THE DEMOCRATIZATION OF PERSONAL CONSUMER LOANS?

DETERMINANTS OF SUCCESS IN ONLINE PEER-TO-PEER LENDING COMMUNITIES

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Abstract

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

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 (P2P) lending communities such as Prosper (www.prosper.com) and Zopa (www.zopa.com) have become increasingly popular among consumers. These sites host and facilitate P2P loan transactions 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 financial institution. Approximately $150 million in P2P loans were issued by June 2008 and that amount is expected to grow to as much as $1 billion by 2010 and $9 billion by 2017 (Kim 2007), making these communities an increasingly important player in the consumer finance domain.

Are P2P lending communities democratizing personal consumer loans? With their emphases on open availability of information, and reliance on social interactions and collaboration for mutual benefit, these communities do leverage key democratizing attributes of Web 2.0 (Tapscott and Williams 2007). P2P lending communities merit research attention for at least two important reasons. First, P2P loans have given 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 viewed as increasing borrower welfare relative to the status quo, because borrowers are able to get a loan at a much lower interest rate than a financial institution (Bruce 2007; Steiner 2007). Perhaps even more important, many borrowers in a P2P lending community would otherwise have to resort to going to a payday lender to obtain an unsecured loan, which prior research has shown to be extremely detrimental to consumers (e.g., Stegman and Faris 2003).

However, to our knowledge, no empirical research has studied how consumers behave when they have a chance to interact with each other in such an environment – are they fair or guided more by stereotypes? Specifically, we ask whether all borrowers are equally successful in funding their loan requests in P2P lending communities. If not, then what determines funding success?

The second reason for studying funding success in P2P lending communities is that the decision making framework under which lenders lend money in them is unique. It combines certain aspects of valuation and bidding processes of online auctions, along with the social influence, intra-group communication, and trust engendering processes of consumer communities within a single mechanism. The transparency of available information raises the possibility that seemingly irrelevant borrower attributes such as race, gender, and marital status could still significantly impact lenders' decisions, for example, by activating stereotypes. The criteria that lenders participating in P2P lending communities use in making their bidding decisions remain to be known. Consequently, the questions of whether and to what degree P2P lending communities are democratizing remain unanswered.

Considerable prior research has examined participation by customers in communities (e.g., Algesheimer, Dholakia, and Herrmann, 2005; Muniz and O'Guinn 2001) but much of this research has focused on customers' interactions with one another for social purposes. In contrast, P2P lending communities are trading communities where consumers participate for fulfilling specific personal motives, and engage in financial transactions with one another (i.e., either borrowing or lending money) for mutual benefit. In this respect, P2P lending communities resemble eBay, which can also be characterized as a trading community.

However, there are significant differences between the P2P lending communities and eBay. Most borrowers only borrow once, and unlike eBay sellers, do not have the opportunity to build their reputation in the community over an extended time period by completing transactions successfully and earning positive feedback. Consequently, visible borrower attributes have the potential to play a greater role in funding success, as do measures of financial strength. Additionally, unlike eBay, lenders interact extensively with most borrowers by asking them various questions regarding their loan requests, and for clarifications and additional information to help them decide whether to lend money. The question-and-answer exchanges are visible to everyone in the lending community. Lenders also personally know, and interact with each other, offering advice, sharing war stories, and seeking assistance. Like other customer communities, there is a strong *consciousness of kind*, or a sense of belonging to the group, *shared rituals and* *traditions* such as making fun of rookie lenders, and perceptions of *moral obligation* manifested, for example, in quick warnings if a lender discovers something suspicious about a loan request or borrower (Muniz and O'Guinn 2001).

Furthermore, although the mechanism by which lenders lend money is based on an auctioning process, a majority of successful bids are posted-price offers. Consequently, the vibrant and growing marketing and economic literature on online auctions is only partially, if at all, applicable to P2P lending communities. There are also important differences in the bidding mechanisms of loan listings and eBay auctions, as we discuss in detail later on.

In the current research, our goals are not only to introduce marketing researchers to this new and interesting form of online community, but we also propose a comprehensive theoretical framework (see Figure 1) to examine drivers of borrowing success in them. The key dependent variable in our framework is funding success in P2P lending communities, which is defined as whether or not a loan request gets fully funded by the time it ends. We include both borrower- and loan listing-related determinants of 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 communities.

First, it allows us to directly study 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 unsecured consumer loans, after controlling for relevant financial strength criteria. We are also able to determine the degree to which financial strength criteria such as a better credit grade, homeownership, and a lower debt-to-income ratio increase funding success and reduce the interest rate borrowers pay on their loans.

Second, in our conceptual framework, the loan decision variables (loan amount requested, starting interest rate, duration) are positioned 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 loan decision variables. Finally, we position borrower characteristics as moderators of the effects of loan decision variables on funding success. By doing so, we obtain additional insights regarding how borrowers' characteristics change lenders' responses to the loan decision variables.

Third, our findings provide practical guidance to borrowers in P2P lending communities regarding effective ways of listing their loan requests. This is important because in this consumer-to-consumer community, the success rate is low (≈ 10%). Through our findings, we are able to begin answering the questions of whether and to what extent P2P lending communities are democratizing by giving access to cheaper unsecured credit to all consumers.

The rest of the paper is organized as follows. In the next section, we describe the research setting in more detail. Then, we develop a theoretical model and research hypotheses regarding the determinants of P2P loan funding success. This is followed by a description of the dataset, a summary of the methodology used to test the hypotheses, and the results. The paper concludes with a discussion of whether P2P lending communities have democratized unsecured consumer loans, along with specific suggestions as to how borrowers can increase their chances of receiving funding, and a discussion of the research limitations and future opportunities.

RESEARCH SETTING

Our research employs a database of P2P loans listed on the Prosper.com website. Prosper is the first, and currently the largest, P2P lending community site in the United States, with more than 750,000 registered members. Since its inception in March 2006, through May 2008, the site has originated over $150 million in personal loans. Prosper is positioned as an online financial marketplace, offering its customers a blend of eBay-like P2P loan auctions and dozens of high-traffic discussion forums that support participant discussions about the loans. 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 lending strategies, to weigh in on the quality of individual loan requests, and to socialize with one another.

On Prosper, loan transactions between borrowers and lenders are conducted in an information-rich environment. For lenders, the available data include individual lenders' loan portfolios, bid amounts, and performance, along with payment history of each borrower. Borrowers on Prosper receive up-to-date information regarding final interest rates for successful loan requests at different credit grades and loan amounts, tips on creating an effective loan request, and access to advice from seasoned lenders. Additionally, they can 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 request 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 request gets funded.

The process of borrowing money through a P2P loan 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 U.S. credit reporting agencies. They also provide financial 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 grades vary from AA, which denotes the borrower as 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 on the site. Following the credit grade assignment, borrowers can list their loan requests as auctions on Prosper.

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.

When listing the loan request, 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 duration for which the request will remain active, which can range from three to ten days. All loans made through Prosper, as well as other P2P lending communities, 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 percent 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 request is listed on the Prosper site, lenders decide whether they want to bid on the loan, and if so, how much money and what interest rate they wish to offer. They use the financial and personal information provided by the borrower in making these decisions. On Prosper, most lenders' strategies are conceptually related to the microfinance model (e.g., Robinson 2001) in the sense that they lend small amounts, usually $50, to individual borrowers. That way, lenders are able to reduce their risk by spreading it over a portfolio of loans. This strategy is not only recommended by Prosper.com but also by seasoned lenders. For example, on a Prosper discussion board, *tjohnsn*, an experienced lender, had this to say:

> "Here's some advice to new Prosper lenders from someone who has made over 270 Prosper loans and invested over 14K... RULE #1: Never, and I mean NEVER, lend more than $50 per loan. RULE #2: After observing rule #1, make sure that you lend to HOMEOWNERS. RULE #3: After observing rule #1, make the most loans to higher credit scores and fewer loans to lower credit scores."[1]

When the aggregate amount offered by lenders exceeds the amount requested by the borrower, the interest rate begins to drop from the borrower's maximum specified rate. Conceptually, the loan's final interest rate is analogous to the final price paid by the winning bidder in eBay auctions. In reality, a majority of loans do not receive additional bids after the amount requested by the borrower has been reached; in these cases, the loan request is similar to a posted-price transaction where the lender offers money to the borrower at the maximum interest rate s/he is willing to pay.

When the specified time has elapsed (i.e., the listing has expired), if the loan request

[1] http://www.wiseclerk.com/advice-to-new-prosper-lenders-t13.html

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, the firm attempts to collect late payments on lenders' behalf through various collection practices.

CONCEPTUAL FRAMEWORK AND RESEARCH HYPOTHESES

All P2P lending communities, including Prosper, operate on the principle of "full financing," i.e., the loan request gets funded only 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 (or starting) price results in a successful auction. An example is helpful to illustrate full financing. Consider a loan request made by a borrower for $10,000 on the Prosper site. When the listing ends, if the total amount offered by lenders equals $9,900 (or even $9,999), the request is deemed to be unsuccessful and the borrower must re-list the loan request or seek credit elsewhere. On the other hand, if the final amount offered by lenders is $10,000 or more, the borrower receives the $10,000 (not more) from the lenders that offered the lowest interest rates. Consequently, we define success in P2P lending communities by the loan request's final outcome – whether it gets fully funded or not. Funding success is the key dependent variable in our analysis. Note that since a majority of loans do not receive additional bids after the amount requested by the borrower has been reached, the final interest rates are very close to the starting interest rates (the correlation is over 0.99). The final interest rate is therefore not an interesting dependent variable for analysis.

Prior online auction literature suggests that two main types of factors determine final prices of listed items (e.g., Ariely and Simonson 2003; Kamins, Dreze and Folkes 2004; Ku, Galinsky, and Murnighan 2006). First, attributes of the seller, for example, his or her reputation, location, etc., can influence the auction's success. Second, auction decision variables, controlled by the seller, such as its starting price and duration, also play important roles in determining the item's final price. (for recent reviews see Milgrom 2004; Ockenfels, Reiley, and Sadrien 2006). In P2P lending communities, we consider two analogous factors that influence whether or not the loan request gets funded: (1) the borrower's attributes, such as credit grade, debt-to-income ratio, gender, race, and marital status, etc. and (2) the loan decision variables such as amount requested, interest rate offered, and duration.

Direct effects of borrower characteristics on loan funding success

Three types of borrower characteristics are considered in this research: demographic characteristics, financial strength, and effort indicators. Prosper requires borrowers to provide information on their income, existing debt, and homeownership (which is verified by the firm); however, borrowers choose whether or not to provide their demographics in the listing. Some borrowers provide extensive personal details revealing their race, gender, marital status, etc. Others are reticent, keeping their demographic attributes hidden. We expect that exploring how borrower characteristics affect the loan funding outcome will shed light on which listing strategy, full disclosure or reticence, is more effective for borrowers in successfully funding their request.

Demographic Characteristics. In P2P lending communities, we expect enduring demographic characteristics of the borrower, specifically gender, race, marital status, and whether s/he has children to matter in determining whether the loan gets funded. These variables are central to how consumers make financial decisions and to outcomes associated with household income, expenses, the ability to save, and the types and amounts of credit needed.

In the United States, 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. 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 on account of 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, which may dampen stereotyping tendencies, P2P lending communities are 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 available demographic information in their lending decisions to an even greater extent than institutional lenders do. Consequently, on Prosper, we expect that loans sought by women (when compared to men), and minorities (when compared to Caucasians) will be less likely to get funded.

Financial Strength. We also considered three borrower characteristics that are more directly related to the person's financial strength – credit grade, debt to income ratio, and homeownership. While the first two 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 plays a significant role in their ability to obtain secured and unsecured credit from financial institutions (Avery Calem, and Canner 2004).

The borrower's credit grade summarizes factors related to the person's previous experience with credit, leases, payment of bills, public records, and credit inquiries. 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 to be 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 better credit grades. Likewise, 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 requests belonging to borrowers with high debt-to-income ratios. Finally, homeownership, which represents not only access to a previous loan but also ownership of an asset, should increase likelihood of funding success of a loan request.

Effort Indicators. The third set of borrower attributes included 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 lending community before making the loan request. They include the degree of personal descriptive information provided in the loan request, and whether the borrower joined an affinity group.

To be successful, borrowers must create a positive image and reputation, engendering trust within the lender community. Prior community research has that shown reputation and trust are crucial in impacting not only the consumer's influence within the community but also instrumental outcomes for him or her (e.g., Ridings, Gefen and Arinze 2002). Creating trust is relatively difficult in P2P lending communities because most loans are "one-shot" events, that is, borrowers usually apply for (and receive) a loan just once. Therefore, the main avenue available in relational settings to engender trust, i.e., through exemplary behavior over time, is not available to most borrowers. They must convince lenders that they can be trusted and will repay the loan *before* they have the opportunity to demonstrate trustworthy behavior. Nevertheless, as discussed earlier, borrowers do have two means at their disposal to engender trust: they can provide detailed personal information about themselves in the listing, and they can join an affinity group.

When listing the 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 duration for which the request will remain active, without providing additional information. On the other extreme, borrowers can provide detailed information such as their personal history, reasons for the loan, current income, detailed current budget, and an action plan for paying off the loan. They may also upload pictures of themselves, their family members, and other information (such as a product they designed). Finally, borrowers may even explain negative aspects of their profile such as a low credit grade, or past delinquencies.

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. In the current analysis, we categorize the personal information into three progressively increasing levels: “no personal information,” “general personal information,” and “specific personal information.” We expect that more personal information provided by the borrower is likely to be useful to lenders and have a positive effect, by reducing the information asymmetry between borrowers and lenders, along with mitigating concerns of fraud, humanizing the borrower, generating empathy, and thus increasing the likelihood of funding success.

Considering affinity group membership, although such a group cannot enforce “good behavior” in the sense of forcing members to repay the loan or pay on their behalf, membership does provide an additional 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 s/he has accepted the group’s norm of regular loan repayment by voluntarily joining the group and subjecting oneself to the group’s peer pressure.

Supporting such a possibility in the context of an open source software community, O'Mahony (2003) showed that developers of open source software who decide to become part of the software community freely accept the norm of "good behavior" such as not stealing, and giving credit to other members' contributions, even when there is no legal protection of intellectual property rights. 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 request.

Direct effects of loan decision variables on auction funding success

In P2P lending communities, when listing their request, borrowers must specify three decision variables: the loan amount, the initial (maximum) interest rate they are willing to pay, and duration for which the listing will be active (similar to duration of an eBay auction). The effects of each of these variables on loan funding success are considered.

Loan Amount. As noted earlier, most P2P lenders tend to bid small amounts on individual loans to disperse their risk. Not surprisingly, in our dataset, the modal amount bid by lenders is $50 (51.8% of all bids) which is also the minimum amount that a lender can bid on a single loan. This means that even for a $1,000 loan request, up to twenty lenders have to place a bid for the loan to be funded. 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 funding success. In addition, lenders' assessments of borrowers' ability to repay loans may be less favorable as the loan amount increases, reducing the probability of funding success.

Initial Interest Rate. Recent research on online auctions is useful in considering effects of initial interest rate in P2P loan auctions. Several studies have 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 both in terms of reservation prices, and attractiveness of the auction, and the higher the number of bidders participating in the auction (Bajari and Hortacsu 2003). In the case of P2P loans, a lower starting price corresponds to a higher initial interest rate offered by the borrower. We expect a higher initial interest rate to increase the loan's attractiveness for more lenders and stimulate them to bid on the loan request, increasing likelihood of full funding of the listing.

Duration of loan request. The third decision variable that can influence loan success is its duration. In P2P lending communities, interpersonal communication between community members, particularly borrowers and lenders, and among lenders themselves, plays a significant role. Such communication may begin before the request is posted (to help borrowers post a listing that has the most chance to be successful), however it usually gains momentum once the loan is listed on the Prosper site. Many borrowers post the link to their request in various discussion forums (such as the "Review My Listing" forum[2]) to obtain feedback, advertise their loan to lenders, and communicate with them. As an example, a borrower called *lulu4700* posted the following message in the Prosper borrower forum:

> "I'm not sure if this is the correct place to post this but I have seen other people asking for advice so I thought I would give it a try. I will warn you before you look, my credit grade is HR. In some of the posts that I've read I see that some lenders are rightfully leery about "hard luck" tales so I am trying to make sure that I have explained my situation well enough without sounding like a charity case. Any feedback would be appreciated: [link to the loan request]"

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 loan request positively.

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

Mediation and moderation in the conceptual framework

In our discussion so far we concentrated on the direct effect of borrower characteristics and loan decision variables on loan funding success. However, some of these variables, for example, borrower's race and gender, are exogenous, and others such as loan amount, are influenced by the borrower. To clarify these different roles we enhance the simple model of direct effects and provide it more flexibility through the use of mediation and moderation.

[Insert Figure 1 about here]

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

To conclude that our conceptual model describes the functioning mechanism of P2P lending communities, 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 loan decision variables (mediation effect.) Third, the direct effect of loan decision variables must vary for different levels of borrower characteristics (moderated mediation; Muller, Judd, and Yzerbyt 2005). The literature and theory that supports each of the requisite relations are considered next.

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

In addition to direct effects of borrower characteristics on loan funding success, these variables also have indirect effects on funding success because they affect the three loan decision variables, requested amount, interest rate, and duration.

Starting Interest Rate. From the lender's perspective, a vast majority approach P2P community lending as an investment decision, and apply the principle of "greater risk equals greater reward" in their decision making (e.g., Fama and MacBeth 1973). This lender norm is well known among borrowers, as it is articulated constantly in the discussion forums and lenders' conversations with borrowers. For example, Matt, a Prosper lender, posted the following comment on prosperlending.blogspot.com:

> "If we look at loans in the B through HR categories, the loans that defaulted had a 1.7% through 2.6% higher interest than other loans in that credit grade. What this means is that prior to defaulting lenders considered these loans a higher risk and didn't bid down the interest rate as low as they did for other loans. This is even more pronounced when you look at the difference in interest rates between loans that are current vs loans that have defaulted. Lenders put as much as a 3.74% risk premium on loans that ended up defaulting; clearly lenders were seeing something they didn't like in the listings compared to other listings of the same credit grade."

Consequently, we expect borrower characteristics that are either *known to be* (through analysis of past completed loan requests, default rates, etc.) or *perceived as* indicative of greater risk to lead borrowers to offer higher starting interest rates in their loan listings.

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 2001). Consequently, we expect that the better the borrower's credit grade, the lower will be the starting interest rate. Likewise, we also expect the two 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.

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, statistical information about prior successful loans (e.g., default rates by credit grade) is freely available on Prosper, so that potential borrowers are usually aware of norms for funding through discussions on the various community forums. 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, homeownership, and lower debt-to-income ratio are all expected to increase the borrower's ability to fund a larger loan. 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 fund a larger loan. Additionally, group membership should negatively affect the requested amount (as the group leader will exert a conservative influence), as will provision of information by the borrower.

Duration. Borrowers must choose the duration for which their loan request will remain active when listing the loan. Prosper provides a default duration of seven days. We expect that borrower characteristics, and specifically the effort measures (whether borrowers join an affinity group, and the degree of detail they provide), will impact the chosen duration. Affinity group leaders are well aware of the importance of a longer duration in influencing funding success, and are likely to advise their group members to choose a higher duration. Consequently, membership in an affinity group is expected to affect 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 loan requests, and are expected to choose longer listings.

Borrower characteristics as moderators of the effect of loan decision variables on loan funding success

Prosper allows lenders to search for listings with specific attributes, for example, listings with an 18% interest rate, or those for amounts no larger than $10,000. The likelihood of success of all listings with the same interest rate, requesting the same amount, and of the same duration is not the same. We have already discussed the direct effects of borrower characteristics on loan funding success as one explanation for these differences. For example, for a given interest rate, requested amount, and duration, borrowers having better credit grades have a higher likelihood of receiving full funding when compared with those having lower credit grades. A second explanation is that borrower characteristics may affect lenders' responses to the loan decision variables. For example, lenders' hypothesized negative reactions to the loan amount requested by the borrower may be less negative if the borrower can demonstrate better ability to pay back the larger loan, for example, by having a lower debt-to-income ratio or group affiliation or by providing more detailed explanations as to their creditworthiness.

Summary of the Research Hypotheses

As we conceptualize in Figure 1 and have developed in the previous discussion of important relationships, the conceptual framework indicates that borrower characteristics potentially have direct, indirect, and moderating effects on loan funding success via loan 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 decision variables (partial mediation hypothesis.)

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

DETAILS OF DATA

Our dataset consists of all the loan requests listed by borrowers on the Prosper site during the month of June 2006. A total of 5,370 loans 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 the decision variables for each individual loan listing from the site.[3] In the second stage, each listing 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 for each listing. No discrepancies were found between the coding of the two assistants, and these data elements were deemed to be accurate.

Variables

For each listing we have information on the borrower's credit grade, 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, the amount of money the borrower requested, the total number of bids, and the starting and ending times of the loan request. 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, 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.

Descriptive Statistics

Of the 5,370 listings, 564 (10.5%) received enough bids to cover the entire requested amount and were fully funded. The summary statistics for funded, unfunded, and all listings are provided in Table 1. Not surprisingly, on average funded listings have higher starting interest rates (19.9% vs. 15.7%, $p < .001$), and lower requested amounts (\$4,114 vs. \$5,060, $p < .001$) when compared to the unfunded listings. Duration is slightly higher for the funded listings than

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

unfunded ones (7.6 vs. 7.4 days, p <.001). Finally, borrowers with funded listings have a lower debt-to-income ratio (16.5 vs. 23.8, $p < .001$).

[Insert Table 1 (a) about here]

The funding success rates for discrete variables are shown in Table 1b. Noteworthy is the high success rate for loan requests 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 loan requests with no explanation. Success rates are higher for borrowers with good credit (e.g., 38.4% of listings for AA borrowers were funded); in contrast, only 4% of listings for borrowers with high risk (HR) credit were funded. Also worth noting, the 40.7% success rate for Hispanic borrowers is based on a total of only 27 listings. Of the 5,370 listings, we set aside 25% (1,339) randomly selected listings to validate the models, leaving 4,031 listings for model estimation.

[Insert Table 1b about here]

MODELS

To test hypotheses regarding the effects of direct, indirect (mediating), and moderating relationships among borrower characteristics, loan decision variables, and loan 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 loan decision variables (starting interest rate, requested loan amount, and duration), we use a multivariate regression model,

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

where X is the N x 3 matrix of loan 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 for the error terms contains only variances of the error terms for the three loan decision variables. Significant relationships in Γ are 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 loan decision variables.

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

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

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 loan funding success can be established using a logit model in which the probability of success is:

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

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 loan decision variables X and borrower characteristics Z affect loan funding success. If Z affects X (eq. 1) and X affects loan funding success (eq. 2) but Z does not affect loan funding success directly, then full mediation would be indicated; the hypothesized and more likely outcome is that Z will also affect loan funding success directly, suggesting that the mediation is partial.

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

(4) $$\beta_i = \Delta z_i + v_i,$$

where β_i is an 4×1 vector of response parameters (the three loan decision variables plus an intercept) for loan listing *i*, Δ is a 4×22 matrix of coefficients linking borrower characteristics z_i to lenders' responses to loan decision variables, and v_i is a normally distributed error term with covariance matrix V_β. The error term allows heterogeneity in lenders' responses to loan 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 loan 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 loan funding success indirectly through the loan decision variables X (mediation) and through the lender responses β_i linking the Xs to loan funding success (moderation). Thus, in a fully specified model, borrower characteristics z_i can affect loan 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 lender 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 loan outcomes, and one in which z_i does not affect the intercept and has no direct effect on loan outcomes. Based on the hypotheses developed earlier, we expect the model that allows z_i to affect loan 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 listings, capturing the impact of only unobserved factors causing heterogeneity in lenders' responses to loan decision variables. We estimate pure random coefficients specifications with and without direct effects of z_i on loan 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.

RESULTS

We begin by testing our 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 loan decision variables do affect loan funding success, which is a necessary condition for mediation to occur. Likewise, we observe in model 3 that borrower characteristics affect loan funding success directly, even when loan decision variables are also included in the model specification (model 4). Thus, there is evidence that borrower characteristics have direct effects on loan outcomes as well as indirect (partially-mediated) effects through the loan decision variables (We provide evidence for the linkage between borrower characteristics and loan decision variables shortly.)

Model 5 introduces random coefficients into model 2, allowing unobserved heterogeneity in lenders' responses to loan 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 lenders' responses to loan decision variables is captured

[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 sample of loan listings. The fit measures are calculated as the averages over the last 10,000 iterations.

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 loan 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 loan listings (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 loan decision variables (mediation effects), and indirect effects through lenders' responses β to loan decision variables (moderation effects.) This model provides the 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 moderation 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, pertaining to direct effects and mediation. We also provide support for the third hypotheses (moderation) although this effect is not so strong.

[Insert Table 2 about here]

Before investigating results from the chosen model, model 8, in more detail, we first establish the regression relationships between loan 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. See Table 3). 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, would be associated with lower interest rates, however our analysis shows that these variables do not affect the starting interest rate. African American borrowers are more likely to offer a lower starting rate, which may partially 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 of variation explained in the duration of loan listing is lower than that of the other two loan decision variables, at just 2%. As expected, borrowers who provide detailed information or affiliated with an affinity group tend to choose longer 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 loan 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 (=21×3) degrees of freedom is extremely significant (<.0001), even though the amount of variance explained is not overwhelming. Thus, since loan decision variables affect funding outcomes (Table 2), loan decision variables therefore mediate the relationship between borrower characteristics and loan funding outcomes, more so through starting interest rate and the loan amount requested than the duration of the listing.

[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 loan funding success. As expected, the following borrower characteristics have a positive effect on loan 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 loan funding success are, as anticipated, debt-to-income ratio and being a minority (African American). The provision of a picture, which affects loan funding success negatively, 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 loan funding success.

Next we examine the direct effect of the loan decision variables on loan funding success (see bottom row of Table 4.) As expected, the average effect of starting interest rate on funding success is positive, and the average effect of loan amount requested is negative. We predicted that duration will have a positive effect on loan 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 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. Not surprisingly, credit grades other than high risk and the provision of general or detailed explanations enhance the positive effect of the starting interest rate on loan funding success, while group membership attenuates the negative affect of loan amount requested on loan 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 decision variables when predicting funding success. We now compare the direct and indirect effects of borrower characteristics on loan funding success across several models. To that end, we calculate the marginal effect of each borrower characteristic (note that the raw model coefficients cannot be compared directly because of scaling issues.)

The marginal effect of some continuous variable is the change in probability of 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 loan listings and averaging:

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

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

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

where $P\left(i \mid X_{ij} = 1\right)$ is the probability that loan listing *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 loan funding success. The second model captures direct and indirect effects via mediation, but bidders' responses to loan decision variables do not vary across listings, 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 loan decision variables, it is also necessary to calculate the marginal effects for the effects of borrower characteristics on loan decision variables from the regressions shown in Table 3. For example, to find the indirect effect of group affiliation on loan funding success via the starting interest rate (.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 loan 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 loan 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 loan funding success for the logit Y=f(Z) model (1.66%) implies that being affiliated with a group improves the probability of 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% + .25% +.21% +.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 borrowers can request (Table 3) and amount requested *decreases* probability of 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 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 (compare the second and third models in Table 5), 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]

GENERAL DISCUSSION

The goal of the current research was to examine how consumers behave when they have an opportunity to transact with each other in P2P lending communities. In this unregulated, information rich, and seemingly egalitarian environment, where individuals borrow from, and lend money to one another based on little more than good faith, we wished to examine which factors affect lenders' decisions. The title of this paper hints that unsecured personal loans may have been democratized through consumer communities such as Prosper.com. In the previous sections, we developed and tested a model of determinants of P2P loan funding success for the purpose of understanding lenders' decision making. Now let us examine our models' results more closely.

Democratizing personal consumer loans

The best fitting model supported our three hypotheses regarding the direct effect of borrower characteristics on funding success and the two indirect effects: a mediation effect wherein loan decision variables mediate the relationships between borrower characteristics and funding success, and a moderation effect wherein borrower characteristics moderate the effect of loan decision variables on funding success. The borrower characteristics examined in this research were classified into three groups: demographics, financial indicators, and effort measures. Naturally, if unsecured consumer loans have been democratized by P2P lending communities, demographic attributes should play no role (or only a very small role.) 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 loan decision variables (the starting interest rate, requested loan amount, and duration) mediate the effect of borrower characteristics on the likelihood of 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 loan 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 the loan's funding success (see the β(Starting interest rate) column of Table 4).

Summarizing the above discussion, we find that although some demographic attributes affect funding success, these effects are very small compared to the other indicators: borrowers' financial strength and their efforts to communicate with, and please, potential lenders. This outcome is substantially different from the documented discriminatory practices of financial institutions. Earlier we provided evidence for gender and race discrimination in institutional lending (Ladd 1998; Munnell et al. 1996; Blanchflower, Levine, and Zimmerman 2003). Even more relevant to our current discussion are articles comparing the *relative* impact of demographic variables and financial indicators in institutional lending decisions.

LaCour-Little (1999) performed a meta-analysis of 35 articles discussing racial discrimination in the mortgage industry. He reviewed articles from 1977 until 1997 and found mixed evidence: 16 articles show that race has a comparable or higher effect than other variables, while 10 articles find no racial discrimination (the other nine articles are inconclusive.) For example, Hunter and Walker (1996) found strong evidence for racial discrimination, such that borderline minority applicants were more likely to be rejected than borderline white applicants.

On the other hand, articles such as Black, Schweitzer, and Mandell (1978) show that while race is a significant parameter in institutions' mortgage decisions, other parameters are also significant. Gender was found to be a powerful variable in institutional lending decisions in several studies, among them Ladd (1998) and Berkovec et al. (1998). We, on the other hand, did not find gender to have a powerful effect on Prosper.com lenders.

Based on these findings, and comparing them to our results, we can conclude that in general there is perhaps less discrimination and more democratization in P2P lending communities when compared with institutional lending, 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. Additionally, in contrast to mortgages which are secured by the borrower's residence, the loans made on Prosper are unsecured. While this result is heartwarming for those who believe in fairness and equal opportunities, we must exercise caution because this conclusion is based on loan information taken from a single community. Even though the Prosper community is the largest and oldest one in the P2P loan market, replication of our results in other P2P lending communities is necessary in order to completely eliminate the hypothesis of discrimination.

Increasing the likelihood of funding success in P2P lending communities

Since borrowers' demographic attributes play almost no role in driving funding success of their loans, P2P lending communities appear to be a particularly congenial venue for certain consumer groups such as women, singles, divorced, and those with children to obtain unsecured loans at more attractive interest rates than they might be able to obtain through other sources such as payday lenders. The exception, as mentioned above, is one race variable that did emerge as significant in affecting funding 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 decision variables. As discussed earlier, the regression of starting interest rate on borrower characteristics did show that African Americans start their loan listings with a significantly lower interest rate than other borrowers. Such a strategy could backfire by dampening bidding momentum and reducing overall level of interest in the loan. One potential explanation for the choice of lower starting interest rate is reverse discrimination, in which banks offer African Americans better loan terms than to others. However, the literature does not support this claim. For example, Black and Schweitzer (1985) found evidence that white couples obtain better loan terms than minority couples. More recently Courchane and Nickerson (1997) found that minorities pay overages more frequently than whites.

Note that providing no race information on a loan request reduced the probability of funding success by roughly 1% compared to Caucasian borrowers, whereas African American buyers disclosing their race have roughly 3% lower probability of funding success. Hispanic borrowers actually had higher success rates than Caucasians, though this finding was based on a small sample size of 27 auctions.

The most influential predictors of a loan's likelihood of being funded successfully are the extent of personal information provided by borrowers, and their credit grades. Even after controlling for the decision variables that are conventionally seen as determining funding success, providing detailed personal information was its most influential driver. Regardless of their other personal attributes, the guidance to potential borrowers from this result is clear-cut: to be successful in P2P lending communities, 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 request 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 more 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 lending communities.

Despite our findings and our guidance to potential borrowers, it should be remembered that in our dataset only 10.5% of all the requests 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 light of this statistic, it is crucial to select all the decision 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.

Limitations and future research

Our research contributes to the growing literature on customer communities by studying decisions and bidding decisions of lenders in P2P lending communities. Prior community literature has shown that a participant's reputation is a crucial factor not only in engendering trust within the community, but in a broader sense, reputation mechanisms are important for the smooth ongoing functioning of customer communities (e.g., Mathwick, Wiertz and de Ruyter 2008). 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 lenders' behavior 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 lending communities. 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. Likewise, the effects of loan performance on such relevant community processes as social identification, attachment to the community, and community advocacy (e.g., Algesheimer et al., 2005) are also an important research issue that merit further attention.

Finally, it may be interesting to examine the aspect of altruism in P2P lending communities. While lenders certainly expect to earn interest, they also understand the risks and social benefits of such transactions. A regular lender, *Kevin*, posted the following message in one of the lender forums on the Prosper site:

> "It is a wonderful feeling to both help someone and generate a return on your money. It is financial voyeurism…once you start you cannot stop. It is highly addictive and enjoyable to invest in p2p lending, but guaranteed results (or even significant past results) are lacking… Proceed with caution, fully diversify, and have fun, but don't bet the farm."

TABLE 1
Descriptive Statistics of Variables in the Analysis
a) Means of continuous variables

Variable	Funded Loan Listings *N*=564		Unfunded Loan Listings *N*=4,806		All Loan Listings *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
Duration of listing (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

b) Loan funding success 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 Loan Decision Variables and Borrower Characteristics on Loan Funding Success

Model	Estimation sample (*N*=4,031) LMD	Estimation sample (*N*=4,031) Hit Prob	Validation sample (*N*=1,339) LOGL	Validation sample (*N*=1,339) 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 funding success (0/1)
X: Loan decision variables
Z: Borrower characteristics

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

	Starting Interest Rate			Loan Amount Requested (000s)			Duration of Listing		
	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

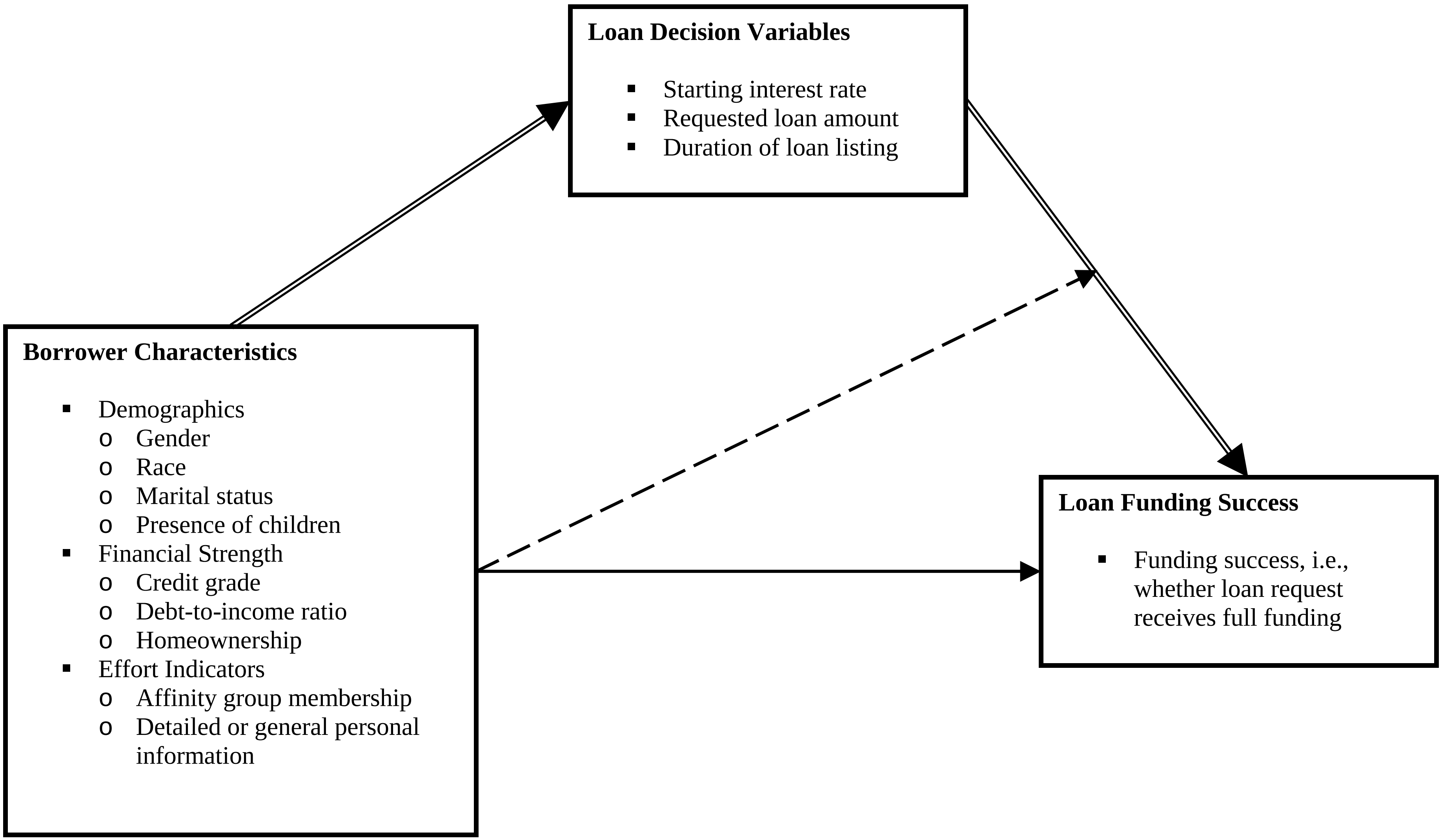
TABLE 4
Parameter Estimation Results from RCL, moderation (eq. 4), Y=f(X, Z)
(+ indicates 95% Highest Posterior Density region is above zero; - indicates 95% HPD region is below zero)

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 Lending Communities



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