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Publication details, including instructions for authors and subscription information:
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To cite this article:
Mingfeng Lin, Siva Viswanathan (2016) Home Bias in Online Investments: An Empirical Study of an Online Crowdfunding Market. Management Science 62(5):1393-1414. http://dx.doi.org/10.1287/mnsc.2015.2206

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MANAGEMENT SCIENCE
Vol. 62, No. 5, May 2016, pp. 1393–1414
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2015.2206
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Home Bias in Online Investments: An Empirical Study of an Online Crowdfunding Market

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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 geographical area rather than outside. Using data from a large online crowdfunding marketplace and employing a quasi-experimental design, we find evidence that home bias still exists in this virtual marketplace for financial products. Furthermore, through a series of empirical tests, we show that rationality-based explanations cannot fully explain such behavior and that behavioral reasons at least partially drive this remarkable phenomenon. As crowdfunding becomes an alternative and increasingly appealing channel for financing, a better understanding of home bias in this new context provides important managerial, practical, and policy implications.

Keywords: home bias; peer-to-peer lending; quasi-experiment; crowdfunding; behavioral explanations; natural experiment
History: Received February 12, 2013; accepted March 4, 2015, by Lee Fleming, entrepreneurship and innovation. Published online in *Articles in Advance* September 2, 2015.

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1. Introduction

We study whether investors in online financial investment platforms such as crowdfunding exhibit home bias, as is common among investors and businesses in off-line 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 the 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 et al. 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 et al. 2004, Cooper and Kaplanis 1994, Coval and Moskowitz 1999, Dziuda and Mondria 2012, Graham et al. 2009, Karlsson and Nordén 2007, Sorenson and Stuart 2001), including entrepreneurial investments (Sohl 1999). In fact, two out of the six major puzzles in international macroeconomics are related to home bias (Obstfeld and Rogoff 2001). Regardless of the context, home bias is generally considered a suboptimal behavior in decision making, leading to economic inefficiencies in the marketplace and making it an important research topic.

It seems promising that the recent growth of electronic commerce should render home bias less relevant. Interestingly and surprisingly, Hortaçsu et al. (2009) show that on the online products market 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 of direct contract enforcement.

These explanations, however, do not apply to online crowdfunding, where contributors or investors provide funds to an individual or business either as donations or in return for a debt repayable over time, an equity share, or a reward. Transactions occur virtually, particularly for debt-based crowdfunding where investors cannot directly enforce the contract by visiting the borrowers in person, and they do not have

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direct legal recourse against borrowers who default.[1] And because of the nature of crowdfunding, each individual investor only has a small stake in each loan, so his or her incentive for direct contract enforcement is minimal. Consequently, home bias should be much less likely to occur in these markets. Nevertheless, whether home bias still exists in this new context remains an open empirical question. We investigate this question using data from a leading debt-based crowdfunding website in the United States, Prosper.com, an online market for unsecured personal loans (Lin et al. 2013, Zhang and Liu 2012). Specifically, we address the following two questions in this paper:

1. Is there home bias in this online crowdfunding market?

2. If so, what is the mechanism that drives home bias in this market? Do investors favor home state borrowers because of higher economic payoffs?

We start with a series of tests to identify whether home bias exists. We first present macrolevel evidence of home bias in this market, including descriptive statistics and dyadic analysis of transactions data from the website. Then in our main empirical specification, we exploit the fact that some borrowers moved across state boundaries during the period we study 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 this site. Such moves are therefore largely exogenous to investor decisions, and we investigate how investors from the borrowers' origination and destination states change their behaviors in response to these moves. If investors indeed favor home state borrowers, as suggested by the home bias hypothesis, then we should observe that after borrowers move, there should be fewer investors from their origination state that bid on their loan requests and more investors from their destination state. This is confirmed in our tests. We then further examine transactions data from a natural experiment that occurred on Prosper.com. During a time that has come to be called the "mini Prosper" period among users of the site, only investors from one state were allowed to lend, whereas borrowers from all states were allowed to borrow. Results from the mini Prosper confirm home bias on the dyadic level.

Once we confirm the existence of home bias in this market, we turn to the second research question: What is the mechanism that drives home bias in this market? Previous research (e.g., Lewis 1999, Graham et al. 2009) has shown that home bias may be due to behavioral or economic reasons. Since this is a financial market where investors receive returns for their investments, it is highly unlikely that economic reasons have no bearing on their decisions. Therefore, a more intriguing and important question is *whether investors favor home state borrowers because of higher economic payoffs or behavioral reasons related to home states also play a role*. Consistent with the literature, in this paper we use "economic" or "rational" reasons in the sense of *homo economicus* (Kahneman 2003), referring to the argument that investors are able to gather and evaluate all relevant information and make a decision that maximizes their economic returns, or the "simple and compelling idea that we are capable of making the right decisions for ourselves" (Ariely 2008, p. xix). On the other hand, with "behavioral reasons" we refer to behavioral biases that are often the result of bounded rationality, cognitive biases (Thaler 1993) or perceptions that deviate from economic optimality (Kahneman 2003). Through multiple tests we show that rational reasons alone cannot fully explain home bias. Specifically, we find that investments on home state borrowers tend to have lower returns, are likely to default sooner, and lose more on their principal than their out-of-state counterparts. Moreover, loans with more texts in their descriptions that repeat the "state of residence" information—which are more likely to evoke geography-based sentiments but provide no additional economic value beyond state of residence—are likely to attract more home state bids. Furthermore, when lenders move to a new state, they increase their investments in their new state, contrary to predictions based on informational advantage explanations for home bias. These and other empirical findings all suggest that behavioral motivations, rather than economic reasons alone, play a role in driving home bias in this market.

Our paper is among the first to document empirical evidence of home bias in online crowdfunding and to try and tease out the mechanism behind it. We also contribute to the broader home bias literature by testing detailed, microlevel transactions data and exploiting a quasi-experimental design and a natural experiment. As entrepreneurs, investors, and policy makers become increasingly interested in online crowdfunding as a new channel for financial transactions,[2] our paper not only contributes to a better understanding of investor behaviors and the role of

[1] This is true of our context, as we will discuss in greater detail in §3. Some international peer-to-peer lending sites may have different rules, however.

[2] Online peer-to-peer lending or debt-based crowdfunding started in the mid-2000s and has received significant interest ever since. Such interest is reflected not only in the growth of peer-to-peer lending sites both within the United States and across the world but also in the passing of recent legislations such as the Jumpstart Our Business Startups (JOBS) Act of 2012. More details on the history of peer-to-peer lending can be found in Zhang and Liu (2012), Lin et al. (2013), and others.

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geography in this market but also helps inform future policies and regulations.

2. Related Research

2.1. Home Bias

Studies of home bias, and more broadly the effect of geography, have flourished in many disciplines such as economics and finance (Ahearne et al. 2004; Disdier and Head 2008; Forman et al. 2009, 2012; Graham et al. 2009; Overman et al. 2003; Sorenson and Stuart 2001; Wolf 2000). Most empirical studies in this literature employ off-line data, such as trade or venture capital investments, and home bias has been consistently found in a wide range of 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 and behavioral ones. Many economists attribute home bias to economic reasons, such as transaction costs that include shipping costs and cultural differences, cost of information acquisition for international equity investments, or informational advantage as a result of geographical proximity (Lewis 1999). A common theme across these explanations is that decision makers are considered utility-maximizing agents who rationally gather and process information, and their decision (including home bias) yields economically beneficial results. Notably, (Lewis 1999, p. 575) notes that none of the major economic explanations offered for home bias has "delivered a definitive answer so far."

By contrast, other researchers propose that behavioral reasons can drive home bias regardless of economic benefits, despite varying terminologies in different literatures. For example, "homophily" in the sociology and management literatures (McPherson et al. 2001) and "familiarity bias" in finance (Huberman 2001) are in fact highly consistent with each other, and both suggest that geographical proximity alone—even when there are no tangible economic benefits to it—can engender trust and overoptimism (a behavioral bias) toward transaction partners or opportunities in local areas (Lai and Teo 2008, Strong and Xu 2003). For our study, the virtual nature of the market makes the economic explanations less likely, though behavioral motivations can still lead to home bias online.

Previous studies on home bias have largely focused on off-line settings, and more recently, several researchers started to examine this phenomenon online. One of the first such studies is Hortaçsu 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 *to* someone else from New York as well. Other potential explanations include the opportunity to enforce contracts directly when the buyer is close to the seller. Shipping costs may also affect buyers' choices (Hortaçsu et al. 2009, p. 73). In a more recent paper, Agrawal et al. (2011) show that in an online crowdfunding site for music bands, SellaBand.com, investors are likely to invest in local bands; however, the authors attribute the effect of geography to friends and family of the musicians.

We contribute to this growing literature by examining whether home bias exists in a general-purpose and broader-based online crowdfunding marketplace, where quantitative financial information plays a much larger role than other crowdfunding sites such as SellaBand. Because of the debt nature and other features of the site, home bias should be less likely to exist, yet we document robust evidence to the contrary through various tests including a quasi-experimental design and an exogenous event related to geography. The presence of "friends and family" that leads to geographical bias in prior studies (Agrawal et al. 2011) does not explain home bias in our context.[3] In addition, we construct a series of tests to identify whether home bias here is economically or behaviorally driven.

2.2. Empirical Tests for Home Bias

Empirical identification of home bias can be challenging, especially given the potential role of unobservable factors. In this section, we review two approaches that have often been used in existing literature, i.e., the gravity equation and the potential dyads approach, and discuss their limitations. Specifically, the gravity-equation approach only focuses on transactions that take place. Although the potential-dyads approach has the advantage that it considers available alternatives, both methods may suffer from potential endogeneity in the geography variable because of either unobservable information or endogenous choice of locations. Therefore in our analysis, we use the potential-dyads approach to provide high-level evidence of home bias, but we resort to a quasi-experimental design that exploits borrowers' moves across states—arguably exogenous to activities on this site—to test for home bias.

The economic geography literature often draws on the gravity equation (Bergstrand 1985) in international

[3] As we will show later in §4.4, bids from friend and family account for only 1.9% of all same state bids in our data; hence, unlike Agrawal et al. (2011), home bias in our context is not driven by friends and family.

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trade. Despite several variations, a typical gravity equation takes the following form (Bergstrand 1985):

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

Here, 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; A_{ij} refers to other factors that facilitate or deter trade; and 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, p. 571). Although both methods are well accepted, these gravity-equation methods only look at the outcomes of choices, i.e., actual asset holdings or realized transactions. Little is considered of the *alternatives* available to agents at the time of their choice. Therefore in this paper, we use a different empirical approach, *potential dyads*, as is common in the management and strategy literature (e.g., Sorenson and Stuart 2001).

In this approach, rather than examining aggregate volumes, we identify all possible pairwise combinations between agents on two sides of the market, and we relate explanatory variables (e.g., being from the same state) to the probability that each potential tie is realized. To illustrate this using an example of entrepreneurial financing (cf. Sorenson and Stuart 2001), let us assume there are M investors $(A_1, A_2, \ldots, A_M)$ and N entrepreneurs seeking funding $(B_1, B_2, \ldots, B_N)$. Suppose further that A_1 invests in B_1 and that A_2 invests in B_2, and these are the only actual transaction ties that occurred in the data. Conceptually, $(B_1, B_2, \ldots, B_N)$ are all possible candidates for $(A_1, A_2, \ldots, A_M)$, respectively, so there should be a total of $M \times N$ possible dyads, from which only two actually occurred. Using the potential-dyads approach, we quantify characteristics for each of $A_1, A_2, \ldots, A_M$ and $B_1, B_2, \ldots, B_N$, and we 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 that the investors and borrowers are from the same state should be positive and significant. This method has the appeal that it can be readily applied to field transaction data but has the disadvantage that potential dyads can grow exponentially in a large market. Nevertheless, results from this method could provide at least some initial evidence for the presence or absence of home bias.[4]

It should be noted that both approaches may further suffer from the endogeneity of the geography variables. Although geography variables are typically assumed to be exogenous, individuals and organizations *can* strategically choose where to locate their activities. For example, Parwada (2008) finds that 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, etc.) tend to gravitate toward a location where the marginal productivity is highest (Redding and Sturm 2008). These observations represent important challenges to the identification of home bias. Our key evidence of home bias comes from the quasi-experimental design that exploits borrowers' moves across state boundaries. We also apply the potential-dyads approach to transactions data generated in the mini Prosper, where lenders only come from one state but borrowers come from all around the United States.

2.3. Studies of Crowdfunding

Our study also contributes to a burgeoning literature related to online crowdfunding, especially peer-to-peer lending. Some of these studies also use data from Prosper. For instance, Zhang and Liu (2012) present evidence of rational herding among investors. Lin et al. (2013) show that friendship connections on Prosper can help mitigate asymmetric information on the market. More broadly, peer-to-peer lending can be considered a debt-based form of online crowdfunding (Massolution 2013), and there has been increasing research interest in other types of crowdfunding markets as well—for example, Agrawal et al. (2011), as was discussed previously in §2.1; Mollick (2014), who analyze data from Kickstarter.com; and Burtch et al. (2013), who study a journalism crowdfunding site. More recent studies include Kim and Hann (2014), and Kim and Viswanathan (2014), among others.

3. Empirical Context

The context of our study is Prosper.com, one of the largest online peer-to-peer lending websites in the United States. In this section, we briefly describe a

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

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typical transaction process on this website and discuss important features that make the typical economic explanations of home bias less plausible in this context.[5]

Prosper is an online market for unsecured personal loans. No collaterals are involved, and all loans are personal debts. A borrower must first register on the website by providing a valid email address. He or she also needs to verify his or her identity using a social security number, driver's license, and other documents. The address as well as a valid bank account where the borrower can receive funds (if the request is successful) and make monthly repayments must be verified. Once verifications are completed, the borrower can create a listing, i.e., a Web page that describes the purpose of the loan. Prosper extracts information from the borrower's credit reports and displays it to potential investors. The borrower's state of residence (part of their 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 identifications, social security numbers, and bank account information; they then electronically withdraw funds from their bank accounts to their non-interest-bearing Prosper account. Once these funds are in place, they can start bidding on loans.

An investor can browse listings and decide in whom to invest. He or she can also search for listings based on criteria such as credit grades, but the investor cannot search for or filter loans based on a borrower's state of residence. If he or she is interested in a borrower's loan request, the investor can participate in the loan by placing a bid. An important feature of Prosper—as is common in online crowdfunding websites—is that an investor need not fund the entire amount of a loan. The investor can place a bid for as little as $50 and specify the minimum interest rate at which he or she is willing to lend. Funds from different investors are pooled to determine the lowest possible interest rate that the borrower will pay to receive the funds from all lenders, and at any time throughout the auction, there is only one ongoing, effective interest rate. All participating lenders receive the same return on the loan. Importantly, no bids can be retracted. Hence, the act of placing a bid indicates at least some level of trust in the borrower.

It should be noted that for privacy reasons, even though Prosper has borrowers' real names, addresses, and contact information, borrowers are forbidden from disclosing such information on their listings. In other words, lenders do not have access to the borrowers' names or actual addresses, so they cannot individually monitor or request the repayment of loans from borrowers. Lenders are also explicitly warned that just like other investments, their investments on Prosper are risky. There is no guarantee that the borrowers will repay the loan. When defaults occur, it is up to Prosper and its collection agency, not the lenders, to try and collect from the borrower. The lenders have no direct access to the borrowers throughout this process, and they cannot sue the borrower either.

Several features of the website make it a particularly interesting context to study home bias in online investments. First, the website displays the borrower's state of residence on all requests. That piece of information is verified and visible, and the borrower cannot turn it off. Second, in this market, geographic proximity per se does not bring much economic benefits. Loans are not secured, so there are no physical assets associated with them. All funds are transferred electronically, making geographic locations less pertinent. Furthermore, lenders do not have legal recourse against borrowers who default, and they cannot physically monitor the borrowers. If a borrower defaults, the lender cannot go to the borrower and ask for repayment, so there is no direct contract enforcement. Hence, being closer to a borrower does not bring any obvious economic benefits. It appears that if investors still exhibit home bias, behavioral reasons are likely to be at play. Nonetheless, there may still be some economic benefits to investing locally. In particular, investors may invest locally because such investments provide better returns, or it may also be possible that investors invest locally because of variance-based statistical discrimination (Cornell and Welch 1996), that it may be easier for them to judge the quality of borrowers who live in the same state as themselves.[6] We design various tests to investigate these motivations. But first, we examine whether investors exhibit home bias.

4. Does Home Bias Exist?

We now address the first question of this paper: Does home bias still exist in this market? We gathered detailed transaction data on all loan requests (including unsuccessful ones) and investors' bids posted on Prosper.com prior to October 2008. During this period, government regulators had not yet intervened in the market; borrowers and lenders freely participated from virtually all states across the United States.

Our tests for home bias proceed as follows. We first present some preliminary evidence of home bias. This

[5] Prosper has undergone notable changes since our data collection; the descriptions that we provide here are accurate for the time period that we study.

[6] We thank a reviewer for suggesting this alternative explanation, and we will investigate it later in the paper.

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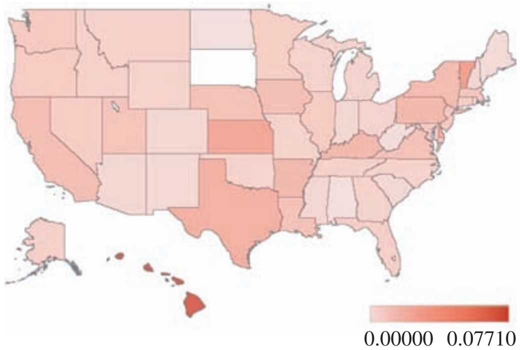
Figure 1 **Macrolevel Evidence of Home Bias by State**



Notes. The darker the color, the higher the degree of home bias on the state level, as measured by the *difference* between (1) the proportion of funds that investors from each state contribute to the funds borrowed by borrowers of that state and (2) the proportion of funds that investors from each state contributes to funds borrowed by all borrowers on the site. The difference is nonnegative for all states. As an example, Florida investors contribute 5.53% of all funds loaned on Prosper, but they contribute 6.37% of funds loaned to Florida borrowers. The difference (shown on the map) is 0.84%. The only state not reported here is South Dakota, where there were no loans made to that state recorded in the Prosper database as of April 2009. Lenders from South Dakota account for 0.14% of all loan amounts on Prosper. The same pattern holds when we use the number of bids instead of dollar amount.

includes some macrolevel descriptive statistics on the market, as well as a dyadic analysis based on the potential-dyads approach of each day's transaction data from this site under regular market conditions. We then present our primary empirical specification for home bias, in which we exploit borrowers' moves across states as exogenous variation to the geographical variable, and we show that the bidding behavior of investors in both the borrowers' origination state and destination state changes in a manner consistent with home bias. And finally, we apply the potential-dyads approach to the mini Prosper period during which lenders from only one state were allowed, whereas borrowers were from all over the United States. All these tests point to the robust finding that home bias, interestingly, still exists in our research context.

4.1. Preliminary Evidence of Home Bias

4.1.1. Market-Level Descriptive Statistics. Since there are 50 states in the United States, the naïve average likelihood that the borrower and lender are from the same state is 2% (1/50). By contrast, in our data, about 7% of all bids occurred between borrowers and lenders of the same state, a much higher ratio. This difference is suggestive of a home bias in this market. Still, although the 2% number provides a simple baseline (one number for all states), it does not account for the fact that each state has a different number of lenders.

We therefore examine whether home bias exists when we consider such a difference. This is indeed the case. Virtually in all states (except South Dakota, where there is no borrower recorded in the data), the share of home state lenders' funds in the amount received by that state's borrowers almost always exceeds these lenders' investment share in the entire marketplace (see Figure 1). In other words, lenders disproportionally contribute to the funds received by their home state borrowers compared with what they contribute to the whole market. For instance, Texas lenders contributed 8.24% of all loans made on Prosper; however, they account for 10.82% of all loans made to Texas borrowers. This pattern persists when we calculate the share of bid count instead of the dollar amount.

4.1.2. Dyadic Analysis of Daily Transactions Data. We now turn to a finer, dyadic-level analysis using the potential-dyads method described in §2.2 (with the caveats discussed therein). 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 more than 200,000 borrowers and a similar number of lenders, the total number of potential combinations is astronomical, especially when compared to the number of bids that actually occurred. It is misleading because of the time span: 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. Creating a potential dyad between them will be artificially deflating the probability of transactional ties.

We therefore examine all active borrowers and lenders on the market on each day during our study period. For each day, we construct a list of all active borrowers who were requesting loans and a list of all active lenders who had placed at least one bid that

Figure 2 **Point Estimate (Red Line) and 95% Confidence Intervals for Coefficient (Vertical Lines) on the *SameState* Variable Over Time**

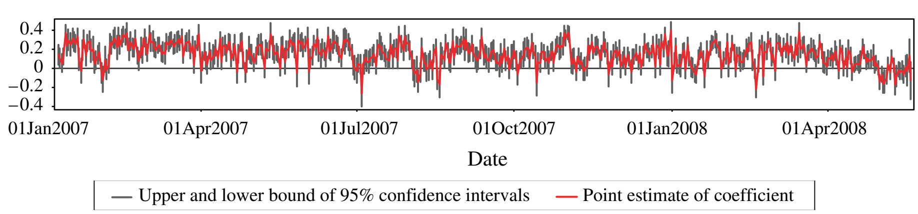


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Table 1 List of Covariates

Variable name	Description
AfterMove	Equals 1 if the listing was created after the borrower moved to a new (destination state); 0 if before.
$1(CreditGrade = x)$	Equals 1 if borrower's credit grade at the time of listing is in grade x ($x \in (AA, A, B, C, D, E, HR)$); 0 otherwise.
$1(z\ loan)$	Equals 1 if the borrower specified that the loan category (purpose) is z, where z can be "debt consolidation," "home improvement," "business," "personal," "student," "auto," or "other"; 0 otherwise.
RequestedAmount	Amount requested by borrower in listing (log).
InitialInterestRate	Borrower's asking interest rate on the listing (the maximum rate at the beginning of listing).
GroupLeaderHasReward	Equals 1 if the borrower's group leader will be rewarded for successful funding of the loan; 0 otherwise.
LenderRiskTaker	Equals 1 if the lender is a risk taker (top quartile among all lenders in holdings of "D" or lower credit grade loans; bottom quartile in terms of "AA" or "A" loans) when bidding; 0 otherwise.
StateUnemployment	Percentage of work force that is unemployed in a state (according to the U.S. Bureau of Labor Statistics). The Δ of this variable is the difference between destination and origination states.
ListingHasImage	Equals 1 if the listing shows any images; 0 if none.
Duration	Length of time for the listing.
ListingDuration	The time length of listing (in days) that the borrower specified.
AuctionType	Equals 1 for a close-format auction or immediate funding; 0 otherwise.
HasFriendorFamilyBids	Equals 1 if the listing has bids from family or friends, either explicit friends or implicit ones identified using the method described in Agrawal et al. (2011); 0 otherwise.
Debt-to-Income_Ratio	Debt-to-income ratio of borrower at time of listing.
LenderMonthsonSite	Number of months since the lender signed up on Prosper.com when bidding (log).
HasGroupBids	Equals 1 if the listing has bids from the group that the borrower is a member of; 0 otherwise.
LenderRiskAverter	Equals 1 if the lender is a risk averter (bottom quartile among all lenders in holdings of "D" or lower credit grade loans; top quartile in terms of "AA" or "A" loans) when bidding; 0 otherwise.
StateDefaultPct	For a given borrower, the percentage of loans that all borrowers from his or her home state had defaulted on at time of listing.
SameGroup	Whether the borrower and the lender were in the same group on Prosper.

day. These two lists are then used to construct all potential dyads that could have taken place that day. We then gather information about the borrower, the lender, and the auctions, and we estimate the following logistic model:

$$\begin{aligned}&\mathrm{Prob}(Lender_i\_bids\_on\_Borrower_j)\\ &\quad = \beta \times SameState_{ij}\\ &\qquad + f(BorrowerInfo_i, LenderInfo_j, AuctionInfo) + \epsilon_{ij}.\end{aligned}$$

Here, 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 on the borrower's loan request, then the outcome variable is equal to 1; otherwise, it is equal to 0. The key independent variable is whether the borrower is in the same state as the lender. 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 *SameState* variable is highly consistent with the literature (Graham et al. 2009, Hortaçsu et al. 2009). We include an extensive set of control variables, as defined in Table 1, as well as lender fixed effects,[7] and we estimate logit models using heteroskedasticity-consistent robust standard errors.

We repeat this analysis for each day during our study period and gather the point estimates and 95% confidence intervals of the coefficients for the *SameState* variable for each day. We then plot the upper and lower bounds of these confidence intervals, as well as the point estimates, over each day as illustrated in Figure 2, where the red line connects point estimates for each day. If there were *no* home bias, we should see the horizontal axis ($\beta_0 = 0$) falling within the confidence interval most of the time. That does not turn out to be the case. Instead, we observe that despite some temporal variations, investors generally exhibit home bias. They are more likely to invest in borrowers from their home state: the coefficient estimate itself (connected by the red line) is mostly above zero, and the 95% confidence interval of the coefficients is mostly above the horizontal axis as well. Across all the dates in the sample, the 95% confidence interval of the coefficients is $[0.136, 0.156]$. Since we estimated logistic models, this means that being from the same state increases the odds of a lender placing a bid on a borrower by between 14.6% (calculated from $e^{0.136} - 1$) and 16.9% (i.e., $e^{0.156} - 1$) (Long and Freese 2006). Despite the limitations of the potential dyads approach, this represents microlevel evidence of home bias on Prosper under regular market conditions.

[7] Including or not including lender fixed effects (FEs), or using borrower fixed effects instead, yields qualitatively consistent results on the *SameState* variable. We use lender FEs here to be consistent with later analyses where borrower FEs are not feasible (in §4.3). Results are also similar when we adjust the standard error estimates by clustering on borrowers or lenders.

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4.2. A Quasi-Experimental Approach to Identify Home Bias

We now turn to more explicit empirical tests for home bias. A typical challenge in geography-related studies is that there may be unobservable factors affecting the choice of locations and investor decisions. We therefore use a quasi-experimental design to test the home bias hypothesis.

We exploit borrowers' move across state boundaries as exogenous variations to the state information. Specifically, we focus on borrowers who moved across state boundaries and requested loans both before and after their move. An important advantage of this approach is that borrowers' state changes can be considered largely exogenous to investor decisions on Prosper. Since Prosper loans are typically small (up to $25,000), it is highly unlikely that borrowers would move across state borders just to appeal to Prosper lenders in some particular states. Moreover, investors can only see the *current* state of residence of the borrower when they place bids. By including borrower fixed effects in the model, we are able to control for borrower-specific unobservables and identify the effect of the state information on the composition of lenders that are attracted to the borrowers' listings. If there is indeed home bias, then bids from lenders of the borrower's origination state (where her or she moved away *from*) should *decrease* after the borrower moved to a new state; by contrast, bids from the borrower's destination state (where he or she moved *to*) should increase after the move.

An important difference between this approach and Figure 2 is the level of analysis. A dyadic-level analysis is not feasible because moving borrowers do not have a separate market from the rest of the borrowers, and there is no convincing way of constructing a corresponding set of *lenders* while keeping the number of potential dyads manageable. Further, bids associated with these moving borrowers will be miniscule compared with the number of potential dyads thus constructed, making statistical analysis difficult. We therefore focus on the listing-level analysis here.

4.2.1. Summary Statistics for Moving Borrowers. We gather data over time to identify borrowers who not only moved across state boundaries between 2006 and the end of 2008 (when the U.S. Securities and Exchange Commission (SEC) temporarily shut down Prosper.com) but also made loan requests both before and after their move. We exclude borrowers who moved more than once as such cases are extremely rare. We obtain information on all bids on those listings (including losing bids, because all bids are not retractable, although excluding them has little impact on the results). Our sample includes 777 borrowers who created 4,358 listings. The average amount requested in these listings was $7,357 (minimum of $1,000, maximum of $25,000), the average duration was 7.5 days, and about one-third used immediate funding where the auctions ended when full funding was reached. Of these listings, 17.7% were funded successfully, with an average interest rate of 17.5%.[8]

4.2.2. Testing Home Bias: Effect of Borrower Moving on Lender Composition. We are interested in the effect of state change on the bidding behavior of lenders from the borrowers' origination states and lenders from the borrowers' destination states. To that end, we construct a panel data set comprising these moving borrowers and their listings. The most important explanatory variable is a dummy variable, *AfterMove*, which equals 1 for listings created *after* the borrower's move and 0 before. Although this variable is considered exogenous, we nonetheless control for a large number of covariates to rule out alternative explanations. These include characteristics of the auctions such as the starting interest rate, duration, and amount requested; whether there were bids from the borrower's group (if any), or from friends and family;[9] whether the borrower's group leader receives financial rewards if the listing is funded; and whether the borrower provided images with the listing. Borrower's credit grade and debt-to-income ratios are controlled for to capture any changes within borrowers. Loan purposes or category dummies are also included. To account for state-level information, we further include a variable capturing the difference in the unemployment rate between the destination state and the origination state.[10]

The first set of outcome variables is the number of bids from the borrowers' origination state lender and destination state lender. Since the outcome variable is a nonnegative integer with overdispersion (e.g., mean $= 1.18$, standard deviation $= 6.16$ for origination state lenders), we estimate a negative binomial model. The second set of outcome variables is the proportion of bids from the borrower's origination state and from the borrower's destination state. Since the dependent variable is a fraction constrained between 0 and 1, but it can be 0 or 1, we estimate a fractional response model (Papke and Wooldridge 2008). For the third outcome variable, *DollarAmount*, we estimate a

[8] It should be noted that the purpose of this analysis is to exploit borrower moves to identify the effect of location change on lenders who participate. To be included in this analysis, a borrower must have requested loans both before and after his or her move.

[9] As we will discuss in §6.1, this variable captures both explicit friends of the borrower via friendship ties on Prosper and implicit friends and family that we infer from their investment behaviors (see Agrawal et al. 2011). Using only explicit friends has negligible impacts on the results.

[10] Using other state-level information, such as education and Internet penetration, yields similar results on our key variable of interest.

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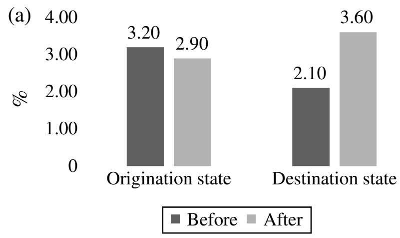
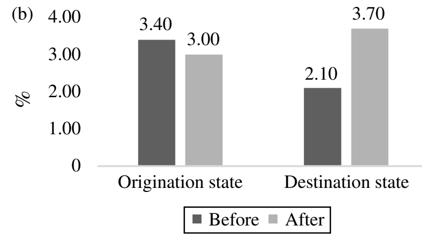
Figure 3 **Lender Composition Change Before and After Borrowers' Moves**





linear model. And finally, for the percentage of dollar amount, we also estimate a fractional response model. Under the home bias hypothesis, the coefficient of *AfterMove* should be negative for the bids from *origin* state lenders and positive for the bids from *destination* state lenders. The models are as follows:

$$Y_{i(\text{Origination})} = \gamma_1 X_i + \alpha_1 AfterMove_i + \beta_1 BorrowerFE + \epsilon_{1i},$$
$$Y_{i(\text{Destination})} = \gamma_2 X_i + \alpha_2 AfterMove_i + \beta_2 BorrowerFE + \epsilon_{2i},$$

where $Y_{i(\cdot)}$ indicates the outcome variables described above for lenders from both the borrowers' origination and destination states, and X_i indicates a vector of control variables. If investors do exhibit home bias, we should observe that, all else equal, $\alpha_1 < 0$ and $\alpha_2 > 0$.

High-level descriptive statistics are consistent with this hypothesis; for brevity, we only discuss the proportion of bids from origin and destination states here. Because of the nature of this market, the absolute proportion of lenders is small. On average, 3.1% of bids came from lenders who were in borrowers' origination states, and 2.8% came from lenders who were in borrowers' destination states; both numbers are still larger than the simplistic 2% baseline in §4.1.1. More importantly, we see that *before* the borrowers' moves, the proportion of bids from origination state lenders was 3.2%, and that decreased to 2.9% *after* the borrowers' moves. Meanwhile, the proportion of bids from destination state lenders was 2.1% before the move, but it increased to 3.6% after (see Figure 3(a)). The pattern is highly similar if we consider the amount of bids instead: origination state lenders decreased their contributions from 3.4% to 3.0%, whereas destination state lenders increased their contributions from 2.1% to 3.7% (see Figure 3(b)).

We report parametric estimation results in Tables 2 and 3. All results on the coefficient of the *AfterMove* variable are consistent with the home bias hypothesis. For instance, the proportion of bids (as a percentage of all bids received on a listing) decreased 10.9% after the borrowers' moves, whereas the proportion of bids from the destination state lenders increased 21.2% after the borrowers' moves.[11] These results remain qualitatively consistent when we use the number of bids, the dollar amount, or the proportion of dollar amount contributed by lenders from those states (see Tables 2 and 3).

To interpret the economic magnitude of the results in Tables 2 and 3, we need to take into account that lenders from one state do not generally contribute to a significant portion of a listing and that we consider all listings including those that did not reach full funding. From the first two columns of Table 2, we see that, all else equal, after the borrowers' moves, origination state lenders decrease 0.14 bids, whereas the destination state lenders increase 0.29 bids. These numbers may appear small at first glance, but the average number of bids from origin and destination state lenders for all listings in the sample is 1.18 and 1.04 bids, respectively (out of an average of 20 bids from all lenders on the market on those listings). Hence, a decrease of 0.14 and an increase of 0.29 bids are not trivial.

Control variable results in Tables 2 and 3 also show some interesting patterns, though it should be noted that the dependent variables refer to a subset of the lenders. For instance, listings with longer durations are more likely to receive bids from both first- and second-state lenders, but their proportions among all bids are largely stable.

4.3. Mini Prosper

The moving borrower analysis supports the home bias hypothesis, albeit on a higher level of analysis than dyadic. To complement that, we now examine home bias at the dyadic level. For identification purposes, we use data generated from a natural experiment on Prosper known as the *mini Prosper*.

Prosper started operating in 2006 in the United States. Since this was a new business model, it did not register with SEC. But in October 2008, SEC ordered Prosper to shut down. Prosper complied and

[11] We also try combining information across listings for each borrower separately before and after his or her move, thereby constructing a balanced version of the panel data. Results are highly consistent, but the control variables are aggregated in that process; hence we retain our main analysis here.

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Table 2 **Effect of State Change (Moving) on Bids from Origination and Destination States**

	No. of *origination* state bids	No. of *destination* state bids	Percentage of *origination* state bids	Percentage of *destination* state bids
AfterMove	−0.135*	0.289***	−0.109*	0.212**
	(0.082)	(0.094)	(0.066)	(0.101)
InitialInterestRate	8.191***	10.413***	1.101**	0.920
	(0.553)	(0.701)	(0.467)	(0.697)
Debt-to-Income_Ratio	−0.112***	−0.055	−0.024	−0.008
	(0.038)	(0.039)	(0.023)	(0.028)
ListingDuration	0.051**	0.052**	0.015	0.020
	(0.020)	(0.021)	(0.014)	(0.022)
AuctionType (1 = closed)	0.240***	−0.037	0.049	0.024
	(0.091)	(0.103)	(0.076)	(0.103)
RequestedAmount	−0.183***	−0.302***	−0.109***	−0.056
	(0.052)	(0.054)	(0.039)	(0.066)
HasGroupBids	1.464***	1.647***	0.041	0.120
	(0.112)	(0.121)	(0.076)	(0.084)
HasFriendorFamilyBids	0.953***	0.837***	−0.531***	−0.372***
	(0.093)	(0.093)	(0.089)	(0.090)
GroupLeaderHasReward	0.321***	0.209**	0.107	0.115
	(0.096)	(0.104)	(0.070)	(0.085)
Δ*StateUnemployment*	−0.071**	−0.008	−0.034	0.046**
	(0.029)	(0.031)	(0.024)	(0.023)
ListingHasImage	0.266***	0.307***	−0.072	0.305***
	(0.090)	(0.095)	(0.067)	(0.099)
1(*CreditGrade* = *AA*)	3.218***	3.672***	0.623***	0.354*
	(0.181)	(0.212)	(0.196)	(0.197)
1(*CreditGrade* = *A*)	2.438***	2.775***	0.438***	−0.098
	(0.162)	(0.186)	(0.135)	(0.174)
1(*CreditGrade* = *B*)	2.072***	2.510***	0.345**	0.262
	(0.151)	(0.168)	(0.152)	(0.164)
1(*CreditGrade* = *C*)	1.693***	1.912***	0.222**	0.071
	(0.131)	(0.147)	(0.111)	(0.124)
1(*CreditGrade* = *D*)	0.735***	0.995***	0.144*	0.145
	(0.118)	(0.127)	(0.084)	(0.123)
1(*Debt_Consolidation_Loan*)	−0.641***	−0.731***	−0.055	0.098
	(0.148)	(0.152)	(0.102)	(0.131)
1(*Home_improvement_Loan*)	−0.648**	−0.298	0.116	0.369
	(0.258)	(0.268)	(0.172)	(0.236)
1(*Business_loan*)	−0.494***	−0.705***	0.089	0.227
	(0.171)	(0.198)	(0.142)	(0.158)
1(*Personal_Loan*)	−0.737***	−0.595***	−0.130	0.221
	(0.201)	(0.186)	(0.158)	(0.139)
1(*Student_Loan*)	−1.091***	−0.858***	−0.278**	0.265
	(0.303)	(0.283)	(0.135)	(0.305)
1(*Auto_Loan*)	−1.134**	−0.702*	−0.497**	0.391*
	(0.459)	(0.362)	(0.208)	(0.222)
1(*Other_Loan*)	−0.971***	−0.887***	−0.204	0.377**
	(0.245)	(0.232)	(0.135)	(0.162)
Intercept	−3.281***	−2.675***	−1.776***	−2.478***
	(0.463)	(0.480)	(0.525)	(0.728)
N	4,358	4,358	4,358	4,358

Notes. Baseline loan category contains loans that did not specify a category. Robust standard errors are reported.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

entered a "quiet period" to go through a registration process. All market transactions were suspended on October 15, 2008. In late April 2009, Prosper completed the registration with SEC but was required to further obtain separate borrower and lender licenses from each state in the United States: one license to allow *lenders* from each state to participate and the other to allow *borrowers* to use the website. On

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Table 3 **Effect of State Change (Moving) on Funds from Origination and Destination States**

	Dollar amount of *origination* state bids (log)	Dollar amount of *destination* state bids (log)	Percentage of *origination* state bid amount	Percentage of *destination* state bid amount
AfterMove	−0.152**	0.220**	−0.124*	0.235**
	(0.063)	(0.089)	(0.066)	(0.102)
InitialInterestRate	5.390***	5.237***	1.357***	0.832
	(0.482)	(0.702)	(0.480)	(0.711)
Debt-to-Income_Ratio	0.012	−0.013	−0.040	−0.004
	(0.028)	(0.044)	(0.027)	(0.029)
ListingDuration	0.028*	0.044**	0.018	0.021
	(0.017)	(0.021)	(0.015)	(0.021)
AuctionType (1 = closed)	0.209***	0.126	0.042	−0.050
	(0.071)	(0.089)	(0.078)	(0.113)
RequestedAmount (log)	−0.124***	−0.216***	−0.096**	−0.061
	(0.046)	(0.066)	(0.039)	(0.070)
HasGroupBids	2.109***	2.125***	0.043	0.077
	(0.150)	(0.193)	(0.089)	(0.116)
HasFriendorFamilyBids	0.637***	0.379***	−0.505***	−0.306***
	(0.063)	(0.081)	(0.090)	(0.091)
GroupLeaderHasReward	0.195**	0.036	0.144*	0.124
	(0.080)	(0.105)	(0.076)	(0.087)
Δ*StateUnemployment*	0.040	0.063	−0.032	0.046*
	(0.073)	(0.234)	(0.025)	(0.024)
ListingHasImage	0.094	0.193*	−0.088	0.310***
	(0.079)	(0.105)	(0.067)	(0.102)
1(*CreditGrade* = *AA*)	2.926***	2.555*	0.669***	0.347*
	(0.343)	(1.332)	(0.220)	(0.204)
1(*CreditGrade* = *A*)	2.263***	3.004***	0.499***	−0.090
	(0.271)	(0.728)	(0.144)	(0.180)
1(*CreditGrade* = *B*)	1.233***	1.946***	0.322*	0.214
	(0.210)	(0.480)	(0.165)	(0.169)
1(*CreditGrade* = *C*)	1.040***	1.367***	0.272**	0.112
	(0.153)	(0.314)	(0.113)	(0.130)
1(*CreditGrade* = *D*)	0.273**	0.474**	0.130	0.168
	(0.123)	(0.237)	(0.086)	(0.124)
1(*Debt_Consolidation_Loan*)	−0.250**	−0.157	−0.052	0.065
	(0.122)	(0.224)	(0.104)	(0.133)
1(*Home_Improvement_Loan*)	−0.211	0.267	0.053	0.246
	(0.300)	(0.636)	(0.181)	(0.258)
1(*Business_Loan*)	−0.106	0.048	0.071	0.171
	(0.171)	(0.291)	(0.141)	(0.165)
1(*Personal_Loan*)	−0.278*	0.468*	−0.121	0.205
	(0.158)	(0.256)	(0.167)	(0.146)
1(*Student_Loan*)	−0.428	−0.497	−0.292**	0.248
	(0.274)	(0.458)	(0.132)	(0.304)
1(*Auto_Loan*)	−0.606	1.485**	−0.586***	0.468*
	(0.410)	(0.650)	(0.221)	(0.254)
1(*Other_Loan*)	−0.499**	−0.068	−0.291**	0.341**
	(0.213)	(0.352)	(0.128)	(0.166)
Intercept	0.625	0.557	−1.762***	−2.491***
	(0.424)	(0.620)	(0.550)	(0.748)
N	4,358	4,358	4,358	4,358

Note. Robust standard errors are reported.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

April 28, 2009, without prior notice, Prosper reopened its doors to borrowers from most states in the United States, as it was able to quickly receive borrower-side approvals. For the lender side, however, only California approved lender participation at that time; therefore, only California lenders were allowed to make investments. This mini Prosper lasted about 10 days until Prosper abruptly decided to reenter

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another quiet period on May 8, 2009, to obtain lender approvals from other states.

This scaled-down version of the website provides a unique opportunity to test home bias on the dyadic level. Since no lenders from non-California states are available, the *SameState* variable in the dyadic model is now exogenously restricted to 1's for borrowers from California (no 0's and, therefore, no variation) and to 0's for those who are not in California (no 1's and no variation). In addition, 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, it remains highly unlikely that a borrower, even if given more time, would move to a different state just to borrow from this website. Hence, the *SameState* dummy variable in the dyadic model is now largely exogenous for the outcome variable during this period, allowing us to identify its coefficient.

During the mini Prosper, 547 borrowers (from around the United States) created 701 listings, and 656 lenders (all from California) placed bids. Of 358,832 potential transaction dyads (547 borrowers × 656 lenders), 3,540 bids actually occurred. On the listing level, 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. The average amount requested by borrowers was \$9,556. The total amount funded to borrowers was \$84,236, of which \$19,636 (23.3%) was for California borrowers. These provide some initial, macrolevel evidence of home bias in this period.

To use the potential-dyads approach, we construct the data set such that each observation corresponds to a potential borrower–lender dyad, and the outcome variable is 1 if the lender places a bid on that borrower and 0 otherwise. The key independent variable is a binary indicator that equals 1 if the borrower and lender were from the same state and 0 otherwise. If there is home bias on the bid level, the coefficient of this variable should be positive and significant. We estimate the following model using a logistic model as well as a rare events logistic model (Tomz et al. 2003):

$$\begin{aligned}&\text{Prob}(Lender_i\_bids\_on\_Borrower_j)\\&\quad=\beta\times SameState_{ij}\\&\qquad+f(BorrowerInfo_i, LenderInfo_j, AuctionInfo)+\epsilon_{ij}.\end{aligned}$$

We estimate robust standard errors and report the results in Table 4. We control for information about the borrower, lender, auction, as well as their dyadic-level information. Lender information includes the (1) number of months that the lender had been on the site at time of bid and (2) lender risk preference measures. For lender risk preference, we examine the portfolio of lender's loan holdings and check the percentage of their investments in relatively "safe" and "risky" loans.[12] We also include the state-level unemployment rate; however, the results are highly similar when this is not included. We further include dyadic-level information between the borrower and lender, i.e., whether they are in the same group on Prosper and whether there are direct or indirect friendship ties between them (up to nine hops away), though the friendship connection parameters cannot be estimated because of limited observations (only three have direct ties, one has a common friend, and none has other indirect connections). And finally, in the final column of Table 4, we report results from a logit model with lender fixed effects.[13]

Results from the logistic model are highly similar to those from the rareevents logistic model, as well as the model with lender fixed effects. They show that there is indeed a statistically significant home bias. Consistent with our previous findings, being a California borrower during the mini Prosper increases the odds of receiving a bid from a lender by at least 21% ($e^{0.192}-1$) across different specifications.

We further conduct an additional robustness test, where we replace the outcome variable with the actual amount of bid from lender i to borrower j. If there was no bid, then the bid amount is \$0. We then estimated a Tobit model with the same right-hand-side variables and report the results in Table 5. They are still remarkably consistent with the bid occurrence model reported in Table 4 and consistent with the home bias hypotheses. California lenders bid an average of \$11–\$16 more on California borrowers.

Some auxiliary results from these models are also meaningful and consistent with those from the previous literature (e.g., Lin et al. 2013). Borrowers who

[12] We capture the lenders' risk preference in the following manner. We consider loans in AA and A credit grades as low-risk loans and those in D, E, or lower credit grades as high-risk loans. Among all lenders, we check the top and bottom quartiles (25th percentile) in terms of their holdings of loans in those categories. We categorize a lender as a "risk taker" if he or she is in the top quartile (specifically, more than 31% of investment) in terms of high-risk loans *and* in the bottom quartile (less than 16% of investment) in terms of low-risk loans. Similarly, we categorize a lender as a "risk averter" if he or she is in the top quartile in terms of low-risk loans and bottom quartile for high-risk loans. These two categories are captured in the model using two separate dummy variables. The baseline (when both dummy variables are 0) indicates other "moderate" investors. Excluding these variables does not affect the results.

[13] It is not possible to use borrower fixed effects instead, because during the mini Prosper the *SameState* variable has no within-borrower variation, unlike the analysis in §4.2.

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Table 4 Home Bias in Mini Prosper: Bid Occurrence

	(1) Model 1: logistic	(2) Model 1: RE-logistic	(3) Model 2: logistic	(4) Model 2: RE-logistic	(5) Model 2: logistic with lender FEs
SameState	0.192***	0.193***	0.250***	0.251***	0.254***
	(0.055)	(0.055)	(0.074)	(0.074)	(0.076)
RequestedAmount (log)	−0.524***	−0.524***	−0.524***	−0.524***	−0.551***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
AuctionType (1 = closed)	1.366***	1.353***	1.366***	1.353***	1.399***
	(0.177)	(0.177)	(0.177)	(0.177)	(0.179)
InitialInterestRate	2.186***	2.184***	2.157***	2.156***	2.259***
	(0.206)	(0.206)	(0.203)	(0.203)	(0.207)
LenderMonthsonSite (log)	0.457***	0.457***	0.457***	0.457***	
	(0.046)	(0.046)	(0.046)	(0.046)	
LenderRiskTaker	−0.488***	−0.484***	−0.488***	−0.484***	
	(0.099)	(0.099)	(0.099)	(0.099)	
LenderRiskAverter	−0.334***	−0.332***	−0.334***	−0.332***	
	(0.069)	(0.069)	(0.069)	(0.069)	
StateDefaultPct	−1.288***	−1.288***	−1.223***	−1.221***	−1.283***
	(0.253)	(0.253)	(0.272)	(0.272)	(0.279)
StateUnemployment			0.001	0.001	0.001
			(0.015)	(0.015)	(0.015)
1(*SameGroup*)	1.274**	1.387***	1.266**	1.379***	1.196**
	(0.524)	(0.524)	(0.523)	(0.523)	(0.549)
1(*CreditGrade* = *AA*)	0.284***	0.284***	0.285***	0.285***	0.298***
	(0.049)	(0.049)	(0.049)	(0.049)	(0.051)
1(*CreditGrade* = *B*)	−0.699***	−0.698***	−0.698***	−0.698***	−0.726***
	(0.057)	(0.057)	(0.058)	(0.058)	(0.058)
1(*CreditGrade* = *C*)	−1.042***	−1.042***	−1.045***	−1.044***	−1.082***
	(0.056)	(0.056)	(0.056)	(0.056)	(0.057)
1(*CreditGrade* = *D*)	−1.074***	−1.072***	−1.082***	−1.080***	−1.116***
	(0.086)	(0.086)	(0.086)	(0.086)	(0.087)
1(*Home_Improvement_Loan*)	−0.191***	−0.190***	−0.189***	−0.188***	−0.200***
	(0.061)	(0.061)	(0.061)	(0.061)	(0.062)
1(*Business_Loan*)	−0.801***	−0.799***	−0.802***	−0.801***	−0.820***
	(0.069)	(0.069)	(0.069)	(0.069)	(0.070)
1(*Personal_Loan*)	−0.601***	−0.597***	−0.615***	−0.611***	−0.645***
	(0.103)	(0.103)	(0.104)	(0.104)	(0.108)
1(*Student_Loan*)	−1.452***	−1.440***	−1.452***	−1.441***	−1.492***
	(0.156)	(0.156)	(0.156)	(0.156)	(0.156)
1(*Auto_Loan*)	0.284***	0.284***	0.281***	0.281***	0.299***
	(0.046)	(0.046)	(0.046)	(0.046)	(0.047)
Intercept	−0.083	−0.082	−1.101	−1.096	0.719
	(0.212)	(0.212)	(0.769)	(0.769)	(0.875)
N	358,832	358,832	358,176	358,176	358,176

Notes. We also tried including whether the borrower and lender were friends (direct tie) or have indirect ties, up until nine degrees away; however, these variables are not identifiable because there were only three friend pairs, one friend-of-a-friend pair, and no other indirect friendship connections existed. Heteroskedasticity-consistent standard errors are reported in parentheses. Column (5) reports results of the full model using logistic regression with lender fixed effects. RE, rare events.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

had better credit, who used closed auction format, and who were willing to pay higher interest rates were more likely to receive bids and to receive larger bids. Hence, even though the mini Prosper may appear unique (inherent to studies exploiting exogenous shocks), it still retains general features of the context.

4.4. Is Home Bias the Result of Friends and Family?

We now consider whether the home bias results above are attributable to activities of the borrowers' friends and family. On Prosper, friends can place bids on a borrower (see Lin et al. 2013). Presumably, friends could be from the same state as the borrower. If

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Table 5 **Home Bias in Mini Prosper: Amount of Bid**

	Model 1	Model 2	Model 2 with lender fixed effects
SameState	10.795**	12.270**	16.468***
	(4.618)	(5.916)	(5.706)
RequestedAmount (log)	−50.312***	−50.187***	−48.718***
	(2.094)	(2.095)	(2.020)
AuctionType (1 = closed)	97.646***	97.655***	99.273***
	(11.917)	(11.918)	(11.773)
InitialInterestRate	182.029***	180.439***	178.935***
	(20.134)	(20.227)	(19.685)
LenderMonthsonSite (log)	36.494***	36.497***	
	(3.390)	(3.390)	
LenderRiskTaker	−33.148***	−33.133***	
	(7.598)	(7.598)	
LenderRiskAverter	−31.429***	−31.430***	
	(5.622)	(5.622)	
StateDefaultPct	−114.244***	−113.710***	−129.454***
	(20.272)	(21.474)	(20.832)
StateUnemployment		0.108	0.524
		(1.432)	(1.390)
1(*SameGroup*)	103.015*	102.712*	89.646*
	(53.297)	(53.315)	(51.902)
1(*CreditGrade* = *AA*)	24.558***	24.715***	22.082***
	(4.213)	(4.221)	(4.032)
1(*CreditGrade* = *B*)	−58.749***	−58.502***	−61.307***
	(4.662)	(4.664)	(4.531)
1(*CreditGrade* = *C*)	−87.342***	−87.452***	−89.373***
	(4.906)	(4.913)	(4.786)
1(*CreditGrade* = *D*)	−84.165***	−84.350***	−83.304***
	(7.316)	(7.327)	(7.106)
1(*Home_Improvement_Loan*)	−14.455***	−14.455***	−15.740***
	(5.227)	(5.229)	(5.083)
1(*Business_Loan*)	−59.463***	−59.621***	−57.404***
	(5.428)	(5.429)	(5.254)
1(*Personal_Loan*)	−48.945***	−49.239***	−44.388***
	(8.033)	(8.052)	(7.689)
1(*Student_Loan*)	−111.435***	−111.459***	−110.533***
	(11.336)	(11.336)	(11.096)
1(*Auto_Loan*)	22.710***	22.550***	23.825***
	(3.895)	(3.897)	(3.748)
Intercept	−57.316***	−86.192	60.350
	(20.422)	(57.294)	(63.397)
N	358,832	358,176	358,176

Note. Robust standard errors are reported in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

investors are mostly borrowers' friends, then the home bias we observe just reflects their private information about the borrowers. Their motivations, be it rational or behavioral, may not apply to other investors. For example, Agrawal et al. (2011) find that on SellaBand, local investors invest because of personal connections with the artists. We therefore investigate whether friends and family drive our home bias findings.

To be conservative, we consider two types of friends and family of borrowers on Prosper. The first type is *explicit* friends of the borrower, indicated by friendship ties on the site (Lin et al. 2013). The second type is *implicit*, since some friends could participate in a loan without creating a friendship tie with the borrower, even though implicit friend bids would not have the signaling value of explicit friends. We use the method of Agrawal et al. (2011) to infer implicit friends through their investment patterns.[14] We find that explicit friends significantly outnumber the implicit ones. When we combine both types, only 17.5% of them has the same state of residence as the borrower, and their bids only account for 1.9% of all same-state bids. We also try relaxing the three criteria used in Agrawal et al. (2011) by not requiring the implicit friend to be the first to bid and allowing the investor to have up to five other investments rather than three. Results are virtually identical. We further test whether loans with more home state bids have disproportionally more friends[15] by estimating a listing-level model where the outcome variable is the proportion of home state bids, and the key independent variable is the proportion of friends among all bidders. Using the same set of controls as in our previous models, we find that the coefficient of friend proportion is not statistically significant. Hence, our home bias findings are unlikely because of friends.

We also consider two other methods to identify implicit friends. They, too, have little influence on our tests. First, an investor may sign up to be a lender only to invest in a friend or family member. This is a more stringent version of the approach used in Agrawal et al. (2011). Bids of these investors account for less than 0.2% of all home state bids. Second, some friendship ties may be revealed *after* loans are funded. This also turns out to be negligible. There were more than 170,000 borrower–lender pairs between borrowers and lenders in our data. When we examine borrowers' *new* friendship ties that appeared within 30 days after funding, only 137 such ties exist, and not all these investors were from the same state as the borrower. This provides further evidence that, regardless of how we measure borrowers' friends and family, they are unlikely driving the home bias results.

[14] For SellaBand, Agrawal et al. (2011) use the following criteria to identify investors who may be family or friends with the band requesting funds: (1) they are the earliest to invest in a particular borrower, (2) that investment is the largest of their investments on the website, and (3) they invest in no more than three other borrowers. We use the same criteria here. It should be noted that, however, unlike SellaBand in Agrawal et al. (2011), where bands are easily identifiable, borrowers on Prosper are prohibited from disclosing personally identifiable information, so it becomes much harder for friends and family to identify them.

[15] We thank an anonymous reviewer for suggesting this test. Results are not reported here because of page limits.

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5. What Drives Home Bias?

5.1. Reasons for Home Bias

Our analyses so far attest to the robustness of the finding that home bias exists in this crowdfunding market. A natural follow-up question is, *why* does home bias exist in this market?[16] Since Prosper is a market for loans—a financial product—economic information such as borrowers' credit profiles can be expected to influence lender decisions. Hence, a more interesting and more important question is, *do lenders exhibit home bias only because of higher economic payoffs, or do behavioral reasons play a role as well*? We now derive and test several competing hypotheses from rational and behavioral explanations.

5.1.1. Economic Reason for Home Bias and Its Implications. Before we proceed, it is important to clarify what we consider as economic or behavioral reasons. Studies in economics and finance often offer economic explanations for home bias, such as risks and costs (Lewis 1999). A common theme for these explanations is that the decision makers are *homo economicus*, that the home bias decision should be economically sensible, helping the agents maximize their profits or utility (Kahneman 2003). Geographic information such as state of residence should have information and economic value that help them make the right decisions and serve their best interests. They should be able to make these decisions free of cognitive bias, emotional hindrance, or psychological influence.

The first and foremost empirical implication of the economic explanation is that investors invest in home state loans because these loans offer better returns on average. This is akin to the first-order statistical discrimination based on group averages (Altonji and Blank 1999, Arrow 1973, Phelps 1972). Second, there may even be a second-order statistical discrimination (SOSD) effect (Cornell and Welch 1996, England 1992), that, *if investors are risk averse*, they may choose to invest in home state loans when the uncertainty associated with home state loans is lower. Second-order statistical discrimination has not been extensively validated in the empirical literature, and it only applies when the decision maker is risk averse (Aigner and Cain 1977, England 1992), but it is still a potential implication of economic reasoning and should be considered.[17]

[16] Note that this section benefited tremendously from the suggestions of the associate editor and the reviewers.

[17] In addition to risk aversion, statistical discrimination arguments also require that (1) there is little other quality information available (Aigner and Cain 1977, Altonji and Blank 1999), and (2) the discriminating factor can be costlessly obtained and processed (cf. gender in labor markets) (Fang and Moro 2010, England 1992). Although these may not always be true in our context, such possibilities should be investigated nonetheless.

5.1.2. Behavioral Reason for Home Bias and Its Implications. By contrast, studies such as Huberman (2001) point out that behavioral biases can lead to home bias without economic benefits. In our context, behavioral reasons for a home state bias can include familiarity with the home state (Huberman 2001), emotional attachment to a place called "home," and simple homophily (McPherson et al. 2001): lenders will feel they are more "similar" to those from their home state than those from elsewhere. Similar to many arguments in behavioral economics such as heuristics and framing (Kahneman 2003, Thaler 1993), such motivations require no economic benefits to engender a home bias; in fact, investors are willing to lend even if the decision is not economically sensible.

If home bias is indeed driven by behavioral reasons, then, first and foremost, investors should be willing to invest in home state loans despite low returns. Second, investors will not require information advantage to show home bias: an investor would exhibit such a bias just because he or she calls a place home and shares that with someone else. And finally, if certain information about a loan strengthens the "cue" about the location, making that information more *salient*, then, all else equal, such a loan should be able to attract more home state investors—even if no additional economic information is revealed.

5.1.3. Tests to Contrast Economic and Behavioral Explanations. Based on the discussions above, we design a series of tests to contrast economic and behavioral reasons.

In our first test, Test 1, we test the relationship between the financial returns of loans and the participation of home state investors. If loans with better performance attract disproportionally more home state investors, then economic reason is likely to be dominant; home state investors may know something about the loans that out-of-state investors do not know. However, if loans that attract more home state investors do not perform better (worse, or no different), then behavioral reasons are more likely than economic reasons to be driving the home bias.

In Test 2, borrowers can include text descriptions with their loans, and these texts may further include information about their state of residence. If "state" has informational value to help investors make the correct decisions, that information is already revealed by the borrower's state of residence, which is objectively verified by the site. In that case, repeating such information in the loan's descriptions adds no informational value and therefore should *not* attract more economically motivated investors. By contrast, if home bias is behaviorally driven—meaning that investors respond psychologically to the state information—then their response (bidding behavior) will be stronger when the cue

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about a state is repeated and reinforced in the texts and therefore more salient.

In Test 3, we investigate SOSD as a rational explanation for home bias in our context. Since testing this argument in archival data is extremely rare in the empirical literature, especially because it only applies to risk-averse investors (Aigner and Cain 1977), we address this in several ways. Because of page limitations, we provide full details only on the first and most important test. We exploit the move of *lenders* on this website from one state to another, which, similar to borrower move, can be considered exogenous. Cornell and Welch (1996) suggest that for the variance-based statistical discrimination to occur, agents should possess knowledge (in particular, cultural knowledge) about one group that would have taken a long time to possess or accumulate.[18] For the short time frame that we study, lenders are unlikely to fully obtain such "insider" information about the new state. Hence, if such a case of statistical discrimination is at play, lenders who move to a new state should *not* increase their investment in the new state compared to their investment in it prior to the move. By contrast, if lenders are at least partially driven by behavioral reasons, they should be expected to increase their investment in the new state. This is because even though the destination state is a *new* home to the lender, the lender is still (1) more familiar with it, (2) more likely to feel an emotional bond with it, and (3) more likely to feel *similar* to borrowers in it (homophily) compared with what he or she had felt about that state prior to the move. In summary, moving lenders' investment changes toward destination state borrowers provide an opportunity to test the variance-based statistical discrimination argument.

We now report these and several additional tests in turn.

5.2. Test 1: Loan Quality and Home State Investor Participation

As discussed above, our first test is the relationship between the financial performance of loans, and the participation of home-state investors. Since our data set contains loans funded prior to the end of 2008, and all were three-year loans, we are able to observe the ultimate outcome of those loans including whether they were repaid or defaulted, the return that lenders received on the loan, the dollar amount defaulted, and the billing cycle (month) in which the default occurred.[19] To capture home state investor participation, it should be noted that for a given loan, some investors may be from the borrower's home state and others from other states. Hence, in general, one cannot classify a loan as a "home state" loan. We therefore aggregate investors' bids to the level of loans: for each loan funded in our study period, we identify all investors who participated and calculate the percentage of funds that came from investors from the same state as the borrower. We study how this participation metric relates to loan outcomes.

The first outcome is the likelihood of default. We estimate a logistic model with the dependent variable being whether the loan defaulted (1 if yes and 0 if no) and the home state fund proportion as the main independent variable. We control for characteristics of the borrowers and their listings, and we report the estimation results in the first column of Table 6. Although a higher proportion is associated with higher likelihood of default in a univariate model (not reported), the coefficient is not statistically significant in the full model. This result weakly supports the behavioral reasons (see §5.1.3), but it also shows the need to look into other loan outcomes, such as the return (including the nominal interest rate and a calculated return on investment (ROI)) of loans, the dollar amount lost on a loan (0 if fully repaid), and the timing of default (billing cycle in which default occurred). From the remaining columns of Table 6, we see that loans with a larger proportion of home state funds offer *lower* returns, are likely to default with a *larger* amount of loss, and are likely to default *sooner*. In other words, overall, home state investments are *less* desirable than their out-of-state counterparts. This finding is consistent with behavioral reasons of home bias rather than the economic explanations.[20]

In addition to the ex post loan performance tests above, we also investigate the ex ante choice of

[18] An important premise underlying the results of Cornell and Welch (1996, p. 543) is that "people who grow up under comparable circumstances will have a common framework for assessing each other's personal history." In other words, this argument is valid only to the extent that the investor had been in a state sufficiently long enough to gain that capability. This may be true for the investor's origination state but unlikely to be the case for the new state that her or she just moved to.

[19] A loan's time-to-default is a useful measure of loan performance that has been used quite extensively in prior management, economics, and finance literatures, such as Bharath and Shumway (2008), Boyes et al. (1989), Gross and Souleles (2002), Lin et al. (2013), and McDonald and van de Gucht (1999), among others.

[20] This analysis is on the loan level. We also conduct a lender-level analysis that requires that we aggregate information about loans within each lender's portfolio. We model the relationship between the proportion of loans in default for each lender and that lender's proportion of investment in home state loans. Controlling for information such as lenders' total portfolio size, time on the market, and aggregated information about the loans that they invested in, we find that the coefficient is positive and statistically significant. When comparing the return from home state versus other state loans within each lender's portfolio, home state loans also offer strictly lower returns. Both findings provide additional support for the behavioral explanation. Since loan-level tests incorporated control variables without the need for aggregation, we use them as the main specification.

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Table 6 Home State Funding Proportion and Loan Outcome

	Likelihood of default (logistic)	Interest rate (linear)	Default amount (Tobit)	Default cycle (Poisson)	Actual ROI (linear)
ListingHomeStateBid %	0.001	−0.009***	23.652***	−1.103***	−0.097***
	(0.001)	(0.002)	(3.906)	(0.023)	(0.031)
RequestedAmount (log)	0.332***	0.002***	1,509.631***	0.116***	−0.061***
	(0.012)	(0.000)	(34.946)	(0.004)	(0.004)
InitialInterestRate	2.750***	0.748***	6,260.581***	−0.205***	0.768***
	(0.139)	(0.005)	(303.824)	(0.042)	(0.061)
Debt-to-Income_Ratio	0.045***	0.000***	165.838***	0.004	−0.016***
	(0.009)	(0.000)	(29.395)	(0.003)	(0.004)
AuctionType (1 = closed)	0.307***	0.037***	523.593***	0.066***	−0.023**
	(0.019)	(0.000)	(44.963)	(0.007)	(0.010)
HasFriendorFamilyBids	−0.008	−0.001***	164.674***	−0.002	−0.002
	(0.010)	(0.000)	(35.621)	(0.003)	(0.004)
HasGroupBids	0.063***	−0.006***	86.139**	0.036***	−0.037***
	(0.018)	(0.000)	(39.256)	(0.006)	(0.007)
Intercept	−4.156***	−0.009***	−127***	2.276***	1.519***
	(0.115)	(0.002)	(29.757)	(0.037)	(0.037)
N	29,422	29,422	29,422	29,422	29,422

Notes. Credit grade and loan types are controlled for. Poisson model is used for default cycles as there is no evidence of overdispersion. Heteroskedasticity-consistent standard errors are reported in parentheses.
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

investors. At the 95% confidence level, each home state bid has between 2.44 and 2.53 strictly better out-of-state alternatives.[21] This interval is larger than that of a random sample of other bids (0.93, 1.11). Further, when we consider the interest rate discount—the difference between the interest rate offered by the listing where the investor placed the bid and the interest rate offered by the best alternative—home state bids gave up on average a 4% interest rate (0.039 versus 0.043), and this difference is statistically significant ($p < 0.02$). Such apparently irrational behaviors are again consistent with the behavioral explanations.[22]

5.3. Test 2: Location Words

As discussed in §5.1.3, texts provided by borrowers could include *redundant* location information since the state of residence is a standard piece of information on all listings. Such redundant texts add no additional economic value to the location information, so if home bias is economically driven, these texts should not affect the participation of home state investors. But if it is behaviorally driven, then the recurrence and reinforcement of such information will make it more salient, make it more likely to elicit a behavioral response from home state investors, and therefore will attract more home state investors to bid.

To test this, we take a 10% random sample of all listings and extracted their text descriptions. We then construct a custom "dictionary" of words and phrases, where, for each state, we identify its name and the name's typical abbreviations, its capital, its largest city, as well as any other city within the state that is among the 100 largest cities in the United States by population.[23] Even though our dictionary is unlikely to be exhaustive, it offers a conservative measure of the redundant textual information that would have elicited emotional responses to the borrower's state of residence. We search for the occurrence of these words in borrowers' text descriptions using the Natural Language Toolkit (NLTK) in Python 2.7.[24] We then estimate the relationship between these words and the bidding behavior of home state investors, measured by the number of bids that the listing received from home state investors, as well as the proportion of home state investor bids among all bids. For the number of bids, since the outcome variable has significant overdispersion (standard deviation = 5.2, mean = 1.5), we estimate a negative binomial model. For the proportion, we estimate the fractional response model. The key independent variable is the percentage of location words detected by our custom-made dictionary. Both models include the same set of

[21] These out-of-state opportunities have strictly lower risks (higher credit grades), strictly higher returns (higher ongoing interest rate), identical loan purposes and funding options, and similar (±5%) cumulative funding level.

[22] There were also out-of-state opportunities that offered strictly lower returns and strictly higher risks, suggesting that home state bids are not purely behavioral either.

[23] We compiled the list from the following *Wikipedia* entries (accessed December 1, 2013): http://en.wikipedia.org/wiki/List_of_states_and_territories_of_the_United_States and http://en.wikipedia.org/wiki/List_of_United_States_cities_by_population.

[24] Available from https://pypi.python.org/packages/2.5/n/nltk/nltk-2.0.4.win32.exe and http://nltk.org (accessed March 27, 2015).

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loan-level control variables used in previous models; in addition, since this test is about texts, we follow prior literature (Lin et al. 2013) and use the standard text analysis software LIWC (Pennebaker et al. 2006) to capture major text categories, including a category for the generic "space" words such as "city" or "east." Results, reported in Table 7, show that the proportion of these "redundant" location words is positively associated with both the number of bids from home state investors and its proportion among all bids received on a listing. As reasoned above, this finding is far more consistent with a behavioral explanation of home bias than an economic one.

Table 7 **Text Content and Home State Investor Bids**

	Number of home state investor bids	Proportion of home state investor bids
Redundant state information words	0.942***	0.175**
	(0.327)	(0.080)
Space words	0.053***	0.004
	(0.014)	(0.003)
WordCount	−0.018	−0.003
	(0.027)	(0.006)
WordspersSentence	−0.040	−0.006
	(0.034)	(0.008)
Tentative words	0.002	−0.001
	(0.031)	(0.007)
Affect words	0.038**	0.008**
	(0.015)	(0.003)
Money words	−0.002	0.001
	(0.009)	(0.002)
Certainty words	0.069**	0.014*
	(0.034)	(0.008)
Number words	−0.012	−0.001
	(0.024)	(0.005)
RequestedAmount (log)	0.872***	0.083***
	(0.038)	(0.008)
InitialInterestRate	2.732***	0.426***
	(0.416)	(0.087)
HasFriendorFamilyBids	0.208***	0.083***
	(0.063)	(0.015)
Debt-to-Income_Ratio	−0.069***	−0.017***
	(0.024)	(0.005)
AuctionType (1 = closed)	−0.279***	−0.051***
	(0.071)	(0.016)
HasGroupBids	−0.052	−0.001
	(0.067)	(0.015)
Intercept	−8.507***	−1.172***
	(0.485)	(0.101)
N	10,451	10,451

Notes. Credit grade and loan purpose dummies are included in estimation but not reported for brevity. *WordCount* and *WordsperSentence* are the number of words in the whole description and each sentence of the description, respectively. The rest of the text variables are largely orthogonal to each other, since they capture different classes of words. *Affect* words include emotion-related words, such as "happy" "nice," or "nasty." Examples of *money* words include "owe" or "cash"; *certainty* words, "always" or "never"; *tentative* words, "maybe" or "perhaps"; *space* words, "city," "east," or "territory"; and *number* words, "thousand" or "first." Heteroskedasticity-consistent robust standard errors are reported.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

5.4. Test 3: Moving Lenders

We now turn to Test 3, which, as discussed in §5.1.3, examines whether the variance-based statistical discrimination is a valid economic explanation for home bias in our context. We track *lenders* who moved across state boundaries and made investments both before and after, and we study how their investment behaviors change toward their *destination* states. For each of these investors, we gather information about their investments and construct a panel data set where each lender has two observations, one for their bids (including those outbid) before the move and the other for after.[25] The outcome variable is the proportion of their bids on borrowers from their *destination* states. The key independent variable is *AfterMove*. We control for information about the listings that they participated in.[26] Similar to moving borrowers, we estimate a fractional response model with investor fixed effects.

Results in Table 8 show that investors *increased* their investment in borrowers of their destination states: the proportion of bids on destination state borrowers *increased* by 42.4% after the move. This observation is consistent with the behavioral explanation of home bias: after moving, the new destination state serves as the new "home" for investors; even though this is a new state, it is already emotionally closer to the investor than it was before the move.[27] This finding contradicts the statistical discrimination argument because in the short time frame we study, moving lenders would not have had the time to accumulate sufficient "local" knowledge to favor borrowers from the new state. It also contradicts other rationality-based explanations for home bias: if investors are

[25] Dyadic analysis on moving lenders is not feasible because these lenders are active at different periods of time; each may be faced with large numbers of potential borrowers to invest in, thereby creating extremely large numbers of potential dyads. A loan-level analysis is also not feasible for moving lenders, because these lenders do not fund entire loans on their own, separate from other lenders.

[26] Readers interested in interpreting findings on these control variables should note that their meaning is now different. For example, by aggregating "auction format" across listings, the new control variable should be interpreted as the proportion of listings of this lender has invested in that used the "immediate funding" format. Such aggregation of control variables is necessary and has been used in prior literature (e.g., Zhang and Liu 2012). Excluding these variables yields highly consistent results.

[27] When we change the outcome variable to investments on the *origination* state borrowers, the coefficient on *AfterMove* is not statistically significant. This, however, is inconclusive regarding the motivations.

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Table 8 Moving Lender Analysis

	Proportion of bids placed on *destination* state borrowers
AfterMove	0.424***
	(0.046)
Percentage_ClosedAuctionType	0.030
	(0.057)
Average_RequestedAmount (log)	−0.000
	(0.000)
Average_Debt-to-Income_Ratio	−0.004
	(0.027)
Average_Duration	0.005
	(0.017)
Average_InitialInterestRate	−0.457
	(0.492)
Percentage_HasFriendorFamilyBids	−0.325***
	(0.074)
Percentage_HasGroupBids	0.807
	(6.049)
Intercept	0.672*
	(0.393)
N	1,142

Notes. Lender fixed effects are included in the estimation, and heteroskedasticity-consistent standard errors are reported in parentheses. Listing information is aggregated over all loans that the lenders participated in before or after the move, as controls.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

purely driven by economic reasons, their investment allocation across states should have remained stable in the short period around the move.

We now report several additional tests that show the home bias is unlikely because of the variance-based SOSD. First, according to the SOSD argument, investors are more likely to invest in home state loans because home state loans are less risky. If this is true, then, when an investor chooses between their home state borrowers and borrowers from states that historically have a lower default risk than their home state, the investor should *not* exhibit a home bias. We test this using the mini Prosper dyadic data by retaining only borrowers from California and states that have default rates (based on loan performance data available at time of the mini Prosper) lower than California—both in terms of the percentage of loans defaulted and the portion of funds defaulted—and see whether California lenders still favor California borrowers. We include all control variables used in §4.3. Our results strongly indicate that even when we only consider states that are *safer* than the investors' home state, investors still show preference toward their home state borrowers.

Second, SOSD is based on the perception that the variance of returns is lower for home state borrowers than those in other states. We directly investigate whether such perceptions are consistent with actual data. We conduct pairwise variance comparisons of loans' actual returns for each pair of states at each credit grade, resulting in a total of 50 (home states) × 49 (other states) × 7 (credit grades) comparisons. For loan performance, we use the actual return of each loan. We find that there is very little variation in the returns' variance across states: of all these possible pairs, 83.68% of them show no statistical difference in variance of returns at the 5% level. We then conduct a more nuanced analysis and focus on the strictly better alternatives of same state bids, and we compare the variance of home state loan performance that the home state investor invested in to the variance of loans in each of the states that the investor had forgone. If SOSD is driving home bias, then each and all of those states should have higher variance in returns than the home state. We find that for 95.16% of all such pairs (home state for the investor and the state of the alternatives), the variances are either not statistically significant or in fact higher for the other state. In addition, 96.24% of the same state bids have at least one alternative that has a lower variance than the home state. Therefore, if home state investments were driven by the belief that investing in the home state is less risky (lower variance) than investing in other states, our findings show that this belief is not rational.

Third, we also examine the possibility that investors may use state as a proxy for race or gender, the two most common factors used as the basis of statistical discrimination in the literature. Gender composition difference across states is small, so we focus on race. If race-based SOSD is driving home bias, then (1) if lenders move away from racially homogeneous to racially diverse states, they should *not* increase their investment in the destination state; (2) for racially diverse states such as California, we should *not* see home bias. Empirical evidence contradicts both.[28] All the above tests suggest that SOSD is unlikely a viable rationality-based explanation for home bias in our context.[29]

Importantly, our tests do not suggest that economic motivations are irrelevant for home bias. Rather, our argument is that economic explanations alone—that investors invest in home state borrowers purely because those borrowers are economically

[28] For the first test, we use the 10 least racially diverse states based on 2009 American Community Survey (see http://www.mainstreet.com/slideshow/lifestyle/least-diverse-states-america; accessed March 27, 2015). The second test is the mini Prosper analysis, because California is the second most racially diverse state (only after Hawaii) in the United States.

[29] We also test whether home bias still exists (using mini Prosper data) when we exclude risk-averse investors (using our definition based on their investment patterns). SOSD is only valid when agents are risk averse. Yet, even when we exclude risk-averse investors, there is still a persistent home bias in the market, again contradicting SOSD.

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preferable—are inconsistent with the empirics. Behavioral motivations play an important role behind home bias that we observe on Prosper.

6. Conclusions and Implications

Our paper is among the first to identify home bias in online debt-based crowdfunding. We first documented preliminary evidence of home bias through macrolevel descriptive statistics, dyadic analysis of transaction data, then analyzed data from a quasi-experiment design (moving borrowers) and a natural experiment (mini Prosper) to show that this phenomenon still exists in online investments. Remarkably, despite the virtual nature of this crowd-based marketplace, home bias persists.

We further examined the mechanism behind home bias in this context. Drawing on existing literature on home bias, we focused on two dominant competing explanations, i.e., economic explanations and behavioral explanations, and their contrasting empirical predictions. Given the financial nature of these transactions, we asked whether rationality-based explanations alone can explain home bias or if behavioral reasons play a role. Results from a series of tests consistently refuted a purely economic explanation of home bias—including variance-based statistical discrimination—and supported the argument that behavioral factors at least partially drive home bias behaviors. These three main tests are (1) financial performance of home state investments; (2) "redundant" location words; and (3) how lenders' investment decisions change toward their destination states after they move.

Our study makes several contributions to the broader home bias literature. First, to our knowledge, our study is one of the few that exploit a quasi-experimental design and a natural experiment to identify home bias (one notable exception is Redding and Sturm 2008). Second, we find evidence of suboptimal outcomes resulting from investors' home bias, which is consistent with behavioral rather than rational explanations of this phenomenon. In fact, whereas Wolf (2000) called for further research into the causes of home bias, to our knowledge, very little research has been done to empirically test competing hypotheses between rational and behavioral explanations. Most of the literature on home bias focuses on economic reasons (Cooper and Kaplanis 1994, Lewis 1999, Obstfeld and Rogoff 2001). Although several studies focus on behavioral explanations, some of them cite informational costs as reasons for home bias (Grinblatt and Keloharju 2001). By contrast, our finding of the suboptimality of home state investments shows that irrational, behavioral explanations indeed drive home bias and have direct social welfare implications (compare to Wolf 2000, p. 562). In addition, the behavioral reason suggests that home bias is unlikely to be eradicated by Internet technologies or disintermediation.

Market participants, analysts, designers, and managers of the online crowdfunding industry will be well advised to heed the home bias that we identified in this study. For instance, borrowers—especially those from states with large lender populations—should pay attention to this tendency so as to maximize their likelihood of success. More importantly, investors should recognize this potential bias and be conscious in their investment decisions. From an efficiency point of view, market designers and policy makers should consider ways of alleviating this bias, such as making out-of-state alternatives more conspicuous. One important question that naturally follows our study is whether it is meaningful or beneficial to display geographic information in online crowdfunding in the first place, especially if it induces bias from investors.

Although debt-based crowdfunding accommodates many types of loans, it has particularly important implications for business-related funding. In 2012, debt-based crowdfunding accounted for 22% of all funds channeled to entrepreneurs via crowdfunding (Massolution 2013), second only to donation-based crowdfunding, where financial return is not a concern. Given that business loan requests are much harder to be fulfilled on peer-to-peer (P2P) lending sites than other forms of crowdfunding, this number is quite remarkable.[30] Our study can lead to further discussions and studies related to entrepreneurial financing theory and practice. For example, to what extent can crowdfunding mitigate the underinvestment in entrepreneurs?[31] Because of information asymmetry, entrepreneurs frequently rely on geographically close individuals, banks, or venture capitalists (Stuart and Sorenson 2003). Yet it is often for economic reasons that those entities invest locally, since geographical proximity improves ex ante information collection and interpretation and ex post monitoring. What we found in this study is that behavioral

[30] Several factors contribute to the low success rate in P2P financing. Unlike other types of crowdfunding, personal credit information is required, and the "economic" aspect of financing is much more salient. In addition, P2P loans are debts that need to be repaid on a monthly basis, hence imposing more stringent requirements on cash flow. However, "success rate" should not be the only metric to compare different types of financing. It is possible that some loans were not funded because investors correctly evaluated that investment opportunity. More importantly, this market allows some high-risk and high-return projects to be funded, since investors need only put in a small proportion of the funds and are able to diversify their risk.

[31] We thank an anonymous reviewer for this comment and other suggestions regarding implications for entrepreneurial financing.

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reasons *can* drive at least some of the capital to businesses, even on a for-profit, debt-based crowdfunding market. Shane (2008) shows that entrepreneurs often rely on personal debt to finance their businesses, and loans from this market are exactly personal debts. Therefore, online debt-based crowdfunding can fill a very important gap in financing entrepreneurs.

In summary, a better understanding of investors' decisions in this market, and the reasons behind these behaviors, has important implications for all stakeholders. The home bias that we identify in this paper is one step in that direction. With additional research into home bias and other behavioral patterns of borrowers and lenders in this market, we will be able to further improve market efficiency and leverage the Internet to truly mitigate geography-induced resource imbalances.

Acknowledgments
The authors thank the department editor, the associate editor, and the reviewers for their constructive comments. They also thank participants at the 2013 Academic Symposium on Crowdfunding in the University of California at Berkeley, 2012 INFORMS Annual Meeting, and 2011 International Industrial Organization Conference, as well as seminar attendees at Georgia Institute of Technology, Pennsylvania State University, the University of Arizona, the University of California at San Diego, and the University of Maryland for their comments and suggestions. M. Lin also gratefully acknowledges the financial support of the Ewing Marion Kauffman Foundation and the Economic Club of Washington.

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