THE GEOGRAPHY OF LENDER BEHAVIOR IN PEER-TO-PEER LOAN MARKETS*

GARRETT T. SENNEY†

This paper empirically investigates the role of geography in online peer-to-peer loan markets. Using transaction level data, I find strong evidence that lenders are more informed about local projects and have higher demand for better performing local projects. This effect is shown to be driven by informational frictions. Additionally, listings with more early local bidding attract more lenders, leading to a higher probability of funding and a lower final interest rate, if funded. My results are consistent with localness embodying some incidentally obtained initial informational advantage which rationally causes persistent information asymmetries.

I. INTRODUCTION

It is well established that inefficiencies will arise when asymmetric information exists between market participants, and the credit market is no exception. Informational frictions associated with geography have long been found to contribute to reducing transactional efficiency when parties are physically separated from each other. This has generally been thought to be why there has been a traditionally heavy reliance on local financiers, who have easier access to hard-to-quantify soft information, for personal and small business lending. However, recent innovations have enabled people to share more information, develop larger networks, and overcome geographic isolation. Utilizing these new online connections in conjunction with emerging crowdfunding platforms, individuals are starting to find novel ways to overcome frictions in the credit market, facilitating potentially large gains from trade that would otherwise not occur.

In this paper, I empirically explore the role of geography in online peer-to-peer (henceforth P2P) loan markets. P2P lending is a mechanism for investors to lend money directly to individual borrowers. Due to the cost savings arising from removing the

*I would like to thank the editor and five anonymous referees as well as Jason Blevins, Maryam Saeedi, and numerous workshop participants for helpful comments. The views in this paper are those of the author and do not reflect those of the Office of the Comptroller of the Currency or the Department of the Treasury.

†Author's affiliation: Economics Department, Office of the Comptroller of the Currency, Washington, DC 20219, U.S.A.
email:Garrett.Senney@occ.treas.gov

intermediary, borrowers can obtain potentially lower interest rates and lenders get the opportunity to invest in short-duration assets with higher rates of return. P2P lending has established itself as an emerging alternative source of funds for startups and people with particularly limited access to traditional means of financing (Mollick [2014]).

Using data from loan auctions on Prosper.com, I examine whether lenders possess an informational advantage on local projects. This informational advantage might consist of borrower-specific or market-specific information that is hard-to-quantify and costly to collect on informationally opaque borrowers, but provides a rich and insightful basis on which to make more informed investment decisions. This paper makes three contributions relative to the previous work. First, I document that lenders behave differently based on local status, and most importantly that lenders are shown to be significantly more informed about local projects. Second, my analysis can rule out that the 'Friends and Family' and home bias explanations as the main causes of the observed geographic frictions. Third, this work expands the rational herding finding of Zhang & Lui [2012] by providing a theoretically founded mechanism to explain the persistence of information asymmetries across lenders over time, and show that the strength and speed of the observed herding depends on the behavior of better informed lenders.

Early work on P2P lending has focused on the determinants of a listing being funded and the final interest rate. The consensus is that soft factors affect lenders' responses to the loan requests; however, they are second order in importance (Pope & Sydnor [2011]; Ravina [2012]) behind verified financial information (Klafft [2008a]). A long literature documents the importance of distance in social and economic behavior. Theoretical work predicts that investors and lenders are sensitive to their distance from the borrower, which is especially true in the early stages of the venture when there is little to no observable history (Arthur [1988]; David & Rosenbloom [1990]). Potential investors collect a sizeable amount of information before deciding to invest, thus the asymmetry between local and nonlocal investors may derive from the informational opacity of startups and small firms. The geographic proximity of local lenders facilitates cheaper and easier access to this information (Sorenson & Stuart [2001]; Wong et al. [2009]). However, Petersen & Rajan [2002] and others find that the average distance between small firms and their lenders has increased since the 1980s. The increased utility and adoption of technology by banks is credited for this change.

The effects of technology have not just been limited to traditional financial sources. Sanchez [2017] finds that the cost reduction of information gathering, due to the IT revolution, has led to the transformation and rapid growth of the unsecured credit market.

Baird [2007] finds that the improved accuracy and timeliness of information have lowered the cost of identifying risks in the consumer credit market. 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 (Goldfarb & Tucker [2011]). Other research has found that online platforms might reduce some, but not all, distance-related frictions (Agrawal et al. [2015]).

Although technology makes it easier for individuals to gather and process information, it is unclear if informational frictions still persist in a material way in online marketplaces. I examine this ongoing empirical question by focusing my analysis on the following questions: (1) do local lenders bid differently, and (2) do local lenders evaluate and price the risk of the listings differently. Using bid-level transaction data, I estimate that lenders tend to bid earlier and larger amounts on local projects, particularly for better performing ones. Furthermore, local lenders also seem better able to evaluate the riskiness of loan requests. They tend to ex-ante bid higher interest rates when the loan ex-post defaults, and lower rates when the loan ex-post pays back in full. This is true even when controlling for the potential peer effects.

After establishing that distance-related frictions do exist, the rest of the analysis investigates aggregate effects and explores the mechanism behind its existence. In particular, I focus on (3) does the difference in lending behavior arise from informational asymmetry or simply a preference on the part of local lenders, and lastly, (4) how does the presence of local lenders in the market affect other lenders' decisions to enter and their behavior after entering. Using listing-level data, I estimate that more early local lending in an auction increases the probability of funding, lowers the expected final interest rate, and is suggestive of better loan outcomes.

These results, in light of theory and previous empirical work, demonstrate strong evidence for the informational-based explanation of the observed behavioral differences between lenders. The efficiency of online markets depends on the transferability of offline information and networks to the online world. P2P loans are particularly subject to information frictions because the platform's design limits lenders' ability to collect valuable soft information; thus preventing lenders from fully eliminating geographic-based frictions in this online credit market.

II.OVERVIEW OVERVIEW OF PEER-TO-PEER LENDING

This paper focuses on the site Prosper.com, which has been called the 'eBay of loans'.[1] Prosper provides unsecured, 36-month, fixed-rate personal loans up to $25,000. Members' true identities, addresses, and other contact information are never publicly disclosed and the borrower is prohibited from releasing that information to lenders. However, the borrower's state of residence is prominently displayed on the listing.

A borrower creates a listing specifying the loan amount, the maximum interest rate that she is willing to accept, a loan category (i.e., Debt Consolidation or Business), and then writes a brief description about her request. Each listing displays a credit profile of the borrower, including items like debt-to-income ratio (henceforth DTI), credit grade (40-point bands of the borrower's Experian credit score), and home ownership status. The listing also has information about the borrower's potential membership in Prosper groups and whether the listing is endorsed by other Prosper users.

Lenders browse listings that contain all the publicly available information from the borrower as well as the bidding history for the auction. The listing's bid history shows the bid amounts and which user placed them, ranked by their interest rate bid. Lenders can click on a lender's username and be shown that lender's profile to learn about their state of residence, potential group membership, and which members they identified as friends on the site. According to interviews conducted with Prosper lenders, most lenders do scrutinize the other lenders' profiles early on during the auction.

The funding mechanism is a descending-price uniform-share auction. The lenders' bids have two components: quantity and price. The bid amount ($50 minimum) is the quantity demanded and bid interest rate is the smallest interest rate that the lender is willing to accept. The bidding process is proxy bidding. 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 the loan request. The auction is partially open; lenders always see the number of bids and the quantity of money pledged in 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.

Given that this platform is a collection of individualized markets for each loan, each market clears when the amount of pledged funds is at least as large as the requested amount, with the interest rate determined by the auction. In the case of ties, bids placed earlier take precedence. The bids with the lowest rates are bundled until the total loan

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

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.[2] If the loan request is not fully funded by the listing's close date, the listing is closed and dismissed. Borrowers who default on their Prosper loans are barred from using the site again.

The site provides members the ability to join groups and identify each other as friends. These features are intended to develop and foster a community of lenders and borrowers, akin to what occurs in relationship lending, contract enforcement via reputation and social pressure. Prosper groups were mostly centered on shared interests (i.e., college alumni, sports fans, or military members). These groups never gained wide traction. In addition, Prosper friends can publicly endorse a borrower's listing; however, this does not imply any offline interaction or co-signing responsibilities. Group membership was not generally found to decrease default rates, as anticipated. The ineffectiveness of group networks accounted for many users' complaints and the lack of the expansion of groups (Jaworski [2007]). The site now de-emphasizes the role of groups altogether.

III. DATA

The data contains all loan requests using the open auction format posted by borrowers with FICO credit scores of 560 or greater that started between December 21, 2007 and October 12, 2008.[3] My sample contains 42,657 listings, 9,624 were fully funded, and 2,022,910 bids. The borrower characteristics that I observe are: DTI, credit grade, homeowner status, occupation, employment status (full-time and if self-employed), number of open credit lines, number of open revolving accounts, number of current accounts delinquent, whether the borrower is in a Prosper group, whether another Prosper user has endorsed this listing, and state of residence. The information that is observed by lenders, but not me is: the free-form text description for the loan request, the number of total delinquencies in the last seven years, and the number of credit inquiries in the last six months. However, Experian credit history data show that the two missing data fields are highly correlated with credit score and the other available financial information.[4] Klafft

[2]Winning bids can be either fully or partially participating in the loan.

[3]Prosper requires a minimum FICO score of 520 to be on the site. Unfortunately, my data does not contain any information on this "No Credit, High Risk' group. However, there were only 3,225 of these listings and just 78 of them were funded over my time period.

[4]This result is not surprising given that delinquency and credit inquiries are components of credit score.

[2008b] confirms that credit grade and DTI are the two most important variables in determining the financial outcomes on the site.

In the loan-level analysis, the *In Group* variable indicates whether a borrower is in any Prosper groups, and the *Endorsement* variable indicates whether a borrower's listing was endorsed by a Prosper friend. In the bid-level analysis, the *In Group* variable indicates whether that particular lender is in the same Prosper group as the borrower and the *Prosper Friend* variable indicates whether the lender and borrower identify as friends on the site. In my sample, lenders posted 746 bids in 663 unique listings where they identified the borrower as a Prosper friend, thus a vast majority of listings did not receive a Prosper friend bid. Of the listings that received a Prosper friend bid, the average listing received about 1.12 bids and $935.83 from Prosper friends.

I also construct variables to measure the competition that each listing faces. The competition measures are the number of listings that are active for at least one full day at the same time as that particular listing. *Total Competition* is the number of total listings, while *Credit Grade Competition* is the number of listings from the same credit grade. At the bid level, I determine the current standing interest rate, money pledged, and bid count that existed in the auction at the exact moment that each lender bid on a particular listing. Additionally, I construct indicators for when the lender has been active on the site for more three and six months. I use these variables as proxies for lender experience.

Table I shows the summary statistics of the all listings.[5] Most of the listings request around $6,000–$9,000. Intuitively, the mean requested amount increases as the credit grade improves, as more credit-worthy borrowers have a better ability to support larger loans. 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 multiple listings.

***** Place Table I Here *****

The auction mechanism does not allow for observing the bid interest rates for winning bids. The current standing interest rate is always shown, which is either the borrower's maximum rate or the interest rate of the smallest losing bid. The final interest rate sets an upper bound on what the actual interest rates are for the winning bids. Following the literature, I assume that winning bids equal the final interest rate. Not surprisingly, the mean and median bid interest rates 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

[5] See online appendix Table A1 for summary statistics of only the completed listing.

0.833).

The completion rate (the proportion of listings that are successfully funded) decreases strictly monotonically as the credit grade worsens.[6] For the listings that are actually originated, I collect data on their ex-post loan outcomes as of September, 21 2011.[7] I do not observe when a borrower defaults, only if any kind of default occurred and if the delinquency was resolved (paid in full or settled in full).[8] The default rate by credit grade ranges from 16% to 39%. These magnitudes are well in line with national delinquency rates for residential mortgages for the same time period.[9]

IV. THEORETICAL FRAMEWORK

In this section, I develop a theoretical framework to model whether lenders, acting mostly on their own information, are better able to evaluate the underlying risk of local listings. The local lenders' actions also serve as signals of their private information to the rest of the market. I will investigate the theoretical implications, on both the intensive and extensive margins, and its predictions for lender behavior.

IV(i). *INDIVIDUAL BIDDING BEHAVIOR*

While technology has made it cheaper for people to gather and share information, localness still embodies some incidentally obtained initial informational advantage. This advantage stems from the limited transferability of some local market-specific information. Some examples include: learning local tastes and risk tolerances, changes to local housing or labor markets, and demand for particular goods or services. Individuals inherently possess a vast quantity of information about their local surroundings that they have obtained through personal experience and general exposure that is unknown and costly for nonlocal individuals to acquire. This aligns with Hauswald & Marquez [2006] who find that banks acquire proprietary information to soften lending competition, but their ability to do so varies with their distance from the borrower.

In an environment where all information is obtainable with some nonzero search cost, initial information asymmetries, no matter how slight, will lead to persistent information asymmetries in equilibrium. Van Nieuwerburgh & Veldkamp [2009] theoretically

[6] See online appendix Table A2 for a breakdown of the listings and completed loans by credit grade.

[7] 9,099 of the listings had reached matured while the remaining listings were still on-going.

[8] Any kind of default ranges from charge-offs, bankruptcies, and being more than 30 days late as of when my data was collected.

[9] Refer to the Richmond Fed Delinquency and Foreclosure Rates Report.

prove that the optimal strategy for investors with some informational advantage is to specialize their information gathering in their area of comparative advantage. If local investors attempted to fully mitigate their information asymmetry in nonlocal markets, they would forfeit the excess returns that could possibly be gained locally. This occurs because when local and nonlocal investors become equally well informed about the same listings, they will both have large demand for the high-return assets, bidding down the expected return. If instead, investors learn more about local listings, they will have knowledge about high-return local listings that others do not have, thus the price of that asset will not fully reflect this information. Thus, learning more about local projects increases the investor's average return. Therefore, investors should seek to make their information set as different from that of the average investor as possible.

Ivković & Weisbenner [2005] show that the more diversification that exists in lenders' information, the larger the expected return from local investments will be. Rational lenders seeking to maximize expected profits will optimally get more informed about markets where they already have an initial advantage and have less costly access to information. Coval & Moskowitz [2001] find empirical evidence for this theory, demonstrating that professional fund managers' local investments generate abnormal returns. Learning amplifies these informational asymmetries among lenders, allowing for the lenders to exploit local knowledge. This advantage is particularly strong when the initial asymmetry is likely to be the most pronounced– among smaller, younger, and lesser known borrowers.

There is an abundance of literature illustrating that early-stage investment overwhelmingly tends to be local, when informational asymmetries are highest, due to distance-related costs; i.e., information gathering and monitoring (Lerner [1995]; Gompers [1995]). Furthermore, Agrawal & Hauswald [2010] show that lender proximity to projects facilitates the acquisition of hard-to-quantify soft information, and that increased distance limits lenders' ability to exploit proprietary information and thus lengthens the time necessary to issue credit.

Applying this theoretical guidance to this setting, lenders will have lower uncertainty about the expected return for local projects given that they have better access to more information about these projects than nonlocal lenders. Thus, it should be expected that lenders will have higher demand for good-performing local projects, their bids should be more in line with the realized returns, and they should be more willing to bid early on in the auction.

IV(ii). *AGGREGATE LENDER BEHAVIOR*

Social learning involves an informational externality where a lender 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 with more early local bidding to have more revealed private information available and thus attract more bidding activity overall.

I abstract away from the auction environment and develop a social learning model with heterogeneous agents in the spirit of Banerjee [1992]. There is a population of identical risk neutral lenders that are maximizing their expected utility from investing.[10] An L share of the lenders are local and a $(1 - L)$ share are nonlocal.[11] Each lender is presented with the same collection of listings indexed by $i \in [0, 1]$. Only one unique listing will yield strictly positive returns, while all other listings will produce returns of zero. This assumption is the same as if there were a single listing with excess return strictly greater than all the other listings. Therefore, the optimal ex-post outcome for all lenders is to invest in that listing.

At the start of the game, all lenders have the same ex-ante uniform priors about the listings. However, lenders with probability $\alpha \in (0, 1)$ will receive a noisy signal about which listing to invest in. Local lenders are assumed to have access to better information, so their signals are more likely to be 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 the same as for local lenders, except the signals are less likely to be informative. Formally, a nonlocal signal is correct with probability $\gamma \in (0.5, 1)$, with $\beta > \gamma$.

The timing of the game is as follows. An individual lender observes the history, potentially receives a private signal, and then computes via Bayes's 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 with each new lender using the observed history and his 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 acts in a way that only a local lender with a signal would, 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, all the uncertainty is resolved and one listing pays out its return. Rationality and the structure of

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

[11] Smith & Sørensen [2000] also study herding with heterogeneous agents, but the types vary along preferences, not the information quality.

the game are common knowledge to all lenders. Consequently, each lender's decision rule is based solely on the history and her signal.[12] Additionally, listing $i = 0$ is assumed to be the default listing that a completed uniformed lender with no prior history to observe will choose.[13]

Lenders do not ex-ante know the local status of the preceding lenders. If previous lenders' 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 the model in addition to the observed history, I impose some mild structure on how much more informed a local lender is. Since lenders move sequentially, in an exogenously set random order, decisions cannot be strategically delayed. Each lender's information set includes the actions of the preceding bidders, the lender's local status, and the lender's private information if the lender receives a signal.

The basic intuition from this model gives rise to some general results for a Bayesian Nash equilibrium. Further details of the model and proofs of the following lemmas can be obtained from the author upon request.

Lemma 1 *If the first three lenders all choose the same nonzero listing, then all subsequent lenders, regardless of their local status, will follow them and choose that listing.*

Lemma 2 *If the first lender chooses $i \neq 0$, and the second, third, and fourth lenders all choose the same nonzero 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.*

These two lemmas are generalizable to the case where all the chosen nonzero listings have the same number and types of lenders, and one of them receives additional bids from either three unknown status lenders or one revealed local and one unknown-status lender. Then all subsequent lenders whose 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 the lenders' choice of this listing. Thus, the model implies that the speed of herding will accelerate as more local lenders are involved. As the most-chosen non-zero listing has been chosen by more

[12] When indifferent, lenders use the three classical tie-breaking assumptions in Banerjee [1992].

[13] As shown by Banerjee [1992], this assumption will minimize misinformation since the first lender choosing the zero listing does not provide any information to subsequent lenders.

local lenders in the early stages, that particular listing 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 better 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 result arises from the fact that the signal of local lenders is more accurate and they are less likely to be persuaded by the herding instinct.

Although simple, the optimal decision rules provide clear intuition and motivation for how lenders behave in the aggregate. In line with Zhang & Lui [2012], this model predicts rational herding from observational learning. However, this model clarifies that the strength and speed of herding depends on the actions of better-informed local agents. Translating these theoretical results to my empirical setting, this 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.

V. EMPIRICAL RESULTS

Intuitively, new technology has made it easier to connect, so P2P markets should reduce at least some of the informational frictions in the credit market. Additionally, several features of this particular platform make the presence of geography-related frictions less plausible: loans are unsecured, and lenders have little legal recourse other than the standard collection process and reporting the loan default to credit reporting bureaus. These constraints minimize the lenders' ability to individually monitor and enforce the contract. Therefore, geographic proximity should be less important in this market.

Considering the above, it has yet to be shown if there still exists a meaningful geographic difference in P2P lending. Following the literature on online markets (Wolf [2000]; Hillberry & Hummels [2003]), I define localness to be when the lender and borrower reside in the same state. Admittedly, a smaller unit of measure is preferred; however, the site discourages this disclosure to prevent borrowers from personally identifying themselves. If the actual effect of information asymmetry is limited to a smaller physical proximity, then my 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 measure. Thus this data limitation means that my estimates are actually a lower bound on the true local effect. To examine the sensitivity of using state as the threshold of localness, I perform multiple robustness checks using dif-

ferent definitions of localness. The results from these robustness checks are qualitatively the same, supporting the claim that the state analysis is a lower bound on the true effect.

I start this analysis by first documenting the fact that lenders behave differently when bidding on local projects. I find strong evidence that information frictions are a major contributor to the observed behavioral differences. Next, I evaluate the predictions of how individual local bidding will affect aggregate lender behavior. The variable *Loan Amount* is measured in $1,000, *Bid Count* is measured in 100 listings, and *Borrower Max Rate* and *Current Rate* are measured in percentage points (1=1%). DTI is bucketed into 20% bins with DTI over 80% being the excluded group. The time fixed effects include quarter, month, day of the week, and hour of the day effects.

V(i). *INDIVIDUAL BIDDING ANALYSIS*

The mean and 75th percentile local bid amounts are around $10 larger than the nonlocal bids (the p-value of both t-tests is less than 0.001).[14] Additionally, both a Mann-Whittney U-test and a Kolmogorov-Smirnov test reject the hypothesis of the equality of the bid amount distributions at the 1% level. Therefore, I run a Tobit regression of log bid amount with left censoring at $\log(\$50)$ while including an indicator for local lender.[15] As seen in left specification of Table II, I find that lenders bid roughly 7% larger amounts on local projects. This effect is of a similar magnitude to the auction's current standing interest rate being roughly 5.3 percentage points higher.

Lenders bidding more for local loans might be consistent with the findings of local preference in other online markets (Hortaçsu et al. [2009]; Lin & Viswanathan [2016]), or that lenders are more informed about local projects and thus only bid on good performing local listings. To examine this, I restrict my focus to the subset of listings that were originated. As can be seen in right specification of Table II, while lenders bid larger amounts on all local projects, the magnitude of the increase is significantly larger for loans that are ex-post paid in full.

***** Place Table II Here *****

The fact that lenders bid slightly more for defaulted local projects still does not necessarily imply that lenders have a local preference. Given my coarse default data, local lenders might be choosing loans that default further into the process and are thus paying back more of the principle prior to defaulting. To test this, I rerun the regression excluding the resolved defaults (paid in full after a delinquency or settled in full) from the defaulted

[14] See online appendix Table A3 for the summary statistics of bid amount by local status.

[15] A Lagrange Multiplier test does not reject the null of homoskedasticity at the 5% level, and a Hausman test of the normality of the Tobit does not reject null at the 5% level.

group, the coefficient on the interaction term of local lender and defaulted decreases to -0.053, suggesting that lenders are not strictly driven by a home bias.[16] Furthermore, I have a limited subsample of 300 defaulted loans where I know the exact date of default; for loans with a large proportion of early local bidding, the default occurs nine months later, on average. While certainly not definitive, this result implies that an appropriate interpretation of lender bid behavior is that lenders have a higher demand for the expected profitable listings. These results are robust to concerns of non-serious throw-away bids. If the sample is restricted to just winning bids, the previous results are not materially changed.[17] This finding is consistent with the theoretical prediction that lenders invest more in better performing local projects.

If local lenders are actually more informed about the underlying riskiness of the borrower and the local market conditions, they should be better able to evaluate the risk. To examine this, I focus on losing bids where I know the actual bid interest rate. The mean and median interest rates bid by local lenders as compared with those of nonlocal lenders, are higher for loans that ex-post default, but are lower for loans that ex-post pay back in full. These two observations strongly suggest that lenders seem to more accurately price the underlying risk of the local listings.[18]

Both a U-test and a K-S test reject the null that the local and nonlocal bid interest rate distributions are equal at the 1% level. Additionally, for loans that default, the local distribution stochastically dominates the nonlocal distribution, and for loans that pay back, the nonlocal distribution stochastically dominates the local distribution. To further explore the difference between the local and nonlocal bid interest rate distributions, I perform t-tests on the means for each credit grade separately by localness. For loans that default, local means are significantly larger. For loans that pay back, the local means are significantly smaller.[19]

***** Place Table III Here *****

I also 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.[20] The regression contains indicators for local lender interacted with credit grade, an indicator for whether the loan defaulted, and the local lender indicator interacted with credit grade and

[16] See online appendix Table A4 for this regression result.

[17] See online appendix Table A5 for full results.

[18] Similar results are observed if I include all bids by assuming the interest rate of winning bids is equal to the final interest rate.

[19] See online appendix Table A6 for the t-statistics and p-values.

[20] A Lagrange Multiplier test does not reject the null of homoskedasticity at the 5% level, and a Hausman test of the normality of the Tobit does not reject null at the 5% level.

the loan's default status. The results displayed in Table III, consistent with the previous findings, show 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 largest potential difference between true 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 bid interest rate is positive if the loan ex-post defaults. The premium that local lenders, relative to nonlocal lenders, give to loans that ex-post default ranges from 0.056 to 0.28 percentage points. Reducing the final interest rate by 1% would lower the total loan payment by a few hundred dollars; this effect would be quite significant when aggregated across a lender's whole portfolio. This finding is consistent with the theoretical prediction that lenders are better able to evaluate the underlying risk of local projects, with the obvious rationale being that lenders are relatively more informed about local projects. These results are robust to concerns of non-serious throw-away bids. If the sample is restricted to bids that are within 3 percentage points of the final winning rate, the previous results are not materially changed.[21]

If lenders are more informed about the quality of local listings, theory predicts that local lenders 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. The average local bid is placed roughly 2.5 hours and the 25th percentile local bid is placed about 5.5 hours earlier than their nonlocal counterparts.[22] A U-test on bid times, results in a p-value of less than 0.001, implying that the distribution of bid times for local lenders tends to be significantly smaller than the distribution of bid times for nonlocal

[21] See online appendix Table A7 for full results.

[22] See online appendix Table A3 for the summary statistics of bid time by local status.

lenders.[23]

To more formally evaluate the timing of bids, I estimate an OLS and Cox proportional hazard model.[24] Relative to a standard seven-day auction, lenders are estimated to bid about 3.5 hours earlier for local projects in the pre-fully funded period, and 2 hours earlier in the post-fully funded period. Additionally, the hazard model estimates that at any time t before a listing is fully-funded, being local increases the relative probability of bidding for a lender by about 3.5%. That falls to 2.5% in the post fully-funded period. The results concur with the predictions of the model; local lenders bid earlier, with the effect dampening in the post-fully funded phase. This occurs because more information about the listing is conveyed from the observed bidding, which closes the informational gap between local and nonlocal lenders.

One might be concerned that it is not just timing that matters in determining if a bid is actually early or not; however, local lenders bid earlier in an auction in terms of previous activity as well. The average local lender bids when there are 14 fewer bids and $700 less pledged in the auction.[25] Local lenders have demonstrated that they are more comfortable bidding in periods when less information is being revealed by other lenders. A K-S distributional equality test was performed for both measures of previous bidding activity. The test finds that the nonlocal distribution stochastically dominates the local distribution.[26] Similar analysis was performed on the number of bids placed and the amount of funds pledged as the measure of auction duration. The findings are in line with the previously shown results that local lenders bid earlier.

V(ii). *TESTING FOR FRIENDS AND FAMILY EFFECTS*

Thus far, I have documented that lenders appear to be more informed about local projects. However, given that I do not observe information about the market participants' offline activity or social networks, it is necessary to check whether the effect of being local is driven by a borrower's 'Friends and Family' (F&F) simply using the site as a way to formalize their lending. This is especially true given that offline connections are a big component for the observed geographic difference in behavior on other crowdfunding platforms.

While F&F would be better informed about the borrower's characteristics, it is unlikely that they would be motivated strictly by profits. If F&F bids are a major part

[23] The results of a K-S distributional equality test are consistent with this finding.

[24] See online appendix Table A8.

[25] See online appendix Table A9 for the summary statistics of the number of bids placed and money pledged in a listing immediately before a lender bids, by local status.

[26] The p-values for all of the distributional tests are basically zero.

of the local bidding, it is reasonable that they would join the site around the time that the borrower creates her listing. It is unlikely that a majority of the borrowers will have a significant number of F&F who have previously been active on the site. The average lender has placed about 50 bids before submitting their first local bid. Fewer than 2% of lenders place their first bid on a local project, and fewer than 8% of local bids are placed during the first three days after the lender joins the site. Furthermore, fewer than 7% of lenders place more than 25% of the bids in local listings.

***** Place Table IV Here *****

Lenders who identify as Prosper friends with the borrower bid larger amounts; however, since I control for those connections in my analysis, we know this group does not drive my results. As illustrated in Table IV, local non-Prosper friend lenders bid significantly larger amounts than nonlocal lenders. However, it is possible individuals are not publicly revealing offline friends by constructing online networks. Therefore, I follow the previous literature and attempt to identify F&F lenders based upon their observed on-site behavior. Agrawal et al. [2015], Lin & Viswanathan [2016], and An et al. [2014] all propose empirical definitions of F&F for crowdfunding platforms based solely on observed online behavior. The definition of Agrawal et al. [2015] translated in this setting requires that: (a) the first bid of a listing is by a F&F lender, (b) the largest bid is by a F&F lender, and (c) the F&F lender bids in no more than 25 other listings.[27] Only 3,534 bids qualify as F&F bids under this definition.

The Lin & Viswanathan [2016] definition states that F&F are highly unlikely to invest in other borrowers, as they have signed up to primarily lend to their friend or family member. Therefore, a F&F bid is defined as a bid by a lender who only bids on one listing regardless of local status. A total of 4,465 bids qualify as F&F bids under this definition. The definition of An et al. [2014] claims that F&F lenders will tend to be geographically close to the borrower and will only be occasional bidders. Under this definition, F&F lenders will be a subset of local lenders who bid fewer than 25 times in total. Under these conditions, 12,841 bids qualify as F&F bids. As seen in Table IV, regardless of the definition used, local non-F&F lenders bid significantly larger amounts than nonlocal lenders.[28] This evidence is strongly suggestive that unobserved social connections are not the primary driver of bid amount behavior.

Next, I turn my attention to the bid interest rates. As can be seen in Table V, F&F lenders uniformly bid lower interest rates (0.5 to 2 percentage points less, depending

[27]Their actual definition restricts F&F to investing in no more than three other projects; however, their setting is a smaller platform with significantly lower transaction volume.

[28]This is holds even when excluding all Prosper friend bids.

on credit grade and definition), regardless of the ex-post loan outcome, than non-F&F lenders. There is no ex-ante risk adjustment, which is in stark contrast to the local non-F&F who do adjust for ex-post outcome. Similar results are seen for Prosper friends bids. I also restrict the comparison to just local non-F&F against local F&F, and find that local F&F lenders bid uniformly lower interest rates than local non-F&F lenders.[29] Furthermore, even after excluding all the F&F and Prosper friend bids, the local non-F&F lenders still better adjust their interest rate bids for the overlaying risk, but now have a larger increase for loans that ex-post default. These findings provide strong evidence that F&F lenders are motivated primarily by altruism and act differently than local non-F&F lenders.

***** Place Table V Here *****

Prosper allows members to network on-site via Prosper groups. Although these groups were never widely used, it is worth evaluating whether these on-site connections might be driving the local results. Similar to the results for the F&F analysis, within-group lenders act altruistically. Within-group lenders tend to bid larger amounts and uniformly smaller interest rates, regardless of the ex-post loan outcome. When excluding the within-group bids, the local not within-group lenders still bid larger amounts and adjust their interest rate to better account for ex-post outcomes.[30]

Moreover, I re-evaluate the individual bid-level Tobit regressions while dropping the differently defined F&F bids, the subset of F&F lenders that bid more than $1,000, Prosper friends bids, bids from lenders with 75% or more of their bids being local, and the strictly within-group bids. I also rerun the regressions while adding an indicator for F&F bid. These new results are quantitatively similar to the previous results. However, similar to Zhang & Lui [2012], I find evidence that F&F bidding on a listing weakens the herding effect. This can be ascribed to lenders attributing more altruistic motives to F&F lenders. F&F lenders uniformly bid larger amounts and lower interest rates, regardless of ex-post outcomes, while local non-F&F lenders adjust their lending behavior for the realized risk. This empirical evidence strongly suggests that, while altruism might play a small part, the dominant channel explaining the observed geographic behavior is that lenders are more informed about local projects, which fits well with information frictions as predicted by theory. Additionally, there is no statistically significant difference in behavior (bid amount, interest rate, timing of bid) for nonlocal listings that are equally far away from a particular lender, even though the borrowers who posted these listings reside in different cultural regions of the country. For example, Ohio lenders demonstrate simi-

[29] See online appendix Table A10.

[30] See online appendix Table A11 and A12 for the bid amount and interest rate comparison.

lar lending patterns when investing in listings from Nebraska as from Mississippi or New Hampshire. If the preference story was true, one would expect more local-like behavior for states with cultures similar to the lender. However, the lenders do not demonstrate any proclivity for this kind of homophily.

V(iii). *DISCRETE CHOICE MODEL OF LENDER ENTRY*

The common mechanism that drives the theoretical predictions for the individual bidding and aggregate lender behavior is that lenders have easier and cheaper access to more information about local projects, which should facilitate lenders having less uncertainty about local projects. This reduced variance in the expected return of an investment in a local project should allow lenders to more accurately assess the underlying risk. Therefore, I also investigate the factors that influence a lender's decision to lend to a particular borrower. I estimate a conditional logit discrete choice model. To generate each lender's choice set, I determine which listings are active at the time when that lender made his bid. My data contains listings with start dates between December 21, 2007 and October 12, 2008, so I need to burn the first 10 days and last five days to ensure that I observe the full universe of listings available to each bidder.[31] Therefore, my new sample contains lenders making 1,973,599 decisions, with the average choice set containing 1,292 alternatives. The data is too sparse to be computationally feasible; therefore, I use a filtering approach to refine the alternatives to reasonably sized choice sets. I assume that each lender is only considering listings that have the same credit grade and category of use as the listing that they actually bid on. Surveys and interviews with Prosper users support this kind of filtering. Under this approach, the average choice set contains about 50 alternatives. This methodology requires that I observe each lender making at least two choices, so I drop the lenders that only make one bid over my sample. My sample contains 31,266 unique lenders making 1,709,293 bids. The results from this estimated discrete choice model are displayed in Table VI.

***** Place Table VI Here *****

The left hand side of the table presents the results from the full subsample, while the right hand side restricts the subsample to just listings that got completed.[32] Not conditioning on ex-post loan outcome, lenders are 6.9% more likely to bid on a local listing. However, after conditioning on loan outcome, I find that for listings that ex-post pay back, lenders are 8.4% more likely to bid on local listings, while for listings that ex-

[31] This forces me to drop 2.4% of the bids from my sample.

[32] This completion restriction brings the sample size down to 73,798,765 observations.

post default, they are only 2.5% more likely to bid. Similar to the bid amount results, I find evidence that lenders have more demand for good performing local projects. These results are robust to excluding or controlling for the previously defined F&F bids. In line with previous findings, ex-post outcomes do not affect F&F lenders' probability of bidding on a listing that they are connected to. The result is consistent with theoretical predictions and the previous bid level findings that lenders appear to be more informed about local projects.

Given the previous findings, it is worth exploring that if local lending is so useful, why only 6% of all the bids are local. Recall that on average, more than 1,200 listings are currently active when a lender makes her bid. On the average day, most states make up fewer than 2% of that day's active listings. Throughout my sample, more than 90% of the active listings are nonlocal to a lender when she makes her bid. As such, most listings are simply nonlocal to most lenders. Like most general investment vehicles, geographic diversification is desirable to minimize the influence of geographic-specific shocks to the asset's return. Additionally, it is important to recall that the previous results have shown that lenders do not simply have a local preference and are biased toward investing in every local listing that they see. The lenders' localness make them more informed, so their uncertainty around the expected value of local projects is smaller than for nonlocal projects. This does not suddenly make all local listings now worth investing in, but lenders are better able to predict expected returns for local projects. I now turn my attention to the listing level analysis of aggregated lender behavior.

V(iv). *AGGREGATE LENDER BEHAVIOR*

The ability of borrowers to signal to lenders on crowdfunding platforms is well studied (Ahlers et al. [2015]). In this section I examine the less studied ability of lenders to signal to other lenders. As shown previously, local lenders tend to bid earlier and appear to be more informed about general market conditions and underlying riskiness. This behavior allows local lenders to partially reveal their private information. Thus, as a listing accumulates more bids, a general sense of quality is signaled that may lead to rational herding behavior in crowdfunding markets (Zhang & Lui [2012]; Burtch et al. [2013]). However, the model's predictions do not require that lenders ex-ante know the local status of other lenders, merely that such information is obtainable and can be revealed.[33] These predictions suggest 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,

[33] If all lenders knew the local status of all other lenders, the local effect would be significantly stronger.

(b) becoming fully funded, (c) getting a lower final interest rate if funded, and (d) after becoming a loan, not defaulting. In this section, I set out to empirically evaluate these predictions for the P2P lending market.

I include variables measuring the total number of early bids (*Total Early Count*) and the amount of money pledged by all lenders (*Total Early Amount*). Additionally, I include the early bidding by local lenders (*Local Early Count* and *Local Early Amount*). 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, on influencing the decisions of other lenders. Using a specification with both variables for total early and local early bidding allows me to separately identify the additional effect of early local bidding from a generic early bid. I examine four definitions of early bidding: pre-fully funded, first two hours, first hour, and first 30 minutes of the auction. My results are robust to changes of the definition of the early period. For the sake of brevity, only results from the first two hours are reported in this paper. The bid amount variables are measured in $100.

To test whether more early local bidding attracts more activity to an auction, I run count regressions using a Poisson specification. The left two specifications of Table VII present the marginal effects of early local bidding on total and total-nonlocal bid count. The coefficients for total early and local early bidding are all positive and significant. This result confirms the model's prediction that more early local bidding attracts, not only more total bidding but also nonlocal bidding activity to a listing. To put the magnitude in context, an extra four $50 local early bids will yield an additional 3.5 bids. While that might seem small, the average listing only receives 47 bids, and 90% of listings receive 150 or fewer bids. Even when focusing just on total-nonlocal bids, one early local bid has roughly the same increase as two nonlocal early bids, given that all the bids are the same amount, in attracting more lenders to the listing. This result is in line with Zeithaml [2012], who finds that lenders seek the wisdom of the crowd when information is extremely limited or dispersed. Local lenders in this setting are a creditable source of local market-specific information.

One might think that early local bidding only has power in attracting lender activity before the listing is fully funded. In the pre-fully funded period of the auction, bids are complementary. 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 the lender to demand positive shares of the listing at an interest rate that is no larger than the borrower's maximum 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. 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.

***** Place Table VII Here *****

Given the differences 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 local early bidding varies across this informational shift in 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. Thus, I use a subsample of listings that are completed. The right two specifications of Table VII present the marginal effects of early local bidding on total pre- and post-fully funded bid count. The coefficients for total early and local early bidding are all positive and significant. These results are similar to the results of the total bid count regression shown previously. The effect of local early bidding is dampened in the post-fully funded period; an extra four $50 local early bids will yield an additional 5.5 bids pre-fully funded, while the same amount only results in an additional three bids post-fully funded. 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.

Local early bidding attracts more lender activity, but it also affects the rate of funding for listings. The left specification of Table VIII presents the marginal effects of local early bidding on the probability of funding from a logit regression. The results are consistent with those on individual lender activity. An additional four local early bids of $50 will increase a listing's funding probability by 0.06 percentage points above the effect of getting four nonlocal early bids. This effect may initially seem small, but comparing it to the effect of decreasing a borrower's DTI from more than 80% to less than 20% (-0.028), increasing the borrower's maximum rate by five percentage points (0.030), or requesting an additional thousand dollars (-0.027), the relative effect of early local bidding is quite significant.

***** Place Table VIII Here *****

A related issue to the probability of funding is the effect that local early bidding has on a listing's final interest. The effect of early bidding is not immediately obvious, since it has been shown that local lenders appear to price listings more appropriately than

nonlocal lenders. If the listing possesses some extra risk that is hidden to uninformed 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 specification of Table VIII shows that the effect of early local bidding is negative and significant. A single additional $50 local early bid will, on average, decrease the expected final interest rate of a completed listing by about half a percentage point in excess of the effect of a listing just receiving a single nonlocal early bid. For comparison, this effect is similar to the effect of requesting $3,000 less. The effect of local early bidding on the probability of funding and the final interest rate is consistent with the predictions of the social learning model. Listings that have more early bidding, especially local activity, will attract more bidding, resulting in these listings being funded at higher rates and enjoying lower final interest rates, if funded.

Lastly, the information theory suggests that local early bids predict the ex-post outcome of a loan. Given that lenders are better informed about local projects, listings with more local early bidding should have a higher probability of not defaulting.[34] The effect of early local bidding is negative; however, the coefficients are hovering around the 5% significance level. 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. This result explains why Herzenstein et al. [2011] find a positive association between herding and subsequent loan performance.

To further evaluate the F&F and the within-group bidding, additional specifications were performed with the social connection bids removed and with new variables that explicitly controlled for their presence. However, since the number of offending bids is so minor relative to the total of regular local bids, the resulting output shows no meaningful differences from the reported results. Combining all of these findings, 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 support for the claim that although technology has made gathering and processing information cheaper for more people, location of the investor relative to the investment opportunity is still important.

[34] See online appendix Table A13.

V(v). *SENSITIVITY ANALYSIS OF LOCALNESS*

Although empirical work on other e-commerce sites also uses state level, it is reasonable to question the sensitivity of this definition of localness to actually generate informational frictions, especially given the vast size difference between states and the potential spillover from neighboring areas in different states. To examine the robustness of my analysis, I define local to be within Census region and within city (for restricted subsample of individuals who list their city). I also investigate the effect of state size and actual distance between states, as well ass identify lenders from neighboring, and near but not adjacent states from the rest of the nonlocal lenders.[35]

The results from the individual-lender and listing-level analysis with the redefined local definition are qualitatively the same as the reported specification, with the estimated local effect being larger when using city as the local definition. The informational difference between local and nonlocal behavior is more pronounced as the definition of local becomes narrower and focused. To see whether the observed localness is being driven disproportionately by a single state, I sequentially drop individual states from my regressions one at a time. To check the other direction of this effect, I restrict the sample to just listings from a single state and perform my analysis for each state individually. The results are qualitatively the same for both groups of specifications. For state size, I add a small-state indicator (population less than 3 million) and interact it with the local lender. Congruent with the asymmetric information story, the effect of being local is stronger for smaller states. Along the same lines, lenders in neighboring states behave similarly to local lenders; however, the adjustments are weaker. Furthermore, lenders from near but not adjacent states also demonstrate the same pattern but with significantly dampened responses. I include indicators for all three types of physical proximity in the regressions. The estimated effects monotonically decrease as the lender is further away from the borrower. Similar results are also found when using physical distance between lender and borrower.[36] Lenders farther than 700 miles away are estimated to be the true nonlocal lenders since their behavior is the most different from that of local lenders and does not change as the distance increases past that threshold.

Another potential alternative narrative to consider is a story about different levels of experience between lenders being the true main driver for the observing signaling. To examine this, I include an indicator for a lender having three and six months' worth of experience on the site in the analysis. The coefficients on the variables of interest are

[35]The full results for this analysis can be found in the appendix.

[36]Distance between lender and borrower is measured using straight-line distance between the population-weighted center of the lender's and borrower's state.

not meaningfully different. The previously observed lender behavior is also found when examining local status for experienced and inexperienced lenders.[37]

Moreover, these results provide further evidence supporting the previous findings that F&F are not the primary cause of the observed geographic difference in lender behavior. In particular, the small-state and physical distance analysis are consistent with the conclusion that information about the borrower and the project is more costly to obtain the further away the lender is, and as such, lenders rationally get more informed about local projects.

VI. DISCUSSION OF RESULTS

The previously shown results illustrate that geographic frictions still exist in online loan markets, and that the primary cause is an informational asymmetry. The existence of asymmetric information is not new. Zhang & Lui [2012] use a loan-level analysis to find evidence of rational herding in P2P loan markets. However, the cause of this asymmetry is an ongoing debate. The Zhang & Lui [2012] model, like most studies in this area, has some lenders receiving private signals about borrower quality through an unspecified information acquisition process. My work builds on this foundation to provide a clear mechanism to explain why certain lenders possess better information about specific borrowers. Additionally, I have empirical evidence to corroborate the existence of informational asymmetry arising from the heterogeneity in lenders' closeness to the different projects. Rational lenders get better informed about local projects, because it is easier and cheaper to do so. This information gap between local and nonlocal lenders contributes to the observed rational herding found in these crowdfunding markets.

While technology certainly has made all individuals more connected, localness still embodies some incidentally obtained initial informational advantage, which causes a natural disparity in lenders' exogenous, starting information set. This advantage arises from the limited transferability of some local market-specific information; this can be thought of alternatively as information that is especially costly to obtain for nonlocal individuals. This barrier arises because certain information about a local environment is difficult to collect, centralize, digitize, and share. Examples include (1) learning local culture and appetite for products and services, adoption rates of new styles and trends, and risk tolerances; (2) changes to housing and labor markets that are only known in the aggregate with some delay and are only mentioned by the local or regional news services; and (3)

[37] See online appendix Table A22 and A223 for full results.

compatibility issues across different platforms and site-specific skills needed to operate the different databases used by local, county, and state governments, and non-profit organizations that might contain valuable information about the potential borrower and his or her area. These factors are informative of borrower performance, but are not easily or accurately converted into a numerical value and, in some cases, difficult to compare across borrowers from different locales. The clear effect of this limited transferability can be seen in the state size analysis. As the state gets smaller, the lender's knowledge about her own local market is more relevant and relatable to borrowers in the rest of the state. A lender in a small state is even more informed about local conditions than local lenders in a larger state.

Another way to empirically test the information story is to create subsamples of loan types where the value of additional information available to local lenders is relatively high (Debt Consolidation, Home Improvement, and Business) and low (Auto and Other). While local lenders in both subsamples behave qualitatively the same as the benchmark case, the information adjustment is stronger in the high-information group. The increase in bid amount for loans that paid back and the absolute differential in bid interest rates by ex-post outcome between local and nonlocal lenders are larger for the high-information group than for the low-information group. As suggested by theory, in markets where the initial information gap is larger or the information is more costly to obtain, the asymmetry between local and nonlocal lenders is more pronounced.

Extending this analysis on high-information loan types further, I restrict my attention to the states that had the largest and smallest change in mean monthly foreclosure and mortgage delinquency rates from 2000-06 to 2007-08.[38] Segmenting this way allows me to examine the amount of risk that is created by local economic conditions that would be known by local lenders but most likely not yet by non-local lenders. I rerun the bid amount and bid interest rate regressions for these two groups separately; Tables IX-X present the results. The left column of both tables shows the results for borrowers from the 10 states that had the largest change in their monthly foreclosure and delinquency rates and the right column shows borrowers from the 10 states with the smallest change. The large change group represents states where the economy experienced the most volatility from 2000-06 to 2008, which increases the importance of not only the timeliness but also the relevance of local information on making correct lending decisions. For bid amount, local lenders are estimated to increase their bids by about 10% in the large fo-

[38]Top 10: California, Colorado, Delaware, Kentucky, Massachusetts, Michigan, New Hampshire, Nevada, Vermont, and Wyoming. Bottom 10: Arkansas, Connecticut, Florida, Indiana, Louisiana, New Mexico, Oklahoma, Pennsylvania, South Carolina, and Tennessee.

reclosure/delinquency change states while the local premium is only 2% for the small change states. For bid interest rates, local lenders in the large change states correctly adjust their bid rates by a larger amount than those in small change states. Local lenders in the large change sample adjust their bid rates down almost one whole percentage point for E loans that pay back in full, while local lenders in the small change sample adjust their bids downward by half a percentage point.

***** Place Table IX Here *****

***** Place Table X Here *****

Additionally, it is important to emphasize that observationally equivalent borrowers (same credit grade, category, etc.) may have vastly different realized outcomes across geographies if local markets have different characteristics. For example, knowledge about a business loan in California would not be that insightful about an auto loan in Ohio. To formally test this, I calculate the default rate for every credit grade-category pair for every state. I can reject the null that the state default rates are the same within credit grade-category pairs at the 5% significance level for 79% of the pairwise comparisons. This heterogeneity confirms the fact that there actually are meaningful differences in local market conditions such that having local relevant information would be instrumental in improving lender's performance. The fact that these differences exist supports the idea that there is heterogeneity in the transmutability of information across locales.

VII. CONCLUSION

Over the past few years, major commercial organizations have noticed the vast potential of crowdfunding and have begun to acquire equity stakes in P2P lending firms, while mainstream financial companies are beginning to offer similar services, mimicking this online marketplace. As P2P lending sites are starting to open and expand worldwide, it is clear that P2P lending, and crowdfunding in general, as an alternative as well as a complement to the traditional finance methods, is a growing trend. Therefore, it is paramount that we better understand the factors that influence the behavior of the marketplace's participants. Using transaction data from Prosper, I document evidence that P2P lending is not immune to the geographic frictions that plague the offline credit market. I find evidence that informational frictions (outside of friends and family) exist and have strong effects on the behavior in P2P loan markets. In particular, I observe that lenders appear to be more informed about local projects and this informational asymmetry leads to the rational herding found by Zhang & Lui [2012]. As shown by my model, this is true even if

lenders do not ex-ante know other lenders' local status, only merely that this information is obtainable.

While the empirical literature is split on whether economic or behavioral motives matter, my results are consistent with the costly information acquisition story of Grinblatt & Keloharju [2013]. It appears that lenders have easier and cheaper access to local market-specific information and, thus, rationally get more informed about local projects. If lenders were only acting altruistically towards local borrowers, then one would expect that 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 better at accounting for riskiness than nonlocal lenders. These findings are strongly related to the rational inattention story from portfolio selection theory in finance (Huang & Liu [2007]). Information collection, noise reduction, and information processing is very costly and these costs will induce the lender's to not become fully informed when making investment decisions. This inattention may cause lenders to under- or overinvest in certain assets relative to the optimal strategy in the full attention case (no search costs). Therefore, my results are consistent with the existing theory and emerging empirical literature that predicts the importance of spatial distance as a barrier to information acquisition even in an internet enabled world.

Although the cost of information gathering and processing is lower now with wide adoption of new technology, my results provide evidence that crowdfunding sites suffer from similar frictions to those in the offline credit markets. The structure of P2P lending markets is designed to protect personal privacy and prevent personal enforcement and monitoring; however, the design actually inhibits the full power of online connections to improve informational efficiencies. What appears to matter is not simply more sharing generically, but the sharing of more insightful and critical soft information about potential borrowers and the economic environment of the markets their projects are located in. Since loans obtained through the site are unsecured and borrowers cannot fully expose all their meaningful information, these loans can alternatively be thought of as an example of the classic 'character loan' given out by smaller community banks based on relationship lending where soft factors are more relevant. Allowing borrowers to link their P2P accounts to their social media presence or to more finely specify their place of residence would provide lenders a fuller and richer profile of the potential borrowers and their projects.

After the limited personal information that borrowers are allowed to disclose, lenders are still left with uncertainty about the hidden characteristics of the borrowers and

their local market, hence the disparity in behavior between local and nonlocal lenders. Platforms like eBay and Amazon have robust seller reputation and buyer feedback mechanisms to facilitate information sharing to overcome this obstacle. However, on Prosper, the previous activity between borrowers and lenders is limited and in most cases nonexistent. Most individuals simply do not request loans very frequently. Furthermore, the lack of a borrower's history on the site amplifies the importance of the lenders' ability to extract valuable information from a borrower's listing. This is exacerbated by the site's prohibition on linking a borrower's listings to his or her social media accounts.

My finding that the reduction in informational cost has yet been of sufficient magnitude to render geography irrelevant in P2P lending markets is not an anomaly in the empirical literature. 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. However, my work contributes to this growing literature by empirically showing that local preference and friends and family cannot explain the observed behavior; while a model of costly search with initial information asymmetries gives rise to the observed situation.

Further research is needed, but placing my results in context of the wider literature implies that the presence of informational asymmetry suggests that the current tools and platforms are unlikely to fully remove barriers and vastly improve the efficiency of the online credit market. This finding helps to explain the results of Brevoort & Wolken [2009] and others that find that many funding relationships are still local, particularly for small or young firms. A better understanding of investors' behavior and decision-making on 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.

References

Agrawal, A.; Catalini, C. and Goldfarb, A. 2015, 'Crowdfunding: Geography, Social Networks, and the Timing of Investment Decisions,' *Journal of Economy and Management Strategy*, 24, pp. 253–277.

Agrawal, S. and Hauswald 2010, 'Distance and Private Information in Lending,' *The Review of Financial Studies*, 23, pp. 2757–88.

Ahlers, G. K.; Cumming, D.; Günther, C. et al. 2015, 'Signaling in Equity Crowdfunding,' *Entrepreneurship Theory and Practice*, 39, pp. 955–980.

An, J.; Quercia, D. and Crowcroft, J. 'Recommending Investors for Crowdfunding Projects,' in Chung, C.-W., ed., *Proceedings of the 23rd International Conference on the World Wide Web* (ACM, New York) 2014, pp. 261–70.

Arthur, B. W. 1988, 'Urban systems and historical path dependence,' in Ausubel, J. and Herman, R., eds., *Cities and their Vital Systems* (National Academy Press, Washington) pp. 85–97.

Baird, D. 2007, 'Technology, Information, and Bankruptcy,' *University of Illinois Law Review*, 2007, pp. 305–22.

Banerjee, A. 1992, 'A Simple Model of Herd Behavior,' *The Quarterly Journal of Economics*, 107, pp. 797–817.

Brevoort, K. and Wolken, J. 2009, 'Does Distance Matter in Banking?,' in Zazzaro, A.; Frantianni, M. and Alessandrini, P., eds., *The Changing Geography of Banking and Finance* (Springer) pp. 27–56.

Burtch, G.; Ghose, A. and Wattal, S. 2013, 'An Empirical Examination of the Antecedents and Consequences of Contribution Patterns in Crowd-Funded Markets,' *Journal of Information Systems Research*, 24, pp. 499–519.

Coval, J. and Moskowitz, T. 2001, 'The Geography of Investment: Informing and Asset Prices,' *Journal of Political Economy*, 109, pp. 811–41.

David, P. and Rosenbloom, J. 1990, 'Marshallian factor market externalities and the dynamics of industrial localization,' *Journal of Urban Economics*, 28, pp. 349–370.

Goldfarb, A. and Tucker, C. 2011, 'Advertising Bans and the Substitutability of Online and Offline Advertising,' *Journal of Marketing Research*, 48, pp. 207–227.

Gompers, P. 1995, 'Optimal Investment, Monitoring, and Staging of Venture Capital,' *Journal of Finance*, 50, pp. 1461–89.

Grinblatt, M. and Keloharju, M. 2013, 'How Distance, Language, and Culture Influence Stockholdings and Trades,' *The Journal of Transport Geography*, 28, pp. 124–36.

Hauswald, R. and Marquez, R. 2006, 'Competition and Strategic Information Acquisition in Credit Markets,' *The Review of Financial Studies*, 19, pp. 967 – 1000.

Herzenstein, M.; Andrews, R. and Dholakia, U. 2011, 'Strategic Herding Behavior in Peer-to-Peer Loan Acutions,' *Journal of Interactive Marketing*, 25, pp. 27–36.

Hillberry, R. and Hummels, D. 2003, 'Intranational Home Bias: Some Explanations,' *Review of Economics and Statistics*, 85, pp. 1089–1092.

Hortaçsu, A.; Martínez-Jerez, F. A. and Douglas, J. 2009, 'The Geography of Trade in Online Transactions: Evidence from eBay and MercadoLibre,' *American Economic Journal: Microeconomics*, 1, pp. 53–74.

Huang, L. and Liu, H. 2007, 'Rational Inattention and Portfolio,' *Journal of Finance*, 62, pp. 1999–2040.

Ivković, Z. and Weisbenner, S. 2005, 'Local Does as Local Is: Information Content of the Geography of Individual Investors' Common Stock Investments,' *Journal of Finance*, 60, pp. 267–306.

Jaworski, M. *Prosper Announces Major Changes to Group Concept* Technical report P2P Lending News 2007,.

Klafft, M. 'Online Peer-to-Peer Lending: A Lenders' Perspective,' in Arabnia, H. R. and Bahrami, A., eds., *Proceedings of the International Conference on E-Learning, E-Business, Enterprise Information Systems, and E-Government* (CSREA Press) 2008a, pp. 371–375.

Klafft, M. 'Peer to Peer Lending: Auctioning Microcredits over the Internet,' in Agarwal, A. and Khurana, R., eds., *International Conference on Information Systems, Technology and Management* (Dubai) 2008b,.

Lerner, J. 1995, 'Venture Capital and Oversight of Private Firms,' *Journal of Finance*, 50, pp. 301–18.

Lin, M. and Viswanathan, S. 2016, 'Home Bias in Online Investment: An Empirical Study of an Online Crowdfunding Market,' *Management Science*, 62, pp. 1393–1414.

Mollick, E. R. 2014, 'The Dynamics of Crowdfunding,' *Journal of Business Venturing*, 29, pp. 1–16.

Petersen, M. A. and Rajan, R. G. 2002, 'Does Distance Still Matter? The Information Revolution in Small Business Lending,' *The Journal of Finance*, 57, pp. 2533–2570.

Pope, D. and Sydnor, J. 2011, 'What's in a Picture?: Evidence of Discrimination from Prosper.com,' *Journal of Human Resources*, 46, pp. 53–92.

Ravina, E. 2012, 'Love and Loans: The Effect of Beauty and Personal Characteristics in Credit Markets,' working Paper.

Sanchez, J. 2017, 'The Information Technology Revolution and the Unsecured Credit Market,' working Paper.

Smith, L. and Sørensen, P. N. 2000, 'Pathological Outcomes of Observational Learning,' *Econometrica*, 68, pp. 371–398.

Sorenson, O. and Stuart, T. 2001, 'Syndication Networks and Social Distribution of Venture Capital,' *American Journal of Sociology*, 106, pp. 1546–1588.

Van Nieuwerburgh, S. and Veldkamp, L. 2009, 'Information Immobility and Home Bias Puzzle,' *Journal of Finance*, 64, pp. 1187–1215.

Wolf, H. C. 2000, 'A Intranational Home Bias in Trade,' *Review of Economics and Statistics*, 82, pp. 555–563.

Wong, A.; Bhatia, M. and Freeman, Z. 2009, 'Angel Finance: The Other Venture Capital,' *Strategic Change*, 18, pp. 221–230.

Zeithaml, A. 2012, 'Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence,' *Electronic Commerce Research and Applications*, 11, pp. 469–83.

Zhang, J. and Lui, P. 2012, 'Rational Herding in Microloan Markets,' *Managment Science*, 58, pp. 555–563.

Table I: Summary Statistics of All Listings

	Max	Mean	Median	Min	S.D.
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
Debt to Income	10.10	1.90	0.31	0	3.60
Homeowner	1	0.49	0	0	0.491
Employed Full Time	1	0.85	0	0	0.348
Self-Employed	1	0.07	0	0	0.262
Open Credit Lines	43	10.08	9	0	5.92
Open Revolving Accounts	41	6.82	6	0	4.82
Current Delinquencies	22	0.41	0	0	1.40
Duration	10	7.10	7	3	1.33
Total Competition	1,701	1,292	1,235	242	117
Credit Grade Competition	508	251	262	74	94
Category Competition	623	399	444	3	121

Table II: Tobit Regression of Localness on Bid Amount

log(Bid Amount)	Coef.	S.E.	Coef.	S.E.
Local Lender	0.069***	0.005	0.070***	0.006
Default			-0.007*	0.003
Local Lender_Default			-0.037***	0.009
log(Loan Amount)	-0.031***	0.002	-0.045***	0.002
In Group	0.031***	0.001	0.027***	0.001
Prosper Friend	0.068***	0.002	0.051***	0.002
Borrower Max Rate	0.012***	5.37E-04	0.008***	4.17E-04
Debt to Income≤ 20	0.266***	0.090	0.170***	0.016
Debt to Income≤ 40	0.075***	0.004	0.130***	0.034
Debt to Income≤ 60	0.074*	0.032	0.100*	0.085
Debt to Income≤ 80	0.062	0.071	0.074	0.084
Homeowner	0.047***	0.002	0.046***	0.002
Employed Full-time	0.043***	0.003	0.036***	0.003
Self-Employed	-0.010*	0.005	-0.010*	0.004
Current Delinquencies	-0.017**	0.005	-0.016**	0.005
Open Credit Lines	0.012***	0.002	0.011***	0.002
Open Revolving Accounts	-0.011***	0.002	-0.012***	0.002
Experienced	-0.052***	0.003	-0.039***	0.003
Fully Funded	0.100***	0.003	-0.070***	0.003
Current Bid Count	-0.043***	1.13E-03	-0.013***	1.26E-03
Current Rate	0.013***	4.02E-04	0.017***	4.36E-04
AA	0.329***	0.010	0.351***	0.009
A	0.317***	0.009	0.302***	0.009
B	0.038***	0.008	0.056***	0.008
C	-0.072***	0.007	-0.064***	0.007
D	-0.176***	0.007	-0.166***	0.007
N	2,022,910		1,598,786	
Pseudo R^2	0.318		0.317	

Notes: FE included borrower and lender state, occupation, category, and time.
Standard errors are clustered at the lender level and competition effects not shown.
Significance levels: †10%, * 5%, ** 1%, *** 0.1%

Table III: Tobit Regression of Localness on Bid Interest Rate

Bid Interest Rate	Coef.	S.E.
LocalAA	-0.142***	0.033
LocalA	-0.071***	0.011
LocalB	-0.032***	0.009
LocalC	-0.051***	0.013
LocalD	-0.241*	0.098
LocalE	-0.907***	0.211
Defaulted	0.041†	0.023
LocalAA_Defaulted	0.282***	0.063
LocalA_Defaulted	0.153*	0.076
LocalB_Defaulted	0.122†	0.067
LocalC_Defaulted	0.332**	0.104
LocalD_Defaulted	0.298*	0.148
LocalE_Defaulted	0.992*	0.414
Loan Amount	-0.036***	0.002
In Group	-0.091***	0.003
Prosper Friend	-0.131***	0.006
Borrower Max Rate	0.072***	0.003
Debt to Income≤ 20	-0.190***	0.047
Debt to Income≤ 40	-0.184***	0.025
Debt to Income≤ 60	-0.073***	0.010
Debt to Income≤ 80	-0.011***	0.001
Homeowner	0.032***	0.002
Employed Full-time	-0.033***	0.003
Self-Employed	0.012*	0.006
Current Delinquencies	0.017**	0.005
Open Credit Lines	-0.012***	0.002
Open Revolving Accounts	0.003**	0.001
Experienced	-0.052***	0.011
Fully Funded	-0.091***	0.008
Current Bid Count	-0.008***	3.92E-04
Current Rate	0.736***	0.001
AA	-0.032***	0.002
A	-0.027***	0.002
B	-0.016***	0.002
C	-0.013***	0.002
D	-0.009***	0.002
N	1,598,786	
Prob $> \chi^2$	0	
Dep. Var. Mean	17.57	

Notes: FE included borrower and lender state, occupation, category, and time. Standard errors are clustered at the lender level and competition effects not shown.

Table IV: Summary Statistics of Bid Amounts by Friends & Family Status

	75%	Mean	Median	N
All Bids	72.30	78.65	50.00	2,022,910
Non-Local Bids	70.68	78.06	50.00	1,904,112
Local Bids	79.00	88.02	50.00	118,798
Prosper Friend Bids	650.78	935.85	150.00	663
Local and Prosper Friend Bids	3,750.00	2,197.17	500.00	39
Local and Non-Prosper Friend Bids	79.00	87.32	50.00	118,759
F&F(Agrawal et al.) Bids	100.00	150.24	50.00	3,534
Local and Non-F&F(Agrawal et al.) Bids	76.29	86.12	50.00	115,264
F&F(Lin & Viswanathan) Bids	100.00	132.79	50.00	4,465
Local and Non-F&F(Lin & Viswanathan) Bids	77.90	86.76	50.00	118,106
F&F(An et al.) Bids	75.00	98.78	50.00	12,841
Local and Non-F&F(An et al.) Bids	80.00	86.72	50.00	105,957

Table V: t-Tests for Difference in Mean for F&F Bids vs. All Other Bids

Agrawal et al. Definition

	Default=1			Default=0		
	t-statistic	p-value	N	t-statistic	p-value	N
AA	4.32	(0.000)	46,093	2.60	(0.009)	170,408
A	2.51	(0.011)	51,091	3.17	(0.001)	132,166
B	3.94	(0.000)	67,556	0.83	(0.408)	122,222
C	1.50	(0.133)	38,115	4.51	(0.000)	72,710
D	2.82	(0.004)	23,380	4.96	(0.000)	46,923
E	1.68	(0.093)	7,342	3.48	(0.000)	11,517

Lin & Viswanathan Definition

	Default=1			Default=0		
	t-statistic	p-value	N	t-statistic	p-value	N
AA	8.55	(0.000)	46,093	9.11	(0.000)	170,408
A	5.61	(0.000)	51,091	8.80	(0.004)	132,166
B	7.87	(0.000)	67,556	7.33	(0.178)	122,222
C	4.82	(0.000)	38,115	5.48	(0.000)	72,710
D	4.54	(0.000)	23,380	5.54	(0.000)	46,923
E	0.59	(0.555)	7,342	0.57	(0.566)	11,517

An et al. Definition

	Default=1			Default=0		
	t-statistic	p-value	N	t-statistic	p-value	N
AA	5.09	(0.000)	46,093	7.03	(0.000)	170,408
A	3.87	(0.000)	51,091	4.65	(0.004)	132,166
B	4.67	(0.000)	67,556	2.09	(0.036)	122,222
C	0.91	(0.358)	38,115	5.41	(0.000)	72,710
D	2.54	(0.000)	23,380	3.94	(0.000)	46,923
E	1.73	(0.082)	7,342	2.04	(0.041)	11,517

Notes: Test statistics are for $(NonF\&F - F\&F)$

Table VI: Conditional Logit Model of Lender Choice

	Coef.	S.E.	Coef.	S.E.
Local Lender	0.067***	0.003	0.081***	0.003
Default			-0.007*	0.003
Local Lender_Default			-0.056**	0.009
Loan Amount	-0.015***	0.001	-0.015***	0.002
In Group	0.031***	0.001	0.029***	0.001
Prosper Friend	0.015***	0.002	0.015***	0.002
Borrower Max Rate	0.054***	1.12E-04	0.053***	1.17E-04
Debt to Income≤ 20	0.110***	0.001	0.112***	0.001
Debt to Income≤ 40	0.091***	0.002	0.093***	0.003
Debt to Income≤ 60	0.058**	0.022	0.064*	0.024
Debt to Income≤ 80	0.028*	0.014	0.034*	0.017
Homeowner	0.113***	0.001	0.046***	0.002
Employed Full-time	0.038***	0.001	0.036***	0.002
Self-Employed	-0.022*	0.004	-0.020***	0.004
Current Delinquencies	-0.053***	0.005	-0.016**	0.005
Open Credit Lines	0.041***	0.002	0.011***	0.002
Open Revolving Accounts	-0.030***	0.002	-0.012***	0.002
Fully Funded	0.015***	0.003	0.012***	0.003
Current Bid Count	-0.013***	1.12E-03	-0.013***	1.16E-03
Current Rate	0.018***	3.01E-04	0.017***	3.36E-04
N	84,404,398		73,798,765	
Pseudo R^2	0.366		0.387	

Notes: FE included borrower and lender state, occupation, category, and time.
Standard errors are clustered at the lender level and competition effects not shown.
Significance levels: †10%, * 5%, ** 1%, *** 0.1%

Table VII: Poisson Regression Marginal Effect of Early Local Bids on Bid Count

	Total BC		Total Nonlocal BC		Total Pre-FF BC		Total Post-FF BC	
	dy/dx	S.E.	dy/dx	S.E.	dy/dx	S.E.	dy/dx	S.E.
Total Early Count	0.331***	0.011	0.149***	0.007	0.644***	0.009	0.176***	0.007
Total Early Amount	1.550***	0.016	1.116***	0.010	0.683***	0.014	0.610***	0.011
Local Early Count	0.406	0.051	0.349***	0.036	0.191***	0.038	0.069***	0.020
Local Early Amount	0.991	0.049	0.713***	0.033	0.349***	0.041	0.405***	0.031
Loan Amount	1.115***	0.002	1.139***	0.014	7.76***	0.002	3.44***	0.001
In Group	6.243***	0.433	6.493***	0.303	4.41***	0.313	4.38***	0.303
Endorsement	1.312***	0.182	1.062***	0.114	1.74***	0.173	1.092***	0.112
Borrower Max Rate	4.016***	0.003	4.405***	0.002	0.60***	0.021	0.473***	0.002
Debt to Income≤ 20	5.782***	0.006	3.841***	0.047	2.02***	0.004	4.32***	0.016
Debt to Income≤ 40	4.982*	0.231	3.795***	0.079	1.99***	0.047	4.05***	0.034
Debt to Income≤ 60	2.853*	0.114	1.129	1.38	1.95***	0.038	3.23***	0.085
Debt to Income≤ 80	2.722***	0.054	0.464	0.384	0.288	0.222	0.167	0.182
Homeowner	4.641***	0.336	5.304***	0.243	0.720***	0.213	0.554***	0.024
Employed Full-time	3.601***	0.086	2.264***	0.051	6.75***	0.466	2.34***	0.051
Self-Employed	2.809***	0.069	2.233***	0.063	14.01***	0.586	2.32***	0.063
Current Delinquencies	-15.641***	0.187	-10.491**	0.137	-4.96***	0.127	-11.12**	0.004
Open Credit Lines	-1.342***	0.066	-0.798***	0.047	-0.533***	0.046	-0.861***	0.047
Open Revolving Accounts	0.953***	0.07	0.428***	0.002	0.439***	0.049	0.527***	0.05
AA	25.964***	0.012	21.76***	0.091	5.34***	0.091	2.24***	0.091
A	23.947***	0.011	18.98***	0.083	5.61***	0.086	1.98***	0.084
B	20.424***	0.011	13.79***	0.075	7.12***	0.081	1.43***	0.075
C	11.865***	0.010	5.51***	0.070	6.52***	0.079	0.551***	0.071
D	6.507***	0.010	0.99***	0.073	5.31***	0.080	0.068***	0.007
N	42,657		42,657		9,624		9,624	
Pseudo R^2	0.823		0.858		0.714		0.539	
Dep. Var. Mean	47.42		21.13		26.67		20.75	

Notes: FE included borrower state, occupation, category, and time.

Standard errors are clustered at the lender level and competition effects not shown.

Significance levels: †10%, * 5%, ** 1%, *** 0.1%

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

	Prob. of Funding		Final Interest Rate	
	dy/dx	S.E.	Coef.	S.E.
Total Early Count	0.027***	0.001	-0.197***	0.004
Total Early Amount	0.013***	0.001	-0.003***	6.04E-04
Local Early Count	0.011*	0.004	-0.105*	0.007
Local Early Amount	0.003*	0.159	-0.008*	1.37E-04
Loan Amount	-0.027***	0.004	0.172***	0.008
In Group	0.033***	0.002	0.328***	0.111
Endorsement	0.017***	0.004	0.130***	0.057
Borrower Max Rate	0.006***	0.001	0.509***	0.008
Debt to Income≤ 20	0.028***	0.004	-0.732***	0.016
Debt to Income≤ 40	0.019***	0.002	-0.706***	0.010
Debt to Income≤ 60	0.012†	0.007	-0.147*	0.075
Debt to Income≤ 80	0.005	0.006	-0.021	0.024
Homeowner	-0.003	0.003	0.224***	0.078
Employed Full-time	0.043***	0.003	-0.027†	0.015
Self-Employed	0.013*	0.005	0.031	0.020
Current Delinquencies	-0.021***	0.004	0.351***	0.027
Open Credit Lines	-0.015***	0.003	0.054***	0.018
Open Revolving Accounts	0.012***	0.002	-0.038***	0.019
AA	0.247***	0.010	-8.15***	0.241
A	0.217***	0.007	-6.93***	0.219
B	0.177***	0.006	-5.74***	0.193
C	0.126***	0.004	-4.63***	0.175
D	0.008***	0.004	-2.99***	0.174
N	42,656		9,624	
Adj R^2	0.552		0.757	
Dep. Var. Mean	22.56		16.61	

Notes: FE included borrower state, occupation, category, and time.
Competition effects not shown.

Table IX: Tobit Regression of High Information Loan Type on Bid Amount

	Large Change State		Small Change State	
log(Bid Amount)	Coef.	S.E.	Coef.	S.E.
Local Lender	0.096***	0.021	0.021*	0.011
log(Loan Amount	-0.053***	0.006	-0.089***	0.007
In Group	0.021***	0.001	0.027***	0.001
Prosper Friend	0.059***	0.002	0.039***	0.002
Borrower Max Rate	0.011***	1.02E-03	0.009***	1.32E-03
Debt to Income≤ 20	0.251***	0.090	0.189***	0.016
Debt to Income≤ 40	0.061***	0.004	0.079***	0.003
Debt to Income≤ 60	0.058*	0.029	0.065*	0.033
Debt to Income≤ 80	0.031	0.071	0.034	0.054
Homeowner	0.044^{***}	0.006	0.053***	0.007
Employed Full-time	0.043***	0.003	0.036***	0.003
Self-Employed	-0.010**	0.003	-0.010**	0.003
Current Delinquencies	-0.017**	0.005	-0.016**	0.005
Open Credit Lines	0.012***	0.002	0.011***	0.002
Open Revolving Accounts	-0.011***	0.002	-0.012***	0.002
Experienced	-0.028 †	0.014	-0.032**	0.016
Fully Funded	0.064***	0.007	0.074***	0.009
Current Bid Count	-0.010***	2.81E-03	-0.011***	3.49E-03
Current Rate	0.012***	1.08E-03	0.018***	1.36E-03
AA	0.393***	0.025	0.386***	0.034
A	0.335***	0.023	0.319***	0.032
B	0.057***	0.021	0.083***	0.030
C	-0.075***	0.019	-0.051***	0.029
D	-0.295***	0.019	-0.225***	0.031
N	376,128		248,476	
Pseudo R^2	0.161		0.177	

Notes: FE included borrower and lender state, occupation, category, and time.
Standard errors are clustered at the lender level and competition effects not shown.
Significance levels: †10%, * 5%, ** 1%, *** 0.1%

Table X: Tobit Regression of High Information Loan Type on Bid Interest Rate

	Large Change State		Small Change State	
Bid Interest Rate	Coef.	S.E.	Coef.	S.E.
LocalAA	-0.138**	0.053	-0.060**	0.023
LocalA	-0.023***	0.006	-0.034*	0.017
LocalB	-0.037***	0.006	-0.030*	0.014
LocalC	-0.048***	0.007	-0.070***	0.016
LocalD	-0.301***	0.085	-0.138***	0.039
LocalE	-0.961***	0.138	-0.562***	0.088
Defaulted	0.019†	0.010	0.021†	0.011
LocalAA_Defaulted	0.207***	0.088	0.146***	0.036
LocalA_Defaulted	0.0.047***	0.010	0.041**	0.014
LocalB_Defaulted	0.049***	0.008	0.036**	0.013
LocalC_Defaulted	0.068***	0.012	0.084**	0.034
LocalD_Defaulted	0.387***	0.134	0.255***	0.082
LocalE_Defaulted	1.260***	0.049	0.694***	0.041
Loan Amount	-0.021***	0.002	-0.020***	0.002
In Group	-0.026***	0.003	-0.024***	0.004
Prosper Friend	-0.091***	0.003	-0.089***	0.003
Borrower Max Rate	0.069***	0.003	0.079***	0.004
Debt to Income≤ 20	-0.121***	0.003	-0.101***	0.002
Debt to Income≤ 40	-0.101***	0.003	-0.081***	0.004
Debt to Income≤ 60	-0.081***	0.003	-0.061***	0.003
Debt to Income≤ 80	-0.012***	0.003	-0.008***	0.002
Homeowner	0.034***	0.002	0.032***	0.002
Employed Full-time	-0.033***	0.003	-0.032***	0.003
Self-Employed	0.012**	0.006	0.014***	0.006
Current Delinquencies	0.017***	0.005	0.017***	0.005
Open Credit Lines	-0.011***	0.002	-0.011***	0.003
Open Revolving Accounts	0.005***	0.001	0.005**	0.002
Experienced	-0.079***	0.002	-0.078***	0.003
Fully Funded	-0.09***	0.008	-0.08***	0.008
Current Bid Count	-0.033***	8.90E-03	-0.015***	1.15E-03
Current Rate	0.719***	0.003	0.694***	0.004
AA	-0.087***	0.006	-0.078***	0.011
A	-0.042***	0.007	-0.069***	0.011
B	-0.031***	0.006	-0.169***	0.010
C	-0.020***	0.002	-0.328***	0.010
D	-0.018***	0.002	-0.527***	0.010
N	297,418		182,797	
Prob $> \chi^2$	0.00		0.00	
Dep. Var. Mean	18.19		17.42	

Notes: FE included borrower and lender state, occupation, category, and time.
Standard errors are clustered at the lender level and competition effects not shown.