THE DEMOCRATIZATION OF PERSONAL CONSUMER LOANS?

DETERMINANTS OF SUCCESS IN ONLINE PEER-TO-PEER LOAN AUCTIONS

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Abstract

Online peer-to-peer (P2P) loan auctions enable individual consumers to borrow from, and lend money to, one another directly. We study the borrower- and auction-related determinants of funding success in these auctions by conceptualizing *auction decision variables* (loan amount, starting interest rate, duration) as mediators between *borrower characteristics* such as their demographic attributes, financial strength, and effort prior to the auction, and the *likelihood of funding success*. Borrower characteristics are also treated as moderators of the effects of auction decision variables on funding success. The results of our empirical study, conducted using a database of 5,370 completed P2P loan auctions, provide support for the proposed conceptual framework, and reveal a strong democratization of lending practices in P2P loan auctions. Although demographic attributes such as race and gender affect likelihood of the auction's funding success, their effects are small when compared to those of borrowers' financial strength and effort when listing and publicizing the auction. These results are substantially different from the documented discriminatory practices of regulated financial institutions in the US, suggesting that individual lenders bid more rationally when their own investment money is at stake. The paper concludes with specific suggestions to borrowers to increase their chances of receiving funding in P2P loan auctions, and a discussion of future research opportunities.

1. Introduction

Long characterized to be one of the internet's great transforming mechanisms, disintermediation has recently come to the unsecured consumer loans industry. Over the last two years or so, peer-to-peer loan auction websites such as Prosper (www.prosper.com), and Zopa (www.zopa.com) have become increasingly popular among consumers. These sites host and facilitate peer-to-peer (P2P) loan auctions in which individual consumers borrow from, and lend money to one another by means of unsecured personal loans up to $25,000, without the mediation of a bank or credit card company. Estimates indicate that approximately $100 million in peer-to-peer loans will be issued in 2007 and that amount is expected to grow to as much as $1 billion by 2010 (Kim 2007).

Are P2P loan auctions democratizing personal consumer loans? With their emphases on open availability of information, the empowerment of individual consumers, and reliance on social interactions and collaboration for mutual benefit, P2P loan auctions do leverage many of the democratizing attributes of Web 2.0 (Tapascott and Williams 2007). These auctions merit research attention for at least two important reasons. First, P2P loans give individual lenders direct access to unsecured consumer debt for the first time, allowing them to potentially earn a higher interest rate than they would earn in a bank savings account. At the same time, they are seen as increasing welfare of borrowers when compared to the status quo, because borrowers are able to get a loan at a much lower interest rate than those of financial institutions (Bruce 2007; Steiner 2007). However, to our knowledge, no empirical research, has studied whether all borrowers are equally successful in funding their loan requests in P2P auctions, and if not, what determines funding success.

The second reason for studying funding success in these auctions is that the decision making framework governing the P2P loan auctioning process is unique. It combines the lender valuation and bidding mechanisms of online auctions, along with the social influence, intra-group communication, and reputation building processes of consumer communities in a single mechanism. At the same time, the transparency of available information raises the possibility that seemingly irrelevant borrower attributes such as race and gender could still significantly impact lenders' decisions, for example, by activating stereotypes. The criteria that lenders participating in P2P loan auctions use in making their bidding decisions remain to be known. Consequently, the question of whether P2P loan auctions are democratizing remains to be answered.

More generally, considerable prior online auction research has examined the impact of auction decision variables such as starting price or reservation price, and duration on auction outcomes (e.g., Ariely and Simonson 2003; Dholakia and Soltysinski 2001; Kamins et al. 2004; Ku et al. 2006; Lucking-Reiley et al. 2007). But less research has examined how seller characteristics influence choice of auction variables, and their impact on auction outcomes. In the current research, we propose an integrated conceptual framework (see Figure 1) to study these effects. The key dependent variable in our framework is funding success in P2P loan auctions, which is defined as whether or not a loan request gets fully funded by the time the auction ends. We also include both borrower- and auction-related determinants of the listing's funding success in the framework. Our subsequent empirical testing of the framework provides interesting insights into a number of important consumer-centric issues related to consumer finance and online auctions.

First, it allows us to directly study the effects of controversial yet crucial demographic attributes of borrowers such as gender, race, marital status, and presence of children in one's household on funding success of auction listings, after controlling for relevant financial criteria such as credit grade, homeownership, and debt-to-income ratio. We are also able to determine the degree to which a better credit grade, homeownership, and a lower debt-to-income ratio are able to increase funding success and reduce the interest rate borrowers pay on their P2P loans.

Second, in our conceptual framework (see Figure 1), we position the auction decision variables (loan amount requested, starting interest rate, duration) as potential mediators of the effects of borrower characteristics on likelihood of funding success. This allows us to better understand not only what drives funding success, but also how borrowers choose levels of the auction decision variables. This conceptualization contributes to the online auction literature by bringing in seller characteristics into a framework for studying auction variables and outcomes. Finally, we also position the borrower characteristics as moderators of the effect of the auction decision variables on its funding success. By doing so, we obtain additional insights regarding the effects of borrower characteristics on lenders' decisions.

Third, our findings provide practical guidance to borrowers in P2P loan auctions regarding effective ways of listing their loan requests. Through the findings of these analyses, we are able to begin answering the question of whether P2P loan auctions are democratizing by giving access to cheaper unsecured credit to all consumers.

The rest of the paper is organized as follows. In Section 2, we describe the research setting in detail. In Section 3, we develop a conceptual model and research hypotheses regarding the determinants of P2P loan auction funding success. Section 4 describes the dataset, and Section 5 presents the models used to test the hypotheses. The results are given in Section 6, and Section 7 concludes the paper with a discussion of whether P2P loan auctions have democratized unsecured consumer loans, along with specific suggestions to borrowers to increase their chances of receiving funding in these auctions, and a discussion of research limitations and future opportunities.

2. Research Setting

Our research employs a database of P2P loan auctions listed on the Prosper.com website. Prosper is the first, and currently the largest, P2P loan auction site in the US, with more than 480,000 registered members. Since its inception in March 2006, through December 2007, the site has originated over $100 million in personal loans. Prosper positions itself as an online financial marketplace, offering its customers a blend of eBay-like P2P loan auctions supplemented with dozens of high-traffic discussion forums. In these online forums, borrowers usually participate prior to, during, and after listing a loan request to give potential lenders more information about themselves, and to answer questions. Lenders participate in the forums to discuss their lending strategies, to weigh in on the quality of individual loan auctions, and to socialize with one another.

Prosper's P2P loan auctions are conducted in an information-rich environment. For lenders, the available data include individual lenders' loan portfolios, bid amounts, and performance, and payment history of each borrower. Borrowers on Prosper receive up-to-date information regarding final interest rates for successful auction listings at different credit grades and loan amounts, tips on creating an effective loan request, and access to advice from seasoned lenders. They can also voluntarily join one of hundreds of affinity groups based on commonalities such as geography, profession, and alma mater (e.g., the active duty military group, Harvard University alumni and students, etc.). Each affinity group is managed by a group leader who verifies the borrower's personal and financial credentials, assists in crafting the listing in an effective way, and generates interest among lenders for the borrower's listing. As compensation, group leaders receive up to 1% of the loan's value when the listing gets funded.

The process of borrowing money through a P2P loan auction works as follows. First, potential borrowers give Prosper permission to verify their identity and allow the firm to access their credit score from Experian, one of the three big US credit reporting agencies. They also provide various documents such as income tax returns, pay-stubs, and proof of homeownership (if applicable). Using this information, Prosper assigns each borrower a credit grade. The credit grade can vary from AA, which denotes the borrower to be extremely low risk, A, B, C, D, E, to HR, which signifies that the borrower is extremely high risk. The historical default rates for each credit grade are available to borrowers and lenders. Following the credit grade assignment, borrowers can list their loan requests as auctions on the Prosper site.

At or before this time, borrowers may join an affinity group and undergo further vetting by the group's leader. The specific requirements and processes of validation to join vary by group. To the borrower, the primary advantage of joining an affinity group is an increased credibility among lenders due to the additional vetting, and a boost from the group leader's endorsement and marketing of the loan auction.

When listing the loan auction, a borrower must choose how much money to ask for (up to a maximum of $25,000), specify the maximum interest s/he is willing to pay, and choose the auction's duration, which can range from three to ten days. All loans made through Prosper, as well as other P2P loan auctions, are unsecured, (i.e., they are not guaranteed by the borrower's personal assets) and have to be repaid to lenders over three years. For every successful loan, Prosper earns a transaction fee, ranging between one and two per cent depending on the borrower's credit grade. The firm also charges annual servicing fees, up to one percent, to lenders for processing monthly payments.

Once the loan auction is listed on the Prosper site, lenders decide whether to bid on the loan, and how much money to bid. They use the borrower's credit grade and other financial and personal information that s/he provides in making these decisions. On Prosper, most lenders' bidding strategies are conceptually related to the microfinance model (e.g., Robinson 2001) in the sense that they bid small amounts, usually $50, on individual loans. That way, borrowers are able to reduce their risk by spreading it over a portfolio of loans. When placing a bid in a loan auction, lenders have to specify the minimum interest they are willing to accept, in addition to the maximum amount they wish to lend. In a particular loan auction, when the aggregate amount bid by lenders exceeds the amount requested by the borrower, the interest rate drops from the borrower's maximum specified rate. Before the auction is funded, a bidder may place a bid with a higher interest rate than the rate the bidder before him or her stated. This feature makes this mechanism unique and different from other types of auctions, such as eBay, in which bids must be incrementally higher. As more lenders bid on the loan at lower rates, the interest rate keeps dropping throughout the auction's duration. The loan's final interest rate is analogous to the final price paid by the winning bidder(s) in eBay auctions.

At the end of the auction, if the loan listing has received enough bids to cover the requested amount, the winning lenders' bids are deducted from their respective Prosper accounts, consolidated, and deposited into the borrower's checking account. Over the next three years, the borrower returns the principal and interest by paying monthly installments to Prosper, usually through a direct deduction from his or her checking account. When Prosper receives the borrower's monthly payment, it divides the installment and deposits it proportionally into the each lender's account. If, for whatever reason, the borrower does not pay one or more scheduled installments in a timely fashion, Prosper attempts to collect late payments on lenders' behalf through various collection practices.

3. Conceptual framework and Research Hypotheses

All P2P loan auction sites, including Prosper, operate on the principle of "full financing," i.e., the loan listing only gets funded if it receives enough bids to cover the entire amount requested by the borrower. This is different from eBay auctions in which a single bid at or above the seller's reservation price (or starting price, if a reservation price is not specified) results in a successful auction. An example is helpful to illustrate full financing. Consider a loan auction listed by a borrower for $10,000 on the Prosper site. When the auction ends, if the total amount bid by lenders only equals $9,900, the auction is deemed to be unsuccessful; the amounts bid on the auction by lenders are returned to them. The borrower must re-list the loan or seek funding through other means. On the other hand, if the final bid amount on the auction is $10,000 or more, the borrower receives the $10,000 (not more) from the lenders that have bid the lowest interest rates. Consequently, we define success in P2P loan auctions by the auction's final outcome – whether it gets fully funded or not. In our analysis, the likelihood of receiving full funding is the dependent variable.

Prior online auction research has shown that final prices of listed items are determined by two main types of factors (e.g., Ariely and Simonson 2003; Kamins, Dreze and Folkes 2004; Ku, Galinsky, and Murnighan 2006). First, *auction decision variables,* controlled by the seller, such as its starting price and duration, play important roles in determining the item's final price. Second, attributes of the seller, for example, his or her reputation, types of items sold, etc., can also influence the auction's success (for recent reviews see Milgrom 2004 and Ockenfels, Reiley, and Sadrien 2006). In P2P loan auctions, we consider two analogous factors that influence whether the loan listing gets funded: (1) the borrower's attributes, such as credit grade, debt-to-income ratio, gender, race, and marital status, and (2) the decision variables of the loan auction such as amount requested, interest rate offered, and duration.

3.1 Direct effects of borrower characteristics on auction funding success

Three types of borrower characteristics are considered in this research: demographic characteristics, financial strength, and effort indicators. It is worth noting here that Prosper requires borrowers to provide information on their income, existing debt, and homeownership (which is verified by Prosper employees); however, borrowers choose whether or not to provide their demographics in the listing. Some borrowers provide extensive personal details revealing their demographic profile and personal history. Others are very brief in their loan requests, keeping their demographic attributes hidden. We expect that exploring how borrower characteristics affect the loan funding outcome is likely to shed light on which of these divulgence strategies is more effective for borrowers in successfully funding their loan request. Next, we consider how these characteristics may influence P2P loan funding success.

Demographic Characteristics. Borrower attributes are analogous to sellers' characteristics in eBay auctions. In P2P loan auctions, the enduring demographic aspects of the borrower, specifically gender, race, marital status, and whether s/he has children are expected to be important. These variables are central to how consumers make financial decisions and to outcomes associated with household income, expenses, ability to save, and the type and amounts of credit needed.

In the US, anti-discriminatory laws such as the Equal Credit Opportunity Act (Section 701) prohibit institutional lenders from treating equally creditworthy borrowers differently based on gender, race, or other demographic characteristics, such as age, marital status, and religion. Despite these laws, however, there is a long history of institutional discrimination against certain borrower groups, in particular, women and minorities (e.g., Ladd 1998; Munnell et al. 1996). For example, many studies from the 1970s showed that mortgage lenders often discounted a wife's income by 50 percent or more when evaluating mortgage applications of dual-income families.

In a comprehensive survey, Ladd (1982) found that banks were more likely to deny mortgage requests from unmarried applicants (both male and females), and from sole applicants who were married women compared to married men. More recently, Carr and Megbolugbe (1993) found that lenders' subjective assessments of a potential borrower's creditworthiness are highly correlated with the borrower's race, even after controlling for the borrower's credit history. Specifically, Caucasians tended to receive more favorable assessments when compared to African American or Hispanic borrowers. Blanchflower, Levine, and Zimmerman (2003) showed that black-owned small businesses were about twice as likely to be denied credit even after controlling for differences in creditworthiness and other financial-performance factors.

Social psychologists have shown that such effects occur due to stereotyping, whereby a person is classified as a member of the target group, and inferences are made about that person based on the group's presumed attributes without the decision maker's conscious awareness (e.g., Wheeler and Petty 2001). Unlike the heavily regulated arena of institutional lending to consumers, the domain of P2P loan auctions is completely unregulated, with no explicit rules governing how lenders should decide who to lend their money to. Under such circumstances, it seems reasonable to expect that lenders should be prone to stereotyping borrowers, and use gender, race, and other demographic information (when available) in their lending decisions. Specifically, we expect that loans sought by women (when compared to men), and minorities (when compared to Caucasians) should be less likely to get funded.

Financial Strength. We also considered three borrower characteristics that are more directly related to his or her financial strength --- credit grade, debt to income ratio, and whether the person owns a house. While the first two of these variables are direct indicators of a borrower's creditworthiness, the third one, homeownership, is indicative of stability and a prior ability to access credit to obtain a mortgage. A large body of empirical studies examining consumer lending have shown that borrowers' financial strength play a significant role in their ability to obtain secured and unsecured loans from conventional financial institutions (e.g., Avery, Calem and Canner 2004.)

The borrower's credit grade summarizes factors related to the borrower's previous experience with credit, leases, non-credit-related bills, money-related public records, and credit inquiries. Ample prior research has shown that individuals' credit scores are strong predictors of their repayment likelihood for both secured and unsecured consumer loans (e.g., Avery et al. 2004; Capon 1982). A majority of lenders on Prosper lend with a conservative mindset, viewing their loan portfolio as a relatively more attractive alternative to a savings account (Kadet 2007), therefore we expect lenders to be inclined to bid in listings of borrowers with higher credit grades (AA is the best credit grade, and then A, B, etc.) Similarly, a borrower's debt-to-income ratio is an indicator of his/her current financial ability to pay back the loan. Lenders are expected to avoid bidding on listings belonging to borrowers with high debt-to-income ratio. Finally, homeownership which represents not only access to a previous loan but also ownership of an asset should increase the likelihood of funding success of the auction.

Effort Indicators. The third type of borrower attributes is the effort indicators that measure the extent to which the borrower takes the trouble to communicate his or her personal information and obtain validation from the Prosper community before and when listing. These include whether the borrower joins an affinity group, and the degree of personal descriptive information provided by the borrower when making the loan request.

When listing the loan request, borrowers decide how much detailed personal information they will provide. On the one extreme, borrowers can simply stipulate the amount requested, initial interest rate, and auction's duration, without providing any additional information. On the other extreme, borrowers can provide detailed specific information such as their personal history, reasons for the loan request, current income, detailed current budget, and an action plan for paying off the loan. They may even upload pictures of themselves, their family members, and other relevant information (such as a product they designed or a poster of a movie they directed).

Additionally, borrowers may explain some questionable attributes of their listing such as a low credit grade. Many borrowers choose not to provide detailed information; instead they provide general qualitative information such as "I have a great income," or "I should have no difficulty paying off the loan given my circumstances", without revealing specific income or budget numbers. In the current analysis, we make the distinction between no personal information, general personal information, and specific personal information, viewing these as increasing levels of personal information.

To be successful, borrowers have to create a positive image and reputation for themselves and to engender trust within the lender community. Prior research has shown that a good reputation impacts seller performance significantly in eBay auctions (e.g., Park and Bradlow 2005). Creating a reputation is relatively difficult in P2P loan auctions because virtually all loans on Prosper are one-shot games (borrowers usually apply for one loan, and once they receive it they do not apply for another. Therefore, they cannot accumulate reputation through making timely payments). Nevertheless, as discussed earlier, there are two means at the borrower's disposal to engender trust: providing detailed personal information, and joining an affinity group.

We expect that in the risky domain of giving unsecured personal loans to strangers, higher levels of personal information are likely to be useful, by reducing the information asymmetry between borrowers and lenders, mitigating concerns of fraud, humanizing borrowers, generating empathy, and thereby increasing the likelihood of auction funding success.

While the affinity group cannot enforce "good behavior" on its members, i.e., force them to repay the loan or pay on their behalf, membership does add another level of information verification that is voluntarily chosen by the borrower. There are also other advantages of membership. First, in many cases, the group leader bids on every loan s/he approves for membership, jumpstarting the bidding process for the borrower's loan. Second, affinity group membership is a positive signal to many lenders who may believe that the borrower is more likely to repay the loan because of the group's peer pressure and the group leader's oversight and relationship with the borrower. O'Mahony (2003) showed that developers of open source and free software who decide to become part of a community that manages software projects, freely accept the norm of "good behavior" even when the legal protection of intellectual property rights is neglected. In Prosper, many group leaders will say in their endorsement of the borrower that from the information they have they believe the borrower will be able to pay back the loan on schedule. Affinity group membership is therefore expected to increase the likelihood of lenders bidding on the loan.

3.2 Direct effects of auction decision variables on auction funding success

In P2P loan auctions, when listing their request, borrowers must specify three decision variables: the loan amount, the initial (maximum) interest rate they are willing to pay, and the auction's duration. The effects of each of these variables on loan funding success are considered.

Loan Amount. Most P2P auction lenders tend to bid small amounts on individual loans to disperse their risk. In fact, in an educational tutorial for new lenders, Prosper explicitly recommends that lenders diversify: "If you place many small bids among many borrowers, the risk that you will lose all of your money is much lower than if you place one large bid with one borrower.[1]" Not surprisingly, in our dataset, the modal amount bid by lenders in individual auctions is $50 (51.8% of all bids) which is also the minimum amount that a lender can bid in a single auction. This means that even for a $1,000 loan request, up to twenty lenders have to place a bid for the auction to be successful. As a result, the larger the amount requested by the borrower, the higher the number of lenders that will be needed to fund the auction completely, which is likely to reduce the probability of the auction's success.

Initial Interest Rate. Although standard auction models (e.g., Milgrom and Weber 1982) suggest that sellers should not set the starting price below the opportunity cost of the item they are offering, recent empirical research has shown that in eBay auctions, lower starting prices actually lead to more bids and higher final prices (Ku et al. 2006; Kamins, Dreze, and Folkes 2004.) This effect occurs because the lower the auction's starting price, the lower the barrier to entry for potential bidders, and the higher the number of bidders participating in the auction (Bajari and Hortacsu 2003.) Furthermore, when an auction starts with a higher initial price, bidders become more sensitive to falling prey to the winner's curse, i.e., a tendency to over-pay,

[1] http://www.prosper.com/help/topics/lender-become_lender.aspx

and hesitate to participate in the auction (Vincent 1995.) Psychologists have also shown that lower starting prices entice bidders to invest time and energy (creating sunk costs), and escalate their commitment to winning the auction (Ku et al. 2006.) Low starting prices create a bidding momentum among early auction participants (Malhotra and Murnighan 2001) which pushes final prices higher. Finally, interest generated by lower starting prices can lead latter entrants into the auction to draw positive inferences about the listing, leading the initial interest to beget more subsequent interest (Dholakia and Soltysinski 2001.)

In P2P loan auctions, a lower starting price corresponds to a higher initial interest rate offered by the borrower. All the reasons discussed above --- lower barriers to entry, creation of a bidding momentum, and early interest generating more late interest --- are applicable when the borrower offers a high initial interest rate. Therefore, we expect a higher initial interest rate offered by the borrower will lead to a greater likelihood of full funding of the listing.

Duration of Auction. The third decision variable that can influence a P2P loan auction's success is its duration. Prior research studies examining the role of duration on final prices in eBay auctions have found conflicting results. Lucking-Reiley et al. (2007) found duration to have a positive effect on final prices and concluded that this effect occurred because longer auctions gave bidders greater opportunity to view the auction, observe others' bidding behaviors, and then bid, which in turn drove prices higher. In contrast, Ariely and Simonson (2002) found duration to have a negative effect on final prices of college football tickets in eBay auctions. They explained their result by suggesting that shorter auctions may stimulate competition among bidders which drives prices up.

In comparison to eBay auctions, interpersonal communication between borrowers and lenders, and among lenders themselves, plays a greater role in P2P loan auctions. Once the loan is listed on the Prosper site, many borrowers post the link to their listing in various discussion forums (such as the "Review My Listing" forum[2]) on the site to obtain feedback, and to advertise

[2] http://forums.prosper.com

their auction in the lender community. Many lenders routinely visit and participate in the discussion forums to discover and vet promising investment opportunities. They inquire about borrowers' personal histories, financial details, loans' purposes, etc. and discuss these credentials with other lenders. These discussions often play an important role in lenders' decisions on whether to bid on a loan. As these discussions usually unfold over several days, we expect a longer duration to influence success of funding a listing positively.

3.3 Mediation and moderation in the conceptual framework

In our discussion so far we concentrated on the direct effect of each variable on auction funding success. However, these variables may be interdependent and their effect on the final outcome may be inconsistent and vary due to the inclusion or exclusion of other variables. A way to clarify these possible inconsistencies is to allow the simple model of direct effects more flexibility through the use of mediation and moderation variables.

[Insert Figure 1 about here]

The conceptual model in Figure 1 distinguishes between predictors of loan funding success that are mediators (the auction decision variables) and those that are antecedent exogenous predictors (the borrower characteristics). The important contributions of this framework and research to the literature on online auctions are: (i) the conceptualization of auction decision variables as partial mediators between the antecedent borrower characteristics and loan funding success (the double line arrows in Figure 1), and (ii) the conceptualization of borrower characteristics as moderators of the effect auction decision variables have on auction funding success (the dotted arrow in Figure 1).

To conclude that our conceptual model describes the mechanism of P2P loan auctions best, several sets of relationships must be present. First, there must be a direct effect of borrower characteristics on loan funding success (which we discussed earlier). Second, there must be an indirect effect of borrower characteristics on loan funding success via the auction decision variables (mediation effect.) And third, the direct effect of auction decision variables must vary for different levels of borrower characteristics (moderation effect.) The literature and theory that supports each of the requisite relations are considered next.

3.4 The indirect effects of borrower characteristics on auction funding success through the auction decision variables

In addition to the direct effect of borrower characteristics on auction funding success, this set of variables also has an indirect effect on auction success because they affect the three auction decision variables, requested amount, interest rate, and auction duration.

Starting Interest Rate. As discussed earlier, prior online auction research suggests that a higher starting interest rate may generate greater interest in the auction, creating bidding momentum among lenders (e.g., Kamins et al. 2004.) From the borrower's perspective, however, a higher interest rate may lead to a higher final rate, and having to pay greater interest payments to lenders over the course of the next three years. Thus, for borrowers, there is a tradeoff between generating interest for the auction and paying more interest to lenders. A vast majority of lenders approach participation in P2P loans as an investment decision. They apply the principle of greater risk being associated with greater reward in their decisions regarding which loans to bid on and which ones to avoid (e.g., Fama and MacBeth 1973.) This lender norm is well known among borrowers, and is articulated constantly in the discussion forums and lenders' conversations with borrowers. It is also provided in Prosper's recommended guidelines for designing auction listings. Consequently, we expect borrower characteristics that are either *known to be* (through analysis of past completed auctions or from other sources such as default rates from the credit rating agency) or *perceived as* indicative of greater risk to lead borrowers to offer higher starting interest rates in their loan listings. Empirical research from eBay auctions supports this idea as well, showing that a stronger track record allows eBay sellers to charge a premium when compared to novice unproven sellers (Park and Bradlow 2005.)

Of all the borrower characteristics, perhaps the most salient indicator of a borrower's default risk is his or her credit grade (Altman and Saunders 1998.) Consequently, we expect that the better the borrower's credit grade, the lower the starting interest rate. Likewise, we also expect the other financial strength measures, homeownership and debt-to-income ratio, to have similar effects on starting interest rate. Finally, we expect that borrowers providing a detailed explanation of why they need the loan and how they will pay it back, are those who are really interested in obtaining a loan, and should therefore be willing to pay a higher starting interest rate. Borrowers who are group members will tend to offer a higher interest rate, as usually advised by their group leaders. Thus, borrowers with different characteristics affect the likelihood their loan will be funded indirectly by stating different initial interest rates.

Requested Loan Amount. Consumers seek unsecured loans through Prosper for many different reasons such as to consolidate existing debt from various sources, start a new business venture, fund college tuition or living expenses, pay for a wedding, replace or repair one's vehicle, and so on. Prior research on consumer finances has shown that consumers' credit needs are driven to a significant degree by the stage of their life cycle, and their existing credit availability and use (e.g., Modigliani 1986, Stone and Vasquez Maury 2006.) This research also shows that the consumer's current income is positively associated with his or her level of credit use and ability to pay back the loan (e.g., Scurlock 2007.)

Furthermore, as noted earlier, information about prior successful loans is freely available on Prosper, so that potential borrowers are usually aware of norms for funding through discussions on the various forums, as well as the statistics and ratings on volunteer-run sites. Through these venues, lenders explicitly encourage potential borrowers who have lower wherewithal to apply for smaller loans. Consequently, we expect the borrower characteristics that are indicative of higher income (and ability to pay back a larger amount) to affect the loan amount requested by borrowers positively. Specifically, higher credit grades, owning one's home and having a lower debt-to-income ratio to all increase the borrower's ability to request a larger loan and eventually fund it. In contrast, being single, or having children are expected to be indicative of a lower ability to pay back and decrease the borrower's ability to have a large loan funded. Additionally, group membership should negatively affect the requested amount (as usually advised by the group leader), and similarly the provision of information (explanation) by the borrower. To summarize, borrowers with different characteristics affect the likelihood their loan will be funded indirectly by requesting different amounts.

Auction Duration. Borrowers must choose the duration for which their auction will run when listing the loan. Prosper provides a default duration of seven days. We expect that borrower characteristics, and specifically the effort measures (whether the borrower joins an affinity group, and the degree of detail he or she provides in the listing), will impact the chosen duration. Affinity group leaders are well aware of the importance of a longer duration in influencing auction funding success, and are likely to advise their group members to choose a higher duration for their auction. Consequently, membership in an affinity group is expected to affect the auction's duration positively. Likewise, borrowers who take the trouble to provide a detailed explanation are more likely to find out and learn about the beneficial effect of longer auctions, and choose longer listings. Therefore, borrowers with different characteristics affect the likelihood their loan will be funded indirectly by choosing different auction durations.

3.5 The borrower characteristics as moderators of the effect of auction decision variables on funding success

Prosper allows borrowers to search for listings with specific attributes, for example, listings that started with an 18% interest rate, or listings for amounts no larger than $10,000. The likelihood of success of all listings that started with the same interest rate, requested the same amount, and lasted the same duration is not the same. One potential reason this likelihood varies is because these listings were posted by different borrowers with different characteristics. For example, for a given interest rate, requested amount, and auction duration, borrowers having better credit grades have a higher likelihood of receiving full funding when compared with those having lower credit grades. This is because, as discussed earlier, borrowers' credit grade is an indicator of financial strength and ability to repay the loan, which is an important input into the decisions of Prosper lenders. Similarly, other financial indicators, demographic characteristics, and effort measures may sway lenders to bid on one auction and not the other even when the auction decision variables are equal.

3.6 Summary of the Research Hypotheses

As we conceptualize in Figure 1 and have developed in the previous discussion of important relationships, the model indicates that borrower characteristics have direct, indirect, and moderating effects on auction funding success via auction decision variables. The following three hypotheses summarize this discussion:

H1: Borrower characteristics have a direct effect on loan funding outcome.

H2: Borrower characteristics have an indirect effect on loan funding outcome via loan auction decision variables (partial mediation hypothesis.)

H3: Borrower characteristics moderate the effect of loan auction decision variables on loan funding outcome (moderation hypothesis.)

4. Data

Our dataset consists of all the loan auctions listed by borrowers on the Prosper site during the month of June 2006. A total of 5,370 auctions were listed during that month. The data were collected in two stages. In the first stage, a computer program collected borrowers' financial strength measures and auction decision variables for each individual auction from the site.[3] In the second stage, each auction was revisited by two research assistants. The assistants recorded the borrower's gender, race, marital status, children, and level of personal information provided (where available) manually, auction-by-auction. No discrepancies were found between the coding of the two assistants, and these data elements were deemed to be accurate.

4.1 Variables

For each auction we have information on a borrower's credit grade, his or her debt-to-income ratio (calculated by Prosper), whether or not s/he is a homeowner, whether or not s/he belongs to an affinity group, the initial (maximum) interest rate offered by the borrower, the final interest rate the borrower will pay (in successful auctions this final interest rate can be much

[3] This program is available from the authors upon request.

lower than the initial rate), the amount of money the borrower requested, the total number of bids, and the starting and ending times of the auction. From the coded information, we also have the borrower's gender (male, female, gender not given), race (Caucasian, African American, Hispanic, race not given), marital status (single, married, divorced, widow(er), marital status not given), whether s/he has children, whether the borrower provided one or more pictures, and whether a general or detailed explanation regarding how the loan would be repaid was given.

4.2 Descriptive Statistics

Of the 5,370 listed auctions, 564 (10.5%) auctions received enough bids to cover the entire requested amount and were fully funded. The summary statistics for funded, unfunded, and all auctions are provided in Table 1. Not surprisingly, on average funded auctions have higher starting interest rates (19.95% vs. 15.74%, $p < .001$), and lower requested amounts ($4,114 vs. $5,060, $p < .001$) when compared to the unfunded auctions. Auction duration is slightly higher for the funded auctions than unfunded ones (7.6 vs. 7.45 days, $p <.001$). Finally, borrowers with funded auctions have a lower debt-to-income ratio (16.5 vs. 23.8, $p < .001$).

[Insert Table 1 (a) about here]

The auction funding success rates for discrete variables are shown in Part (b) of Table 1. Noteworthy is the high success rate for loans with detailed explanations (90.7% success) and even general explanations (52.0%) of the need for the loan, in contrast to the almost complete failure of loans with no explanation. Success rates are higher for borrowers with good credit (e.g., 38.4% of auctions for AA borrowers were funded); in contrast, only 4% of auctions for borrowers with high risk credit were funded. Also worth noting, the 40.7% success rate for Hispanic borrowers is based on a total of only 27 auctions.

Of the 5,370 auctions, we set aside 25% (1,339 auctions) to validate the models, leaving N=4,031 auctions for model estimation.

[Insert Table 1 (b) about here]

5. Models

To test hypotheses regarding the effects of direct, indirect (mediating), and moderating relationships among borrower characteristics, auction decision variables, and auction funding success, we formulate a number of models, as discussed below.

First, to establish the existence of relationships between 21 variables coded to represent borrower characteristics and the three auction decision variables (starting interest rate, requested loan amount, and duration of auction), we use a multivariate regression model,

$$X = Z\,\Gamma + \eta \tag{1}$$

where X is the N x 3 matrix of auction decision variables, Z is the N x 22 matrix of borrower characteristics (including an intercept), Γ is a 22 x 3 matrix of regression coefficients, and η is a matrix of normally distributed error terms. The covariance matrix of the stacked η is assumed to be diagonal, containing only the variances of the error terms for the three auction decision variables. Significant relationships in Γ will be a necessary condition for mediation effects to occur. We perform a likelihood ratio test to establish that the 21 borrower characteristic variables jointly affect the three auction decision variables.

Next, we establish the existence of relationships between the three auction decision variables and auction funding success using a logit model in which the probability of funding success for auction *i* is given by:

$$P_i = \frac{\exp(X_i \beta)}{1 + \exp(X_i \beta)}. \tag{2}$$

Significant relationships in β will also be a necessary condition for mediation effects to occur. Based on hypotheses developed earlier, we expect to find significant relationships in regression (1) and in logit model (2), both sets of relationships being necessary for the demonstration of mediating effects.

Similarly, direct effects between borrower characteristics and auction funding success can be established using a logit model in which the probability of success is:

$$P_i = \frac{\exp(Z_i \phi)}{1 + \exp(Z_i \phi)}, \tag{3}$$

where Z contains borrower characteristics. Based on hypotheses developed earlier, we expect to find significant relationships reflected in ϕ. In addition, we estimate a logit model in which both auction decision variables X and borrower characteristics Z affect auction funding success. If Z affects X (eq. 1) and X affects auction funding success (eq. 2) but Z does not affect auction funding success directly, then full mediation would be indicated; the hypothesized and more likely outcome is that Z will also affect auction funding success directly, suggesting that any mediation is only partial.

To introduce moderator effects in eq. (2), we use a random coefficients specification in which the bidders' responses to auction decision variables for auction *i* (β_i) are functions of borrower characteristics:

$$\beta_i = \Delta\, z_i + v_i\,, \tag{4}$$

where β_i is an 4x1 vector of response parameters for auction *i* (for the three auction decision variables plus an intercept), Δ is a 4x22 matrix of coefficients linking borrower characteristics z_i to bidders' responses to auction decision variables, and v_i is a normally distributed error term with covariance matrix V_β. The error term allows heterogeneity in bidders' responses to auction decision variables to be a function of both observed borrower characteristics (z_i) and unobserved effects (v_i).

Note that since the intercept term is included in β_i in (4) and is a function of z_i, then z_i affects auction funding success directly (making the intercept a function of z_i is exactly the same as incorporating z_i directly into the utility function). z_i also affects auction funding success indirectly through the auction decision variables X (mediation) and through the bidder responses β_i linking the Xs to auction funding success (moderation). Thus, in a fully specified model, borrower characteristics z_i can affect auction funding success in three different ways, as we hypothesized earlier. If the intercept is not a function of z_i, then z_i potentially affects funding success in only two ways: indirectly through X (mediation) and through the bidder responses β_i (moderation). We estimate two versions of the random coefficients specification in eq. 4 – one in which z_i affects the intercept in β_i and therefore has a direct effect on auction outcomes, and one in which z_i does not affect the intercept and has no direct effect on auction outcomes. Based on the hypotheses developed earlier, we expect the model that allows z_i to affect auction outcomes in three ways (directly, indirectly through mediation, and indirectly through moderation) to fit the data best.

As an additional benchmark, we also estimate a pure random coefficients specification in which the β_is (including the intercept) vary randomly across auctions, capturing the impact of only unobserved factors causing heterogeneity in bidders' responses to auction decision variables. We estimate pure random coefficients specifications with and without direct effects of z_i on auction funding success. Comparison of the pure random effects specifications with the specifications in eq. (4) provides insight on the moderating impact of the borrower characteristics on response parameters.

We estimate all logit models using hierarchical Bayesian techniques since the number of parameters estimated for the random coefficients specification (eq. 4) would be prohibitive for classical inference. We base the model specification on that of Rossi, McCulloch, and Allenby (1996). For the fully-specified random coefficients model, the Gibbs sampler cycles through three sets of conditional posteriors: (i) $V_\beta \mid \{\beta_i\}, \Delta$; (ii) $\beta_i \mid \Delta, V_\beta$; and (iii) $\Delta \mid \{\beta_i\}, V_\beta$. We use a Metropolis-Hastings algorithm to draw the values of $\beta_i \mid \Delta, V_\beta$. Like Rossi et al. (1996), we assume an inverse Wishart prior for V_β and a normal prior for $\delta = vec(\Delta)$ (see their study for details on the prior specifications, which we follow closely.) For all models, 50,000 iterations were used for burn-in, with an additional 10,000 iterations used for calculating the posterior means and percentiles.

6. Results

We begin by testing our three hypotheses (see Table 2). For the estimation sample, we provide results for the log marginal density (LMD), which is comparable to BIC in classical inference (Andrews, Ainslie, and Currim 2002), and the hit probability, which is the average predicted probability of the actual outcome. Both statistics are computed using the last 10,000 iterations of the sampler. For the validation sample, we calculate the log likelihood and the hit probability.[4]

Comparing the logit Y=f(X) model (model 2) to the null model (model 1), we see that the auction decision variables do affect auction funding success, which is a necessary condition for mediation to occur. Likewise, we observe in model 3 that borrower characteristics affect auction funding success directly, even when auction decision variables are also included in the model specification (model 4). Thus, there is evidence that borrower characteristics have direct effects on auction outcomes as well as indirect (partially-mediated) effects through the auction decision variables.

Model 5 introduces random coefficients into model 2, allowing unobserved heterogeneity in bidders' responses to auction decision variables. The model fits and forecasts far better than model 2. Model 6 demonstrates that borrower characteristics still explain significant variation, even when unobserved heterogeneity in bidders' responses to auction decision variables is captured through the random coefficients specification.

Moderation is introduced in model 7. Though allowing moderation clearly improves the model relative to the basic logit model with only auction decision variables as predictors (model 2), the model does not fit the data as well as other random coefficients specifications. One factor that negatively affected the performance of this model is that the results of the model lacked face validity when the intercept term was allowed to vary randomly across auctions (the intercept is not a function of borrower characteristics in this model). Thus, the intercept was forced to be constant across auctions in order to obtain stable and believable results.

Finally, in model 8, we accommodate direct effects for borrower characteristics, indirect effects through the auction decision variables (mediation effects), and indirect effects through bidders' responses β to auction decision variables (moderation effects.) This model provides the

[4] To calculate the validation sample fit statistics for the models with random coefficients, we run the sampler again, holding the hyperparameters Δ and V_β constant at the values determined from the estimation sample while taking draws of β_i for the new validation sample of auctions. The fit measures are calculated as the averages over the last 10,000 iterations.

best fit to the estimation sample and the best validation results. However, the improvement over model 6, which does not accommodate moderator effects through βs other than the intercept, is relatively small. Thus, the moderator effects appear to be fairly weak. Therefore, we would not expect to find many significant relationships in Δ for βs other than the intercept (see eq. 4). In sum, our analysis of the above eight models strongly supports the first two hypotheses – regarding direct effect and mediation. We also provide support for the third hypotheses (moderation) although this effect is not so strong.

[Insert Table 2 about here]

We now turn to investigate results from the chosen model, model 8. We begin by examining in Table 3 the regression relationships between auction decision variables and borrower characteristics described in eq. 1 (a necessary condition for mediation and the basis for further testing the results of model 8.) For the starting interest rate, we see that as expected, group affiliation and the provision of general or detailed explanations are associated with a higher starting rate, while better credit grades are associated with lower interest rates. We expected that the financial strength measures, homeownership and debt-to-income ratio, will be associated with lower interest rates, however our analysis shows that these variables do not affect the starting interest rate. Interestingly, African American borrowers are more likely to offer a lower starting rate, which may explain why their listings have lower success rates. Overall, about 10% of the variation in starting interest rate is explained by the borrower characteristics.

With regard to the loan amount requested, as we expected the borrower characteristics having a positive relationship include homeownership and better credit grades. We further confirm our prediction that indicators of a lower ability to pay, such as the presence of children, will reduce the requested amount. Group affiliation and the provision of information (general or detailed) reduce the requested loan amount, as we posited. Interestingly, males and those who did not provide information about their gender request higher amounts when compared with females. The total amount of variance explained is about 11%.

The percentage if variation explained in the duration of auction variable is lower than that of the other two auction decision variables at just 2%. As expected, borrowers affiliated with an affinity group and those who provide detailed information tend to choose longer auction durations. Homeownership is negatively associated with duration, which may be explained by the confidence of these borrowers to fund their loan (after all they have already received a loan for their house.)

Considering the effects of all 21 borrower characteristics variables on the three auction decision variables jointly, we calculate a likelihood ratio test of this model versus the null model, which contains only the intercepts for the three dependent variables. The likelihood ratio of 982 with 63 (=21 x 3) degrees of freedom is extremely significant (<.0001), even though the amount of variance explained is not overwhelming. Thus, there is the potential for the auction decision variables to mediate the relationship between borrower characteristics and auction funding outcome, more so through starting interest rate and the loan amount requested than the duration of the auction.

[Insert Table 3 about here]

After establishing the basic condition for mediation we now turn to investigate the nature of the relationships indicated by the best-fitting model (see Table 4). The β (Intercept) column indicates the direct effects of borrower characteristics on auction funding success. As expected, the following borrower characteristics have a positive effect on auction funding success: group affiliation, all credit ratings other than high risk, and the provision of a general or detailed explanation. Homeownership, which was expected to be positively associated with success likelihood, has no significant effect. The borrower characteristics having a negative effect on auction funding success are, as anticipated, debt-to-income ratio and being a minority (African American). The provision of a picture, which affects negatively on auction funding success, is not independent of credit rating—borrowers with high-risk credit are more likely to provide a picture, hence the effect is non-surprising. Finally, while we hypothesized that men have a better likelihood to get their listings funded, results, while marginal, show the reverse. For comparison purposes, the effects of the logit model with borrower characteristics only are shown in the rightmost column; the results are similar to those of the more fully-specified model, though not as many borrower characteristics have direct effects on auction funding success.

Next we examine the direct effect of the loan auction decision variables on auction funding success (see bottom row of Table 4.) As expected, the average effect of starting interest rate on auction funding success is positive, and the average effect of loan amount requested is negative. We predicted that auction duration will have a positive effect on auction funding success, however this effect is weak and inconsequential (we further investigate it in Table 5).

The moderation effect of borrower characteristics on the loan auction decision variables are presented in columns 3-5 in Table 4. Because the addition of moderation in model 8 over model 6 only slightly improved the fit, we do not expect many borrower characteristics to significantly affect the βs other than the intercept. As we anticipated, credit grades other than high risk and the provision of general or detailed explanations enhance the positive effect of the starting interest rate on auction funding success, while group membership attenuates the negative affect of loan amount requested on auction funding success. Additionally we find that Hispanic race, divorce, and children intensify the negative effect of loan amount requested.

[Insert Table 4 about here]

From the above discussion and results it is clear that borrower characteristics have more explanatory power than loan auction decision variables when predicting auction funding success. We now compare the direct and indirect effects of borrower characteristics on auction funding success across several models. To that end, we calculate the marginal effect of each borrower characteristic (note that the coefficients cannot be directly compared because of scaling issues.)

The marginal effect of some continuous variable is the change in probability of auction funding success resulting from a one-unit change in the variable. For continuous variable j, the marginal effect is computed as the partial derivative of the likelihood of success with respect to the variable of interest, evaluated by computing the derivative for all auctions and averaging:

$$Mar\_ef_j = \sum_{i=1}^{N} P_i \left(1 - P_i\right) \beta_{ij} / N \qquad (5)$$

For a dummy variable, the marginal effect is the change in the probability of auction funding success resulting from changing the dummy variable from zero to one. For binary variable *j*, the marginal effect is computed as:

$$Mar\_ef_j = \sum_{i=1}^{N} \left[P(i \mid X_{ij} = 1) - P(i \mid X_{ij} = 0)\right] / N \qquad (6)$$

where $P\left(i \mid X_{ij} = 1\right)$ is the probability that auction *i* is successful given that dummy variable X_j takes a value of 1.

Table 5 shows the direct and indirect marginal effects for several model specifications. The first model captures only direct effects of borrower characteristics on auction funding success. The second model captures direct and indirect effects via mediation, but bidders' responses to auction decision variables do not vary across auctions, and hence there are no moderator effects. The third model captures direct and indirect effects, though both mediation and moderation. To calculate indirect effects through the auction decision variables, it is also necessary to calculate the marginal effects for the effects of borrower characteristics on auction decision variables from the regressions shown in Table 3. For example, to find the indirect effect of group affiliation on auction funding success via the starting interest rate (0.25%), we would need to multiply the marginal effect of group affiliation on starting interest rate by the marginal effect of starting interest rate on auction funding success. The indirect effect is positive because the effect of group affiliation on starting interest rate is positive (Table 3), and the effect of starting interest rate on auction funding success is also positive (Table 4), so the product of their effects is positive also.

Continuing with the example of group affiliation, the marginal effect of group affiliation on auction funding success for the logit Y=f(Z) model (1.66%) implies that being affiliated with a group improves the probability of auction funding success by 1.66%. For the logit Y=f(X,Z) model, the direct marginal effect of group affiliation is 1.14%, and the indirect effect is 0.25% +

0.19% + 0.03% = 0.47%, so the total marginal effect is 1.61%. For the RCL model, the total marginal effect of group affiliation is 1.00% + 0.25% + 0.21% + 0.06% = 1.52%.

According to the RCL model, the indirect effects of borrower characteristics are generally smaller than the direct effects. However, for several borrower characteristics, the indirect effects are fairly large relative to the direct effects. For example, for homeownership, the indirect effect through amount requested (which is negative because homeownership *increases* the amount of loan requested (Table 3) and amount requested *decreases* probability of auction funding success) is larger than the direct effect. For group affiliation, total indirect effects are about half as large as direct effects. The total indirect effect of male gender is about as large as the direct effect. The indirect marginal effects of credit grades AA, A, and B via the starting interest rate (which are negative because borrowers with better credit can offer a lower starting interest rate, and lower starting interest rates are associated with lower probability of auction funding success) exceed 2%, though these are not large in comparison to the direct effects.

In general, the indirect effects are quite consistent whether or not moderation effects are included in the model, which is consistent with the finding of fairly weak moderation effects discussed earlier. But there is much variability across models in terms of the estimates of direct effects. For example, the marginal effect of AA credit is 13.12% for logit Y=f(Z) (with no indirect effects), 45.59% for logit Y=f(X,Z), and 19.57% for RCL. Likewise, for credit A, the effects are 18%, 42%, and 54%, respectively, and for credit B, the effects are 11%, 25%, and 39%. Thus, it appears that accounting for indirect mediation and moderation effects can have significant impact on the estimates of direct effects.

[Insert Table 5 about here]

7. General Discussion

The goal of the current research was to examine the determinants of funding success in P2P loan auctions. In this unregulated, information rich, and seemingly egalitarian environment, where individuals borrow from, and lend money to, one another directly based on little more than good faith, we wished to examine which factors affect lenders' bidding decisions. The title of this paper hints that personal consumer loans may have been democratized through websites such as Prosper.com. In the previous sections, we developed and tested a model of determinants of P2P loan auction success for the purpose of understanding lenders' decision making and answering our opening question: has democratization occurred? Or are lenders still influenced by stereotypes and attributes such as race, gender, or marital status of borrowers? To answer these questions, let us examine our models' results more closely.

7.1 Democratizing personal consumer loans

The best fitting model supported our three hypotheses regarding the direct effect of borrower characteristics on auction success, and two indirect effects: one through a mediation effect wherein auction decision variables mediate the relationships between borrower characteristics and auction funding success, and one through a moderation effect wherein borrower characteristics moderate the effect of auction decision variables on auction success. The borrower characteristics examined in this research were classified into three groups: demographics, financial indicators, and effort measures. Naturally, demographic attributes should play no role (or only a very small role) if consumer loans have been democratized by P2P loan auctions. Let us begin our examination of the role of demographic attributes in the direct effect.

As presented in Table 5 (the direct effect column of the RCL moderation model), the strongest direct effects belong to the effort measures (especially the provision of detailed explanation regarding borrowers' needs and their ability to repay the loan), and the financial indicators (especially, the better credit grades.) Demographic characteristics, such as gender, race, and marital status have little effect (if at all) on the likelihood of funding success.

Our results indicate that auction decision variables (the starting interest rate, requested loan amount, and auction duration) mediate the effect of borrower characteristics on the likelihood of auction funding success. This effect is especially pronounced for the starting interest rate and requested loan amount. The borrower characteristics that affect these parameters the most are, again, the financial indicators and effort measures (see Table 3). Specifically, better credit grades strongly affect borrowers' stated starting interest and requested amount, and the provision of detailed or general explanation affect borrowers' starting interest rate. Borrowers' demographic attributes play a little or no role at all in affecting the three decision variables. The African American race is one important exception, which will be discussed later.

Finally, our results show that borrower characteristics weakly moderate the effect of auction decision variables on its success. Particularly, the financial indicators and effort measures moderate the extent of the positive effect the initial interest rate has on auction success (last three columns in Table 5).

Summarizing the above discussion, we find strong evidence for the democratization of lending practices in P2P loan auctions. Even though demographic attributes significantly affect funding success, these are small effects compare to the other indicators: borrowers' financial strength and their efforts to communicate with, and please, potential lenders. This result sheds light on bidders' behavior: they seem more rational (bid according to what is best for them financially) and less influenced by stereotypes (bid according to old notions and stigmas). This outcome is substantially different from the documented discriminatory practices of financial institutions (e.g., Ladd 1998; Munnell et al. 1996; Blanchflower, Levine, and Zimmerman 2003), which is remarkable given that financial institutions operate in a highly regulated industry while individual lenders are free to lend their money as they wish.

7.2 Increasing the likelihood of auction funding success

Since borrowers' demographic attributes play almost no role in driving lending success, P2P loan auctions appear to be a particularly congenial venue for certain consumer groups such as women, single and divorced individuals, and those with children to obtain unsecured loans at more attractive interest rates than they might be able to obtain through more conventional sources. The exception, as mentioned above, is one race variable that did emerge as significant in affecting auction success. African American borrowers are less likely to receive funding when compared to borrowers of other races, and this difference remained significant even after controlling for the mediating auction variables. As discussed earlier, the regression of starting interest rate on borrower characteristics did show that African Americans start their auctions with a significantly lower interest rate than other borrowers. This may make African American borrowers' auctions less attractive to potential bidders when compared to auctions listed by others. Such a listing strategy could also backfire by dampening bidding momentum and reducing overall level of interest in the auction. Nevertheless, the lower average starting rate is not enough to account for the entire difference in funding success between African Americans and other races. On the basis of this study's findings, African American borrowers may be advised either not to reveal their race when listing their loan request, or to compensate for the potential negative impact of doing so by offering a higher starting interest rate or asking for a lower amount than other borrowers of comparable financial strength.

The most influential predictors of an auction listing's likelihood of being funded successfully are the extent of personal information provided by borrowers, and their credit grades. Even after controlling for the auction decision variables that are conventionally seen as determining auction funding success, providing detailed personal information was the most influential driver of auction funding success. Regardless of their other personal attributes, the guidance to potential borrowers from this result is clear-cut: to be successful in P2P loan auctions, provide an in-depth explanation of why you wish to borrow the money, your current sources and amounts of income, and your monthly budget.

Membership in an affinity group has a significant positive effect on the borrower's likelihood of success, although smaller than that of good credit grades and provision of explanation. Affinity group members, as usually advised by their group leader, ask for less money, start their auction at a significantly higher interest rate, and choose a longer duration relative to comparable non-members of affinity groups. All of these decision variable selections work in the borrower's favor, facilitating funding success. These findings indicate that potential borrowers may be well-advised to join an affinity group, and enlist the assistance of a seasoned group leader, even if it means paying out a service fee, to increase likelihood of funding success.

Of course, all affinity groups are not created equal and some of them may have more cache and signal credibility to lenders than others. The drivers of the affinity group's contribution to the individual lender's listing success merit future research attention given the community orientation of P2P loan auctions.

Despite our findings of democratization of consumer loans, and our guidance to potential borrowers, it should be remembered that in our dataset only 10.5% of all the auctions listed on the Prosper site received full funding. This implies that close to 90% of all the listings remained unfunded; these unsuccessful borrowers had to seek funding elsewhere, perhaps through conventional, more expensive means. Based on these numbers, it appears that the odds are stacked against borrowers who seek funding on the Prosper site. In the light of this statistic, it is crucial to select all the auction variables carefully and make a concerted effort, such as crafting a detailed and convincing (honest) description of one's personal history and budget and joining an affinity group to increase one's chances of receiving full funding.

7.3 Limitations and future research

Quite a lot is known regarding how the auction's decision variables and seller's reputation drive final prices from prior empirical studies done with eBay auctions. Specifically, several studies show that a seller's reputation has a positive, statistically significant, but small impact on the final price, if at all (e.g. Melnik and Alm 2002; Resnick and Zeckhauser 2002). On the other hand, Lucking-Reiley et al. (2007) show that a seller's reputation, and especially the number of negative remarks, has a larger effect on the final price than minimum bids and reservation prices have. Our results are consistent with these of Lucking Reiley and his colleagues. Specifically, in our study, the borrower's characteristics played a much more important role on the likelihood of auction success than the auction decision variables. Recently Prosper incorporated a group rating system to allow groups to accumulate reputation (which is not possible for individual borrowers, as discussed earlier in the paper.) It will be interesting to examine how the new rating system affects bidder behavior and decision making and compare it to the documented effect that eBay sellers reputations have on the auction outcome.

Another potential avenue for future research is the examination of payment performance. Whereas our findings provide extensive and clear guidance to borrowers, they have much less to say to lenders participating in P2P loan auctions. This is because the relevant outcome variable for lenders is not funding success; instead, it is the performance of the loan once it has funded, i.e., whether the lender receives timely payments from the borrower over the three-year term of the loan, that determines success for the lender. Future research studying performance of loans issued through P2P loan sites will help ascertain whether borrower characteristics (and which ones) and/or auction decision variable are predictors of timely payments.

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TABLE 1. Descriptive Statistics of Variables in the Analysis

a) Means of continuous variables

Variable	Funded Auctions *N*=564		Unfunded Auctions *N*=4,806		All Auctions *N*=5,370	
	Mean	SD	Mean	SD	Mean	SD
Starting interest rate	19.95	6.15	15.74	7.04	16.18	7.07
Final interest rate	18.93	6.45	15.73	7.04	16.07	7.05
Requested amount ($)	4,114.3	3,519.0	5,060.6	4,813.6	4,961.2	4,703.2
Total amount bid ($)	6,974.6	7,868.6	168.9	868.5	883.7	3,394.4
Auction duration (days)	7.60	2.08	7.44	2.08	7.46	2.08
Number of bids	62.6	67.4	1.6	6.8	8.0	29.5
Number of winning bids	35.7	28.3	0.0	0.0	3.8	14.3
Debt-to-income ratio	16.5	15.4	23.8	45.5	23.1	43.4

TABLE 1. Continued

b) Auction funding success (funding) rates for discrete variables (overall rate is 10.5%)

Variable		**Success Rate**	***n***
Homeownership		15.6	1328
Group membership		12.8	3342
Gender:	Male	11.5	2134
	Female	8.7	2244
	Not specified	12.8	992
Race:	Caucasian	12.5	1845
	African American	3.9	539
	Hispanic	40.7	27
	Not specified	10.3	2952
Marital status:	Married	12.0	1473
	Single	4.9	759
	Divorced	12.0	382
	Not specified	11.1	2756
Children		9.6	2206
Picture		9.3	3053
Explanation:	General	52.0	531
	Detailed	90.7	298
	No explanation	0.4	4541
Credit grade:	AA	38.4	125
	A	40.2	97
	B	32.7	150
	C	28.9	341
	D	19.7	415
	E	11.4	1106
	HR	4.0	3136

TABLE 2. Logit Model Results: Effects of Auction Decision Variables and Borrower Characteristics on Auction Funding Success

Model	Estimation sample (n=4031) LMD	Estimation sample (n=4031) Hit Prob	Validation sample (n=1339) LOGL	Validation sample (n=1339) Hit Prob	Comments
1. Null model	-1382	0.807	-435	0.814	Intercept only
2. Logit, Y=f(X), eq. 2	-1301	0.816	-405	0.823	X affects Y; **necessary for mediation**
3. Logit, Y=f(Z), eq. 3	-328	0.956	-129	0.954	Z affects Y
4. Logit, Y=f(X, Z)	-228	0.972	-85	0.969	X and Z both affect Y, **direct effects and partial mediation**
5. RCL, Y=f(X)	-401	0.958	-85	0.961	βs vary randomly across auctions
6. RCL, Y=f(X, Z)	-204	0.975	-69	0.972	Z affects intercept only, βs vary randomly across auctions
7. RCL+ moderation, Y=f(X), eq. 4	-703	0.924	-214	0.925	Z affects all βs except intercept, which is constant across auctions
8. RCL+ moderation, Y=f(X, Z), eq. 4	**-183**	**0.977**	**-65**	**0.973**	Z affects all βs, including intercept; evidence for **direct effects, partial mediation, and moderation**

Where:
RCL: Random Coefficient Model
LMD: Log Marginal Density (like BIC); Hit Prob is the average predicted probability of actual outcome
Y: Loan auction funding success (0/1)
X: Loan auction decision variables
Z: Borrower characteristics

TABLE 3. Multivariate regression of: (a) starting interest rate, (b) loan amount requested, and (c) duration of auction on borrower characteristics

	Starting Interest Rate			Loan Amount Requested (000)			Duration of Auction		
	Estimate	S.E.	P-value	Estimate	S.E.	P-value	Estimate	S.E.	P-value
Intercept	16.92	0.41	0.00	4.27	0.28	0.00	7.47	0.13	0.00
Debt to income ratio	0.00	0.00	0.85	0.01	0.00	0.00	0.00	0.00	0.56
Homeowner	-0.10	0.26	0.71	1.16	0.17	0.00	-0.22	0.08	0.01
Group membership	0.64	0.22	0.00	-0.51	0.15	0.00	0.34	0.07	0.00
No gender	0.08	0.35	0.82	0.80	0.23	0.00	-0.24	0.11	0.02
Male	-0.09	0.25	0.72	0.68	0.17	0.00	-0.02	0.08	0.82
No race	-0.19	0.32	0.56	-0.05	0.21	0.80	-0.17	0.10	0.09
African American	-1.17	0.39	0.00	0.36	0.26	0.16	0.09	0.12	0.47
Hispanic	0.74	1.37	0.59	-0.92	0.91	0.31	0.42	0.42	0.31
No status	-0.06	0.29	0.83	-0.27	0.20	0.18	0.02	0.09	0.80
Single	-0.59	0.36	0.10	-0.25	0.24	0.30	0.06	0.11	0.59
Divorced	-0.15	0.44	0.73	-0.03	0.29	0.91	0.20	0.14	0.15
Children	0.38	0.26	0.15	-0.34	0.18	0.06	-0.11	0.08	0.18
Picture	-0.67	0.30	0.03	-0.14	0.20	0.49	-0.02	0.09	0.83
Credit AA	-8.77	0.71	0.00	2.30	0.48	0.00	-0.08	0.22	0.73
Credit A	-7.53	0.83	0.00	3.19	0.55	0.00	0.30	0.25	0.24
Credit B	-5.29	0.68	0.00	3.59	0.46	0.00	0.34	0.21	0.10
Credit C	-3.36	0.45	0.00	2.91	0.30	0.00	0.23	0.14	0.10
Credit D	-1.37	0.41	0.00	1.77	0.27	0.00	-0.01	0.12	0.96
Credit E	-0.77	0.28	0.01	0.52	0.18	0.00	-0.19	0.08	0.03
General Explanation	2.36	0.36	0.00	-1.47	0.24	0.00	-0.03	0.11	0.80
Detailed Explanation	5.65	0.47	0.00	-1.10	0.31	0.00	0.30	0.14	0.04
Standard Error	6.71	0.07	0.00	4.47	0.05	0.00	2.06	0.02	0.00
R^2	0.10			0.11			0.02		

Compared to intercepts only model, likelihood ratio LR=982, 63 d.f., P<.0001

TABLE 4. Parameter Estimation Results from RCL, moderation (eq. 4), Y=f(X, Z)
(+ indicates 95% Highest Posterior Density region is above zero; - indicates 95% HPD region is below zero)

Borrower Characteristic Z	β (Intercept)	β (Starting interest rate)	β (Amount requested)	β (Auction Duration)	Y=F(Z) model
Intercept	-				-
Debt to income	-				-
Homeowner					
Group	+		+		+
No gender	+				
Male	-				
No race	-				
African American	-				-
Hispanic			-		
No marital status					
Single					
Divorced			-		
Children			-		
Picture	-				-
Credit AA	+				+
Credit A	+	+			+
Credit B	+	+			+
Credit C	+	+			+
Credit D	+	+			+
Credit E	+	+	+		+
General Explanation	+	+			+
Detailed Explanation	+	+		+	+
Mean β value across auctions	-8.372	0.214	-0.506	-0.006	

TABLE 5. **Marginal Effects: Direct and Indirect Effects of Borrower Characteristics on Loan Success (%)**

	Logit: Y=f(Z)	Logit: Y=f(X,Z)				RCL moderation (eq. 4): Y=f(X, Z)			
			Indirect effect via…				Indirect effect via…		
Borrower Characteristic	Direct effect	Direct effect	Rate	Amt	Drtn	Direct effect	Rate	Amt	Drtn
Debt to income	-0.04	-0.03	0.00	-0.01	0.00	-0.04	0.00	-0.01	0.00
Homeowner	0.19	0.34	-0.04	-0.42	-0.02	0.36	-0.04	-0.49	-0.04
Group	1.66	1.14	0.25	0.19	0.03	1.00	0.25	0.21	0.06
No gender	-0.17	0.74	0.03	-0.29	-0.02	0.84	0.03	-0.33	-0.04
Male	-0.40	-0.21	-0.03	-0.25	0.00	-0.34	-0.03	-0.29	0.00
No race	-0.74	-0.77	-0.07	0.02	-0.02	-0.90	-0.07	0.02	-0.03
African American	-3.57	-2.45	-0.46	-0.13	0.01	-2.62	-0.46	-0.15	0.02
Hispanic	1.95	1.47	0.29	0.33	0.04	0.57	0.29	0.39	0.08
No marital status	-0.57	-0.82	-0.02	0.10	0.00	-0.36	-0.02	0.11	0.00
Single	-0.89	-0.72	-0.23	0.09	0.01	-0.77	-0.23	0.10	0.01
Divorced	1.05	-0.14	-0.06	0.01	0.02	-0.54	-0.06	0.01	0.04
Children	0.31	0.06	0.15	0.12	-0.01	0.42	0.15	0.14	-0.02
Picture	-1.58	-0.89	-0.26	0.05	0.00	-0.59	-0.26	0.06	0.00
Credit AA	13.12	45.59	-3.43	-0.83	-0.01	19.57	-3.41	-0.96	-0.01
Credit A	18.15	42.06	-2.95	-1.15	0.03	54.02	-2.93	-1.34	0.05
Credit B	10.96	24.53	-2.07	-1.30	0.03	39.31	-2.06	-1.50	0.06
Credit C	6.86	12.86	-1.32	-1.05	0.02	18.23	-1.31	-1.22	0.04
Credit D	5.61	7.50	-0.54	-0.64	0.00	5.84	-0.53	-0.74	0.00
Credit E	3.19	2.87	-0.30	-0.19	-0.02	1.61	-0.30	-0.22	-0.03
General Explanation	44.21	27.70	0.92	0.53	0.00	26.73	0.92	0.62	-0.01
Detailed Explanation	81.30	57.57	2.21	0.40	0.03	60.74	2.20	0.46	0.05

FIGURE 1: Conceptual Framework of Funding Success in P2P Loan Auctions