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PERSON-TO-PERSON LENDING: THE PURSUIT OF (MORE) COMPETITIVE CREDIT MARKETS

*Le prêt de particulier à particulier : à la recherche de marchés de crédit (plus)
concurrentiels*

Completed Research Paper

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Abstract

Person-to-person lending (P2PL) on the Internet is a relatively new credit market. The success of these markets hinges on their ability to provide both borrowers and lenders the chance to improve on the opportunities available in traditional intermediated credit markets. In essence, P2PL must create a more competitive market. Empirical observations provide evidence that frictions exist in these markets, which generally move markets away from competitive outcomes. Currently, auctions are the most popular mechanism for P2PL. This paper develops and analyzes an equilibrium competing auction model of P2PL. Coordination frictions and the presence of non-creditworthy borrowers create an environment where many potentially productive transactions are not made and interest rate dispersion is observed. Additionally, if the market naturally segments into groups of similar borrowers then increased frictions in a segment may lead some portion of lenders to migrate to a different segment.

Keywords: Person-to-Person Lending, Price Dispersion, Competing Auction

Résumé

Le prêt de particulier à particulier sur internet est relativement nouveau sur le marché de crédit. Le succès de ces marchés dépend de leur capacité à créer un environnement plus concurrentiel. Nous présentons des preuves empiriques de frictions sur ces marchés. Ces frictions empêchent les marchés d'obtenir des résultats compétitifs. Nous développons et analysons un modèle d'enchères compétitives de prêt de particulier à particulier.

Introduction

Person-to-person lending (P2PL) on the Internet is a relatively new innovation. In these markets, prospective borrowers seeking unsecured personal loans create a loan request, a listing, and lenders offer to fund small portions of any particular loan. New websites facilitating P2PL continue to emerge with some focusing on formally structuring lending arrangements between family and friends, some facilitate P2P loans to borrowers in developing nations, and others deal in consumer loans between people who do not necessarily have a prior personal relationship. This paper investigates the last of these P2PL markets.

There are at least two motivating concepts behind P2PL. One is that individuals participating in these markets derive some social utility from borrowing directly from and lending directly to individuals. Another is that there are financial incentives for operating in such a market. Assuming financial intermediaries earn positive economic profits, P2PL offers borrowers and lenders the opportunity to cut out the intermediaries' role and enhance the surplus in credit markets.

There is burgeoning academic interest in P2PL on such topics as the value added services in P2PL markets (Berger and Gleisner 2008), and racial discrimination (Pope and Sydnor 2008), but there has not been much discussion on the fundamental promise of Person-to-Person lending to enhance welfare in credit markets and its ability to deliver on that promise. The purpose of this paper is to begin such a discussion.

Traditionally, intermediaries such as banks have played the central role in the transfer of funds between borrowers and lenders. In this paper we will use the term lender to mean individuals who supply funds to a credit market, be they P2P lenders or bank depositors. The market for consumer loans in the US is large – thousands of intermediaries, and millions of borrowers and lenders. One might expect this market to be well approximated by a model of perfect competition. In which case, similar borrowers would obtain identical interest rates on comparable loans. The reality is that traditional consumer credit markets do not behave in a perfectly competitive fashion. This is evident when one considers the presence of two similarly featured credit cards that carry different interest rates in a person's wallet or purse.

This is good news for P2PL proponents, but also an important reminder of the value proposition that P2PL must offer to be successful in the long run. Namely, P2PL must enhance credit market competitiveness.

There is evidence that the Internet can drive markets to a more competitive position (Brown and Goolsbee 2002). Yet, price dispersion on the Internet is still the rule rather than the exception even for homogeneous goods (Baye et. al. 2004; Brynjolfsson and Smith 2000; Clay et. al. 2001). With respect to P2PL the question remains, can direct lending through the Internet create a more competitive credit market?

This paper does not go so far as to provide a direct empirical or theoretical comparison of the competitive environment in traditional and P2P credit markets. We do provide some key empirical observations that P2PL markets cannot currently be described as competitive as well as a highly stylized competing auction model of P2PL which results in market imperfection.

The competing auction framework specifically considers the coordination frictions and need for search that dampen the efficiency of P2PL markets. Moreover, the models allow us to consider market equilibrium when there are distinct market segments, i.e. credit grade. We assume a market segment can be characterized by a ratio of creditworthy and non-creditworthy borrowers and some ability of lenders to distinguish between the two. Increasing the entrance of non-creditworthy borrowers to a market segment can cause lenders to migrate from the segment. This alters outcomes – interest rates and loan quantity – not just for members of the segment with the increased number of non-creditworthy borrowers, but market-wide. The model produces interest rate dispersion as a

consequence of stochastic levels of competition for individual loans and the posterior belief that a borrower is creditworthy conditional on the level of competition.

Next we provide a brief introduction to P2PL. The following section outlines the key empirical observations that being a P2P lender is not a frictionless proposition, antithetic to the notion of perfect competition, and that these frictions manifest themselves in substantial interest rate dispersion for similar borrowers. We proceed with a discussion of the price dispersion and competing auction literature before presenting and analyzing our competing auction models of P2PL.

P2PL Described

The following description of P2PL draws on the largest American P2P website Prosper.com as an example. The data analyzed in the next section are also from Prosper. Other P2PL markets are similar.

P2PL borrowers create loan requests, or listings, for three-year, unsecured loans in an amount ranging from \$1,000 to \$25,000 dollars. Posting a listing means consenting to the disclosure of credit information to certified lenders (see Table 1 for the credit and other information in a listing). In addition to credit information, prospective borrowers are allowed to describe the purpose of the loan, their financial situation, post photos, and publicly and/or privately answer questions submitted to them by lenders.

Table 1. Listing Information

Credit Related:	Other:
Credit Grade (AA, A, B, C, D, E, HR)	Descriptive Listing Title
Current Delinquencies	Description (free form text)
Bankcard Utilization	Images (picture of borrower, car to be purchased, etc.)
Occupation	Publicly Answered Lender Queries
Current Credit Lines	Amount Requested
Delinquencies Last 7 Years	Funding Option (Autofund or Auction style)
Employment Status	Maximum Allowable Interest Rate
First Recorded Line Of Credit	Borrower City
Income Range (top coded at 100K)	Borrower State
Credit Inquires in the Last 6 Months	
Time with Current Employer	
Number of Open Credit Lines	
Number of Public Records in the Last 10 Years	
Number of Public Records in the Last 12 Months	
Revolving Credit Balance	
Total Credit Lines	
Homeowner Status	
Debt-to-Income Ratio	

A listing only becomes a loan if lenders bid enough funds to cover the entire amount requested. This feature of the market requires some consensus on the part of a number of lenders that the listing should become a loan. Lenders choose how much they are willing to invest in the loan from a current minimum of \$50 to the full amount requested. Many lenders choose to bid the minimum amount on each loan thus diversifying across a large number of loans. Until recently, listings could run anywhere from three to ten days as chosen by the prospective borrower, but this was standardized to seven days for all listings. If a listing does not fully fund during the run-time then it expires. Borrowers may also withdraw a listing at any point before a loan is originated.

Prosper has two mechanisms for determining the interest rate on loans. First, a borrower can specify the interest rate they are willing to pay. This type of listing is called an autofund listing, and a listing closes at this borrower specified interest rate immediately upon receiving sufficient funding within the listing run-time. Second, the interest rate is set through a reverse auction mechanism. In auction style listings lenders bid what portion of the loan they want to fund as well as what interest rate they are willing to accept. Borrowers set the starting interest rate, or reservation price, which represents the maximum interest rate a lender can bid. At the end of the auction the interest rate on the loan is set to the minimum required to obtain a fully funded loan (a K + 1st price auction). So, those lenders that bid the lowest interest rates become the participating lenders on the loan, but the final interest rate is determined by the lowest outbid lender. The current paper will focus solely on the auction style P2P markets.

Prosper manages all payments on loans and the disbursement of payments to the individual lenders. Servicing the loan also includes reporting to the credit bureaus and initiating collections procedures and selling delinquent loans. Prosper's revenues come from two sources: 1) Prosper charges the borrower an origination fee when a listing becomes a loan, 2) Prosper assesses a service fee to lenders on each incoming payment.

Key Empirical Observations on P2PL

This section outlines some evidence of market frictions on Prosper.com. First, we show that substantial manual bidding takes place despite the availability of automated bidding tools. Second, there is evidence of interest rate dispersion on loans to borrowers with similar credit grades. If the market were competitive we would expect a uniform price. Finally, we provide evidence consistent with the notion that some lenders, and therefore the market, can discriminate between higher and lower risk borrowers within an objectively defined credit grade. Hence, lenders will engage in search. This evidence of market imperfection leads to questions about P2PL's ability to create a more competitive credit market.

Most data used in this analysis are readily accessible from Prosper's webpage which provides a data download of all current and historical publicly available information from the marketplace. Some data, such as payment histories, are available only to registered lenders.

Before discussing the empirical data, it is worthwhile to consider some anecdotal evidence the authors have gained from actual P2P lenders. First, lenders corroborate the importance and costly nature of search. Some lenders cite the time consuming aspect of being a lender as a reason for exiting the market. At a recent Prosper users conference, a lender who employs rather sophisticated models for identifying desirable listings confirmed that he still finds it necessary to review each listing before bidding and chooses not to bid on almost half the listings identified.

The data also point to search as an important component of lender behavior. Prosper allows lenders to place bids manually and with automated bidding agents. Data on which bids were placed by which method are not publicly available; however, one can assume that almost all bids placed shortly after a listing is posted (within five minutes) were automatically generated. This is because the agents continuously monitor the market and place bids when certain criteria are met. We use the term immediate bids rather than automatic bids to highlight that we are using a proxy for the number of bids placed by automated agents.

Figure 1 shows the proportion of lenders with at least two immediate bids in a given month out of those lenders with at least two total bids. At the end of October 2007 Prosper introduced and began actively promoting Portfolio Plans – predefined sets of automatic bidding criteria – which may account for the recent surge in immediate bids. Still, most lenders choose to place bids manually. Many people behave as though even relatively simple online transactions are surprisingly costly (Hann and Terwiesch 2003; Terwiesch, et. al. 2005), so rational lenders must derive some benefit from choosing to bid manually. One explanation, supported anecdotally, is that manual bidding provides lenders a chance to screen and evaluate listings before making bidding decisions. This information gathering is synonymous with search. Another explanation is that some lenders are trying to strategically time bids. If it is in fact possible to improve one's market outcomes through strategic behavior then this is further evidence of market imperfection.

Moreover, these data are consistent with P2P lending as a costly activity. The non-trivial number of lenders who appear to use automatic bidding underscores that for some people and in some situations the cost of manual bidding does not outweigh the benefits.

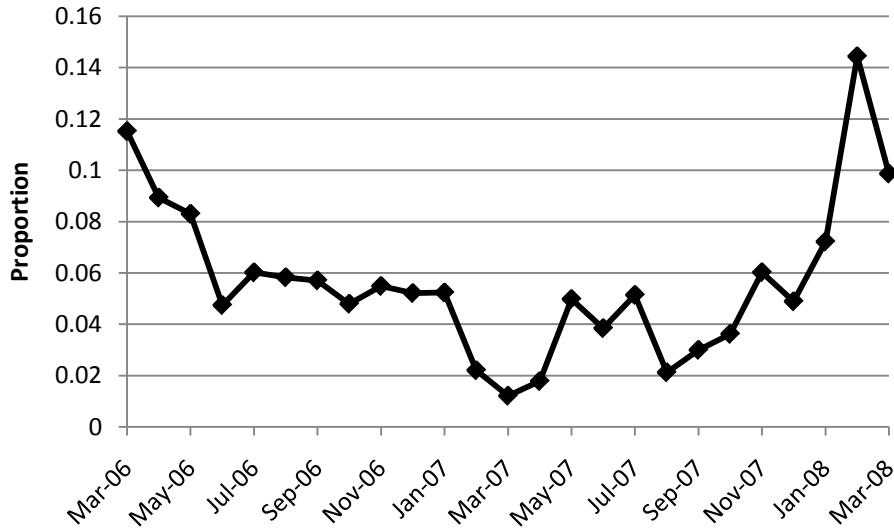


Figure 1: Proportion of Lenders Placing at Least Two Immediate Bids in a Month

Figure 2 is a scatter plot of interest rate by loan amount for all C credit grade borrowers receiving a loan during the second quarter of 2007. The actual APR of a borrower is slightly higher when origination fees are included, but these fees are not passed on to lenders. The points labeled late are those borrowers that went at least 31 days past due at some point in the first 12-15 months of the loan, while timely refers to all other loans. The dashed and solid lines are a non-parametric smoothing of the interest rate conditional on loan amount.

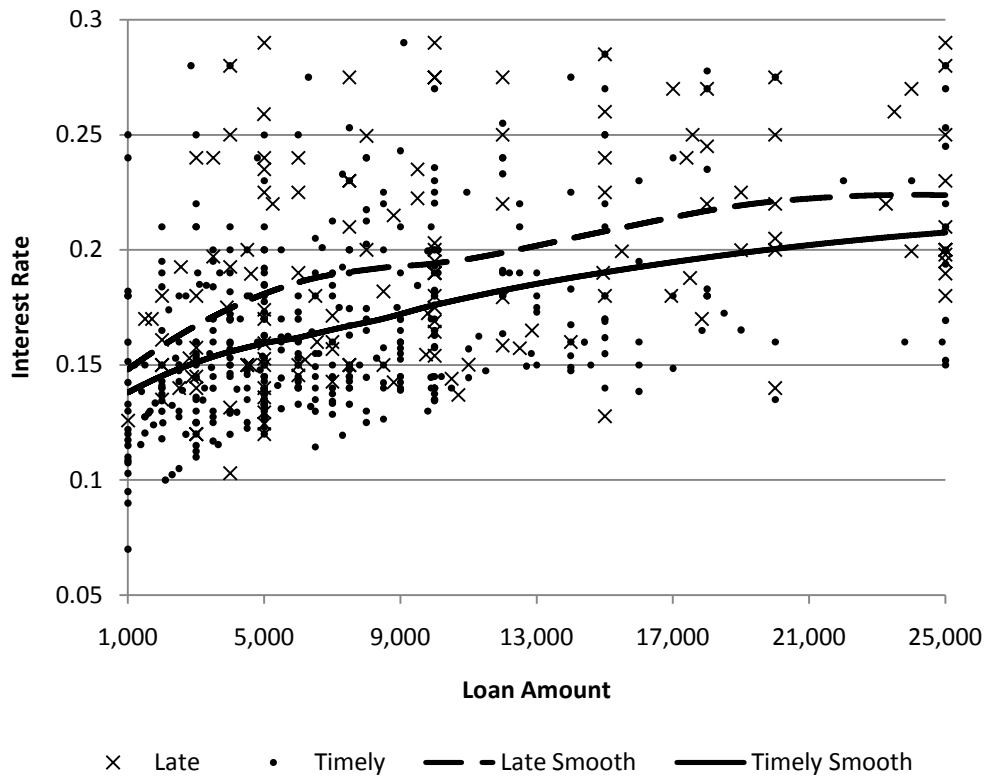


Figure 2. C Credit Grade Loan Interest Rates

Credit grades are based on Experian's Scorex PLUS model for predicting default risk on new credit accounts (Experian 2008; Prosper.com 2008). Considering the C grade borrowers in this figure all share similar default risk, we would expect a competitive credit market to offer them more or less the same interest rate on a similarly sized loan. But, the data show a striking amount of interest rate dispersion. Plots of other credit grades are similar.

Additionally, we see that those borrowers that become late are on average paying higher interest rates. There are multiple explanations for this observation. For instance, those people that obtain higher interest rates are burdened with larger payments which may increase the likelihood of late payments and default. Although, the difference between the average interest rates for the two groups is only about 2-3%. These data are also consistent with the idea that at least some lenders have an ability to distinguish higher and lower credit risks based on the additional information in listings. It is this possibility that makes search a part of these markets. In the models below we assume lenders have at least some ability to distinguish higher and lower credit risks within a market segment.

Literature Review

In his classic paper, Stigler (1961) points out that “[price] dispersion is ubiquitous even for homogeneous goods.” Why is it that markets for similar goods with large numbers of buyers and sellers do not necessarily converge to a single market clearing price? One important answer to this question is information. Market outcomes depend on who and how many people have access to certain information, how much information costs and how much effort is required to gather it, and the time constraints decision makers face.

A half-century of economic inquiry has produced numerous models that support equilibrium price dispersion and lend insight into how market frictions such as search costs lead to non-competitive market outcomes. The interested reader is referred to one of the many excellent surveys on search theory for a broad discussion of the topic (see for example Baye, et. al. 2006; McCall and McCall 2008; Rogerson, et. al. 2005).

As the preceding section outlined, P2PL markets do not seem aptly described as a frictionless marketplace. The information that borrowers provide above and beyond that found in a credit report may contain valuable signals about creditworthiness. In an auction setting, interest rates and the number of loans made will depend on how many lenders converge on individual listings. In a large market, complete coordination is not something we should expect.

In the following sections we develop a competing auction model of P2PL. The typical set up for competing auctions is as follows. There are a large number of sellers of a homogeneous indivisible good and a large number of buyers with unit demand. Buyers typically have heterogeneous valuations for the good. Sellers offer second price auctions for the good and are free to set a reserve price for the auction. Buyers observe the reserve prices and simultaneously choose a single auction to attend.

Julien et al. (2000) model a labor market in a competing auction framework. In their model, homogeneous employees offer their services to the highest bidder above some reservation wage. Homogeneous employers simultaneously choose employees to recruit. In a large market, employees post reservation wages equal to their best alternative to employment. This is not an uncommon result in competing auctions (McAfee 1993; Peters & Severinov 1997). Wage dispersion arises because the wage depends on whether one or more employers recruit the same employee.

Our models diverge from the typical models in a few important ways. In P2PL markets it is the sellers (lenders) that try to locate a buyer (borrower) in a reverse auction. However, the borrowers may differ in their creditworthiness, and lenders only receive a signal of a borrower's creditworthiness after selecting the auction. Additionally, we consider multiple market segments characterized by different creditworthy to non-creditworthy borrower ratios. This partially corresponds to the work of Burdett et al. (2001) in which some sellers have more than one unit of a good to sell making it more likely that a buyer will be served if she visits the seller.

P2P Lending as Competing Auctions

The general structure of a P2PL market is as follows. Borrowers come to the market to purchase credit. Upon arriving at the market they will post a maximum price, or reservation price, that they are willing to pay for the credit. Final prices are determined via auction. Lenders come to the market to find borrowers to whom they will extend credit. They submit interest rate bids on borrowers' credit requests at or below the posted reservation prices.

Lenders have access to structured objective credit information on prospective borrowers which they use to segment the market into groups of similar borrowers. Within these segments there is still diversity in creditworthiness and additional screening may be carried out to further determine a borrower's creditworthiness. For instance lenders may evaluate the completeness of the subjective information or its consistency with the objective data. Additionally, a more thorough evaluation of the objective data may also be possible.

For simplicity, borrowers may be either creditworthy (*C*) or non-creditworthy (*NC*). Creditworthy borrowers fully intend to repay their loan and have the potential to do so, but non-creditworthy borrowers come to the market intending to default or with no means to actually repay the loan. Creditworthy borrowers repay their loan with certainty and non-creditworthy borrowers default and pay nothing with certainty.

We consider two market segments, $s \in \{l, h\}$, where all *l*-borrowers (low risk) are creditworthy but only a fraction, Γ , of *h*-borrowers (high risk) are creditworthy. In the first model presented below lenders can always identify a non-creditworthy borrower, whereas in the second model there will be some probability that a lender incorrectly classifies a non-creditworthy borrower as creditworthy.

Borrowers are in the market to purchase one unit of credit and each lender has one unit to sell. Prices in this market are interest rates. The loans are either paid back in full with interest, in which case a lender earns a return equal to the final interest rate on the loan, or the borrower defaults and repays nothing, which corresponds to a payoff of -1. Assume lenders who do not participate on a loan leave the market with a payoff of 0. Lenders are risk neutral. In a dynamic model this fallback value would be the expected value of participating in the market again in a future period.

We will also assume creditworthy borrowers have access to a financing option outside the market. This modeling choice reflects the current position of P2PL as an alternative to traditional credit markets. Let ω_l and ω_h represent these alternative options for creditworthy low and high risk borrowers, respectively. The non-creditworthy borrowers will behave as if they have ω_h as an outside option because to do otherwise would signal their type.

We present a one-period, three-stage game. First, borrowers set their reservation prices. Second, lenders choose a single borrower for inspection. Third, if the lender has chosen a borrower she believes is creditworthy, she competes in an English auction in which her strategy is to bid until she is indifferent between the expected value of winning and taking the outside option of 0.

Perfect Screening

This section assumes non-creditworthy borrowers can be identified by a lender inspection. The perfect screening model is a special case of the model presented in the next section, which is a more general but less analytically tractable model.

Lenders will observe B_l and B_h borrowers in the two segments with each borrower posting a respective reservation price. Additionally, it is common knowledge that only ΓB_h high risk borrowers are creditworthy and that there are $L + 1$ lenders searching for loans. Much of the analysis that follows is from the perspective of a single lender, so L is the number of other lenders in the market from the perspective of an individual lender.

We seek a symmetric equilibrium in which all *l*-borrowers post the same reservation price ρ_l^* , all *h*-borrowers post ρ_h^* , and the probability that a lender inspects a specific *l*-borrower or *h*-borrower is $q_l^*(\rho_l^*, \rho_h^*)$ and $q_h^*(\rho_l^*, \rho_h^*)$, respectively.

Lender Strategy

Consider a scenario in which one *l*-borrower posts ρ_l^d while the rest post ρ_l and all *h*-borrowers post ρ_h . The symmetric mixed strategy lender response is to inspect a nondeviating *l*-borrower with probability q_l , the deviating *l*-borrower with probability q_l^d , and an *h*-borrower with probability q_h .

In accord with standard game theoretic analysis, a lender must be indifferent between selecting any particular borrower when all other lenders play the equilibrium mixed strategy; therefore, an equilibrium will satisfy:

$$\begin{aligned}\rho_l \cdot (1 - q_l)^L &= \rho_h \Gamma \cdot (1 - q_h)^L \\ \rho_l \cdot (1 - q_l)^L &= \rho_l^d \cdot (1 - q_l^d)^L \\ q_l^d + (B_l - 1)q_l + B_h q_h &= 1 \\ q_l^d \geq 0, q_l \geq 0, q_h &\geq 0.\end{aligned}$$

The first two expressions simply equate the expected return from playing any individual pure strategy when all other lenders employ the equilibrium mixed strategy. The expected payoff is the probability of being the only lender on a creditworthy listing times the reservation price of the listing. Any outcome other than being the sole lender on a creditworthy borrower yields a payoff of 0. The last two expressions assure the probabilities sum to one and all probabilities are non negative.

The first three expressions form a system of equations that can be solved for $q_l^d(\rho_l^d, \rho_l, \rho_h)$, $q_l(\rho_l^d, \rho_l, \rho_h)$, $q_h(\rho_l^d, \rho_l, \rho_h)$:

$$q_l^d = \frac{\left(2 - B_l - B_h + (B_l - 1)\left(\frac{\rho_l^d}{\rho_l}\right)^{\frac{1}{L}} + B_h \cdot \left(\frac{\rho_l^d}{\rho_h \Gamma}\right)^{\frac{1}{L}}\right)}{\left(1 + (B_l - 1)\left(\frac{\rho_l^d}{\rho_l}\right)^{\frac{1}{L}} + B_h \cdot \left(\frac{\rho_l^d}{\rho_h \Gamma}\right)^{\frac{1}{L}}\right)}, q_l = \frac{\left(-B_h + \left(\frac{\rho_l}{\rho_l^d}\right)^{\frac{1}{L}} + B_h \cdot \left(\frac{\rho_l}{\rho_h \Gamma}\right)^{\frac{1}{L}}\right)}{\left(-1 + B_l + \left(\frac{\rho_l}{\rho_l^d}\right)^{\frac{1}{L}} + B_h \cdot \left(\frac{\rho_l}{\rho_h \Gamma}\right)^{\frac{1}{L}}\right)}, q_h = \frac{\left(1 - B_l + \left(\frac{\rho_h \Gamma}{\rho_l^d}\right)^{\frac{1}{L}} + (B_l - 1)\left(\frac{\rho_h \Gamma}{\rho_l}\right)^{\frac{1}{L}}\right)}{\left(B_h + \left(\frac{\rho_h \Gamma}{\rho_l^d}\right)^{\frac{1}{L}} + (B_l - 1)\left(\frac{\rho_h \Gamma}{\rho_l}\right)^{\frac{1}{L}}\right)}.$$

One can derive similar expressions for the scenario of an h -borrower deviating.

Borrower Strategy

With the lender responses to a vector of interest rates specified, we can determine the reservation prices borrowers will post in equilibrium. We must consider the deviation of an individual borrower from the reservation price posted by similar borrowers, and this must be done for both l - and h -borrowers.

Let $\rho_l = \{\rho_l^d, \rho_l, \rho_h\}$ and $D_l^d(\rho_l) = \frac{\partial}{\partial \rho_l^d} [q_l^d(\rho_l)]$. An l -borrower who is considering deviating from the reservation price posted by similar borrowers, ρ_l , will choose ρ_l^d to:

$$\min_{\rho_l^d} \omega_l P(\text{no bidders}) + \rho_l^d P(\text{exactly one bidder}),$$

or

$$\min_{\rho_l^d} \omega_l \cdot (1 - q_l^d(\rho_l))^{L+1} + \rho_l^d \cdot (L + 1) \cdot q_l^d(\rho_l) \cdot (1 - q_l^d(\rho_l))^L.$$

The first order condition for the preceding minimization problem is,

$$\begin{aligned}-\omega_l \cdot (1 - q_l^d(\rho_l))^L \cdot (L + 1) \cdot D_l^d(\rho_l) + (L + 1) \cdot q_l^d(\rho_l) \cdot (1 - q_l^d(\rho_l))^L + \\ \rho_l^d \cdot (L + 1) \cdot (D_l^d(\rho_l)) \cdot (1 - q_l^d(\rho_l))^L - \rho_l^d \cdot (L + 1) \cdot q_l^d(\rho_l) \cdot (1 - q_l^d(\rho_l))^{L-1} \cdot (L) \cdot D_l^d(\rho_l) = 0.\end{aligned}$$

Again, we are interested in the symmetric equilibrium where all l -borrowers find it optimal to post ρ_l^* . Therefore, the first order condition must be satisfied when we replace ρ_l^d with ρ_l . If this were not the case then the deviator would find it beneficial to set a different reservation price. Ideally we would make this substitution and solve for ρ_l thus deriving the l -borrowers' reaction to a posted ρ_h , but this is not possible. We can however solve for ρ_h ,

$$\rho_h = \frac{\rho_l \cdot (B_h)^L}{\Gamma} \left[\frac{\omega_l \cdot (1 - B_h - B_l) - \rho_l \cdot (1 - B_h - B_l - L)}{\omega_l \cdot (1 - 2B_l + B_l^2 + B_l B_h - B_h) - \rho_l \cdot (1 - 2B_l + B_l^2 + B_l B_h - B_h + L - LB_h)} \right]^L.$$

This results in an inverse reaction function – given ρ_l , for which ρ_h is it a best response. Repeating the preceding steps for a deviating h -borrower yields,

$$\rho_l = \Gamma \rho_h \cdot (B_l)^L \left[\frac{\omega_h \cdot (1 - B_h - B_l) - \rho_h \cdot (1 - B_h - B_l - L)}{\omega_h \cdot (1 - 2B_h + B_h^2 + B_h B_l - B_l) - \rho_h \cdot (1 - 2B_h + B_h^2 + B_h B_l - B_l + L - LB_h)} \right]^L.$$

The equilibrium reservation prices, ρ_l^* and ρ_h^* , simultaneously solve these two equations. Solving this system numerically for a number of examples reveals that in a large market $\rho_l^* \approx \omega_l$ and $\rho_h^* \approx \omega_h$. Figure 3 is a representative example. In this example the model parameters are: $\Gamma = .9$, $\omega_l = .1$, $\omega_h = .15$. Also, the horizontal axis shows the number of creditworthy borrowers in each segment ($B_l = \Gamma B_h$). Each line is for a separate lender to *creditworthy* borrower ratio. As the market scale increases the posted reservation price approaches the value of the external financing option.

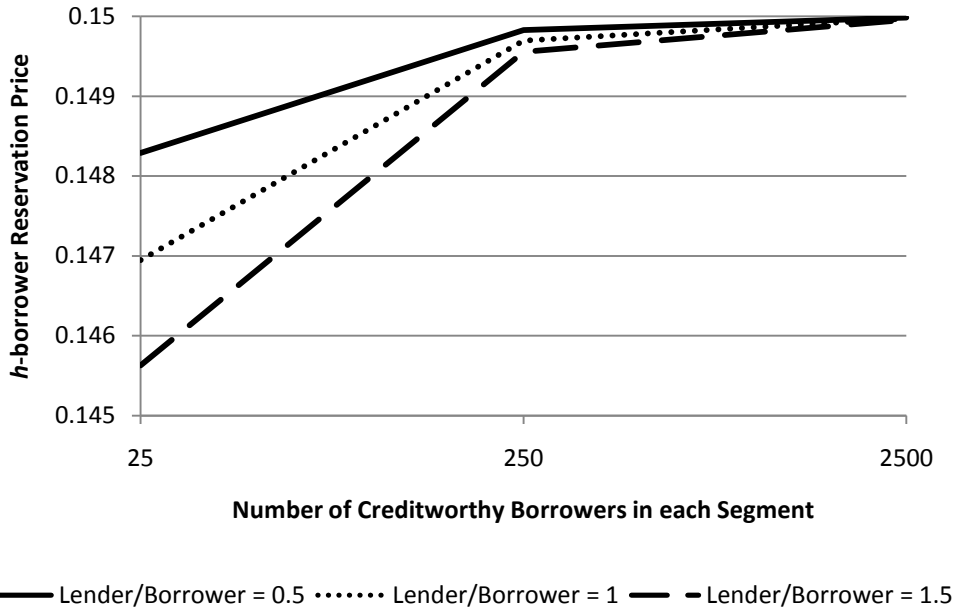


Figure 3. Reservation Price Converging to Best Alternative

Imperfect Screening

We now modify the model presented in the previous section to include the possibility that a non-creditworthy borrower will receive a loan. This is both more realistic and actually gives non-creditworthy borrowers a reason to be in the market. Again the market contains B_l l -borrowers, B_h h -borrowers (of which Γ are creditworthy), and $L + 1$ lenders. Assume creditworthy borrowers are classified as creditworthy with probability 1, $P(\text{deem } C|C) = 1$; however, lenders independently misclassify non-creditworthy borrowers as creditworthy with probability p , $P(\text{deem } C|NC) = p$.

Again, lenders will compete in an English auction. If a lender deems a borrower to be non-creditworthy she does not participate in the auction, so lenders will only observe the number of other lenders that have deemed a borrower to be creditworthy. Observing competing lenders will lead to a higher degree of confidence that an h -borrower is

creditworthy. This increased probability that a borrower is creditworthy will be reflected in the lowest rate a lender is willing to accept – her reservation value. Hence, lenders have a *reservation value* for a borrower's listing which is based on the likelihood the loan is repaid, not to be confused with borrowers' *reservation price*, which is the posted maximum interest rate on the listing.

The stages (reservation price posting, borrower selection and inspection, and bidding) remain the same. We assume that after selecting a borrower for inspection lenders ignore all market activity on other listings. So, reservation values are conditioned on the number of competing lenders on the selected borrower instead of all market activity.

Lender Reservation Values

If a lender believes an h -borrower is creditworthy there is still the possibility that the borrower is non-creditworthy, and the amount she is willing to bid will depend on the likelihood the borrower was misclassified. When lenders independently select a borrower with probability q , then from an individual lender's perspective $N \sim \text{binomial}(L, q)$ is the random number of other lenders that select the same listing. Lenders do not observe this value. Rather, they observe bids from other lenders who think the borrower is creditworthy; therefore, $X \sim \text{binomial}(N, p)$ when borrower type = NC and $X = N$, when borrower type = C .

Let $\phi(x)$ denote the probability that a borrower is creditworthy given that a lender believes the borrower is creditworthy and observes x competing lenders (who have also deemed the borrower creditworthy). By application of Bayes rule,

$$\begin{aligned} \phi(x) &= \frac{P(\text{lender} + x \text{ deem } C|C)P(C)}{P(\text{lender} + x \text{ deem } C|C)P(C) + P(\text{lender} + x \text{ deem } C|NC)P(NC)} \\ &= \frac{P(N = x)\Gamma}{P(N = x)\Gamma + p \cdot (1 - \Gamma)P(X = x|NC)}, \end{aligned}$$

where

$$P(X = x|NC) = \sum_{n=x}^L \binom{n}{x} p^x (1-p)^{n-x} P(N = n).$$

After some manipulation,

$$\phi(x) = \frac{\frac{\Gamma}{(L-x)!}}{\frac{\Gamma}{(L-x)!} + p^{x+1}(1-\Gamma) \sum_{n=x}^L \frac{1}{(n-x)!(L-n)!} \left(\frac{q(1-p)}{1-q}\right)^{n-x}}.$$

In the perfect screening model competition on a listing drove interest rates to lenders' fall back option, 0, because there was no uncertainty about a borrower's type after evaluation. In the current model competition will drive rates to the point where expected return is 0, and these rates will differ depending on the number of competing lenders. In the previous model observed interest rates are either reservation prices or 0, but in this model a greater variety of prices will be observed based on the amount of competition.

Let $b(x)$ be the reservation value of a lender when she observes x competing lenders and believes the borrower is creditworthy. This reservation value makes the lender indifferent between her fall back value 0 and the expected return from a winning bid; therefore, $\phi(x) \cdot b(x) + [1 - \phi(x)] \cdot (-1) = 0$, and $b(x) = [1 - \phi(x)]/\phi(x)$.

Equilibrium

Characterizing equilibrium in this model is more difficult because we cannot get nice closed form expressions for the equilibrium lender mixing strategy. We outline below the procedure we used to numerically arrive at the equilibrium values q_l^* , q_h^* , ρ_l^* , and ρ_h^* . The general idea is to iteratively propose candidate borrower reservation prices until a fixed point is found where the deviators' best response and the candidate reservation prices match. We have not developed a formal proof that convergence to this fixed point necessarily constitutes an equilibrium.

As before the expected payoff to a lender from selecting any particular borrower must be the same. Recall that competition among lenders on a listing drives interest rates to the point where the expected return of a winning bid is 0. So, the only scenarios that enter into the expected payoff from selecting a particular listing are those when the lender is the only bidder. All terms when competition is observed net out.

The expected payoff to a lender from selecting an h -borrower posting ρ when all other lenders are searching this borrower with probability q is,

$$\begin{aligned} V_h(\rho, q) &= \rho \cdot P(X = 0|C)P(C) + (-1)p \cdot P(X = 0|NC)P(NC) \\ &= \rho \cdot P(N = 0)\Gamma - p \cdot (1 - \Gamma)P(X = 0|NC) \\ &= \rho\Gamma \cdot (1 - q)^L - p \cdot (1 - \Gamma) \sum_{n=0}^L \uparrow(1 - p)^n \binom{L}{n} q^n (1 - q)^{L-n}. \end{aligned}$$

The first part of the expression is the probability the lender faces no competition on a creditworthy borrower times the payoff that occurs. The second part is the probability that no other lenders bid and the borrower is non-creditworthy, resulting in a payoff of -1.

All l -borrowers are creditworthy, so a lender's expected payoff when selecting an l -borrower posting ρ when all other lenders select this borrower with probability q is:

$$V_l(\rho, q) = \rho \cdot (1 - q)^L.$$

If one l -borrower posts ρ_l^d while the rest post ρ_l and all h -borrowers post ρ_h , then a condition for a symmetric equilibrium is $V_l(\rho_l, q_l) = V_h(\rho_h, q_h)$ and $V_l(\rho_l, q_l) = V_l(\rho_l^d, q_l^d)$. Similarly, when one h -borrower deviates an equilibrium condition is $V_l(\rho_l, q_l) = V_h(\rho_h, q_h)$ and $V_l(\rho_l, q_l) = V_h(\rho_h^d, q_h^d)$.

Consider the decision problem of a deviating l -borrower. Because ρ_l and ρ_h are treated as fixed, the deviator will select ρ_l^d with the knowledge that it will affect the probability lenders assign to the selection of all borrowers. In choosing ρ_l^d , the borrower also effectively chooses q_l^d , q_l , and q_h . The deviating borrower faces the following non-linear optimization problem in which she minimizes her expected payout with decision variables $\rho_l^d, q_l^d, q_l, q_h$:

$$\min \omega_l \cdot (1 - q_l^d)^{L+1} + \rho_l^d \cdot (L + 1)q_l^d \cdot (1 - q_l^d)^L$$

subject to:

$$V_l(\rho_l, q_l) = V_h(\rho_h, q_h)$$

$$V_l(\rho_l, q_l) = V_l(\rho_l^d, q_l^d)$$

$$(B_l - 1)q_l + B_h q_h + q_l^d = 1$$

$$q_l, q_h, q_l^d \geq 0, \rho_l^d \leq \omega_l.$$

Likewise, a deviating h -borrower will minimize her expected payout by choosing $\rho_h^d, q_h^d, q_l, q_h$:

$$\min \omega_h \cdot (1 - q_h^d)^{L+1} + \rho_h^d \cdot (L + 1)q_h^d \cdot (1 - q_h^d)^L + \sum_{n=2}^{L+1} \uparrow b(n-1) \binom{L+1}{n} (q_h^d)^n (1 - q_h^d)^{L+1-n}$$

subject to:

$$V_l(\rho_l, q_l) = V_h(\rho_h, q_h)$$

$$V_l(\rho_l, q_l) = V_h(\rho_h^d, q_h^d)$$

$$B_l q_l + (B_h - 1)q_h + q_h^d = 1$$

$$q_l, q_h, q_h^d \geq 0, \rho_h^d \leq \omega_h.$$

An equilibrium $\{\rho_l^*, \rho_h^*, q_l^*, q_h^*\}$ is identified if: 1) a deviating l -borrower's best response to $\rho_l = \rho_l^*$ and $\rho_h = \rho_h^*$ is to post $\rho_l^d = \rho_l^*$, 2) a deviating h -borrower's best response to $\rho_l = \rho_l^*$ and $\rho_h = \rho_h^*$ is to post $\rho_h^d = \rho_h^*$, and 3) all lenders are indifferent between selecting any individual borrower given all other lenders select borrowers using q_l^* and q_h^* .

A procedure for finding such an equilibrium proceeds as follows:

1. Set ρ_l^c and ρ_h^c to a candidate equilibrium
2. Set $\rho_l = \rho_l^c$ and $\rho_h = \rho_h^c$
3. Solve the deviating l -borrower's optimization problem
4. Round the optimal ρ_l^d to four decimal places in the direction that yields the lower objective function value inclusive of lender response
5. Set $\rho_l = \rho_l^d$, where ρ_l^d is the rounded value from step 4
6. Solve the deviating h -borrower's optimization problem
7. Round the optimal ρ_h^d to four decimal places in the direction that yields the lower objective function value inclusive of lender response
8. Set $\rho_h = \rho_h^d$, where ρ_h^d is the rounded value from step 7
9. If $\rho_l = \rho_l^c$ and $\rho_h = \rho_h^c$, then $\rho_l^* = \rho_l$ and $\rho_h^* = \rho_h$
10. Else, Set $\rho_l^c = \rho_l$ and $\rho_h^c = \rho_h$ and return to step 3

Based on the results from the previous section and the common result that reservation prices in competing auctions tend toward the poster's best alternative (Julien et al. 2000; McAfee 1993; Peters and Severinov 1997), our initial candidate was $\rho_l^c = \omega_l$ and $\rho_h^c = \omega_h$. Rounding is consistent with the fact that interest rates in these markets are to 4 decimal places. The numerical examples we present below were derived with the preceding procedure. In all cases ρ_l^* and ρ_h^* are very close to ω_l and ω_h . This is consistent with the prior competing auction results. Furthermore, when $p = 0$ we have a special case of the perfect screening model. For the numerical results we present in the following section, when $p = 0$ this procedure and the equilibrium from the analytical results are the same (accounting for rounding). This suggests that for the cases we present, we have identified an equilibrium.

Analysis

As we pointed out in the introduction, the model we have outlined does not get us to the point where we can make any firm statements about person-to-person lending's capacity to create more competitive credit markets. In fact, the structure of the current model actually forces the conclusion that P2PL is welfare enhancing. The worst case scenario for all market participants is that they receive their fallback option and there is the possibility to do better. Additionally, this outside option is exogenous and is not tied to the other parameters of the model. However, a slightly richer dynamic model that incorporates search costs will be a basic building block of a more comprehensive model.

That disclaimer aside, this model does produce several of the empirical facts found in the Prosper data and allows us to consider how market frictions impact outcomes. The analysis that follows is based on numerical results. In all cases we assume the number of lenders is 500, the number of l -borrowers is 250 and the external financing options are $\omega_l = .1$ and $\omega_h = .15$ for l -borrowers and h -borrowers, respectively. The misclassification probability, p , and the fraction of creditworthy h -borrowers, Γ , will be varied. In all cases we hold the number of creditworthy h -borrowers at 250, so $B_h = 250/\Gamma$. With this setup there is the potential for all lenders to participate on a loan, but in a competing auction framework this is far from the expected outcome.

An important empirical observation from Figure 2 was the substantial interest rate dispersion for borrowers with similar credit grades. Table 2 provides a specific example of h -borrowers' equilibrium outcomes for a given scenario. The table shows the interest rate that would prevail on a loan when different numbers of competing bidders arrive. The model does in fact produce a distribution of interest rates as a result of the lender evaluations and the random number of arriving lenders. The table also provides the probability that each specific number of bids is observed conditional on creditworthiness. Also evident is the higher average interest rate for non-creditworthy borrowers, mirroring what we observed in Figure 2. For the same set of parameters the average interest rate for an l -borrower is .052 and the probability an l -borrower gets a loan is almost .7. So an l -borrower gets a loan with higher probability and when she gets a loan the expected savings when compared to the outside option is greater than the expected savings for an h -borrower that receives a loan. All creditworthy borrowers are in fact the same in this model, but being associated with the high risk segment means creditworthy h -borrowers do worse than creditworthy l -borrowers.

Table 2. *h*-borrower Equilibrium Outcome ($\Gamma = .9$, $p = .5$)

Bids	Int. Rate	P(bids=x C)	P(bids=x NC)
0	NA	0.48	0.69
1	0.1500	0.35	0.25
2	0.0400	0.13	0.05
3	0.0200	0.03	0.01
4	0.0100	0.01	0
5	0.0050	0.00	0
E(Loan Int. Rate C):		0.1131	
E(Loan Int. Rate NC):		0.1308	

Another empirical observation is that the probability a prospective borrower gets a loan decreases with credit grade. This is evident in Table 3 which summarizes Prosper listings that ran between March 1, 2007 and October 30, 2007 and had an amount requested below \$5000, debt-to-income ratio below .4, current delinquencies equal to 0, and delinquencies in past 7 years less than 4. Pope and Sydnor (2008) also find that credit grade is an important predictor of a successful listing even after adding other controls. This pattern is also noticeable in our competing auction framework.

Figure 4 shows the total probability a lender selects a listing from the *l*-segment of the market ($250 \cdot q_i^*$). Each curve is for a different misclassification probability and the horizontal axis shows the fraction of creditworthy borrowers in the *h*-segment. In general, as more non-creditworthy borrowers enter the *h*-segment (as Γ decreases), more of the traffic becomes concentrated in the *l*-segment. The effect is more pronounced when it is more difficult for lenders to tell the creditworthy from the non-creditworthy. Tying this result to the Prosper data, it is more appropriate to think of borrowers as being “sufficiently” creditworthy within a given credit grade. It is certainly the case that borrowers with AA credit are more likely to repay their loans than a high risk HR borrower, but this is presumably compensated for in the interest rates. Even within the HR category there may be borrowers that represent a good risk/return trade-off and others that do not, hence the “sufficiently” creditworthy. If lower credit grades generally have fewer sufficiently creditworthy borrowers, then the frictions are higher in those markets (finding a sufficiently creditworthy borrower takes more effort) and lenders may choose to investigate more listings in the better credit categories. This could produce outcomes as in Table 3.

Table 3. Empirical Funding Outcomes

Credit Grade	Listings	Funded Listings	Funding Probability
AA	426	293	0.688
A	287	187	0.652
B	276	164	0.594
C	427	233	0.546
D	663	230	0.347
E	472	110	0.233
HR	964	120	0.124

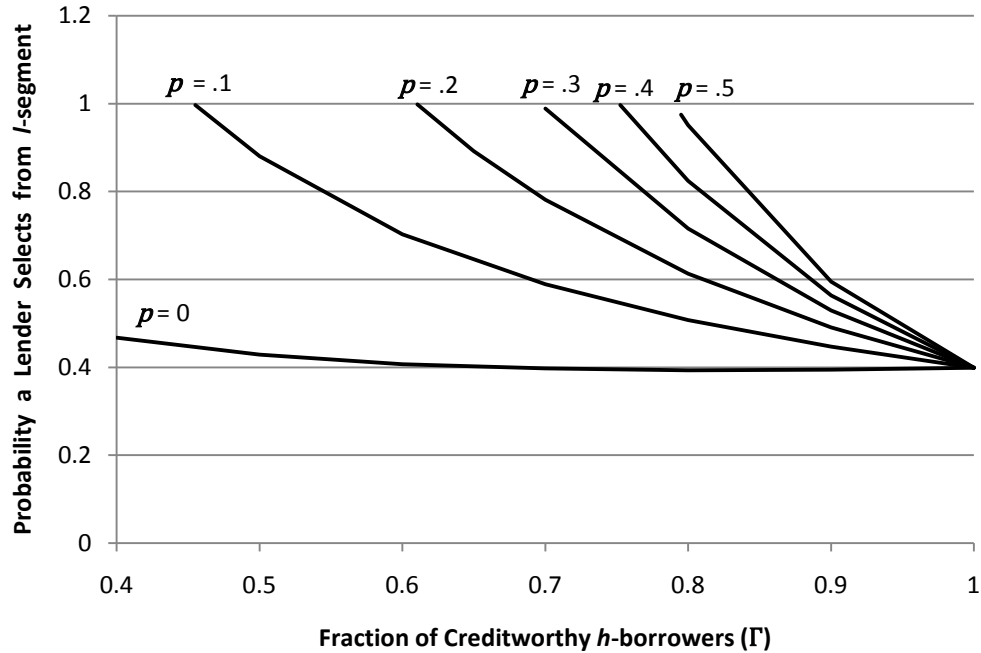


Figure 4. Lender Migration to l-segment

An important point is that the number of loans to h -borrowers decreases when more non-creditworthy borrowers are present not only because these entrants are less likely to get a loan, but also because lenders in aggregate are less likely to select from the h -segment. Simply looking at the empirical summaries as in Table 3 may overstate the number of non-creditworthy borrowers because they ignore the impact frictions have on what market segments lenders search most frequently. The reduced competition for h -borrowers when frictions are high also means higher average interest rates in that segment.

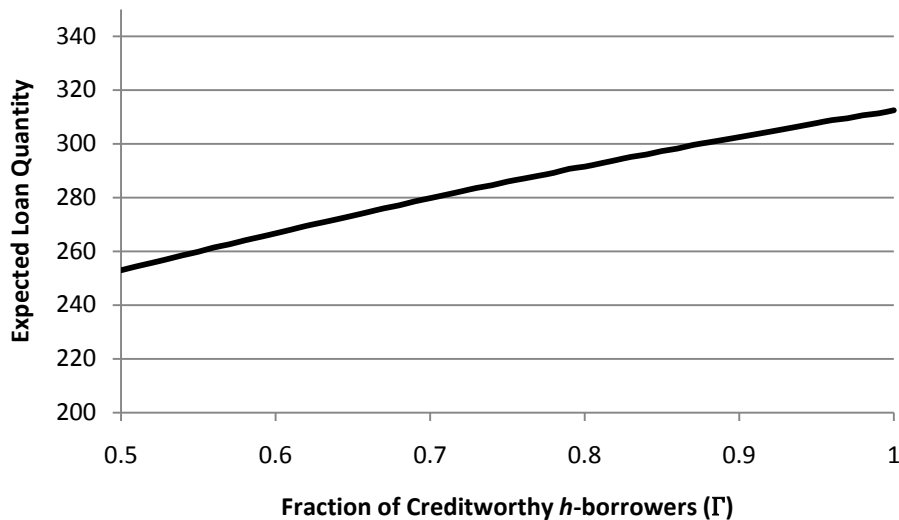


Figure 5. Expected Number of Loans Market-Wide

Figure 5 shows the expected number of loans created in the perfect screening model ($p = 0$) as the number of non-creditworthy borrowers is varied. Even when all borrowers are creditworthy, the expected number of loans is less than 320 out of the 500 possible. The addition of non-creditworthy borrowers causes additional difficulty in the productive matching of borrowers and lenders.

Clearly the competing auction environment of P2PL, with its interest rate dispersion and missed opportunities for productive matches, does not lead to a competitive market outcome.

Conclusion

In this paper we have provided empirical evidence that P2PL markets involve search and that the interest rates for similar borrowers exhibit substantial dispersion. We developed a highly stylized competing auction model, which despite its simplifying assumptions still exhibits many of the features found in P2PL data. The motivation for this research was to consider the potential for P2PL in creating a more competitive credit market. A more comprehensive model is needed to fully understand the potential for P2PL, but the competing auction framework appears to be a reasonable departure point.

A more complete model would have a number of moving parts. First, we have completely abstracted from the fact that it typically takes a group of lenders to fund a loan. In some ways this adds friction, the listing a lender has bid on may never become a loan, but it also has a coordination aspect. A complete model should also allow for the endogenous entry of market participants and for interaction between the intermediated and P2P credit markets. The one period assumption in this paper is also very restrictive and should be replaced by a richer dynamic model that accounts for search costs and perhaps other opportunity costs borne by market participants. A particularly interesting path for future research is to empirically estimate the parameters of a model like the one presented above.

The primary parameters in the model are in some ways under the control of P2P market operators or perhaps a third party service provider. Tools could be provided to aid in screening listings and policies could be put in place to reduce the entry of non-creditworthy borrowers. Prosper has indeed taken some steps along these lines. Prospective borrowers are given guidance on a starting interest rate. This could be the difference between a borrower being “sufficiently” creditworthy and not. Similarly, lenders receive warnings if they bid an interest rate too low to compensate for the observed historical default rate on similar listings.

The power of the Internet to link one individual to another for all manner of human activity is profound, and person-to-person lending is a bright new example of that power. Time will tell if these markets truly have the ability to bring about competitive change in the credit markets.

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