The Geography of Bidder Behavior in Peer-to-Peer Credit Markets*

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Abstract. *Theoretical and empirical research on the traditional credit market finds strong evidence that investors and lenders are sensitive to their distance from the borrower, especially early on in a venture. This is due to the cost of information gathering and monitoring. However, new online platforms could overcome the 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 lenders tend to bid earlier, both chronologically and relatively to other bidders in the auction, and bid larger amounts than nonlocal lenders. Additionally, local lenders 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 they 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 lenders, 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 lenders are driven mostly by informational frictions and not merely preferences. Local lenders 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

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Weiss, 1981; Dell'Ariccia and Marquez, 2004). However, the modern financial ecosystem is 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). Empirical work on the economic consequences of the internet consistently find two facts: the Internet can overcome geographic isolation (Balasubramanian, 1998; Forman, Ghose, and Goldfarb, 2009; Choi and Bell, 2011), and search costs are lower online than compared to offline (Bakos, 1997; Baye, Gatii, Kattuman, and John, 2009). Utilizing these new and cheaper online connections and crowdfunding websites, individuals are starting to find novel ways to address and overcome the asymmetry in the credit market. In this paper, I explore the informational frictions, arising due to geography, that have traditionally plagued the offline 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 groups of investors to lend money directly to individual borrowers 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 of lenders bid the same way when faced with similar investing options, it is most likely that the internet has removed the geography-based 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.

A long literature documents the importance of distance in social and economic behavior; famously the first law of geography states "all things are related, but near things are more related than far things," (Tobler, 1970). Additionally, there is an extensive theoretical work on early investing and capital ventures that predicts that investors and lenders are sensitive to their distance from the borrower– especially true in the early stages of the venture when there is little to no observable history.[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. 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

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

[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); French and Poterba (1991); 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).

collect a sizeable amount of information before deciding to invest and determining the rate. The geographic proximity of local lenders 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 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]

[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).

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 geographic frictions exist on the online credit market, and if so what factors contribute to their existence. My analysis centers on how geography affects lender 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 lenders: (1) do local lenders bid different amounts, (2) do local lenders evaluate and price the risk of the listings differently, and (3) do local lenders 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 lenders, and lastly, (5) how does the presence of local lenders in the market affect other lenders' 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 lenders tend to bid earlier and larger amounts than nonlocal lenders. Furthermore, local lenders 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 lenders' interest rate bids demonstrate support for the informational-based explanation of the observed behavioral differences between lenders.

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. Combined, they issued almost $5 billion in loans in 2014 and are predicted to issue about $8 billion in 2015 (NSR Invest, 2015). In this paper I 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 lenders. 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 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, see Figure 1. The funding mechanism is a descending price uniform share 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, lenders 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

[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.

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 lender receives 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. 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.[12] 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 lender 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

[12]This Prosper group never quite took out and are not widely used.

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 lender bids on a particular listing. This process allows me to observe the current state of the listing as each lender 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. 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 any kind 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. While these default rates seem rather, it is important to recall that this is a measure of any kind of default. However, these magnitudes are well in line with national residential mortgage delinquency rates from the same time period.[13]

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

[13]Source: https://www.richmondfed.org/-/media/richmondfedorg/banking/markets_trends_and_statistics/trends/pdf/delinquency_and_foreclosure_rates.pdf

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).[14] 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 lenders tend to diversify across listings by pledging small amounts in any one particular listing. The mean bid amount is non-monotonic across credit grades; lenders 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 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 rates appears to increase as the credit grade worsens (the correlation between credit grade and standard deviation of bid interest rate is 0.833).

[14] 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).

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 little legal recourse other than the standard collection process and reporting the loan default to all credit reporting bureaus. 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 lenders 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 lenders should be observationally equivalent. However, if there are differences between behavior based upon the location of the lender 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 lenders are not any better informed than nonlocal lenders, but they simply prefer local projects.

Following the literature on online markets (Wolf, 2000; Hillberry and Hummels, 2003; Hortaçsu et al., 2009), I define localness to be when the lender and the borrower reside in the same state. Admittedly, a smaller unit measure is preferred; however, Prosper does not require individuals to publicly post their city, and they actually discourage it to prevent borrowers from personally identifying themselves. If the actual effect of information asymmetry is limited to a smaller physical proximity, then my state definition of localness is counting a significant amount of nonlocal lenders as local. Therefore, I am making the two groups of lenders more similar and weakening the potential differences that I can measure. Thus this data limitation mean that my estimates are actually a lower bound on the true effect of localness. As a robustness check, I also run my analysis using the smaller, restricted sample where local status is determined by the lender living within the same city as the borrower. The results are qualitatively the same but suffer from power issues due to the small sample size; thus for brevity, the tables can be found in the appendix.

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

All regressions include Borrower and lender State (where applicable), Credit Grade, Category of use, Quarter, Month, and Day of the Week fixed effects.[15] 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.

4.1. Local lenders 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

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

nonlocal bids; these differences are significant at the 1% level. It is clear that local lenders bid larger amounts than their nonlocal counterparts.

To formally test the question of whether local lenders bid larger amounts than nonlocal lenders, I run a Tobit regression of log bid amount with left censoring at $\log(\$50)$ while including an indicator for local lender. Standard errors are clustered at the lender level to control for any unobserved correlation between the bidding activity of the same lender. Table 7 shows the results; I find that even after controlling for all the observable listing characteristics, local lenders bid roughly 7% larger amounts than nonlocal lenders. This effect is of the similar magnitude to the increase in bid amount that occurs if lender 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 lender's behavior on the site, and not on the lenders themselves. It is well documented that demographic characteristics like age, educational attainment, marital status, gender, race, and risk tolerance all affect asset holdings.[16] More information about the heterogeneity of lenders would likely improve the fit of this regression.

Knowing that local lenders have a larger demand for local loans suggests that lenders 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). Regardless of the ex-post outcome, local lenders bid larger amount than their nonlocal counterparts; however the magnitude of the difference is significantly larger for loans that pay back in full. As can be seen in Table 8, while the differential between local and nonlocal lenders is significantly greater than zero regardless of loan outcome, it is 2.7 percentage points larger for loans that ex-post pay back. This behavior suggest that there does exist a preference for local loans, but the local lenders are better informed and thus demand larger amounts of the less risky local loans.

4.2. Local lenders Evaluate the Probability of Default Better than Nonlocal lenders

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

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

be better able to evaluate the risk of the listing. For example, if there are two listings that look identical to nonlocal lenders, but one is riskier than another, local lenders 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 9 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 lenders 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 lenders tending to bid lower ex-ante interest rates. These two observations strongly suggest that local lenders seem to more accurately price the underlying risk of the listings than nonlocal lenders.

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 10 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 10 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.[17]

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 alternative hypothesis (i.e., the local distribution stochastically dominates the nonlocal

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

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 lenders' bid interest rates seem to better reflect the true revealed riskiness of a local listing.[18]

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 lender level. The regression contains indicators for local lender interacted credit grade, an indicator for if the loan defaulted, and the local lender indicator interacted with credit grade and the default dummy. The results displayed in Table 11 are consistent with the previous results, showing that local lenders 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 lenders 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 lenders 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 lenders 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 lenders give to loans that ex-post default, relative to nonlocal lenders, 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 do not default. E listings generally get the smallest premium followed very closely by A,

[18] 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.

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 lender behavior supports the idea that local lenders seem better able to evaluate a listing's underlying risk than nonlocal lenders, with the obvious rationale being that local lenders 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 lenders 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 lenders.

4.3. Local lenders Bid Earlier

If local lenders 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 lenders are learning from local bids, then local lenders should be bidding earlier in the auction so that nonlocal lenders 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 lenders tend to bid earlier during the auction than nonlocal lenders. 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 lenders do bid significantly earlier than nonlocal lenders, 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 lenders tends to be significantly smaller than the distribution of bid times for nonlocal lenders.[19] To further illustrate that local lenders 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 order stochastically dominates the local bid time distribution. The distance between the

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

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.[20] 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 lenders. End-of-auction bidding is a common practice for both local and nonlocal lenders 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 12 displays the summary statistics for the number of bids placed and money pledged in a listing immediately before a lender bids by local status. As can be clearly seen, local lenders bid earlier in an auction not just chronologically. Local lenders have demonstrated that they are more comfortable bidding in periods where limited information is being revealed by other lenders.

I have documented that local lenders tend to bid earlier and larger amounts, on average, than nonlocal lenders. Additionally, local lenders bid different interest rates from nonlocal lenders 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 lenders are better informed than other lenders, which fits well with theory. This asymmetric information based on physical geography creates a situation where social learning can occur as local lenders, through their bidding behavior, reveal their private information to nonlocal lenders. 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, the following section constructs a theoretic framework grounded in the previously established facts to better understand and explain how the differential behavior of local lenders will affect P2P lending auctions. I develop a simple information-based social-learning model to explain and predict how better informed local lenders reveal their private information to nonlocal lenders through their actions. The model produces the testable hypothesis that listings with more early local lenders will attract more lenders to the listing.

5. Motivating Model

The central proposition of this paper is that local lenders are more informed about local listings than nonlocal lenders. Thus, local lenders are better able to correctly evaluate the underlying risk in the listing when they bid. Being better informed allows local lenders

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

to be more comfortable bidding earlier, acting mostly on their own private information. Similar to Sorensen (2006) and Smith and Sørensen (2008), local lenders' actions serve as signals of their private information. As pointed out by Devenow and Welch (1996), social learning involves an informational externality where lenders may gain useful information from observing previous lenders' decisions. Due to the existing informational asymmetry, nonlocal lenders can learn from observing the actions of others, particularly local lenders. 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 lenders, with vNM utility, who are maximizing their expected utility of monetary payoff from investing.[21] The heterogeneity comes from the existence of two different types of lenders: local and nonlocal. An L share of the lenders are local, who are better informed, and a $(1-L)$ share are nonlocal.[22] Each lender is presented with the same collection of listings indexed by $i \in [0, 1]$. The monetary return from investing in the ith listings is $z(i) \in \mathbf{R}$, which is the same for all lenders. 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 lenders is to invest in that listing. Although in Prosper lenders decide how much money to pledge in a particular listing, for simplicity, each lender's decision is restricted to simply choosing which listing to invest in.[23]

At start of the game, all lenders have the same ex-ante uniform priors about which listing will pay positive returns. However, some lenders have an idea of which listing is the likely candidate for i^*. Formally, with probability $\alpha \in (0, 1)$, lender 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 lenders are assumed to be more informed than nonlocal lenders, so their signals will be more informative. The signal of a local lender 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 lenders is

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

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

[23] It is possible that a lender'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.

the same as of local lenders, except it is less informative. Formally, a nonlocal signal is correct with probability $\gamma \in (0.5, 1)$, with $\beta > \gamma$.

lenders do not ex-ante know the local status of the preceding lenders. If their behavior does not reveal their status, the current lender will assume that the preceding lender is as informed as the average lender 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 lender is than a nonlocal one.[24] Given that the local lenders 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 lenders act in unison. lenders move sequentially in a fixed order, a lender cannot decide to delay his decision, which is exogenously set randomly before the game begins. Each lender's information set includes only the actions of the preceding lenders, 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 lender 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 lender then chooses to invest in that listing. The rest of the game proceeds in this way, with each new lender using the observed history and their own signal, if he has one, to make his choice. Due to the symmetry between lenders, some actions, after a particular history, will reveal that a preceding lender must be local. This revealing behavior occurs when a lender chooses to act in a way that only a local lender with a signal would act given the decisions made by the preceding lenders. I refer to these lenders as revealed local lenders. All following lenders will rationally update their beliefs when optimizing to account for this fact. After all the lenders 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 lenders. Consequently, each lender's decision rule is based solely on the history and his signal. When indifferent, lenders use the three classical tie-breaking assumptions in Banerjee (1992): (A) If a lender has no signal and everyone else before her has chosen the zero listing, then she will always choose the zero listing, (B) if a lender is indifferent between following her own signal or someone else's choice, she always follows her own signal, and (C) if a lender is indifferent between following more than one other lenders' 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 lender that is completely uninformed. Assumption (B) follows from the idea that when in doubt, lenders will trust their own information, and

[24] See the appendix for the condition.

Assumption (C) is just purely a tie-breaking rule.[25]

Because each lender'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 lenders 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 lenders. 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 lenders later in the auction.

The first lender 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 lender 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 lender 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 lender choose zero does not provide any information to the subsequent lenders.

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

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

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

The third lender will follow his signal, if he has one, if: (a) all preceding lenders choose the zero listing, (b) he is a local lender, or (c) his signal matches a choice made by a preceding lender. Otherwise, the third lender will follow the choice of the second lender. It is important to point out here that whenever a lender's signal matches the choice made by one the preceding lenders, he should always follow his signal. This result follows from the fact that the probability of two lenders 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 lender in history (3). In this history, both previous lenders choose the same non-zero listing, but by doing so neither of them reveals their local status. Therefore, a local third lender will still follow his own private signal while a nonlocal lender would follow the preceding two lenders. This is an example of local lenders 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 lenders all choose the same non-zero listing, then all subsequent lenders, regardless of their local status, will follow them and choose that listing.*
If the first three lenders all choose the same non-zero listing, then the fourth lender is certain that the first lender received a signal. Additionally, if any of the other lenders also received a signal and were local, their signal must have matched the first lender'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 lender 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 lenders 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 lender. All subsequent lenders will choose this listing, except if the lender receives a signal that matches an already chosen listings, then the lender will find his signal. Therefore, if a particular listing is chosen by three unknown status lenders, in excess of the next most chosen listing, a herd starts and no more information will be revealed from lenders' actions.

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

status lenders. As long as the fifth lender's signal does not match the first lender's choice, then one of the unknown status lenders choosing listing j, in a loose sense, cancels out the first lender'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 lender and one unknown status lender. 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 lenders, and one of them receives an additional bid from a revealed local and one unknown status lender. Then all subsequent lenders who's signals do not match an already chosen listing, regardless of local status, will choose the listing with the most lenders. After this event occurs, a herd starts and no more information will be revealed from lenders' choice of this listing, resulting in the relative information structure remaining unchanged.

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

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

Given that local lenders 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 lenders is more accurate than that of a nonlocal lender 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 lenders 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 lenders, (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 lenders tend to bid earlier and appear to be more informed about general market conditions and underlying riskiness of the borrower than nonlocal lenders. 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 early bids ($TEBC$) and the amount of money pledged by all lenders ($TEBA$), as well as just number of bids submitted by local lenders ($LEBC$) and the amount of money pledged by them ($LEBA$). Having the total early bids and 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 lenders (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. The results are robust to changes of the definition of the early period.[26] For the sake of brevity, only results from the first two hours are reported in this paper.

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 13 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 bid count. Even when focusing just on total-nonlocal bids, one early local bid has roughly

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

the same effect as two nonlocal early bids, given that all the bids are the same monetary size, in attracting more lenders 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 lender'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 lenders. 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 lender will be funding. This means that that lender 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, lenders 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 14 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 15 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.[27] This result implies that for the same amount of local money pledged, having more local lenders bid smaller individual amounts will have a larger impact on the number

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

of post-fully funded bids than less local lenders bidding larger amounts. The bidding behavior of preceding lenders only partially reveals their private information, so having more local lenders accumulating and transmitting their better information will have a larger and more meaningful effect on later lenders than a single local lender bidding larger amounts. Reflecting back to the theoretical framework, the expected value of a listing increases as more local lenders, especially early on in the auction, choose it. This result seems to suggest that the intensity of the individual demand of a lender does not convey much information beyond the fact that a lender 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 16 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 lenders 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 17 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 lender 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 lenders appear to better price listings than nonlocal lenders. If the listing possesses some extra risk that is hidden to uninformed nonlocal lenders, then the local lenders 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 17 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 lenders are better informed than nonlocal lenders, listings with more early local bidding should have a higher probability of not defaulting. Table 18 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 lenders accumulates as more of them bid early in the auction and this information is transmitted to other lenders, 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 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.

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 fully overcome the traditional 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 lenders 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 lenders have easier and cheaper access to information and, thus, are better informed about local listings than their nonlocal counterparts. If local lenders were only acting altruistically towards local borrowers, then local lenders should generally be bidding lower interest rates on local listings regardless of the ex-post loan outcome. However, the data shows clearly that local lenders are bidding differentially based on the inferred quality of the borrower. Local lenders appear to be accounting for riskiness that nonlocal lenders are not, implying that local lenders can better evaluate the probability of default of local projects. That being said, it is evident from the fact that local lenders have a larger demand for local listings, regardless of the ex-post loan outcome, that there exists some degree of local preference among lenders. 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 lender behavior, but information-based frictions play a major role in explaining the behavioral difference

between local and nonlocal lenders 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.[28] Additionally, work like Ghose, Goldfarb, and Han (2013) even finds that the type of device used to access information online affects search costs. 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 vastly 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.

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

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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 Lender	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: Effect of Local Status on Bid Amount by Ex-Post Outcome

log(Bid Amount)	**Coef.**	**Std. Err.**
ln(Loan Amount)	-0.045^{***}	0.002
In Group	0.078^{***}	0.003
Local Lender	0.070^{***}	0.006
Default	-0.008^{**}	0.002
Local Lender_Default	-0.027^{**}	0.009
Borrower Max Rate	0.008^{***}	4.264E-04
Borrower Max Rate_35	-0.040^{***}	0.005
DIR	0.007^{***}	4.550E-04
Homeowner	0.046^{***}	0.002
Duration	0.006^{***}	0.001
Total Competition	$-7.590E-06^{**}$	2.410E-06
Credit Grade Competition	$2.864E-04^{***}$	2.580E-05
Fully Funded	0.070^{***}	0.003
Current Bid	$-1.319E-04^{***}$	1.230E-05
Current Rate	0.017^{***}	4.454E-04
N	1,598,786	
Pseudo R^2	0.157	

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 9: 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 10: 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 11: 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 > χ^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 12: 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 13: 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: $0.10^{\dagger}$, 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 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†, 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 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	$6.56\text{E-}3^{***}$	9.09E-5	$6.24\text{E-}3^{***}$	8.85E-5
Early Local Bid Count	0.16^{***}	0.035	0.16^{**}	0.036
Early Local Bid Amount	$-2.43\text{E-}3^{***}$	3.08E-4	$-2.71\text{E-}3^{***}$	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	$-2.70\text{E-}3^{***}$	2.24E-4	$-2.66\text{E-}3^{***}$	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: $0.10^{\dagger}$, 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 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	$8.25\text{E-}3^{***}$	2.97E-5	$7.76\text{E-}3^{***}$	2.88E-5
Early Local Bid Count	0.11^{***}	0.012	0.08^{***}	0.013
Early Local Bid Amount	$-1.28\text{E-}3$	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	$-1.98\text{E-}3^{***}$	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: $0.10^{\dagger}$, 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 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	$1.30\text{E-}4^{***}$	1.07E-5	$-3.95\text{E-}3^{***}$	5.80E-4
Early Local Bid Count	$8.49\text{E-}3^{*}$	3.67E-3	-0.030^{**}	0.011
Early Local Bid Amount	$-4.53\text{E-}5^{***}$	1.59E-5	$-6.10\text{E-}3^{***}$	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	$-3.18\text{E-}3^{***}$	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	$1.41\text{E-}4^{\dagger}$	8.20E-5
Credit Grade Competition	-3.504^{***}	2.75E-5	$-5.96\text{E-}3^{***}$	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 18: 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

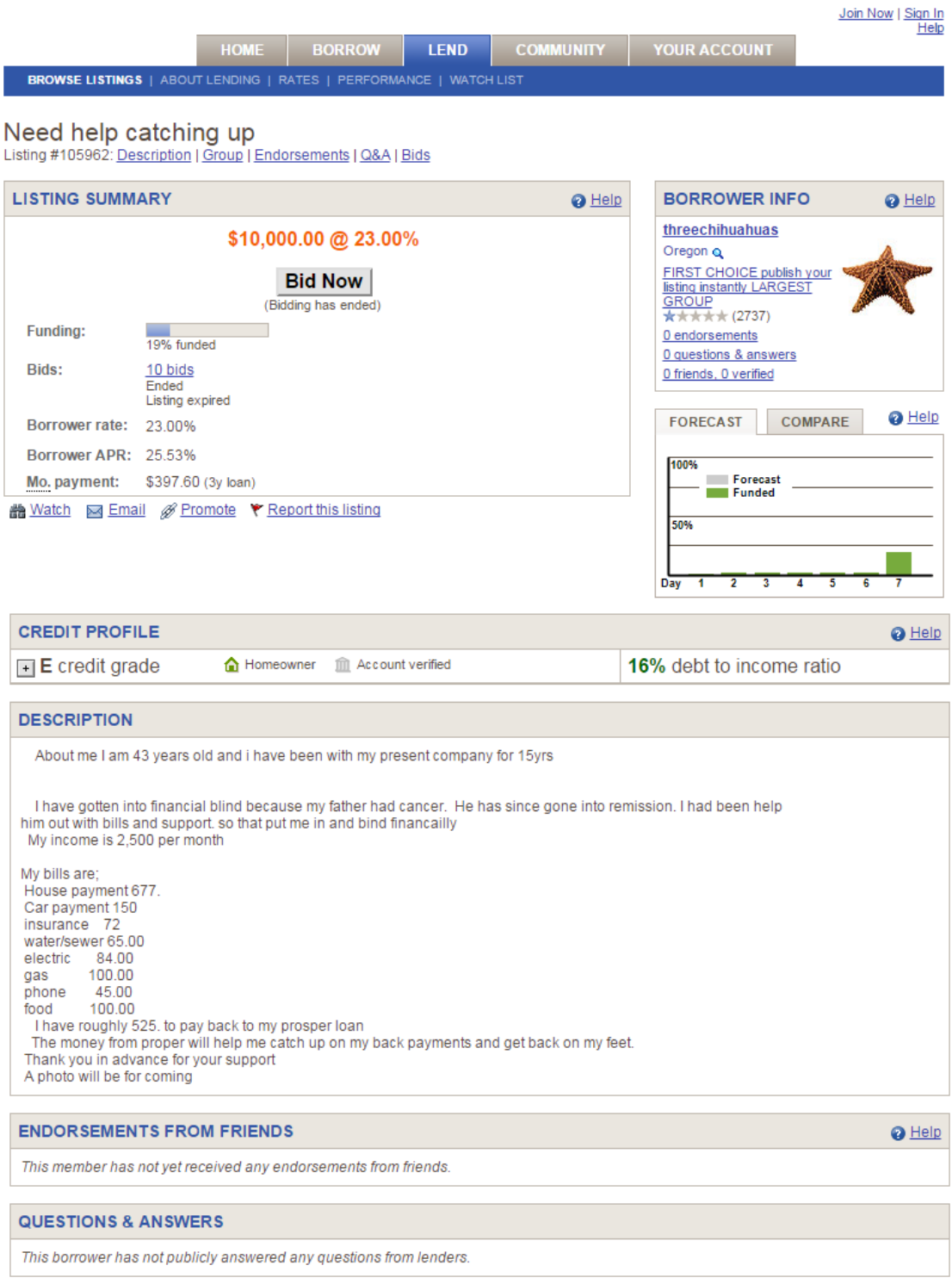

Figure 2: CDF of Bid Times by Local Status