Home Bias in Online Investments: An Empirical Study of an Online Crowd Funding Market

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Abstract

An extensive literature in economics and finance has documented "home bias," the tendency that transactions are more likely to occur between parties in the same country or state, rather than outside. Can the Internet help overcome this spatial divide, especially in the context of online financial investments? We address this question in the context of a large online crowd funding marketplace. We analyze detailed transaction data over an extended period of time under typical market conditions, as well as those from a natural experiment, a period in which investors were restricted to only one state due to regulations. We further employ a quasi-experimental design by tracking borrowers who moved across state boundaries, and study how investors' behaviors change when those borrowers moved. Home bias appears to be a robust phenomenon under all three scenarios. This finding has important implications not just for the home bias literature, but also more broadly for the growing research and policy interest on Internet-based crowd funding, especially as a new channel for entrepreneurial financing.

Key words: home bias; entrepreneurial financing; peer-to-peer lending; natural experiment; quasi-experiment; crowd funding

1. Introduction

We study whether investors in online financial investment platforms such as crowd-funding and peer-to-peer lending exhibit home bias, as is common among investors and businesses in offline contexts. "Home bias" refers to the phenomenon wherein agents (businesses, funds, etc.) are more likely to conduct transactions with parties who are geographically closer to them, either in the same country or same state, rather than those outside. Since French and Poterba (1991), a long and growing literature has documented this phenomenon in many contexts, and it bears important implications for market structure, policy-making, and social welfare. For instance in international trade, trade is more likely to occur within a country than between countries (Disdier and Head 2008, Overman, Redding and Venables 2003). Within a country, transactions are also more likely to occur within a particular area rather than across boundaries (Hillberry and Hummels 2003, Wolf 2000). More prominently, home bias is also observed in financial investments in terms of the asset holdings and investment decisions (Ahearne, Griever and Warnock 2004, Cooper and Kaplanis 1994, Coval and Moskowitz 1999, Dziuda and Mondria 2012, Graham, Harvey and Huang 2009, Karlsson and Nordén 2007, Sorenson and Stuart 2001). Understanding home bias is especially important for early-stage entrepreneurs and investors who finance them (Sohl 1999). Both economic and behavioral reasons have been proposed to explain home bias (Lewis 1999). In general, home bias is considered a sub-optimal behavior in decision-making, leading to economic inefficiencies in the marketplace.

It seems promising that the recent growth of electronic commerce should render home bias much less relevant. Interestingly and surprisingly, Hortacsu, Martinez-Jerez and Douglas (2009) show that in electronic products markets such as eBay.com, transactions are still more likely to occur between buyers and sellers from the same area. Even though the market is virtual, the authors suggest that geography can still play a role because of shipping charges, localized consumption of the goods (e.g. event tickets), and the possibility for direct contract enforcement.

These explanations however do not apply to online crowd-funded investments. In online investment platforms, all funds are routed electronically. Investors cannot directly enforce the contract by visiting the borrowers in person; and they also do not have direct legal recourse against the borrowers in the event of a default[1]. Moreover due to the nature of crowd funding, each individual investor only has a small stake in each loan, so their incentive for direct contract enforcement is minimal. Consequently, we would expect such online crowd-funding markets to be devoid of any home bias. Nevertheless, whether home bias still exists in this new context remains an open empirical question. We investigate this question

[1] This is true of our context, as we will discuss in greater detail later. Some international peer-to-peer lending sites may have different rules, however.

using data from a debt-based crowd-funding website in the US, Prosper.com, an online market for unsecured personal loans (Lin, Prabhala and Viswanathan 2013, Zhang and Liu 2012).

We perform a series of tests to investigate whether home bias exists. The first one employs detailed transaction data under regular market conditions over an extended period of time. While this test is appealing in terms of its generality, investors from different states may interact with each other in the funding process, making it challenging to rule out alternative explanations. We therefore complement it with a second analysis, using transactions data from a unique natural experiment. During a period that has come to be called "mini Prosper" among users of the site, only investors from one particular state were allowed to lend, while borrowers from all states were allowed to borrow. This period serves as a unique natural experiment that overcomes some important confounding factors in our first test.

Further complementing these two sets of dyadic tests, we conduct a third test using a quasi-experimental design. We exploit the fact that some borrowers moved during the study period, and requested loans both before and after their move. Since Prosper loans are typically small, it is highly unlikely that borrowers moved across states just to obtain funding from Prosper.com. Such moves are therefore largely exogenous to investor decisions, and we investigate how investors in the borrowers' origination and destination states change their behaviors in response to these moves. Through these three sets of tests, it appears that home bias persists in this emerging market of online financial investments.

We further explored several potential explanations for home bias in this context. Previous research has shown that home bias may be due to emotional or economic reasons. In our context however, many of the economic reasons mentioned in previous research no longer apply. In addition, through a number of tests, we found that home bias cannot be explained away by social networks or other economic reasons. Home bias in this market is therefore much more likely driven by emotional reasons.

Our paper is among the first to document empirical evidence of home bias in online crowd-funding markets. In particular, we take multiple complementary methods to ensure the robustness of this finding. As entrepreneurs, investors and policy-makers increasingly turn to online crowd-funding as a new channel of entrepreneurial financing[2], our paper not only contributes to a better understanding of investor behaviors and the role of geography in this market, but also helps inform future policies and regulations.

[2] Online peer-to-peer lending and debt-based crowdsourcing started out in the mid-2000s and have received significant interests ever since among entrepreneurs, investors, and policy makers. Such interests are not only reflected in the growth in peer-to-peer lending sites both within the US and across the world, but more strikingly in the recent legislations such as the JOBS Act (Jumpstart Our Business Startups Act) signed into law in April 2012. More details on the history of peer-to-peer lending can be found in Zhang and Liu (2012), Lin, Prabhala and Viswanathan (2013), and others.

2. Related Research

2.1 Home bias

Studies of home bias have flourished in many disciplines such as economics and finance (Ahearne, et al. 2004, Disdier and Head 2008, Graham, et al. 2009, Overman, et al. 2003, Sorenson and Stuart 2001, Wolf 2000). Most empirical studies in this stream of literature employ offline data such as trade or venture capital investments, and home bias has been consistently found in all these different contexts.

Researchers have proposed various explanations for home bias since it was first identified. The debate however, is still ongoing. Two classes of explanations have been offered: rational (economic) explanations, or emotional (behavioral) ones. Many economists attribute home bias to economic reasons, such as transaction costs that include shipping costs and cultural differences, or cost of information acquisition for international equity investments. Other researchers have taken a behavioral approach and identified over-optimism toward home equity markets in survey data (Lai and Teo 2008, Strong and Xu 2003), which may have resulted in home bias as well. Related to this stream of research is a literature in sociology and management, where home bias is often attributed to psychological factors such as homophily (McPherson, Smith-Lovin and Cook 2001).

Previous studies on home bias have largely focused on offline settings, and more recently several researchers started to examine this phenomenon online. One of the first such studies is Hortacsu et al. (2009), where the authors identify home bias in eBay transactions. They also offer some explanations as to why geography is still relevant in their data. For instance, some purchases on eBay are for event tickets in a specific area. A ticket to a performance in New York is certainly more likely to be sold by someone from New York, and also more likely to be purchased by someone else from New York. Other potential explanations include an opportunity to enforce contracts directly when the buyers are close to the seller. Shipping costs may also affect buyers' choices (page 73).

We contribute to this growing and intriguing literature by examining whether home bias exists in an online crowd-funding platform. Due to the nature of financial transactions and features of the site, geography should not matter. Specifically, the reasons that drive home bias in eBay transactions (Hortacsu et al. 2009) are largely irrelevant for online investments. It is therefore interesting to explore whether home bias still exists in this new context. The focus of our paper is to test whether there is such an empirical regularity, and also explore some potential explanations.

2.2 Empirical Tests for Home Bias

We now survey two major empirical modeling strategies, as commonly found in (1) the economics and finance literature, and (2) the management and strategy literature. In particular, we present the rationale for our choice of the latter, "potential dyads" approach.

The economic geography literature typically draws from the gravity equation (Bergstrand 1985) in international trade. Despite several variations, a typical gravity equation takes the following form (Bergstrand 1985):

$$PX_{ij} = \beta_0 Y_i^{\beta_1} Y_j^{\beta_2} D_{ij}^{\beta_3} A_{ij}^{\beta_4} u_{ij}$$

where the dependent variable is the aggregate volume of trade from region i to region j. Y_i and Y_j are the economy volume of two entities (e.g. two countries), respectively. D_{ij} is the distance between these two entities, and A_{ij} refers to other factors that facilitate or deter trade. U_{ij} is the error term. These models are typically estimated by taking a logarithm on both sides of the equation. The equity home bias literature in finance takes a related but slightly different approach (Lewis 1999). Specifically, home bias is said to exist when "*the proportion of foreign assets held by domestic investors is too small relative to the predictions of standard portfolio theory*" (Levy and Sarnat 1970, Lewis 1999). Researchers have also identified home bias in a descriptive manner, for example, when there are only a small proportion of investors that own foreign assets (Graham, et al. 2009). While both methods are well accepted, they only look at the outcomes of choices, i.e. the asset holdings or the realized transactions. Little is considered of the alternatives of agents at the time of their choice. Therefore in this paper, we use a different empirical approach – the study of "potential dyads" – as is common in the management and strategy literature (e.g. Sorenson et al. 2001).

In this approach, rather than examining aggregate volumes, we identify all possible pair-wise combinations between agents on two sides of the market, and relate explanatory variables (e.g. being from the same state) to the probability that each potential tie is realized. To illustrate this using the context of investors investing in entrepreneurs (c.f. Sorenson and Stuart, 2001), let us assume there are M investors $(A_1, A_2, \dots, A_M)$ and N entrepreneurs seeking funding $(B_1, B_2, \dots, B_N)$. Suppose further that A_1 invests in B_1 and A_2 invests in B_2, and these are the only actual transaction ties that occurred in the data. Conceptually, $(B_1, B_2, \dots, B_N)$ are all possible candidates for $A_1, A_2, \dots, A_M$, respectively, so there should a total of $M \times N$ possible dyads, out of which only 2 actually occurred. Using the "potential dyads" approach, we quantify characteristics for each of $A_1, A_2, \dots, A_M$ and $B_1, B_2, \dots, B_N$, and conduct a dyadic level analysis. The outcome is 1 for the A_1B_1 and A_2B_2 dyads (since they actually occurred), and 0 for all other dyads. By modeling the alternatives faced by each investor, this approach allows us to study whether investors are more likely to invest in someone from the same state as they are. If there is home bias, the coefficient on the variable indicating "same state" should be positive and significant. We therefore adopt this for our analysis[3].

It should be noted that both the gravity-equation and potential-dyads approach might further suffer from the endogeneity of the geography variables. They are typically assumed to be exogenous. Yet individuals and organizations can strategically choose where to locate their business activities. For instance, Parwada (2008) finds that several factors, such as the presence of investment firms, systematically affect the location choices of fund managers. More generally in the long run, economic production factors (labor, capital and so on) tend to gravitate to a location where the marginal productivity is highest (Redding and Sturm 2008). For these reasons, we not only study home bias under general market conditions, but also complement that with two additional tests – a natural experiment and a quasi-experiment approach. These are described in sections 4.3 and 4.4.

3. Empirical context

The context of our study is Prosper.com, one of the largest online peer-to-peer lending websites for unsecured personal loans in the US. We first briefly describe a typical transaction process on this website, and then discuss some features that make several economic explanations of home bias less relevant in this context[4]. We also describe "mini Prosper," the natural experiment that provides a unique opportunity to study home bias.

3.1 General features

Prosper.com is an online market for unsecured personal loans. No collaterals are involved, and all loans are personal liabilities. A borrower must first register on the website by providing a valid email address. He also needs to verify his identity using his social security number, driver's license, and other documents. His address must be verified, as well as a valid bank account where he can receive funds (if the request is successful) and make monthly repayments. Once verifications are complete, the borrower can create a listing, i.e. a web page that describes the purpose of the loan. Prosper.com extracts information from his credit profile and displays it to potential investors. The borrower's state of residence (part of his verified address), is displayed on the listing as well.

On the other side of the market, investors (lenders) go through a similar verification process before they can invest. They provide valid identification, social security number and bank account

[3] In contrast, the gravity equation approach described previously looks at the portfolio distribution of A_1 and A_2, and examines if B_1 is from the same location as A_1, and B_2 is from the same location as A_2. Meanwhile, $A_3, \dots, A_M$, and $B_3, \dots, B_N$ are not taken into consideration.

[4] Prosper.com has undergone notable changes in recent months; the descriptions that we provide here are accurate for the time period that we study.

information; then withdraw funds from their bank accounts (electronically) to their non-interest bearing Prosper.com account. Once these funds are in place, they can start bidding on loans.

An investor can browse listings and decide whom to invest in. If she is interested in a borrower's loan request, she can participate in the loan by placing a bid. An important feature of Prosper.com – as is common in online crowd-funding websites – is that an investor does not need to fund the entire amount of a loan. She can place a bid for as little as $50, and specify the minimum interest that she is willing to lend at. Funds from different investors are pooled to determine the interest rate that the borrower will receive. An important feature of the website is that no bids can be retracted. For this reason, the act of placing a bid indicates at least some trust in the borrower.

It should be noted that for privacy reasons, even though Prosper.com has borrowers' real name, address and contact information, borrowers are forbidden from disclosing such information on the listings. Lenders are also explicitly warned that just like other investments, their investments on Prosper.com are risky. There is no guarantee that the borrowers will repay the loan. More important, when defaults occur, lenders cannot contact the buyer to ask for money back. It is up to Prosper.com and its collection agency, not the lenders, to try and collect from the borrower. The lenders have no access to the borrowers throughout this process.

We now summarize several features of the website that make it a particularly interesting context to study home bias in online investments. First, by default, the system automatically displays the borrowers' state of residence on all requests. That piece of information is verified and visible, and the borrowers cannot turn it off. Second, in this market, geography itself is largely irrelevant. Loans are not secured, so there are no physical assets associated with them. All funds are transferred and debited electronically, making geographic locations less pertinent. Furthermore, lenders do not have legal recourse against borrowers who default, and they cannot physically monitor the borrowers either. If the borrower defaults on the loan, the lender cannot go to the borrower and ask for repayment, so there is no means of direct contract enforcement. For these reasons, being closer to a borrower does not bring any economically meaningful benefits. This is very different from the prior study on home bias in online transactions using eBay data (Hortacsu et al. 2009). Prosper.com therefore provides a unique and interesting context to test whether online investors are still more likely to invest in someone from their home state. What makes the context even more appealing is the occurrence of a unique natural experiment, which we turn to next.

3.2 "Mini Prosper"

Prosper.com started operating in 2006 in the United States. Since this was a new business model at that time, Prosper.com did not register with the Securities and Exchange Commission (SEC). In October

2008, SEC ordered Prosper.com to shut down. Prosper.com complied and entered a "quiet period" to go through the registration process. All market transactions were suspended on October 15th, 2008. In late-April 2009, Prosper.com obtained the permission from SEC, but was required to further obtain approvals from each and every state in the United States – one license for allowing *lenders* from each state to participate, and another to allow *borrowers* to use Prosper.com. On April 28th, 2009, without prior notice, Prosper.com re-opened its doors to borrowers from most states in the United States. For lenders however, only those from California were allowed to participate, as California was the first state to approve Prosper.com for lenders. This "mini Prosper" lasted for about 10 days until Prosper.com abruptly decided to re-enter another "quiet period" on May 8th, 2009 to obtain lender approvals from other states.

This scaled-down version of the website, or "mini-Prosper," provides a unique context to test home bias. Geography was largely exogenous during this period: Both the beginning and end of this 10-day window were unannounced, and in such a short period of time, borrowers and lenders were highly unlikely to have moved from one state to another. In fact, even if given more time, it remains highly unlikely that a borrower would move to a different state just to borrow from this website. "Mini Prosper" also helps rule out the possibility that investors from different states may influence each other when they participate in the same market, another potential confounding factor.

4. Testing for Home Bias: Data, Models and Results

As a first step to test for home bias under regular market conditions, we gathered all transaction data on Prosper.com between January 2007 and May 2008 (all listings and all bids placed on those listings). During this period, major features of Prosper.com were relatively stable and the SEC had not yet intervened in the market. More important, borrowers and lenders freely participated from all states across the US. Using this dataset, we first present some macro-level evidence of home bias, focusing only on loans that were actually funded. Then we turn to the potential-dyads approach to examine whether investors are indeed more likely to invest in someone from their home state. The same approach is then applied to transaction data from "mini Prosper" to further verify the robustness of our finding. Taking advantage of the manageable size of data from mini Prosper, we also test several potential economic explanations for home bias later in the paper. Last but not the least, we take an entirely different approach (with a different level of analysis) to test home bias by focusing on borrowers who moved across state boundaries during our study period. If there is home bias, then the proportion of bids that they received from their origin state should decrease after the move, while the proportion of bids that they received from their destination state should increase after the move.

4.1 Initial Evidence of Home Bias under Regular Market Conditions

Among all bids that became part of loans in our study period (2007-2008), about 7% occur between borrowers and lenders of the same state. Considering that there are 50 states in the US, the *naïve* average likelihood that the borrower and lender are from the same state is 2% (1/50). In other words, the actual occurrence of same-state lending relationship is about 3.5 times the likelihood in a random network. This pattern persists even after we account for the fact that each state has a different number of lenders, and the total investments from lenders of each state are also different. Virtually in all states (except South Dakota where there is no borrower recorded in the data), the share of home-state lender in the amount received by the state's borrowers uniformly exceeds these lenders' investment share in the entire marketplace (Table 1). For instance, Texas lenders contributed 8.24% of all loans made on Prosper.com. They, however, account for 10.82% of all loans made to Texas borrowers. The same pattern exists when we calculate the share of bids (count) placed by home-state lenders, and compare it to the ratio in the overall market (Table 2).

[Insert Tables 1 and 2 about here.]

These macro-level statistics, however, do not consider the choices that investors faced when they placed bids. The "potential-dyads" approach will be much more informative. Yet conducting a dyadic analysis on the entire market over this entire period is not only computationally intractable, but also misleading. It is computationally intractable because with over 200,000 borrowers and a similar number of lenders, the total number of potential combinations is astronomical, especially when compared to the number of dyads that actually occurred (bids). It is misleading because of the time span of our study period; a borrower who requested a loan and was funded in January 2007 would not be in the consideration set of a lender who joined the site after, say, January 2008. Placing them on two sides of the market at the same time will artificially deflate the probability of transactional ties occurring and lead to biased estimates.

We therefore take a different approach. We segment the market by time (specifically, every day), apply the potential dyads approach on all active borrowers and lenders on the market on each day, and repeat the analysis for each day throughout the study period. We then gathered results from these day-to-day analyses to investigate the extent of home bias. This not only tells us if there is a home bias, but also if there are any temporal variations.

4.2 Dyadic Analysis of Home Bias under Regular Market Conditions

We examine all active borrowers and lenders on the market on each day during our study period. Specifically for each day, we construct a list of all active borrowers who were requesting loans on the market, and the listing had not yet ended. We construct a list of all active lenders on the market who had placed at least one bid that day. These two lists are used to construct all "potential dyads" for that day. We then gather information about the borrower, the lender, and the auctions, and estimate the following model.

$$Prob(Lender_i \ bids \ on \ Borrower_j) = \beta * SameState_{ij} + f(BorrowerInfo_i, LenderInfo_j, AuctionInfo) + \epsilon_{ij}$$

Our level of analysis is a borrower-lender dyad, and the main outcome of interest is the probability that a transaction occurred for that dyad (i.e. a bid was placed). If a lender places a bid in the borrower's loan request, then the outcome variable is equal to 1. Otherwise it is 0. The key independent variable is whether the borrower is in the same state as the lender at the time of the request. If there is home bias, then the coefficient on this variable should be positive and statistically significant; equivalently and more accurately, if we examine the 95% confidence interval of the estimate, it should not include 0. The focus on this "same state" variable is highly consistent with the literature (Graham, et al. 2009, Hortacsu, et al. 2009). To facilitate interpretation of their effect size, we use a logistic model. We include an extensive set of control variables, as defined in Table 3. Standard errors are also conservatively estimated using clustered sandwich estimators to allow for intra-state correlation, since there are multiple borrowers from the same state.

[Insert Table 3 about here.]

We estimate this model for all dyads on each day during our study period, and gather the 95% confidence interval of the coefficient on the "same state" variable. We plot the upper and lower bounds of this confidence interval over time, and show it in Figure 1. If there is *no* home bias, we should see the horizontal axis ($\beta = 0$) falling within the shaded area in Figure 1 most of the time, if not all. That is not the case. Overall, we observe that despite some temporal variations, investors generally exhibit home bias in this online market. They are more likely to invest in borrowers from their home state, as the shaded area above the horizontal axis is much larger than the area below.

[Insert Figure 1 about here.]

This analysis provides stronger evidence than the previous summary statistics for home bias in this market, although it is still possible that lenders from different states are interacting and affecting each other's choices. We therefore exploit "mini Prosper," a period in which lenders from only one state are allowed in the market.

4.3 Home Bias in "mini Prosper"

As described earlier, the "mini Prosper" was a 10-day regulation-induced window where borrowers came from all across the US, but lenders only came from California. During "mini Prosper," 547 borrowers (from around the US) sought loans on 701 listings, and 656 lenders (all from California) placed bids. Out of 358,832 possible transaction dyads (547 × 656), 3540 bids actually occurred. On the listing level, out of 701 listings, 94 listings or 13.4% were from California borrowers. Also during this window, 29 loans reached 100% funding. Five of these (17.24%) were for California borrowers.[5] These provide some initial, macro-level evidence of home bias in this period.

We next perform the potential-dyads analysis of home bias in mini-Prosper, using the same logistic model. The main results are reported in Table 4. There remains a statistically significant home bias, consistent with our findings from the previous section. In terms of economic significance, being a Californian borrower increases the odds of being funded by 13%.

[Insert Table 4 about here.]

Some auxiliary results from the regression are also noteworthy and meaningful, and consistent with those from the longer period that we studied earlier. Borrowers who had better credit information, who used closed auction format (immediate funding), and who were willing to pay higher interest rates were more likely to receive bids. While these are not the focus of our analysis, they provide some assurance that even though "mini Prosper" is unique, it is not so special that it loses general features of the website.

4.4 Borrower Migration: An Alternative Approach to Detect Home Bias

The previous tests based on the potential dyads approach suggest that home bias is quite robust in this online investment platform. To further test the robustness of this finding, we take an entirely different approach and track borrowers who move from one state to another. This enables us to estimate a borrower fixed effect model so as to control for borrower-specific unobservables.

One important advantage of this approach is that the borrowers' address change is largely exogenous to investor decisions on Prosper.com. Since Prosper.com loans are typically small (up to $25,000), it is highly unlikely that borrowers would move across state borders just to appeal to lenders in some particular states. Moreover, investors can only see the *current* state of residence of the borrower. Therefore, we gather data on the bids that the borrower received on his listings before and after the move, and examine the proportion of bids from lenders in the borrower's origin state (where he moved from), and those in his destination state (where he moved to).

Specifically, we gather data over time to identify borrowers who not only moved across state boundaries during our study period, but also made loan requests both before and after their move. We

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[5] Our focus in this paper is the probability of placing bids. However, we also examined the amount of bid and interest rate of the loans, which are only observable conditional on a bid being placed. If we examine the total amount funded in mini-Prosper listings, the total amount funded to borrowers is $84236, out of which $19636 (23.3%) was for California borrowers. Furthermore, in terms of interest rate, CA borrowers' average interest rate on these loans is 11.58%, while borrowers from other states pay an average of 15.21%. These statistics are also consistent with the home bias argument.

exclude borrowers who moved more than once as such cases are extremely rare (only 5 in our sample). We gather information about bids placed on those listings. In all, we identify 841 listings from borrowers who moved, all the bids placed on them, and the state of residence of the investors at time of bid.

We next conduct *listing* level analysis and estimate the following model. The outcome variables are the proportion of bids from the borrower's origin state and the destination state, respectively. We create a dummy variable *move* that equals 1 for listings created after they moved, and 0 before; this is our main variable of interest. If there is indeed a home bias, we should observe that the coefficient of the *move* dummy is negative for the bids from origin state lenders, and positive for the bids from the destination state lenders. We include borrower fixed-effects in the estimate as well. Since the outcome variables are constrained between 0 and 1, we estimate the following Tobit models:

$$\%Bids\ from\ lenders\ in\ origination\ state\ = f_1(\cdot) + \alpha_1 Move_i + \beta_1 BorrowerFE + \epsilon_{1i}$$

$$\%Bids\ from\ lenders\ in\ destination\ state\ = f_2(\cdot) + \alpha_2 Move_i + \beta_2 BorrowerFE + \epsilon_{2i}$$

where $f(\cdot)$ indicates a vector of control variables as used in the logistic model previously. If investors do exhibit home bias, we should observe that all else equal, $\alpha_1 < 0$, and $\alpha_2 > 0$.

We report the results in Table 5. Consistent with the home bias argument, in the listings created by the borrowers who moved, the proportion of bids from their origin-state lenders *decreased* after their move, whereas the proportion of bids from the destination-state lenders *increased* after the move. Results for other variables, such as borrower characteristics and auction information, are largely consistent with the prior literature (e.g. Lin et al. 2013), lending further support to this analysis.

[Insert Table 5 about here.]

5. Exploring Explanations for Home Bias using Mini Prosper data

It is quite remarkable that investors in the online peer-to-peer lending market exhibit preference toward borrowers from their home states. Unlike online product markets where geography is still important due to the potential of contract enforcement and the delivery of products (c.f. Hortacsu et al., 2009), the borrower's physical location is largely irrelevant in the investment context, especially given the features of Prosper.com. Therefore, even though the primary goal of this paper is to empirically document whether home bias exists in this new market, we nonetheless explore some potential explanations for this phenomenon. For this part of our analysis, we mostly use the data from "mini Prosper" because the sample size is much more manageable. We test two potential explanations: (1) private information through social networks, such as friends or friends of a friend (FOAF); and (2) state as a proxy, or surrogate, for borrower quality. While both appear promising, neither is able to explain away home bias in our data.

5.1 Friends and FOAF: Is Home Bias due to Private Information?

On Prosper.com, friends may place bids on a borrower because they know the borrower well, and can exert offline influence on them to repay (c.f. Lin et al. 2013). Friends are also more likely to be from the same state as the borrower. If most investors are in fact friends (or friends of a friend) of the borrower, then the home bias we observe is just a reflection of investors' private information about the borrowers. In fact, using data from Sellaband.com where bands seek funding online, Agrawal, Catalini and Goldfarb (2011) find that in their data, local investors invest early because they often have a personal connection with the artists. It is therefore possible that the home bias could be explained by friendship ties, and we investigate this in this section.

We first construct the friendship network on Prosper.com during the "mini Prosper" period, and then submit all potential dyads to this graph and identify possible connections. Specifically, for each combination of investor i and borrower j, we first test whether there is a direct connection between them on the friendship network. Out of over 300,000 possible transaction dyads, only 3 borrower-lender friendship ties existed. Neither do we find indirect connections, or "friends of a friend" (FOAF) connections, between potential pairs of borrowers and investors. None of the potential borrower-lender dyads during this time period shares a common friend. In fact, we do not observe friends on the third (friend of a friend of a friend), fourth, up to the 7th degree (i.e. separated by 6 degrees) in the data.

However, the above analysis assumes that all friends and families should be connected by network ties on Prosper.com, yet friends and families of a borrower can sign up as investors to help the borrower *without* revealing their friendship ties on the site. This would have also led to the home bias we found, but will not be captured in the friendship network data that we studied in the previous test. We examine the implications of this potential explanation in two ways.

First, we observe that under this hypothesis, these "friend and family" investors will be highly unlikely to bid on *other* borrowers, as they only signed up to help their borrower friend or family members. We are able to test this using the larger dataset from 2007-2008 that we use for the first analysis, instead of just the mini Prosper. This does not turn out to be a significant explanation for home bias either. Specifically, out of more than 200,000 bids placed during the 2007-2008 study period where the investor and the borrower were from the same state, less than 0.2% were from investors who exclusively placed bids on a single borrower (possibly their friend) after signing up on Prosper.com. Hence, even if some friends and families did sign up to support borrowers, it explains a negligible portion of the home bias that we observe.

Second, some friendship ties may be revealed after loans are funded but the private information may still drive the bidding behavior. This scenario may arise when investors recognize a friend from a listing, or, albeit unlikely, the investor and borrower become friends after a loan. Both could potentially explain the home bias, yet this also turns out to be almost negligible. Specifically, there were over 170,000 borrower-lender pairs in the 2007-2008 study period between those who request funds and those who invest in them. When we study *new* friendship ties that showed up on borrowers' profiles within 30 days after funding during this period, only 137 such ties exist. Moreover, not all these investors are from the same state as the borrower. These tests and statistics show that the home bias that we observe are not because of the actions of friends and family, but more general.

5.2 State as a Proxy for Borrower Quality?

Another potential explanation for home bias is that investors may be using state of residence as a proxy for other information. It should be noted that even if this is true, it does not contradict the home bias finding. In fact, it is highly consistent with the typical "economic" explanations for home bias in the literature. Yet this does not turn out to be a significantly reason for the home bias that we observe in our context, either. We aggregate information about loans in all states up until the start of the "mini Prosper" period. For each state, we calculate the number of loans that were defaulted, percentage of loans in default, and the amount lost in investment (default amount). We then include these variables as additional covariates to our main model. They did not qualitatively change the results on the "same-state" variable.[6]

6. Conclusions and Implications

Our paper is one of the first to identify home bias in online financial investments, specifically in a debt-based crowd-funding website, Prosper.com. We find that, in addition to macro-level statistics, home bias appears to be a consistent finding across a variety of tests using (1) transactions data under generic market conditions; (2) transactions data from "mini Prosper," a regulation-induced period on the market where investors can only come from one state; and (3) a quasi-experimental design where we exploit borrowers' move across state boundaries to identify the effect of "state of residence" on investor decisions.

Establishing the empirical regularity of home bias in online crowd-funding markets has important implications for market participants, researchers, as well as designers and managers of this emergent industry. For instance, borrowers or entrepreneurs seeking funding may want to pay attention to this behavioral pattern of investors, so as to maximize the likelihood of success – especially for those from states with larger lender populations. Investors on the other hand, will be better off recognizing this potential bias and be conscious in their investment decisions.

Our analyses also contribute to the ongoing discussion on what drives home bias. Two major schools of thought in this area are economic reasons and behavioral reasons (see Lewis 1999 for a

[6] For sake of brevity we do not report these results here but they are available from the authors upon request.

comprehensive survey), and it has long been challenging to determine which factors are more important in each context. Our study is unique because most, if not all, economic explanations for home bias either do not apply in this context, or cannot explain away home bias. While future research is needed to determine its causes through controlled experiments, it appears that this tendency is more likely emotionally or psychologically driven. To some extent, our finding is consistent with a recent study on twins' investment behaviors (Cronqvist and Siegel 2012): it may be that investment biases (including home bias) are due to genetic factors; i.e. we were born with it.

More important, once we understand how investors react to borrower's geography information, we will be able to answer additional questions of interest to market designers and policy-makers. An important question is whether it is meaningful or beneficial to display geographic information in online crowd-funding in the first place, especially if it unnecessarily induces bias from investors. Unlike offline contexts or online product markets such as eBay (Hortacsu, et al. 2009), geography information is largely irrelevant in debt-based crowd funding when direct contract enforcement is forbidden. We cannot directly investigate this because there has been no variation in the website's policy of displaying geographical information. Nevertheless, with a better understanding of home bias in this new industry, especially with future studies focusing on its explanations, we will be able to further improve market efficiency and leverage the Internet to truly mitigate geography-induced resource imbalances.

Tables and Figures

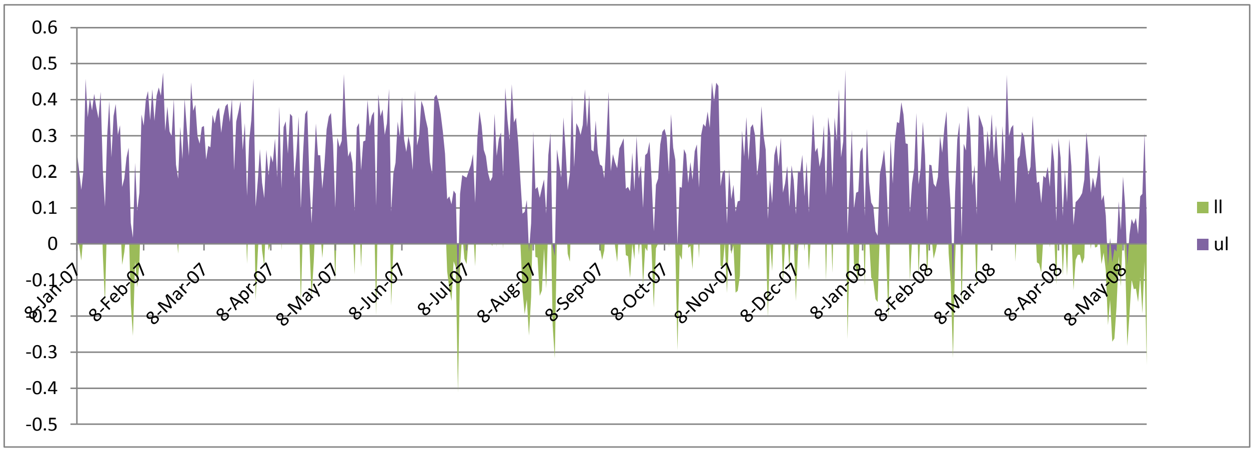

Figure 1: 95% confidence interval for the coefficient on the "same state" variable over time

Table 1: Macro evidence of home bias (1)

This table reports "macro" evidence of investors' bias toward same-state borrowers in all lending activities on Prosper.com up until April, 2009. This bias exists for virtually all states: the percentage of lending amount from home-state lenders (Column 3) exceeds the share of home-state lenders' investment in the entire marketplace (Column 2) [7].

State	Total investment of lenders in this state / total investment from all states	Funding amount from home-state lenders / total amount to borrowers in this state
AK	0.37%	1.20%
AL	0.47%	0.60%
AR	0.40%	2.40%
AZ	1.75%	2.20%
CA	22.39%	24.11%
CO	2.01%	2.54%
CT	1.10%	2.03%
DC	0.48%	0.52%
DE	0.26%	3.36%
FL	5.53%	6.37%
GA	2.45%	3.17%
HI	0.61%	8.32%
IA	0.50%	2.11%
ID	0.39%	1.17%
IL	5.75%	6.81%

[7] The only state not reported here is SD, where there is no loans made to that state recorded in the Prosper database as of April 2009. Lenders from SD account for 0.14% of all loaned amount on Prosper.com.

IN	0.78%	1.28%
KS	0.53%	3.66%
KY	0.45%	2.53%
LA	0.68%	2.18%
MA	2.69%	3.90%
MD	2.98%	4.08%
ME	0.15%	0.44%
MI	1.94%	2.59%
MN	1.37%	2.28%
MO	0.84%	1.55%
MS	0.19%	0.71%
MT	0.24%	0.99%
NC	2.17%	2.90%
ND	0.09%	0.20%
NE	0.39%	1.93%
NH	0.66%	1.13%
NJ	3.24%	4.40%
NM	0.67%	1.09%
NV	1.11%	2.10%
NY	7.08%	8.96%
OH	1.80%	2.47%
OK	0.53%	1.18%
OR	1.55%	2.56%
PA	2.81%	4.88%
RI	0.17%	0.17%
SC	0.60%	1.02%
TN	0.78%	1.57%
TX	8.24%	10.82%
UT	1.11%	2.52%
VA	5.00%	6.51%
VT	0.13%	3.95%
WA	3.55%	4.66%
WI	1.02%	1.72%
WV	0.17%	0.38%
WY	0.07%	0.78%

Table 2: Macro evidence of home bias (2)

This table provides the same comparison as Table 1, except using the number of bids rather than the amount.

State	share of bid count of the state's lenders in the entire dataset	share of bid count from same-state lenders
CA	20.40%	21.10%
GA	2.66%	2.90%
FL	5.61%	5.90%
IL	5.07%	5.40%
TX	7.56%	8.30%
NY	7.18%	7.90%
WA	3.85%	4.30%
MI	2.05%	2.40%
MD	3.08%	3.30%
OH	1.98%	2.20%
AZ	1.95%	2.20%
NC	2.40%	2.60%
MO	0.97%	1.40%
OR	1.60%	1.90%
MN	1.60%	1.90%
MA	2.66%	3.00%
CO	2.07%	2.20%
VA	4.63%	5.20%

Table 3: Major control variables used in analyses

Variable Name	Variable Description	Variable Name	Variable Description
CreditGradeAA	1 if borrower's credit grade at time of listing is in grade AA; 0 otherwise. This is the baseline grade, not included in estimation.	DebtToIncomeRatio	Debt-to-income ratio of borrower at listing
CreditGradeA	1 if borrower's credit grade at time of listing is in grade A; 0 otherwise	InquiriesLast6months	Number of credit inquiries in the prior 6 months before listing
CreditGradeB	1 if borrower's credit grade at time of listing is in grade B; 0 otherwise	YearsSinceFirstCredit	Number of years between the the borrower's first credit line and the time of listing
CreditGradeC	1 if borrower's credit grade at time of listing is in grade C; 0 otherwise	AuctionFormat	Dummy: 1 for a close auction
CreditGradeD	1 if borrower's credit grade at time of listing is in grade D; 0 otherwise	BorrowerMaxRate	Borrower's asking interest rate on the listing
CreditGradeE	1 if borrower's credit grade at time of listing is in grade E; 0 otherwise	AmountRequested	Amount requested by borrower in listing

Table 4: Evidence of home bias in "Mini Prosper"

Covariates	Odds ratios
Dummy for Same-State borrowers	1.130**
	(0.058)
Loan amount requested by borrower	0.592***
	(0.013)
Borrower asking interest rate	0.087***
	(0.019)
Auction format	0.232***
	(0.044)
Dummy for grade A borrowers	2.922***
	(0.250)
Dummy for AA borrowers	4.215***
	(0.373)
Dummy for B borrowers	1.469***
	(0.129)
Dummy for C borrowers	1.108
	(0.099)
Loan purpose dummy: debt consolidation	0.885***
	(0.040)
Loan purpose dummy: home improvement	0.741***
	(0.049)
Loan purpose dummy: Business loan	0.428***
	(0.033)
Loan purpose dummy: Student loan	0.513***
	(0.053)
N	**358832**

For easier interpretations, we report odds ratio in the table instead of coefficients. An odds ratio greater than 1 means the variable has a positive effect on the probability of occurrence. Standard errors are in parentheses. Dependent variable: 1 if a bid is placed, 0 otherwise. For brevity some control variables are suppressed from the table. Heteroskedasticity-consistent standard errors are reported in parentheses. (* p<0.1 ** p<0.05 *** p<0.01)

Table 5: Effect of state change (moving) on the percentage of bids from origin and destination states

	Column 1: Percentage of ***origin*** state bids	**Column 2**: Percentage of ***destination*** state bids
Moved (0 if listing occurred before move; 1 after)	-0.051***	0.037***
	(0.006)	(0.005)
Credit grade AA	0.305***	0.772***
	(0.009)	(0.006)
Credit grade A	0.161***	0.634***
	(0.006)	(0.005)
Credit grade B	0.049***	0.545***
	(0.007)	(0.007)
Credit grade C	0.027***	0.347***
	(0.008)	(0.007)
Credit grade D	-0.020**	0.271***
	(0.008)	(0.008)
Debt-to-income ratio	0.010***	0.018***
	(0.002)	(0.002)
Auction type (1=closed)	0.047***	-0.002
	(0.003)	(0.003)
Intercept	-0.298***	-0.670***
	(0.007)	(0.006)
N	841	841

This table reports the results of home bias tests using listings by borrowers who moved from one state to another, exploiting the fact that borrower's moving decision can be largely exogenous to activities on the site, and that the borrowers' current state of residence is shown. We first estimate how "moving" affects the percentage of bids that the listing receives from lenders in the *origin* state (where they moved from). We estimate a Tobit model with borrower fixed-effects. We find that after borrowers moved away, the percentage of bids from the origin state is significantly lower. By contrast in Column 2, we show that the percentage of bids from the *destination* state increases significantly after the move. Listing categories are also controlled for, though not reported to conserve space. Robust standard errors reported. (* p<0.1 ** p<0.05 *** p<0.01)

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