might have an extra influence in the behavior of our bidders later in the auction.

The first bidder has no previous history to observe, so the only source of information available is his own signal, if he received one, regardless of his local status. Clearly, the first bidder will follow his signal if he has one, and, by Assumption (A) will choose the default zero listing if no signal is received. As shown by Banerjee (1992), this choice will minimize misinformation since the first bidder will only choose the zero listing if: (a) he did not receive a signal, or (b) the signal received is the zero listing. Getting a signal for the zero listing is a zero probability event, so case (b) can be safely ignored. Seeing the first bidder choose zero does not provide any information to the subsequent bidders.

The second bidder's information set includes her local status, her signal, and the first bidder's choice. She will follow her own signal, given that she receives one, if the first bidder chooses the zero listing or she is local. Otherwise, the second bidder will follow the choice of the first bidder. If the first bidder chooses a non-zero listings, then she knows that the first bidder received a signal. Recall that bidders do not exogenously know the local status of the preceding bidders; the second bidder will assume that his signal accuracy is that of an average bidder. As a result, a nonlocal second bidder will ignore her private signal, if she has one, and follow the choice of the first bidder of unknown status, $\theta > \gamma$ since $\beta > \gamma$.

The third bidder will observe one of four different possible histories: (1) both preceding bidders choose the zero listing, (2) the first bidder chooses the zero listing and the second bidder chooses a non-zero listing, (3) both bidders choose the same non-zero listings, and (4) both bidders choose a different non-zero listing. Starting with the third bidder, the results of this social learning model deviates from the classic Banerjee (1992) model. In history (4), the second bidder reveals her local status since only a local bidder with a signal will rationally follow her own signal when the preceding first bidder of unknown status has chosen a non-zero listing. All subsequent bidders will rationally observe this fact and update their beliefs after seeing this event occur.

[23]Refer to Morone (2012) for an analysis of the effects of changing these tie-breaking rules.

The third bidder will follow his signal, if he has one, if: (a) all preceding bidders choose the zero listing, (b) he is a local bidder, or (c) his signal matches a choice made by a preceding bidder. Otherwise, the third bidder will follow the choice of the second bidder. It is important to point out here that whenever a bidder's signal matches the choice made by one the preceding bidders, he should always follow his signal. This result follows from the fact that the probability of two bidders receive the same signal and both of them being wrong, regardless of local status, is zero.

The effects of the informational asymmetry in this social learning model can clearly be illustrated with the third bidder in history (3). In this history, both previous bidders choose the same non-zero listing, but by doing so neither of them reveals their local status. Therefore, a local third bidder will still follow his own private signal while a nonlocal bidder would follow the preceding two bidders. This is an example of local bidders being more trusting of their private information than their nonlocal counterparts.

The basic intuition from this example gives rise to more general results that deserve to be emphasis. The proofs of the following lemmas can be found in the appendix.

**Lemma 1:** *If the first three bidders all choose the same non-zero listing, then all subsequent bidders, regardless of their local status, will follow them and choose that listing.*

If the first three bidders all choose the same non-zero listing, then the fourth bidder is certain that the first bidder received a signal. Additionally, if any of the other bidders also received a signal and were local, their signal must have matched the first bidder's choice. Given the current amount of information that is available, this non-zero listing is the most probable listing to be correct, regardless of what private information the fourth bidder has, even if he is local. This result is generalizable to the case where the most chosen non-zero listing has at least three unknown status bidders choosing it in excess of what the other chosen non-zero listings have. Following the same intuition, after this point the most chosen non-zero listing is the most probable listing to produce positive returns, regardless of the local status of the next bidder. All subsequent bidders will choose this listing, except if the bidder receives a signal that matches an already chosen listings, then the bidder will find his signal. Therefore, if a particular listing is chosen by three unknown status bidders, in excess of the next most chosen listing, a herd starts and no more information will be revealed from bidders' actions.

**Lemma 2:** *If the first bidder chooses $i$, a non-zero listing, and the second, third, and fourth bidders all choose the same non-zero listing that is different from the one chosen by the first bidder, $j \neq i$. Then all subsequent bidders, regardless of their local status, will choose listing $j$, unless they receive a signal that matches the choice of the first bidder. In which case, they will choose listing $i$.*

In this situation, listing $i$ is chosen by only the first bidder who is of unknown local status. Listings $j$ is chosen by one revealed local bidder, the second bidder, and two unknown

status bidders. As long as the fifth bidder's signal does not match the first bidder's choice, then one of the unknown status bidders choosing listing $j$, in a loose sense, cancels out the first bidder's choice of listing $i$. Therefore, this history can be thought of as listing $j$ being the only listing that has been chosen, and it has been chosen by one local bidder and one unknown status bidder. Similar to the situation described in Lemma 1, this result is generalizable to the case where all the chosen non-zero listings have the same number and types of bidders, and one of them receives an additional bid from a revealed local and one unknown status bidder. Then all subsequent bidders who's signals do not match an already chosen listing, regardless of local status, will choose the listing with the most bidders. After this event occurs, a herd starts and no more information will be revealed from bidders' choice of this listing, resulting in the relative information structure remaining unchanged.

These two lemmas describe the cases where social learning stops and bidders start to herd around a particular listing. Having a revealed local bidder choose a particular listing carries more weight than the choices of two unknown status bidders. The implication of these theoretical results, given there is heterogeneity in the accuracy of signal, is that if early bidders start acting in concert, other bidders will follow them. When other bidders observe a revealed local bidder, especially early on, it will draw other bidders to that listing more quickly.

**Lemma 3:** *As the most chosen non-zero listing has been chosen by more local bidders in the early stages, that particular listings becomes more likely to be the ex-post listing that has positive returns.*

Given that local bidders are more likely to rationally follow their own private information, having more of them choose the same listings in the early period, before information transmission stops, increases the likelihood that the correct listing is being chosen. This results arises from the fact that the signal of local bidders is more accurate than that of a nonlocal bidder and is less likely to be persuaded by herd.

Although simple, the optimal decision rules that arise from this model provide clear intuition and motivation for how bidders behave on Prosper. Translating these theoretical results to Prosper, this social learning model produces the following testable hypotheses: a listing with more early local bidding will (a) attract more bidders, (b) have a higher probability of being funded, (c) conditional on being funded, have a lower final interest rate, and (d) have a larger probability of not defaulting. In the following section, I will use the transactional data described above to empirical test these hypotheses about the effects of geography on behavior in P2P lending markets.

## 6. Results

As shown previously, local bidders tend to bid earlier and appear to be more informed about general market conditions and underlying riskiness of the borrower than nonlocal bidders. The simple social learning model presented in the previous section suggests that in this market, the amount of early local bidding is influential and should be a strong predictor of a listing's success in (a) attracting bidding activity, (b) becoming fully funded, (c) getting a lower final interest rate if funded, and (d) after becoming loan, not defaulting. In this section, I will now set out to empirically evaluate these predictions for the P2P lending market. The regression equation that I estimate to test prediction (a) and (c) is

$$Y_i = \beta_0 + \beta_1 TEBC_i + \beta_2 TEBA_i + \beta_3 LEBC_i + \beta_4 LEBA_i + \delta X_i + \varepsilon_i$$

while prediction (b) and (d) are tested using a logit model.

I include variables measuring the total number of bids ($TEBC$) and the amount of money pledged by all bidders ($TEBA$), as well as just number of bids submitted by local bidders ($LEBC$) and the amount of money pledged by them ($LEBA$). Having the total early bids and total money pledged in the specification controls for the effect that more early bidding has in general, regardless of local status, influencing the decisions of other bidders (Kim and Hann, 2014). Including both variables for total early and local early bidding allows me to separately identify the additional effect of early local bidding from just getting an early bid. The variable $X_i$ contains all the listing-specific covariates. I examine four definitions of early bidding, pre-fully funded, first two hours, first hour, and first 30 minutes of the auction. For the sake of brevity, only results from the first two hours are reported in this paper. The results are robust to changes of the definition of the early period.[24]

*More Early Local Bidding Attracts More Bidding Activity*

To test whether more early local bidding will attract more bidding activity to the auction, I run count regressions using a Poisson specification. The bidding activity outcomes I use as dependent variables are total and total-nonlocal bid count during different parts of the auction. Table 12 presents the marginal effects from the Poisson regressions on the effect early local bidding has on total and total-nonlocal bid count. The coefficients for total early and early local bidding are all positive and significant. More early local bidding attracts more bidding activity to a listing. To put the regression results into context, four extra $50 early local bids will increase the total bid count by more than one bid, while it would take eight additional nonlocal early bids to result in the same increase in the total

[24]The regression results from the other specifications are available from the author upon request.

bid count. Even when focusing just on total-nonlocal bids, one early local bid has roughly the same effect as two nonlocal early bids, given that all the bids are the same monetary size, in attracting more bidders to the listing.

One might think that early local bidding only has power in attracting bidding activity before the listing is fully funded. In the pre-fully funded period of the auction, bids are complementary. Since there are no losing bids, no information about the actual interest rates of the bids in the auctions is revealed. An additional bid in the pre-fully funded phase moves the listing closer to completion and demonstrates that the bidder's private information is strong enough to induce him or her to demand positive shares of the listing at an interest rate that is as least as large as the borrower's max rate. After the listing is fully funded, bids become substitutes and real competition starts between bidders. In this period of the auction, future bidding could cause older bids to become losing; therefore, the interest rate of those bids will start to be shown. If a new bid does not lower the standing interest rate, it will reduce the amount of the loan that a previous bidder will be funding. This means that that bidder with the larger interest rate will have the share of the loan that he or she is funding reduced.

Given the difference in the nature of the auction and information available across these different phases of the auction, bidders might no longer consider the previous bidding history and only focus on the current standing interest rate. To examine if the strength of the attraction of early local bidding varies across this informational shift that arises due to the auction mechanism, I restrict attention to bidding in just the pre-fully funded and post-fully funded phases of the auction. Note that only listings that are fully funded will have a post-fully funded phase. I only use the subsample of listings that are completed in both the pre- and post-fully funded regressions. Table 13 presents the marginal effects of early local bidding on pre-fully funded bid count and nonlocal pre-fully funded bid count. The coefficients for total early and early local bidding are all positive and significant. These results are similar to the results of the total bid count regression shown previously. If all listings, not just completed listings, are included in the regression, qualitatively similar results are found; however, the magnitude of the early bidding coefficients is reduced. This is unsurprising given that if all listings are included, the average amount of bidding is decreased by the addition of uncompleted listings.

Table 14 displays the regression results for the marginal effects for total post-fully funded and total-nonlocal post-fully funded bid count. The effect is similar to the previous result on total bid count, except that the coefficient on early local bid amount is negative in this specification. However, the net effect of more local bidding will generally still be positive.[25] This result implies that for the same amount of local money pledged, having

[25] As long as the average bid amount for the additional local bids is less than $98.

more local bidders bid smaller individual amounts will have a larger impact on the number of post-fully funded bids than less local bidders bidding larger amounts. The bidding behavior of preceding bidders only partially reveals their private information, so having more local bidders accumulating and transmitting their better information will have a larger and more meaningful effect on later bidders than a single local bidder bidding larger amounts. Reflecting back to the theoretical framework, the expected value of a listing increases as more local bidders, especially early on in the auction, choose it. This result seems to suggest that the intensity of the individual demand of a bidder does not convey much information beyond the fact that a bidder chooses to bid on this listing.

Comparing the effects of early local bidding on bidding activity in the two different informational phases of the auction reveals that although the net effect of early local bidding is positive in attracting more bidding activity, the effect is weaker post-fully funded. The new information sources of actual bid interest rates that are revealed along with a potentially decreasing current standing rate appear to dampen the attraction effect of early local bidding.

As a robustness check, I also use total bid count after the first two hours as the dependent variable. Table 15 displays these results, which match the findings of the post-fully funded regressions. The results are qualitatively similar to the post-fully funded specification. It is worth noting that the effect of total overall early bidding is more pronounced on post-fully funded bid count, so the positive effect of strictly local early bidding is slightly reduced. These results confirm the first prediction of the social learning framework, i.e., more early local bidding tends to attract more bidders to a listing up and above the normal effect of a listing simply getting more early bids.

*More Early Local Bidding Increases the Probability of Funding*

I have shown that early local bidding attracts more bidding activity, but does it affect the rate of funding for listings? The left part of Table 16 presents the marginal effects, evaluated at the means, of early local bidding on the probability of funding. The results concur with those in the previous section on bidder entry: the coefficients are positive and significant. An additional four early local bids of $50 will increase a listing's funding probability by 0.054 percentage points above the effect of just getting more early bids. This effect may initially seem small, but comparing it to the effect of decreasing the DIR by one unit (-0.0032), being a homeowner (0.0034), increasing the borrower's max rate by a percentage point (0.0069), or requesting an additionally thousand dollars (-0.0271), the relative effect of early local bidding is strong.

*More Early Local Bidding Decreases the Final Interest Rate*

A related issue to the probability of funding is the effect that early local bidding has on the final interest that a listing receives after completion. The effect of early local bidding is not immediately obvious since it has been shown that local bidders appear to better price listings than nonlocal bidders. If the listing possesses some extra risk that is hidden to uninformed nonlocal bidders, then the local bidders will bid larger interest rates. In this scenario, the positive effect of attracting more bidding activity might be negated if there are enough local bids in the auction.

The right part of Table 16 shows that the effect of early local bidding is negative and significant. A single additional $50 early local bid will, on average, decrease the expected final interest rate of a completed listing by 0.062 percentage points in excess of the effect of a listing just receiving a single nonlocal bid. For comparison, this effect is of similar absolute magnitude to the effects of requesting an additional thousand dollars or having the borrower's reported debt increase by an amount equal to his income (DIR increases by 1 unit). The effect of early local bidding on the probability of funding and the final interest rate are consistent with the predictions of the social learning model. Listings that have more early local bidding will attract more bidding, resulting in these listings being funded at higher rates and enjoying lower final interests, if funded.

*More Early Local Bidding Might Suggest Better Quality*

Lastly, the motivating social learning model presented in Section 5 suggests that early local bids predict the ex-post outcome of a loan. Given that local bidders are better informed than nonlocal bidders, listings with more early local bidding should have a higher probability of not defaulting. Table 17 displays the marginal effects, evaluated at the means, for a logit regression predicting whether a completed listing will default using pre-fully funded local bidding as well as local bidding in the first two hours. The effect of early local bidding is negative; however, the results are statistically insignificant. More detailed information, about when the default occurred and how much of the principle was repaid, would allow for a finer measure of loan performance. Admittedly, this result is suggestive at best, but the direction of the effect is consistent with social learning. The better information of the local bidders accumulates as more of them bid early in the auction and this information is transmitted to other bidders, affecting how they bid on the available listings.

Combining all of these results, it can be inferred that geography, acting mainly through the channel of informational frictions, still matters and has a strong effect on P2P lending markets. This research provides more supportive evidence for the claim that although the

internet has made gathering and processing information cheaper for more people, location of the investor relative to the investment opportunity is still important and local lenders have an informational advantage over their nonlocal counterparts.

The analysis in this paper is concerned with the geographic proximity of bidders and borrowers. Following the previous literature, I consider a bidder local if that bidder is located within the same state as the borrower.[26] It is an empirical question as to whether state level analysis is too large to meaningfully study the existence of informational frictions. As a robustness check, I also run my analysis using a restricted sample where local status is determined by the bidder living within the same city as the borrower. The results are qualitatively the same, so for brevity, the tables can be found in the appendix. The following section constructs a theoretic framework grounded in the previously established facts to better understand and explain how the differential behavior of local bidders will affect P2P lending auctions

## 7. Conclusion

Over the past few years, major commercial organizations have noticed the vast potential of crowdfunding and have begun to acquire stakes in P2P lending firms, while mainstream financial companies are beginning to offer similar services mimicking this online marketplace (Corkery, 2015). As P2P lending sites are starting to open and expand worldwide, it is clear that P2P lending, and crowdfunding in general, as an alternative to the traditional finance methods is a growing trend and not just a fad. Therefore, it is paramount that we better understand the factors that influence the behavior of this online marketplace's participants. In this paper, I investigate the role frictions caused by geography play in online P2P lending markets. Using transaction data from Prosper.com, I document evidence that the adoption and use of the internet has not fostered the creation of a more unified national market, with new online tools overcoming the traditionally asymmetry in investing. I find support for the conclusion that geography-related informational frictions exist and have strong effects on the behavior in P2P lending markets. In particular, I observed that local bidders bid earlier, bid larger amounts, and appear to be better informed in the sense that submit bid interest rates that more accurately account for the ex-post revealed riskiness of borrowers.

While the empirical literature is split on whether economic or behavioral motives matter, my results are mostly consistent with the Grinblatt and Keloharju (2001) informational cost theory. It appears that local bidders have easier and cheaper access to information and, thus, are better informed about local listings than their nonlocal counterparts. If local

[26] Wolf (2000); Hillberry and Hummels (2003); Hortaçsu et al. (2009).

bidders were only acting altruistically towards local borrowers, then local bidders should generally be bidding lower interest rates on local listings regardless of the ex-post loan outcome. However, the data shows clearly that local bidders are bidding differentially based on the inferred quality of the borrower. Local bidders appear to be accounting for riskiness that nonlocal bidders are not, implying that local bidders can better evaluate the probability of default of local projects. That being said, it is evident from the fact that local bidders have a larger demand for local listings, regardless of the ex-post loan outcome, that there exists some degree of local preference among bidders. While this coincides with previous work with online markets (Hortaçsu et al., 2009; Lin and Viswanathan, 2014), strictly preference is not sufficient to fully explain the observed behavior. Thus, it is safe to conclude that preference is an important factor affecting bidder behavior, but information-based frictions play a major role in explaining the behavioral difference between local and nonlocal bidders in P2P lending markets.

Although the cost of information gathering and processing is lower now than before the widespread adoption of the internet, my results suggest that crowdfunding sites suffer from the same informational asymmetry that exists in the offline credit markets. This finding that the reduction in informational cost has yet to be of a sufficient magnitude to render geography irrelevant in P2P lending markets is not an anomaly in the empirical findings. Similar results have been found across online markets; many studies find that the internet does not universally lower market prices and lead to less price dispersion.[27] Further research is needed, but placing my results in context of the wider literature implies that the presence of local preference in addition to an apparent informational asymmetry suggests that current tools and platforms are unlikely to remove barriers and improve efficiency in the credit market. A better understanding of investors' behavior and decision-making on online crowdfunding sites is important, not just for market participants, but also for the financial market in its entirety. As more research pushes the frontier on this issue, it can be hoped that better designed mechanisms and policies will be able to remove informational barriers, and that online lending can be leveraged to improve the efficiency of the credit market.

[27]See Brown and Goolsbee (2002); Janssen, Moraga-González, and Wildenbeest (2005); De los Santos, Hortaçsu, and Wildenbeest (2012); Blevins and Senney (2014) for references.

## References


Adams, C. and I. Ramos (2010). The past, present and future of social networking and outsourcing: Impact on theory and practice. UK Academy for Information Systems Conference Proceedings 2010. [5]

Agrawal, A., C. Catalini, and A. Goldfarb (2011). The geography of crowdfunding. Working Paper. [4, 7, 15]

Anderson, J. and E. van Wincoop (2004). Trade costs. *Journal of Economic Literature 42*(3), 691–751. [3]

Ariely, D., A. Ockenfels, and A. Roth (2005). An experimental analysis of ending rules in internet auctions. *The RAND Journal of Economics 36*(4), 890–907. [15]

Ariely, D. and I. Simonson (2003). Buying, bidding, playing, or competing? Value assessment and decision dynamics. *Journal of Consumer Psychology 13*, 113–123. [15]

Arthur, B. W. (1986). Industry location patterns and the importance of history. Working Paper 84. [3]

Arthur, B. W. (1988). Urban systems and historical path dependence. In J. Ausubel and R. Herman (Eds.), *Cities and their Vital Systems*, pp. 85–97. Washington: National Academy Press. [3]

Arthur, B. W. (1990). Silicon Valley locational clusters: When do increasing returns imply monopoly? *Mathematical Social Sciences 19*, 235–251. [3]

Bajari, P. and A. Hortaçsu (2003). The winner's curse, reserve prices, and endogenous entry: Empirical insights from ebay auctions. *Rand Journal of Economics 34*(2), 329–355. [9, 15]

Baker, H. K. and J. A. Haslem (1974). The impact of investor socioeconomic characteristics on risk and return preferences. *Journal of Business Research 2*(4), 469–476. [11]

Banerjee, A. (1992). A simple model of herd behavior. *The Quarterly Journal of Economics 107*(3), 797–817. [16, 17, 18]

Belleflamme, P., T. Lambert, and A. Schwienbacher (2010, June). Crowdfunding: An industrial organization perspective. Working Paper. [2]

Berger, S. and F. Gleisner (2009). Emergence of financial intermediaries in electronic markets: The case of online P2P lending. *Business Research 2*(1), 39–65. [3]

Bikhchandani, S., D. Hirshleifer, and I. Welch (1992). A theory of fads, fashion, custom, and cultural change as informational cascades. *Journal of Political Economy 100*(5), 992–1026. [16]

Blevins, J. R. and G. T. Senney (2014). Dynamic selection and distributional bounds on search costs in dynamic unit-demand models. Working Paper 14-02, The Ohio State University. [26]

Blum, B. S. and A. Goldfarb (2006). Does the internet defy the law of gravity? *Journal of International Economics 70*(2), 384–405. [4]

Brevoort, K. P. and T. H. Hannan (2003). Small business lending and distance: Evidence from CRA data. Mimeo. [4]

Brown, J. R. and A. Goolsbee (2002). Does the internet make markets more competitive? evidence from the life insurance industry. *Journal of Political Economy 110*(3), 481–507. [26]

Brynjolfsson, E., Y. Hu, and M. Rahman (2009). Battle of retail channels: How product selection and geography drive cross-channel competition. *Management Science 55*(11), 1755–1765. [4]

Burtch, G., A. Ghose, and S. Wattal (2013). An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets. *Journal of Information Systems Research 24*(3), 499–519. [15]

Corkery, M. (2015, July 16). Treasury to examine online lending industry. *New York Times*, B2. [25]

Cortese, A. (2014, May 3). Loans that avoid banks? Maybe not. *New York Times*, BU1. [2]

Cowley, S. (2015, April 8). Online lenders offer a faster lifeline for small businesses. *New York Times*, B4. [2]

Cyrnak, A. and T. Hannan (2000). Non-local lending to small businesses. Technical report, Board of Governors of the Federal Reserve. Working Paper. [4]

David, P. and J. Rosenbloom (1990). Marshallian factor market externalities and the dynamics of industrial localization. *Journal of Urban Economics 28*, 349–370. [3]

De los Santos, B., A. Hortaçsu, and M. Wildenbeest (2012). Testing models of consumer search using data on web browsing and purchasing behavior. *American Economic Review 102*(6), 2955–2980. [26]

Degryse, H. and S. Ongena (2003). Distance, lending relationships, and competition. Technical report, Center for Economic Studies, KU Leuven. Discussion Paper 02-16. [4]

Dell'Ariccia, G. and R. Marquez (2004). Information and bank credit allocation. *Journal of Financial Economics 72*(1), 185–214. [1]

Devenow, A. and I. Welch (1996). Rational herding in financial economics. *European Economic Review 40*(3–5), 603–615. [16]

Duarte, J., S. Siegel, and L. Young (2012). Trust and credit: The role of appearance in Peer-to-Peer lending. *Review of Financial Studies 25*(8), 2455–2483. [3]

Elyasiani, E. and L. Goldberg (2004). Relationship lending: a survey of the literature. *Journal of Economics and Business 56*(4), 315–330. Research Perspectives Special Issue. [4]

Figner, B. and E. U. Weber (2011). Who takes risks when and why?: Determinants of risk taking. *Current Directions in Psychological Science 20*(4), 211–216. [11]

Florida, R. and M. Kennedy (1988). Venture capital, high technology and regional development. *Regional Studies 22*, 33–48. [3]

Florida, R. and D. Smith (1988). Venture capital formation, investment, and regional industrialization. *Annuals of the Assiociation of American Geographers 83*(3), 434–435. [3]

Goldfarb, A. and C. Tucker (2011). Advertising bans and the substitutability of online and offline advertising. *Journal of Marketing Research 48*(2), 207–227. [4]

Grinblatt, M. and M. Keloharju (2001). How distance, language, and culture influence stockholdings and trades. *The Journal of Finance 56*(3), 1053–1073. [25]

Harrison, R., C. Mason, and P. Robson (2010). Determinants of long-distance investing by business angels in the UK. *Entrepreneurship & Regional Development 22*(2), 113 – 137. [4]

Herzenstein, M., R. Andrews, U. Dholakia, and E. Lyandres (2008). The democratization of personal consumer loans? determinants of success in online Peer-to-Peer lending communities. Working Paper. [3]

Hettmansperger, T. and J. T. McKean (1998). *Nonparametrics Statistical Methods* (2 ed.). Boca Raton, FL: CRC Press. [12]

Hillberry, R. and D. Hummels (2003). Intranational home bias: Some explanations. *Review of Economics and Statistics 85*(4), 1089–1092. [25]

Hortaçsu, A., F. A. Martínez-Jerez, and J. Douglas (2009). The geography of trade in online transactions: Evidence from eBay and MercadoLibre. *American Economic Journal: Microeconomics 1*(1), 53–74. [4, 11, 25, 26]

Iyer, R., A. Khwaja, E. Luttmer, and K. Shue (2009). Screening in new credit markets: Can individual lenders infer borrower creditworthness in Peer-to-Peer lending? Working Paper. [3]

Janssen, M., J. L. Moraga-González, and M. Wildenbeest (2005). Consumer search and pricing behavior in internet markets. Working Paper. [26]

Kim, K. and I.-H. Hann (2014). Crowdfunding and the democratization of access to capital: A geographical analysis. Working Paper. [21]

Klafft, M. (2008a). Online peer-to-peer lending: A lenders' perspective. In H. R. Arabnia and A. Bahrami (Eds.), *Proceedings of the International Conference on E-Learning, E-Business, Enterprise Information Systems, and E-Government*, pp. 371–375. CSREA Press. [3]

Klafft, M. (2008b). Peer to peer lending: Auctioning microcredits over the internet. In A. Agarwal and R. Khurana (Eds.), *International Conference on Information Systems, Technology and Management*, Dubai. [3, 7]

Kreinin, M. E. (1959). Factors associated with stock ownership. *Review of Economics and Statistics 41*(1), 12–23. [11]

Krugman, P. (1991a). *Geography and Trade*. Cambridge: MIT Press. [3]

Krugman, P. (1991b). Increasing returns and economic geography. *The Journal of Political Economy 99*(3), 483–499. [3]

Lehmann, E. L. and H. J. M. D'Abrera (2006). *Nonparametrics: Statistical methods based on ranks*. San Francisco, CA: Springer. [12]

Lendle, A., M. Olarreaga, S. Schropp, and P.-L. Vézina (2013). There goes gravity: How eBay reduces trade costs. Discussion Papers 9094. [4]

Lieber, R. (2011, Februar 5). The gamble of lending peer to peer. *New York Times*, B1. [9]

Lin, M., N. Prabhala, and S. Viswanathan (2013). Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. *Management Science Management Science 59*(1), 17–35. [3, 7]

Lin, M. and S. Viswanathan (2014). Home bias in online investment: An empirical study of an online crowdfunding market. Working Paper. [4, 8, 11, 26]

Mann, H. B. and D. R. Whitney (1947). On a test of whether one of two random variables is stochastically larger than the other. *The Annals of Mathematical Statistics 18*(1), 50–60. [12]

Martin, R., P. Sunley, and D. Turner (2002). Taking risks in regions: The geographical anatomy of Europe's emerging venture capital market. *Journal of Economic Geography 2*, 121–150. [3]

Mason, C. (2007). Venture capital: A geographic perspectice. In Landström (Ed.), *Handbook of Research on Venture Capital*, pp. 86–112. Edward Elgar. [3]

Mason, C. and R. Harrison (2002). The geography of venture capital investments in the UK. *Transactions, Institute of British Geographers 27*, 427–451. [3]

Massolution.com (2013). The crowdfunding industry report. Technical report, Crowd Sourcing. [8]

Massolution.com (2015). The crowdfunding industry report. Technical report, Crowd Sourcing. [5]

Mollick, E. R. (2014). The dynamics of crowdfunding. *Journal of Business Venturing 29*, 1–16. [2]

Morone, A. (2012). A simple model of herd behavior, a comment. *Economics Letters 114*, 208–21. [18]

NSR Invest (2015). Accumulative monthly funds. Technical report, Nickel Streamroller, LLC and Lend Academy Investment, LLC. Data obtained from Prosper and Lending Club. [5]

Ockenfels, A. and A. E. Roth (2006). Late and multiple bidding in second price internet auctions: Theory and evidence concerning different rules for ending an auction. *Games and Economic Behavior 55*(2), 297–320. [15]

Petersen, M. A. and R. G. Rajan (2002). Does distance still matter? the information revolution in small business lending. *The Journal of Finance 57*(6), 2533–2570. [4]

Pope, D. and J. Sydnor (2011). What's in a picture?: Evidence of discrimination from Prosper.com. *Journal of Human Resources 46*(1), 53–92. [3]

Powell, W., K. Koput, J. Bowie, and L. Smith-Doerr (2002). The spatial clustering of science and capital: Accounting for biotech firm-venture capital relationships. *Regional Studies 36*(3), 291–305. [3]

Ratchford, B., X. Pan, and V. Shankar (2003). On the efficiency of internet markets for consumer goods. *Journal of Public Policy & Marketing 22*(1), 4–16. [4]

Ravina, E. (2012). Love and loans: The effect of beauty and personal characteristics in credit markets. Working Paper. [3]

Schwienbacher, A. and B. Larralde (2010, September). Crowdfunding of small entrepreneurial ventures. Working Paper. [2]

Smith, L. and P. N. Sørensen (2000). Pathological outcomes of observational learning. *Econometrica 68*(2), 371–398. [16]

Smith, L. and P. N. Sørensen (2008). Informational herding and optimal experimentation. Working Paper. [16]

Sohl, J. (1999). The early stage equity markets in the USA. *Venture Capital: An International Journal of Entrpreneurial Finance 1*, 101–120. [3]

Sorensen, A. (2006). Social learning and health plan choice. *RAND Journal of Economics 37*(4), 929–945. [16]

Sorenson, O. and T. Stuart (2001). Syndication networks and social distribution of venture capital. *American Journal of Sociology 106*(6), 1546–1588. [3]

Stiglitz, J. and A. Weiss (1981). Credit rationing in markets with imperfect information. *American Economic Review 71*(3), 393–410. [1]

Tribus, M. (1970). Panel on government and new business proceedings. In *Venture Capital and Management*, Management Seminar. Boston College. [3]

Weiss, G., K. Pelger, and A. Horsch (2010). Mitigating adverse selection in P2P lending: Empirical evidence from Prosper.com. Working Paper. [3]

Wilcoxon, F. (1945). Individual comparisons by ranking methods. *Biometrics Bulletin 1*, 80–83. [12]

Wolf, H. C. (2000). A intranational home bias in trade. *Review of Economics and Statistics 82*(4), 555–563. [25]

Wolken, J. and D. Rohde (2000). Changes in the location of small businesses' financial suppliers between 1993 and 1998. Technical report, Federal Reserve Board. Memo. [4]

Wong, A., M. Bhatia, and Z. Freeman (2009). Angel finance: The other venture capital. *Strategic Change 18*(7–8), 221–230. [3]

Zhang, J. and P. Lui (2012). Rational herding in microloan markets. *Managment Science 58*(5), 555–563. [15]

Zook, M. (2002). Grounded capital: Venture financing and geography of the internet industry. *Journal of Economic Geography 2*(2), 151–177. [3]

## 8. Tables & Figures

Table 1: Summary Statistics for Loan Request Listings

| All Listings N=42,657 | | | | | |
|---|---|---|---|---|---|
| | **Max** | **Mean** | **Median** | **Min** | **Std Dev** |
| **Loan Amount** | 25,000 | 8,349.23 | 6,000 | 1,000 | 6,558.28 |
| **Bid Count** | 1,124 | 47.4 | 5 | 1 | 102 |
| **Borrower Maximum Rate** | 0.360 | 0.232 | 0.224 | 0.010 | 0.092 |
| **DIR** | 10.10 | 1.90 | 0.31 | 0 | 3.60 |
| **Homeowner** | 1 | 0.49 | 0 | 0 | 0.49 |
| **Duration** | 10 | 7.10 | 7 | 3 | 1.33 |
| **Total Competition** | 3,401 | 2,119.1 | 2,158 | 484 | 428.9 |
| **Credit Grade Competition** | 508 | 206.6 | 201 | 1 | 93.6 |

Table 2: Listing and Loan Breakdown by Credit Grade

| | **All Listings** | **Completion Rate** | **All Loans** | **Default Rate** |
|---|---|---|---|---|
| **All** | 42,657 | 0.2256 | 9,099 | 0.3013 |
| **AA** | 3,471 | 0.4676 | 1,533 | 0.1768 |
| **A** | 4,272 | 0.3373 | 1,349 | 0.2491 |
| **B** | 6,118 | 0.3213 | 1,862 | 0.3287 |
| **C** | 9,462 | 0.2313 | 2,070 | 0.3193 |
| **D** | 11,082 | 0.1543 | 1,633 | 0.3588 |
| **E** | 8,252 | 0.0842 | 652 | 0.4233 |

Table 3: Category of Use by Credit Grace

**Frequency Distribution**

| | **AA** | **A** | **B** | **C** | **D** | **E** |
|---|---|---|---|---|---|---|
| **Debt Consolidation** | 28.35 | 38.27 | 45.00 | 47.00 | 48.95 | 49.96 |
| **Home Improvement** | 8.82 | 6.16 | 5.41 | 4.64 | 3.87 | 3.34 |
| **Business** | 30.60 | 28.28 | 23.8 | 19.50 | 13.65 | 11.46 |
| **Personal** | 16.22 | 13.69 | 14.35 | 15.78 | 18.37 | 20.95 |
| **Student** | 2.74 | 3.37 | 2.80 | 3.18 | 3.99 | 3.45 |
| **Auto** | 2.33 | 2.43 | 2.17 | 2.07 | 2.42 | 2.01 |
| **Other** | 10.95 | 7.79 | 6.47 | 7.83 | 8.74 | 8.81 |

**Completion Rate**

| | **AA** | **A** | **B** | **C** | **D** | **E** |
|---|---|---|---|---|---|---|
| **Debt Consolidation** | 46.14 | 33.46 | 31.27 | 22.49 | 15.41 | 8.17 |
| **Home Improvement** | 47.39 | 33.08 | 35.65 | 22.55 | 14.69 | 9.42 |
| **Business** | 39.55 | 26.82 | 25.07 | 15.50 | 10.38 | 4.23 |
| **Personal** | 55.42 | 42.74 | 39.29 | 29.40 | 16.11 | 9.2 |
| **Student** | 36.84 | 39.58 | 36.84 | 28.24 | 20.36 | 9.82 |
| **Auto** | 54.32 | 48.08 | 36.09 | 31.12 | 21.27 | 7.23 |
| **Other** | 56.05 | 37.84 | 41.92 | 29.55 | 18.47 | 12.79 |

Table 4: Summary Statistics of Bid Components by Credit Grade

| | Bid Amount | | | | | |
|---|---|---|---|---|---|---|
| | **Max** | **Mean** | **Median** | **Min** | **Std Dev** | **N** |
| **AA** | 25,000 | 81.36 | 50.00 | 50.00 | 165.92 | 487,604 |
| **A** | 20,000 | 83.45 | 50.00 | 50.00 | 163.36 | 417,263 |
| **B** | 25,000 | 75.36 | 50.00 | 50.00 | 144.67 | 493,833 |
| **C** | 15,000 | 74.77 | 50.00 | 50.00 | 142.6 | 343,720 |
| **D** | 16,000 | 74.24 | 50.00 | 50.00 | 147.33 | 223,038 |
| **E** | 12,000 | 89.29 | 50.00 | 50.00 | 177.76 | 57,452 |

| | Bid Interest Rate | | | | | |
|---|---|---|---|---|---|---|
| | **Max** | **Mean** | **Median** | **Min** | **Std Dev** | **N** |
| **AA** | 35.0 | 12.3 | 11.5 | 0.5 | 4.1 | 487,604 |
| **A** | 34.0 | 15.9 | 14.7 | 3.0 | 5.4 | 417,263 |
| **B** | 35.0 | 18.4 | 17.4 | 1.0 | 5.3 | 493,833 |
| **C** | 35.0 | 20.6 | 19.8 | 2.0 | 6.9 | 343,720 |
| **D** | 35.0 | 22.7 | 20.9 | 2.0 | 7.1 | 223,038 |
| **E** | 35.0 | 28.6 | 30.0 | 1.0 | 6.3 | 57,452 |

*Note:* Winning bids are assumed to be equal to the final interest rate.

Table 5: Bidding Activity of Bidders Prior to Their First Local Bid

| | **Max** | **75%** | **Mean** | **Median** | **25% Std Dev** | **N** | |
|---|---|---|---|---|---|---|---|
| **Days on Site** | 1041.90 | 375.36 | 210.30 | 124.59 | 13.47 | 222.98 | 17,852 |
| **Previous Bid Count** | 5,209 | 45 | 49.47 | 15 | 4 | 135.74 | 17,852 |

Table 6: Bid Amount and Bid Timing by Local Status

| | Bid Amount | | | Bid Time | | | |
|---|---|---|---|---|---|---|---|
| | **75%** | **Mean** | **Median** | **Mean** | **Median** | **25%** | **N** |
| **All Bids** | 72.30 | 78.65 | 50.00 | 0.634 | 0.791 | 0.304 | 2,022,910 |
| **Local Bids** | 79.00 | 88.02 | 50.00 | 0.619 | 0.769 | 0.272 | 118,798 |
| **Nonlocal Bids** | 70.68 | 78.07 | 50.00 | 0.635 | 0.792 | 0.304 | 1,904,112 |

Table 7: Effect of Local Status on Bid Amount, Tobit with censoring at log($50)

| **log(Bid Amount)** | **Coef.** | **Std. Err.** |
|---|---|---|
| **log(Loan Amount)** | $-0.032^{*}$ | 0.013 |
| **In Group** | $0.085^{***}$ | 0.009 |
| **Local Bidder** | $0.069^{***}$ | 0.013 |
| **Borrower Max Rate** | $0.011^{***}$ | 0.002 |
| **Borrower Max Rate_35** | $-0.076^{***}$ | 0.017 |
| **DIR** | $0.007^{**}$ | 0.002 |
| **Homeowner** | $0.042^{***}$ | 0.008 |
| **Total Competition** | -3.63E-06 | 2.75E-06 |
| **Credit Grade Competition** | 7.93E-05 | 1.12E-04 |
| **Fully Funded** | $0.084^{***}$ | 0.017 |
| **Current Bid Count** | $-2.99\text{E-}04^{***}$ | 7.47E-05 |
| **Current Rate** | $0.013^{***}$ | 0.002 |
| **N** | 2,022,910 | |
| **Pseudo $R^2$** | 0.159 | |

Significance: $0.10^{\dagger}$, $0.05^{*}$, $0.01^{**}$, and $0.001^{***}$.

FE: borrower & bidder state, category, credit grade, quarter, month, and day of the week.

Standard errors are clustered at the bidder level, intercept not shown.

Table 8: Ex-Ante Bid Interest Rate by Local Status and Ex-Post Loan Outcome

| | | Default=1 | | | | | Default=0 | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **Mean** | **Median** | **75%** | **N** | | **Mean** | **Median** | **75%** | **N** |
| **Local** | **AA** | 14.8 | 14.0 | 17.0 | 2,900 | **AA** | 11.7 | 11.0 | 13.0 | 9,283 |
| | **A** | 18.0 | 17.5 | 20.9 | 2,954 | **A** | 14.7 | 13.5 | 16.8 | 7,476 |
| | **B** | 19.9 | 19.1 | 22.0 | 3,763 | **B** | 17.6 | 17.0 | 19.1 | 6,887 |
| | **C** | 22.2 | 21.4 | 26.0 | 1,933 | **C** | 20.1 | 19.7 | 23.7 | 4,260 |
| | **D** | 24.1 | 23.5 | 29.0 | 1,333 | **D** | 22.2 | 21.3 | 26.0 | 3,074 |
| | **E** | 29.2 | 30.0 | 33.3 | 448 | **E** | 26.8 | 27.7 | 31.8 | 782 |

| | | Default=1 | | | | | Default=0 | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **Mean** | **Median** | **75%** | **N** | | **Mean** | **Median** | **75%** | **N** |
| **Nonlocal** | **AA** | 14.5 | 13.0 | 16.0 | 43,193 | **AA** | 12.0 | 11.5 | 14.0 | 161,125 |
| | **A** | 17.7 | 17.0 | 20.0 | 48,137 | **A** | 14.8 | 13.9 | 17.4 | 124,690 |
| | **B** | 19.5 | 19.0 | 20.4 | 63,793 | **B** | 17.7 | 17.0 | 19.8 | 115,335 |
| | **C** | 21.9 | 21.2 | 24.9 | 36,182 | **C** | 20.8 | 20.0 | 25.0 | 69,450 |
| | **D** | 23.3 | 22.9 | 26.0 | 22,047 | **D** | 22.6 | 22.0 | 27.0 | 43,849 |
| | **E** | 28.6 | 29.0 | 32.7 | 6,894 | **E** | 27.2 | 28.8 | 32.0 | 10,735 |

*Note:* Only observed interest rates from losing bids are used here.

Table 9: Tests for Difference Between Nonlocal and Local Bid Interest Rate Distributions

**$t$-Test for Difference in Mean**

| | **Default=1** | | **Default=0** | |
|---|---|---|---|---|
| **AA** | -3.14 | (0.001) | 4.47 | (0.000) |
| **A** | -2.97 | (0.002) | 1.23 | (0.215) |
| **B** | -6.00 | (0.000) | 0.83 | (0.406) |
| **C** | -1.70 | (0.088) | 6.93 | (0.000) |
| **D** | -4.30 | (0.000) | 3.79 | (0.000) |
| **E** | -2.53 | (0.011) | 2.40 | (0.016) |

**Mann-Whitney (Wilcoxon) $U$-test**

| | **Default=1** | | **Default=0** | |
|---|---|---|---|---|
| **AA** | -3.28 | (0.001) | 3.45 | (0.000) |
| **A** | -5.15 | (0.000) | 2.86 | (0.004) |
| **B** | -7.94 | (0.000) | 0.92 | (0.178) |
| **C** | -3.73 | (0.000) | 7.32 | (0.000) |
| **D** | -4.25 | (0.000) | 3.69 | (0.000) |
| **E** | -2.40 | (0.016) | 1.34 | (0.090) |

*Note:* Test statistics are for $(Nonlocal - Local)$
p-values are in parentheses.

Table 10: Effect of Local Status on Bid Interest Rate, Type II Tobit censored at Final Rate

| **Bid Interest Rate** | **Coef.** | **Std. Err.** |
|---|---|---|
| **Loan Amount** | $-0.037^{***}$ | 0.002 |
| **In Group** | $0.222^{***}$ | 0.016 |
| **LocalAA** | $-0.142^{***}$ | 0.033 |
| **LocalA** | $-0.071^{***}$ | 0.011 |
| **LocalB** | $-0.032^{*}$ | 0.013 |
| **LocalC** | $-0.051^{*}$ | 0.017 |
| **LocalD** | $-0.241^{**}$ | 0.098 |
| **LocalE** | $-0.907^{***}$ | 0.311 |
| **Defaulted** | $0.041^{***}$ | 0.010 |
| **LocalAA_Defaulted** | $0.282^{***}$ | 0.063 |
| **LocalA_Defaulted** | $0.1536^{\dagger}$ | 0.086 |
| **LocalB_Defaulted** | $0.122^{\dagger}$ | 0.067 |
| **LocalC_Defaulted** | $0.332^{***}$ | 0.104 |
| **LocalD_Defaulted** | $0.298^{*}$ | 0.148 |
| **LocalE_Defaulted** | $0.992^{*}$ | 0.414 |
| **Borrower Max Rate** | $0.072^{***}$ | 0.003 |
| **Borrower Max Rate_35** | $0.514^{***}$ | 0.050 |
| **DIR** | $0.012^{**}$ | 0.004 |
| **Homeowner** | $0.323^{*}$ | 0.012 |
| **Total Competition** | $-8.40\text{E-}5^{***}$ | 8.29E-6 |
| **Credit Grade Competition** | $8.44\text{E-}3^{***}$ | 2.27E-4 |
| **Current Bid Count** | $1.13\text{E-}3^{***}$ | 1.04E-4 |
| **Current Rate** | $0.698^{***}$ | 0.005 |
| **N** | 1,598,786 | |
| **Prob >** $\chi^2$ | 0 | |

Significance: $0.10^{\dagger}$, $0.05^{*}$, $0.01^{**}$, and $0.001^{***}$.

FE: borrower & bidder state, category, credit grade, quarter, month, and day of the week.

Standard errors are clustered at the bidder level, intercept not shown.

Table 11: Bid Count and Amount Pledged in an Auction Before a Bidder Bids by Local Status

**Number of Previous Bids**

| | **75%** | **Mean** | **Median** | **25%** | **N** |
|---|---|---|---|---|---|
| **All Bidders** | 186 | 132.9 | 84 | 28 | 2,022,910 |
| **Local Bidders** | 166 | 117.4 | 73 | 23 | 118,798 |
| **Nonlocal Bidders** | 186 | 132.7 | 84 | 28 | 1,904,112 |

**Amount Pledged**

| | **75%** | **Mean** | **Median** | **25%** | **N** |
|---|---|---|---|---|---|
| **All Bidders** | 14,433.25 | 10,579.39 | 6,369.95 | 2,250 | 2,022,910 |
| **Local Bidders** | 12,891.95 | 9,396.56 | 5,550.23 | 1,800 | 118,798 |
| **Nonlocal Bidders** | 14,393.88 | 10,558.23 | 6,358.73 | 2,252 | 1,904,112 |

Table 12: Marginal Effect of Early Local Bids on Bid Count

| | **Total Bid Count** | | **Nonlocal Bid Count** | |
|---|---|---|---|---|
| | **dy/dx** | **Std. Err.** | **dy/dx** | **Std. Err.** |
| **Total Early Bid Count** | 0.04*** | 0.003 | 0.03*** | 0.002 |
| **Total Early Bid Amount** | 1.46E-3*** | 3.96E-5 | 1.40E-3*** | 2.13E-5 |
| **Early Local Bid Count** | 0.06*** | 0.013 | 0.02* | 0.008 |
| **Early Local Bid Amount** | 2.01E-3*** | 1.30E-4 | 1.19E-3*** | 7.46E-5 |
| **Completed** | 124.75*** | 0.136 | 101.17*** | 0.187 |
| **In Group** | 3.27*** | 0.106 | 1.96*** | 0.068 |
| **Loan Amount** | 2.53*** | 0.006 | 0.91*** | 0.004 |
| **Borrower Max Rate** | 1.68*** | 0.007 | 0.98*** | 0.005 |
| **Borrower Max Rate_35** | −12.39*** | 0.143 | −4.65*** | 0.096 |
| **DIR** | −2.64*** | 0.014 | −0.94*** | 0.009 |
| **Homeowner** | 0.63*** | 0.075 | 0.77*** | 0.051 |
| **Total Competition** | −9.20E-4*** | 7.63E-4 | −6.11E-4*** | 5.12E-5 |
| **Credit Grade Competition** | 0.08*** | 0.001 | −0.09*** | 0.001 |
| **N** | 42,657 | | 42,657 | |
| **Pseudo $R^2$** | 0.8302 | | 0.8584 | |

Significance: 0.10†, 0.05*, 0.01**, and 0.001***.

FE: state, category, credit grade, quarter, month, and day of the week, intercept not shown.

Table 13: Marginal Effect of Early Local Bids on Pre-Fully Funded Bid Count

| | **Total Pre-FF Bid Count** | | **Nonlocal Pre-FF Bid Count** | |
|---|---|---|---|---|
| | **dy/dx** | **Std. Err.** | **dy/dx** | **Std. Err.** |
| **Total Early Bid Count** | 0.65*** | 0.009 | 0.63*** | 0.009 |
| **Total Early Bid Amount** | 6.88E-3*** | 1.44E-4 | 6.58E-3*** | 1.42E-4 |
| **Early Local Bid Count** | 0.20*** | 0.039 | 0.20* | 0.040 |
| **Early Local Bid Amount** | 4.20E-3*** | 4.13E-4 | 4.86E-3*** | 4.25E-4 |
| **In Group** | −5.44*** | 0.306 | −5.48*** | 0.298 |
| **Loan Amount** | 7.74*** | 0.020 | 7.31*** | 0.019 |
| **Borrower Max Rate** | −0.69*** | 0.021 | −0.65*** | 0.020 |
| **Borrower Max Rate_35** | −3.00*** | 0.456 | −2.71*** | 0.444 |
| **DIR** | −1.53*** | 0.042 | −1.48*** | 0.041 |
| **Homeowner** | −1.39*** | 0.212 | −1.27*** | 0.206 |
| **Total Competition** | 1.65E-4 | 2.13E-4 | 1.63E-4 | 2.07E-4 |
| **Credit Grade Competition** | 2.51E-2*** | 1.94E-3 | 2.44E-2*** | 1.88E-3 |
| **N** | 9,624 | | 9,624 | |
| **PseudoR$^2$** | 0.7108 | | 0.7053 | |

Significance: 0.10$^{\dagger}$, 0.05*, 0.01**, and 0.001***.

FE: state, category, credit grade, quarter, month, and day of the week, intercept not shown.

Table 14: Marginal Effect of Early Local Bids on Post-Fully Funded Bid Count

| | **Total Post-FF Bid Count** | | **Nonlocal Post-FF Bid Count** | |
|---|---|---|---|---|
| | **dy/dx** | **Std. Err.** | **dy/dx** | **Std. Err.** |
| **Total Early Bid Count** | 0.18*** | 0.006 | 0.17*** | 0.006 |
| **Total Early Bid Amount** | 6.56E-3*** | 9.09E-5 | 6.24E-3*** | 8.85E-5 |
| **Early Local Bid Count** | 0.16*** | 0.035 | 0.16** | 0.036 |
| **Early Local Bid Amount** | −2.43E-3*** | 3.08E-4 | −2.71E-3*** | 3.20E-4 |
| **In Group** | 9.19*** | 0.297 | 8.35*** | 0.289 |
| **Loan Amount** | 3.84*** | 0.019 | 3.65*** | 0.018 |
| **Borrower Max Rate** | 4.47*** | 0.022 | 4.21*** | 0.021 |
| **Borrower Max Rate_35** | −20.46*** | 0.423 | −19.03*** | 0.411 |
| **DIR** | −4.13*** | 0.042 | −3.87*** | 0.041 |
| **Homeowner** | 3.90*** | 0.224 | 4.01*** | 0.218 |
| **Total Competition** | −2.70E-3*** | 2.24E-4 | −2.66E-3*** | 2.18E-4 |
| **Credit Grade Competition** | −0.45*** | 0.003 | −0.42*** | 0.003 |
| **N** | 9,624 | | 9,624 | |
| **Pseudo $R^2$** | 0.5270 | | 0.5243 | |

Significance: 0.10†, 0.05*, 0.01**, and 0.001***.

FE: state, category, credit grade, quarter, month, and day of the week, intercept not shown.

Table 15: Marginal Effect of Early Local Bids on Bid Count After the First Two Hours

| | **Total Bid Count** | | **Nonlocal Bid Count** | |
|---|---|---|---|---|
| | **dy/dx** | **Std. Err.** | **dy/dx** | **Std. Err.** |
| **Total Early Bid Count** | 0.20*** | 0.002 | 0.19*** | 0.002 |
| **Total Early Bid Amount** | 8.25E-3*** | 2.97E-5 | 7.76E-3*** | 2.88E-5 |
| **Early Local Bid Count** | 0.11*** | 0.012 | 0.08*** | 0.013 |
| **Early Local Bid Amount** | −1.28E-3 | 1.19E-4 | −1.79*** | 1.25E-4 |
| **Loan Amount** | −0.163*** | 0.005 | −0.15*** | 0.005 |
| **In Group** | 9.15*** | 0.100 | 8.54*** | 0.097 |
| **Borrower Max Rate** | 2.99*** | 0.006 | 2.81*** | 0.006 |
| **Borrower Max Rate_35** | −29.21*** | 0.127 | −27.25*** | 0.124 |
| **DIR** | −5.47*** | 0.014 | −5.13*** | 0.013 |
| **Homeowner** | −2.48*** | 0.069 | −2.21*** | 0.067 |
| **Total Competition** | −1.98E-3*** | 7.15E-5 | -1.85E-3 | 6.94E-5 |
| **Credit Grade Competition** | -8.94E-4 | 8.05E-4 | -8.55E-6 | 7.82E-4 |
| **N** | 42,657 | | 42,657 | |
| **Pseudo $R^2$** | 0.4411 | | 0.4392 | |

Significance: 0.10†, 0.05*, 0.01**, and 0.001***.

FE: state, category, credit grade, quarter, month, and day of the week, intercept not shown.

Table 16: Marginal Effect of Early Local Bidding on Probability of Funding and Final Interest Rate

| | **Probability of Funding** | | **Final Interest Rate** | |
|---|---|---|---|---|
| | **dy/dx** | **Std. Err.** | **Coef.** | **Std. Err.** |
| **Total Early Bid Count** | 0.027$^{***}$ | 0.001 | $-$0.0193$^{***}$ | 0.002 |
| **Total Early Bid Amount** | 1.30E-4$^{***}$ | 1.07E-5 | $-$3.95E-3$^{***}$ | 5.80E-4 |
| **Early Local Bid Count** | 8.49E-3$^{*}$ | 3.67E-3 | $-$0.030$^{**}$ | 0.011 |
| **Early Local Bid Amount** | $-$4.53E-5$^{***}$ | 1.59E-5 | $-$6.10E-3$^{***}$ | 1.37E-4 |
| **Loan Amount** | $-$0.027$^{***}$ | 4.32E-4 | 0.160$^{***}$ | 0.008 |
| **In Group** | 0.033$^{***}$ | 0.003 | $-$0.335$^{**}$ | 0.109 |
| **Borrower Max Rate** | $6.93E-3^{***}$ | 2.77E-4 | 0.518$^{***}$ | 0.007 |
| **Borrower Max Rate_35** | $-$0.026$^{***}$ | 0.004 | 1.216$^{***}$ | 0.147 |
| **DIR** | $-$3.18E-3$^{***}$ | 4.42E-4 | 0.051$^{***}$ | 0.014 |
| **Homeowner** | -3.43E-3 | 2.79E-3 | 0.270$^{***}$ | 0.079 |
| **Total Competition** | 2.66E-4 | 2.97E-4 | 1.41E-4$^{\dagger}$ | 8.20E-5 |
| **Credit Grade Competition** | $-$3.504$^{***}$ | 2.75E-5 | $-$5.96E-3$^{***}$ | 6.44E-4 |
| **N** | 42,656 | | 9,624 | |
| **Adj $R^2$** | 0.5521 | | 0.7542 | |

Significance: 0.10$^{\dagger}$, 0.05$^{*}$, 0.01$^{**}$, and 0.001$^{***}$.

FE: state, category, credit grade, quarter, month, and day of the week, intercept not shown.

Table 17: Marginal Effect of Early Local Bidding on Probability of Default

| | **Pre-Fully Funded** | | **First 2 hr** | |
|---|---|---|---|---|
| **Default** | **dy/dx** | **Std. Err.** | **dy/dx** | **Std. Err.** |
| **Early Local Bid Count** | -0.143 | 0.089 | -0.019 | 0.181 |
| **Early Local Bid Amount** | -6.16e-4 | 6.44E-4 | -1.09E-3 | 1.60E-3 |
| **Loan Amount** | $0.777^{***}$ | 0.120 | $0.847^{***}$ | 0.000 |
| **In Group** | $-5.007^{***}$ | 1.409 | $-5.038^{***}$ | 1.411 |
| **Borrower Max Rate** | $0.675^{***}$ | 0.117 | $0.674^{***}$ | 0.117 |
| **Borrower Max Rate_35** | $-5.233^{**}$ | 1.757 | $-5.230^{**}$ | 1.757 |
| **Loan Rate** | $0.892^{***}$ | 0.120 | $0.876^{***}$ | 0.121 |
| **DIR** | $0.373^{***}$ | 0.186 | $0.354^{\dagger}$ | 0.186 |
| **Homeowner** | $7.148^{***}$ | 1.007 | $7.135^{***}$ | 1.008 |
| **Total Competition** | -4.52E-4 | 1.05E-3 | -4.64E-4 | 1.05E-3 |
| **Credit Grade Competition** | 6.18E-4 | 8.05E-3 | -6.53E-3 | 8.06E-3 |
| **N** | 9,091 | | 9,091 | |
| **Pseudo $R^2$** | 0.0872 | | 0.0870 | |

Significance: $0.10^{\dagger}$, $0.05^{*}$, $0.01^{**}$, and $0.001^{***}$.

FE: state, category, credit grade, quarter, month, and day of the week, intercept not shown.

Figure 1: An Example of a Loan Request Listing

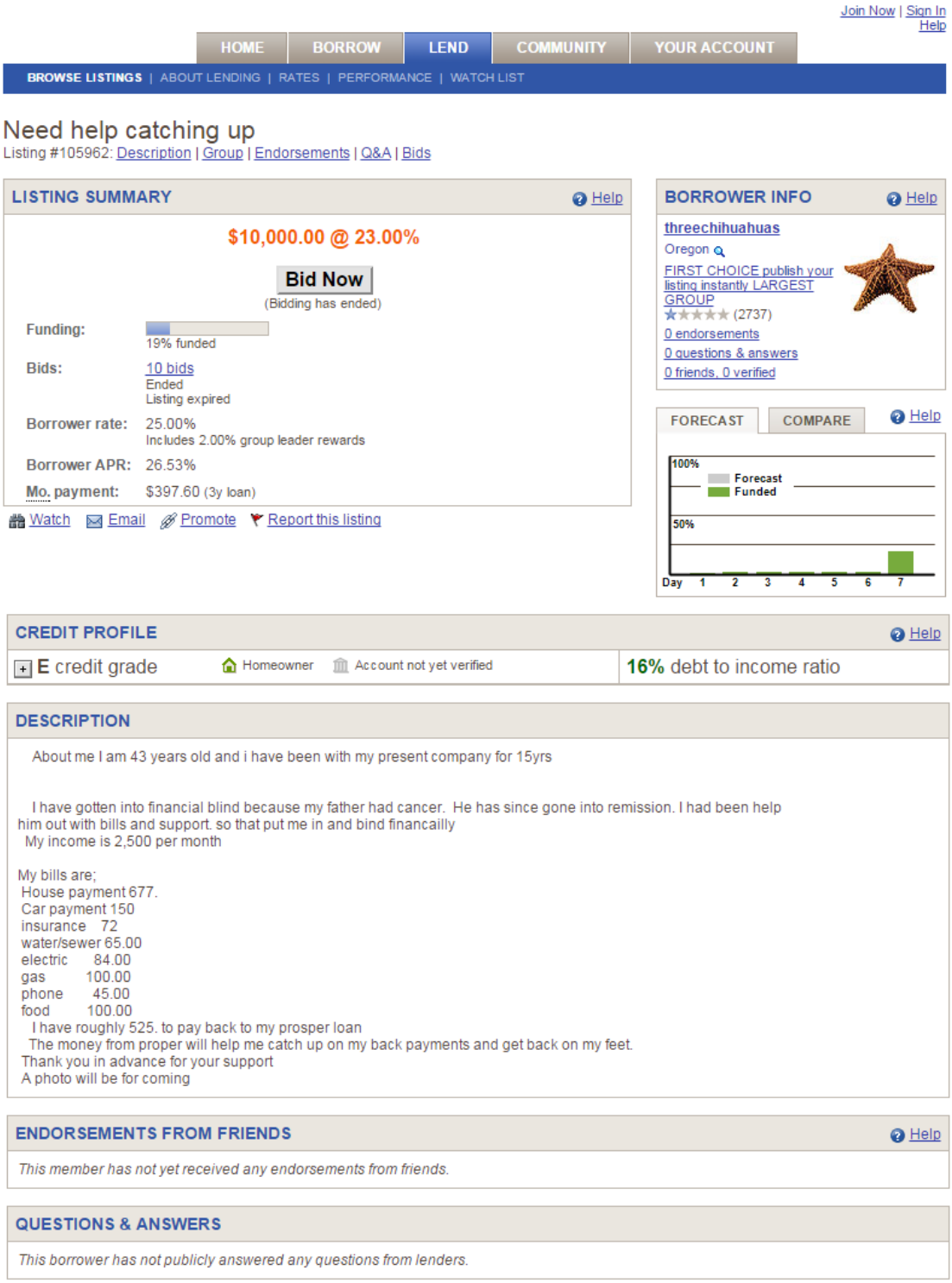

Figure 2: CDF of Bid Times by Local Status