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Mingfeng Lin, Nagpurnanand R. Prabhala, Siva Viswanathan,

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Judging Borrowers by the Company They Keep: Friendship Networks and Information Asymmetry in Online Peer-to-Peer Lending

Mingfeng Lin
Eller College of Management, University of Arizona, Tucson, Arizona 85721, mingfeng@eller.arizona.edu

Nagpurnanand R. Prabhala, Siva Viswanathan
Robert H. Smith School of Business, University of Maryland, College Park, Maryland 20742
{nprabhal@rhsmith.umd.edu, sviswana@rhsmith.umd.edu}

We study the online market for peer-to-peer (P2P) lending, in which individuals bid on unsecured microloans sought by other individual borrowers. Using a large sample of consummated and failed listings from the largest online P2P lending marketplace, Prosper.com, we find that the online friendships of borrowers act as signals of credit quality. Friendships increase the probability of successful funding, lower interest rates on funded loans, and are associated with lower ex post default rates. The economic effects of friendships show a striking gradation based on the roles and identities of the friends. We discuss the implications of our findings for the disintermediation of financial markets and the design of decentralized electronic markets.

Key words: peer-to-peer (P2P) lending; value of social networks; signaling; information asymmetry; credit markets
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1. Introduction

The ability of online markets to efficiently bring together buyers and sellers has transformed businesses, spawned success stories, and redefined the roles of traditional intermediaries. In this paper, we study the online market for peer-to-peer (P2P) lending, where individual lenders make unsecured loans to other individual borrowers. This market was virtually nonexistent in 2005 but has since grown. The biggest market, Prosper.com, has logged over 200,000 listings seeking $1 billion in funding since its inception.

We study the relation between the online friendships and transactional outcomes on the P2P market. We find that borrowers with friends are more likely to have their loan requests funded and that these loans have lower interest rates. We then examine why friendships matter. Lenders may use friends as a signal because friendships serve as an informational cue of a borrower's credit quality. Alternatively, friendships could have no pecuniary implications and mislead lenders to irrational lending choices. To test these possibilities, we examine ex post outcomes of loans on the P2P market. We find that friendships lower default probability. Both the ex ante and ex post results show a striking gradation along friend *type*, with greater effects when friends have roles and identities that signal better credit quality. Our evidence suggests that friendships serve as informational cues of a borrower's credit quality. More generally, they support the central premise of signaling models that agents facing asymmetric information adapt by using signals to mitigate adverse selection. The results also highlight how technology aids this process by facilitating the generation and transmission of new sources of information.

To motivate our empirical strategy, we briefly consider the literature on adverse selection and signaling. As Spence (2002) notes in his Nobel prize lecture, this strand of research is pioneered by Akerlof (1970), who studies the used car market. Akerlof points out that when sellers of used cars know more about car quality than buyers, cars are treated as "lemons" by buyers. High-quality car sellers unable to communicate quality cannot charge for it and withdraw from the market, leading to a market failure. Spence (1973) argues that the Akerlof adverse selection problem can be mitigated if high-quality types use "signals" to communicate quality. Low-quality types do not mimic this behavior due to the costs of acquiring signals.

While Spence focuses on using education to signal worker productivity, the framework has led to a rich literature in economics.[1]

The signaling framework makes both ex ante and ex post predictions. For instance, consider the Spence (1973) model in which workers signal quality through education. Ex ante, educated workers should be more likely to find employment and get paid more, given that they are signaling high quality. Ex post, these workers should be more productive, given their higher quality. Likewise, in the used car market, warranties could signal used car quality (Grossman 1981). If so, cars with warranties should command better prices ex ante and should have fewer quality problems ex post. These tests readily map to the P2P lending context. If friendship signals better credit quality, borrowers with friends should be more likely to attract funding at lower interest rates. Ex post, these borrowers should default less given their higher-credit quality. These are the baseline empirical predictions that we test.

To gain more insights into the role played by friendships, we consider the *type* of friends. These tests can be motivated by the observation in Spence (2002) that a signal's effectiveness is more when the cost of acquiring it is greater. Some "friends" on Prosper.com are little more than (potentially fake) email addresses. These friends should have little signaling value. It is harder for borrowers to establish friendships in which friends undergo screening to verify identity, credit history, and meet the income and wealth screens required of Prosper.com lenders. The bar is higher for friends with established histories of bidding and especially successful bids that require outlay of capital. These friend types should have especially high signaling value.

Multiplicative effects on friend type are produced by the *social stigma* costs of default. The personal finance literature points out that a default not only lowers credit scores, but also imposes an additional stigma cost on a borrower, which is disutility suffered by a defaulter when a friend learns about the default (see e.g., Thorne and Anderson 2006, Cohen-Cole and Duygan-Bump 2008).[2] If stigma costs matter, borrowers who are more likely to default should avoid friendships. This occurs because borrowers with no friends on Prosper.com are known only by user IDs with identities protected for privacy concerns. However, the borrower identity is unmasked to friends in the email invitation establishing the friendship. Thus, borrowers more prone to defaulting should avoid forming friendships to avoid stigma costs. This makes friendships a credible signal of default, particularly for friends active as lenders who may be more attentive to defaults on Prosper.com.

Figure 1 illustrates the empirical implementation of the tests based on friend types. At the top level in Figure 1 are friends who have registered on Prosper.com. These friends amount to little more than an email address. Friends who have roles pass Prosper.com identity screens for a social security number, bank accounts, and driver's license. These friends can be further differentiated by roles as lenders or borrowers. Lenders must pass minimum income and wealth screens. Level 3 differentiates lenders between those who are merely registered and those who actually have a lending history. Friendship with lenders who actually bid is a more credible signal of quality. Levels 4 and 5 indicate borrowers with lender-friends who bid on the borrower's listing, and bid and win on the listing, respectively.

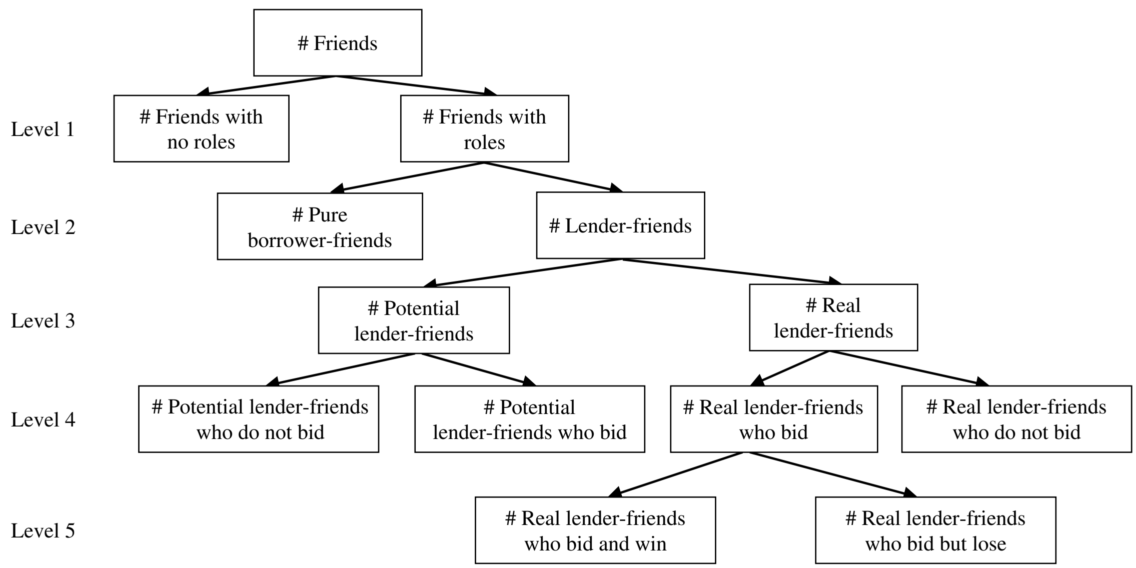
The numerically higher levels of friendship in Figure 1 should convey progressively stronger informational cues of borrower quality. For instance, whereas it is costless for lower-quality borrowers to create ties with nonverified friends, it is progressively more difficult for these borrowers to find lender-friends, lender-friends with bidding histories, and lender-friends who are willing to personally take the risk and invest in their loans. The stigma costs also increase along this hierarchy, because defaults are likely to be more visible to lender-friends who participate actively in the P2P market. Such costs are especially elevated when a borrower's friends participate in the borrower's listing because the participating friends are instantaneously informed when a borrower defaults. The bottom line prediction is that as we go down the friendship hierarchy, the signal of credit quality conveyed by friends should be stronger and result in greater economic effects.

Our first empirical tests focus on two ex ante outcomes, the probability of successful funding and the interest rate of loans. Consistent with the signaling hypothesis, friendships increase the probability of a successful listing and lower loan interest rates with more pronounced effects as we go down the friendship hierarchy in Figure 1. Thus, lenders in the P2P market do appear to judge borrowers by the (quality of) company they keep. For the ex post tests, we follow the literature on consumer defaults (Gross and Souleles 2002) and estimate Cox survival models.

[1] See the Nobel prize address of Spence (2002), as well as Weiss (1995) and Bedard (2001), on education signaling. Other applications include warranties (Grossman 1981), capital structure (Ross 1977), initial public offerings (Leland and Pyle 1977), and dividends (John and Williams 1985).

[2] In Thorne and Anderson (2006, p. 83), survey respondents say that "…[bankruptcy] is a mark against my name…it was too embarrassing…that's a sign of failure." Other work in economics establishes stigma as an important force in individual behavior. For instance, influential work by Moffitt (1983) and Bertrand et al. (2000) explains low welfare participation as a consequence of stigma.

Figure 1 **Hierarchy of Friends**



We find that friendships lower the default hazard along the friendship hierarchy. We also show that the weight placed on the friendship signal is economically sensible relative to its effects on default. We conduct extensive robustness tests. We estimate panel models, model the fraction of a loan funded rather than the funding probability, funding from nonfriend lenders, subsamples of first time listings, and controls for text and images. Our results are robust.

The rest of this paper is organized as follows. Section 2 reviews the literature and theory motivating our work. Section 3 summarizes our research context and describes the data used in the study. Sections 4 and 5 describe our data set and empirical methodology, respectively. Section 6 contains the results of the study. Section 7 discusses the robustness of the results to alternative specifications of controls, images, and text. This section also discusses a method to quantify the value of the friendship signal. Section 8 concludes this paper.

2. Theoretical Motivation

Our study draws on and contributes to research in multiple disciplines including economics, finance, information systems, and sociology. To place our contributions in perspective, we review the relevant literature and discuss how our findings add to the work in these areas.

2.1. Adverse Selection and Signaling

We add to the signaling literature pioneered by Akerlof (1970) and Spence (1973). Our contribution to this body of work is to offer new empirical evidence on the importance of signaling in markets where agents face information asymmetry. Our evidence is especially interesting because of the unusual research context. The "information gap" between buyers and sellers that drives adverse selection (Spence 2002) is particularly elevated in P2P loans. This is an anonymous credit market with no face-to-face contact between agents. Agents lend as little as \$50 apiece, less than 1% of the typical loan request. Moreover, the signal i.e., friendship, is subtle. Inferring its relation to credit quality requires sophisticated economic reasoning. Yet, agents adapt remarkably in line with the predictions of economic theories of signaling.

Our findings also add to the work on adverse selection specifically related to credit markets. The finance literature (see, e.g., Gorton and Winton 2003 for a review) argues that information asymmetry is an important feature of credit markets. In such environments, gathering "soft" information about credit quality beyond credit scores and standard ratios is critical to successful lending outcomes (Petersen and Rajan 2002). Almost all work in this area views financial intermediaries as repositories of such information because of their incentives, expertise, and economies of scale and scope (Fama 1985, Granovetter 1985, Petersen and Rajan 1994, Uzzi 1999, Agarwal and Hauswald 2007).

We add to this literature in two ways. First, we show that soft information can be produced and used *without* financial intermediaries. In our study, friendship is borrower-generated and is used by individuals putting small sums of money to work. Second, we identify a new source of soft information, viz., friends and friendship types. We show that they add to the standard hard credit variables such as Fair Isaac Credit Organization (FICO) scores or debt-to-income ratios used in the literature (Rajan et al. 2010, Agarwal et al. 2006). We illustrate how information technology hardens this soft information into usable form for lenders. Our evidence also establishes a counterpoint to the policy concern that decentralized electronic markets lead to loss of soft information (Hauswald and Marquez 2003). Although it is certainly correct that information technology could subtract some forms of soft information, our point is that it could also facilitate production and transmission of new sources of soft information.

The literature on eBay auctions also considers adverse selection, and emphasizes the role of seller reputation through buyer feedback in mitigating it (see, for instance, Dellarocas 2003, Bolton et al. 2004, Houser and Wooders 2006, Ghose and Ipeirotis 2011, Hill et al. 2006, Resnick et al. 2006). There are several differences between the eBay literature and our study. Buyer feedback on eBay establishes *seller* credibility. In P2P lending, standards for verifying roles and identities establish the *friend's* credibility. In the eBay context, the scores establishing seller reputation come from post-purchase feedback from buyers. The informational cue here, friendship, is not derived from post-purchase feedback by the buyer (lender). Rather, friendship is a characteristic of the seller known ahead of and formed outside the product purchase context of the loan listing. There are also differences in the product. Here, the product is not a consumable, but is like a durable good whose utility (repayment) flows over 36 months as the loan is repaid. Finally, our study focuses on the gradation along the roles and identities of the *friends* rather than the star rating of the seller, i.e., the borrower.

2.2. Social Capital and Economic Outcomes

A growing strand of research examines how social capital facilitates economic exchange. The literature originates in sociology, but has attracted considerable attention in economics of labor, prices setting, production, innovation, and entrepreneurship (Granovetter 2005, Guiso et al. 2004, Sapienza et al. 2007). We offer methodological and substantive contributions to this literature.

Our methodological contribution is on the identification of social capital. Granovetter (2005) writes that social capital is best thought of as being generated by actions, patterns, or processes of people outside the economic setting being studied. The challenge is to find such metrics that reflect outside interactions. We offer such a setting. The social capital of borrowers i.e., their friendships, are formed outside Prosper.com. We study their effect on economic outcomes, precisely the approach favored by economists and sociologists (see Granovetter 1985).[3]

We also offer substantive evidence on the *channels* through which social capital matters. As Granovetter (1972) writes, social capital is conventionally conceptualized as an individual attribute that generates an economic benefit, or as a group attribute of a collection of individuals that enhances the transactional efficacy for economic gain (Coleman 1988, Mizruchi 1992, Putnam 1993). Our results indicate that social capital between individuals plays another role: It facilitates transactions with third parties outside the dyad creating the social capital. In our study, social capital reflected in friendships generates additional credit information that is harvested to facilitate transactions with outsiders such as nonfriend lenders in financial markets. In the framework of Podolny (1993, 2001) or Granovetter (1972), social connections can be beneficial not only because they are pipes that convey resource flows to individuals, but also because the ties act as prisms, or informational cues that outsiders can use to infer the quality of an agent.[4] Our results also show that such effects are enhanced when the ties are credible and when outsiders have granular information on the individuals forming ties. For instance, friendships help when the skepticism from lenders is mitigated by verified, credible data on the roles and identities of the friends.

2.3. Online Networks

Our study is of separate interest because it examines the economic value of *online* networks, an area in which there is little prior research. We show that online networks have economic value, especially when data on the friendship network is made credible and granular. Our study also addresses a major limitation of the received work on online networks, i.e., the difficulties in measuring objective outcomes, and in identifying the ties relevant to the economic decision, which necessitate costly methods such as surveys or interviews (e.g., Karlan 2007, Moran 2005, Uzzi 1999), or accepting subjective measures of outcomes (e.g., Bagozzi and Dholakia 2006, Uzzi and Lancaster 2003). More recently, information systems researchers are increasingly interested in

[3] Burt (1992) also states that a promising avenue to identify social capital is using "friends, colleagues, and more general contacts…" (p. 9). In a careful survey, Durlauf and Fafchamps (2005) suggest that the most compelling empirical work is likely to be based on friendships of individuals (formed outside the economic context under study).

[4] A related point is made by education signaling models. As Spence (1973, 2002) points out, education does not need to cause productivity to increase to serve as a useful signal. Acquiring education can separate high and low-quality workers. Likewise, friendships on Prosper.com do not need to increase the physical resources of a borrower. Friendships, graded by the roles and identities of friends, can serve as an informational cue that helps borrowers signal their creditworthiness to outside lenders. We later show that friendships attract funding from strangers, i.e., bidders outside a borrower's friendship network.

online social networks. Studies draw from networking websites where network ties are explicit (e.g., Aral and Walker 2011, Susarla et al. 2012, Gnyawali et al. 2010) or copurchase and recommendation networks (e.g., Oestreicher-Singer and Sundararajan 2012). In our study, the network itself and the economic outcomes are quantifiable using relatively objective measures such as funding probability, interest, or default rates.

Finally, we add to the literature on P2P lending. A small but but growing body of research in this area exploits data on personal characteristics of borrowers to test theories of taste-based discrimination. Pope and Sydnor (2011) examine loan listings between June 2006 and May 2007. Ravina (2008) examines listings for a one-month period between March 12, 2007, and April 16, 2007. Both papers focus on facial attributes such as race and beauty of the borrowers, addressing the literature on racial bias and the beauty premium (Hamermesh and Biddle 1994, Mobius and Rosenblat 2006). We control for race and beauty in our tests, but our focus is different. We examine the role of friendships. Our specific focus is on the use of the roles and identities of friendship as economic signals that mitigate adverse selection and information asymmetry. The flavor of our findings is similar to that of Iyer et al. (2009), who find that loans in the P2P marketplace seem to reflect default information beyond the traditional hard credit variables.

3. Institutional Background

Our data come from the online P2P lending website, Prosper.com, which opened on February 5, 2006. By the end of 2008, it had 830,000 members and over $178 million in funded loans. Borrowers are limited to a maximum of two concurrent loans with total amount less than $25,000. Loans amortize over a 36-month period. Loan proceeds are credited to the bank account from which repayments are automatically withdrawn. The rest of the section describes the lending process and information provided by borrowers on this network.[5]

3.1. Verification and Listing

Users join Prosper.com by providing an email address, which is verified by the website. To engage in a transaction, users must go through additional verification. Borrowers must reside in the United States, have a valid social security number, a valid bank account number, a minimum FICO credit score of 520, and a valid driver's license and address. The details are verified by Prosper.com, which also extracts a credit report from Experian, a major U.S. credit reporting agency. Prosper.com lenders are also subject to verification of the social security number, driver's license number, and bank account number. To protect privacy, the true identity of borrowers and lenders is never publicly revealed on the website. All users are identified with user-names that are chosen when signing up.

To seek funding, a borrower makes an online listing, which indicates the loan amount, the maximum interest rate, and optionally, free format text description and images that are not verified by the website. Listings can be funded as *closed* auctions that end as soon as the total amount bid reaches the amount sought at the borrower's asking rate. Alternatively, in the *open* format, the auction remains open for up to seven days even if amount and rate criteria are met to let lenders bid down the interest rate of the loan. The listing includes the borrower-supplied information such as amount, rates, or loan purpose as well as other hard credit data such as the number of credit inquiries in the last six months and a letter credit grade from AA (high quality) to HR (low quality), which is a coarse version of the borrower's FICO score.[6] The listing shows friendship data but excludes (prohibited) personal information such as phone or address.

3.2. Bidding, Funding, and Repayment

Before bidding, lenders transfer sufficient funds to their noninterest bearing Prosper.com account. An individual lender can can bid an amount of $50 or more and specify the minimum interest rate she desires for the bid. The actual bidding process uses a proxy bidding mechanism. If the loan has not yet been funded 100%, the ongoing interest rate is the borrower's asking rate, even if the lenders' minimum rate is lower. After 100% of the requested funding has been reached, the auction closes if it is of closed format, but remains open for lenders to lower rates if it is an open format. All bids are firm commitments with no withdrawals allowed. From a lender's viewpoint, a bid could win or be outbid, in which case the lender can place a second bid to rejoin the auction. If the loan is not fully funded by the end of the auction, the request is deemed to have failed and no funds are transferred: No partial funding is allowed.

Successful auctions go to Prosper.com staff for further review. If documentation is in order, funds are collected from the winning bidders' Prosper.com accounts and transferred to the borrower's account, after deducting fees of up to 2% of the loan amount. Loans on Prosper.com have a fixed maturity of 36 months with repayments in equated monthly

[5] The descriptions are accurate for the time period that we study. Some features have changed since then.

[6] Specifically, AA = (FICO score $\geq$ 760); A = 720–759; B = 680–719; C = 640–679; D = 600–639; E = 560–599; HR = 520–559.

installments that are automatically deducted from a borrower's bank account and distributed to lenders' Prosper.com accounts. If the monthly payment is made on time, the loan status for that month is considered current. If a monthly bill is not paid, the loan status will be changed to "late," "one month late," "two months late," etc. If a loan is late for two months or more, it is sent to a collection agency. Lenders on Prosper.com must agree that the proceeds of the collection represent the full settlement of loans. Delinquencies are reported to credit report agencies and can affect borrowers' credit scores. Borrowers who default on their loans are not allowed to borrow using Prosper.com again.

3.3. Friendships and the Company That Borrowers Keep

Any Prosper.com member with a verified email account can create or join a friendship network. To form friendships, the inviting member fills out the friend's email address and a short message on Prosper.com. Prosper.com then generates an email message with a link that the recipient can click to establish a friendship. Thus, individuals who are friends on Prosper.com have at least some offline, nonpublic information about each other, such as an email address. Although Prosper.com users are normally identified by user IDs (e.g., "banker234"), this situation changes with friends. Members on either end of a friendship tie know the real person behind the ID. Thus, friends can link user IDs of a borrower who defaults to the actual identities of the defaulter, potentially imposing social stigma costs on borrowers with friends.

From an empirical viewpoint, the important point is that a member's friend information is highly visible on the members' profile pages. Friendship data are prominently displayed in a listing. Indeed, it is one of the most prominent pieces of information outside the credit information and listing data about the borrower. Friends who bid on a listing are also tagged very clearly by a special icon in the list of bids, so they are readily visible to other potential bidders. Data on friend types are also accessible in a straightforward way by clicking on links to see the profile of friends.

4. Data Set

Our sample comprises all listings that seek funding on Prosper.com between January 2007 and May 2008.[7] We obtain information on borrowers' credit histories, unique Prosper IDs, friendships, and outcome of their loan listings using an API provided by Prosper.com. Importantly, we ensure that the descriptive fields in our analysis are in the information set of potential lenders. We gather information on loan requests in real time so that information about borrowers' friends is current at the time of the loan requests. We describe the variables used in our analysis and discuss some descriptive statistics.

4.1. Friendships

In our data set, 56,584 listings report friends. A key focus of our analysis is friend *type*. Figure 1 describes the hierarchical levels of the roles and identities of friends underlying our analysis. Level 1 distinguishes friends according to whether their identities are verified on Prosper.com or they are mere email addresses. Level 2 categorizes the verified friends based on their specific roles as borrowers or lenders. Lenders are individuals with extra financial capital. Level 3 further differentiates lender-friends by whether they are *real* lender-friends who have lent to other borrowers before the current listing. Level 4 differentiates real lender-friends according to whether they bid on the specific borrower's listing. Level 5, the finest classification, distinguishes between lender-friends who bid on the borrower's listing and won and those who bid but did not win. As we progress from level 1 to level 5, the relationship between the borrower and lender strengthens. The difficulty in mimicking or "faking" a friend type, i.e., setting one up where one does not exist, becomes greater as we go from level 1 to level 5.

4.2. Control Variables

Table 1 lists the control variables included in our analysis. Among the hard credit variables is the Prosper.com letter grade for each borrower, which ranges from AA to HR as described previously. Rather than a numerical score (e.g., AA = 1, A = 2, etc.), we include a full set of dummy variables for each letter grade. We also include other hard credit information on the listing such as a borrowers' debt-to-income ratio and the number of credit inquires in the six months before the listing.[8] These variables allow for the possibility that the letter grade itself is not a sufficient statistic for credit risk.

We include an extensive set of controls in our analysis. One of them is auction type because closed auctions are likely to indicate that the borrower has more urgent financial needs. Some states have usury

[7] An advantage of this time frame is that website features remain largely consistent throughout this period. In October 2008, Prosper.com shut down and started a registration process with the U.S. Securities and Exchange Commission. When they fully reopened over a year later, some features were introduced or modified, partly to comply with SEC regulations. Interestingly, friendship information remained unchanged, but there is too much noise to combine data generated before 2008 and that generated after 2009.

[8] This does not include requesting loans on Prosper.com.

Table 1 Main Variables and Their Descriptions

Hard credit information

Hard credit information variables include the following information about the borrower at the time of listing:

- A series of dummy variables indicating borrower's credit grade (*CreditGradeAA, CreditGradeA, CreditGradeB, CreditGradeC, CreditGradeD, CreditGradeE, CreditGradeHR*).
- Borrower's debt-to-income ratio (*dti*).
- Borrower's bank card utilization (*bankcardutilization*), or the percentage of credit line that the borrower has used; quadratic term of bank card utilization.
- Number of credit inquiries on borrower's credit report in the six months before listing (*InquiriesLast6month*).
- Borrower's credit history length (*YearsSinceFirstCredit*), or the number of years between borrower's first credit line and the time of listing.

Auction characteristics

Auction characteristics variables include the following:

- Auction format (*auctionformat*), or whether the auction is "immediate funding" or "open for duration".
- The maximum interest rate specified by the borrower (*borrowermaxrate*) and its quadratic term.
- Loan amount requested by the borrower (*amountrequested*).
- Logarithm of the total length of text on borrower's listing (*logttltext*).
- A series of dummy variables indicating the loan category that the borrower specified (*listingcatX*), where $X = 0$ (no category specified—this is the baseline and not included in regressions), 1 (debt consolidations), 2 (home improvements), 3 (personal loans), 4 (business loans), 5 (student loans), 6 (automobile loans), and 7 (other loans).
- A series of dummies for the duration of auctions (*durationY*), where $Y = 3, 5, 7$, or 10; *Duration3* is the baseline dummy and not included in the regressions.
- Borrower's closing fees charged by Prosper.com at time of listing (*BorrowerFee*).
- Lender's closing fees charged by Prosper.com at time of listing (*LenderFee*).

Variables about groups

- Logarithm of the number of members in the group that the borrower belongs to at time of listing (log*groupsize*).
- Dummy variable for whether the borrower's group leader is awarded for successful borrowing (1 if yes, 0 otherwise) (*groupleaderrewarded*).
- A series of dummy variables indicating the nature of the group that the borrower belongs to: *_Alumni* for alumni groups related to a school or an employer; *_Geography* for geographically-oriented groups; *_Military* for groups for military members and their families; *_Medical* for groups related to medical reasons for borrowing or lending; *_Demographic* for groups highlighting particular demographics, such as single parents or Hispanics; *_Hobbies* for groups targeting people with particular hobbies; *_Religion* for religiously oriented groups; and *_Business* for groups highlighting small businesses, or business development.

Variables about borrowers' friendship ties

- Number of friends of the borrower (*ttlFriends*).
- Number of borrower's friends whose identities have been verified (either as borrower or lender) (*ttlRole*).
- Number of borrower's friends whose identities have not yet been verified (neither borrower nor lender) (*ttlNorole*); note that $ttlFriends = ttlRole + ttlNorole$.
- Number of borrower's friends who are borrowers and not lenders (*ttlpureborrow*).
- Number of borrower's friends who are lenders (*ttllend*); note that $ttlRole = ttlpureborrower + ttllend$.
- Number of borrower's friends who are *real* lenders, i.e., friends who are not only lenders but also had lent to other borrowers on Prosper.com before the current borrower's auction (*ttlreallend*).
- Number of borrower's friends who are *potential* lenders, i.e., friends who are signed up as lenders but have yet to make a loan at the time of borrower's auction (*ttlpotentlend*). Note that $ttllend = ttlreallend + ttlpotentlend$.
- Number of borrower's real lender-friends who place bids on the current listing/auction (*ttlrealbid*).
- Number of borrower's real lender-friends who do not bid on the current listing (*ttlrealnobid*); note that $ttlreallend = ttlrealbid + ttlrealnobid$.
- Number of borrower's potential lender-friends who place bids on the current listing (*ttlpotentbid*).
- Number of borrower's potential lender-friends who do not place bids on the current listing (*ttlpotentnobid*).
- Number of borrower's real lender-friends whose bids are among the final winning bids (i.e., those who actually became one of the funding lenders to the borrower) (*ttlrealbidwin*).
- Number of borrowers' real lender-friends who bid on the listing, but are outbid, and therefore are not contributing to the final loan; note that $ttlrealbid = ttlrealbidwin + ttlrealbidlose$.

Additional control variables

- A dummy variable for whether the borrower is constrained by usury laws (i.e., the maximum rate allowable) at the time of listing (*usurystate*).
- The average interest rate on a 36-month consumer loan from a bank in the same market as the borrower, in the same month as the time of listing, and in the same credit grade range as the borrower (*bankrate*).
- A dummy variable for abnormal search activities on Google for Prosper.com (*spikedays*).
- A dummy variable for whether the borrower also had a lender role on his/her profile (*lendrrole*).
- A dummy variable for whether the borrower is also a group leader (*leaderrole*).

laws that enforce a cap on the maximum interest rates on consumer loans. Although usury laws are intended to protect customers, they could reduce the chances of successful funding if the supply curve intersects the demand curve at a rate above a state's usury limit. Whether the laws have this bite is an empirical issue. After April 15, 2008, Prosper.com started collaboration with a bank in an effort to circumvent that limit. Our sample spans both periods, so we include a control for listings if a usury law is in effect. Each borrower indicates a maximum borrowing rate that he or she is willing to pay. Whereas low rates indicate less profitable loans, high rates could also indicate less profitable loans because of greater likelihood of default for borrowers willing to pay high rates (Stiglitz and Weiss 1981). Thus, we include this term in quadratic form. We control for broad lending rates through a proprietary data set from a professional company. The data include the average interest rate for borrowers in each credit grade in each regional market for each month on 36-month loans. This variable proxies for outside borrowing and lending options controlling for temporal and regional variations in consumer lending.

We further control for the purpose of loans. Borrowers indicate several types of needs, including debt consolidation, home improvement, business loans, personal loans for a variety of purposes (including vacations), student loans, or auto loans. The loan purpose is self-indicated by borrowers and can thus be thought of as cheap talk. However, potential lenders may communicate with borrowers during the auction process and seek more tangible details. On balance, it is likely that there is some information in the loan purpose, so we include this in the regressions. Prosper.com has received significant media exposure since its inception. Articles in the media make it more likely for the website to attract new borrowers and lenders after their publication. To proxy for this effect, we download the search volume on Google for Prosper.com and construct a dummy variable based on whether there is a significant change in search volume, which we call *spikedays*.[9] Finally, we include quarterly fixed effects to control for unobserved time effects.

5. Empirical Modeling and Identification

The theoretical motivation for our study comes from economic theories such as Spence (1973), which posit signaling as a mechanism to alleviate asymmetric information and adverse selection. These problems are especially elevated in P2P lending where lenders are small and have neither the close relationships nor the sophisticated analytics of institutions such as banks. The key question is whether a borrower's friendship ties help potential lenders adapt by acting as informational cues or signals of credit quality. If so, a testable hypothesis is that friendship ties should be associated with better ex ante outcomes, or greater probability of a successful listing and lower interest rates on consummated loans.

We begin by testing the relation between ex ante outcomes and the number of friends. To further identify the economic channels through which friendship acts, we next focus on the *types* of friends based on roles and identities of friends. These tests examine if the effects on transactional outcomes are stronger when borrowers have better quality friends. Affirmative evidence would support the joint hypothesis that (i) investors rationally adapt to informational asymmetry by relying on signals of credit quality; and (ii) a borrower's friendship ties provide such a signal. While such a role of friendships, and friendship types, can be viewed as part of our null hypothesis, the variables are equally well motivated by economic theories of social stigma in the context of defaults (Crocker et al. 1998, Thorne and Anderson 2006).

To gain further insights on *why* friendships matter, specifically whether they are useful because they harbor information about default, we conduct ex post performance tests. We test whether friendship ties are associated with lower ex post defaults in funded loans. Furthermore, we test whether this association follows a gradation along friend type, i.e., whether better quality friendships that delve deeper into the hierarchy in Figure 1 are associated with lower rates of default. Following the consumer finance literature (e.g., Gross and Souleles 2002), we model time-to-default using a flexible Cox hazard model. This test represents an out-of-sample test of the adverse selection hypothesis implemented on a disjoint database far removed from transactional data on loan funding or interest rates.

A familiar concern in empirical modeling is endogeneity. One concern is reverse causality (e.g., Doreian 2001 in the context of networks). Although this is a key issue in the traditional peer effects literature (e.g., Manski 1993, Kremer and Levy 2008), it is less relevant in our context. The key question in the peer effects literature is whether an individual's peers have causal effects on behavioral outcomes. The reverse causality issue is that an individual may select peers based on shared traits or preferences. As Manski (1993) points out, the reflection problem makes it difficult to separate peer and contextual effects.[10] This is less important in our context where borrowers form friendships outside the P2P platform, and the actions leading to loan success largely come from individuals outside a borrower's friendship network. The overwhelming majority of lenders are arm's-length (stranger) lenders funding small portions of a borrower's request. Moreover, the possibility of lending leading to friendships is remote because all

[9] This variable can serve as an exclusion restriction for one of our empirical models. We discuss this in §6.1.

[10] For instance, a regression of a student's outcomes on peers' outcomes commingles two confounding effects: A high-achieving student may choose peers who are also high achieving, or high achieving peers may causally improve a student's own performance. The reflection problem (Manski 1993) is not relevant here as we do not examine the behavior of friends in a peer friendship network. We examine the behavior of small, anonymous, arm's-length lenders who respond to friendship ties of borrowers.

operational transactions such as fund transfers and ex post monitoring of repayments are carried out by Prosper.com. There is no room for borrower-lender interaction after origination, preserving the mutual anonymity of borrowers and lenders. These factors mitigate concerns about reverse causality, or the view that loans are made to form friendships.[11]

Unobservables represent a second concern. Do our estimates pick up the effect of friendship variables or unobservable variables used by agents that happen to be correlated with friendships? Our setting mitigates this concern about unobservables. The unobservable argument is most credible when the econometrician does not have access to as much data as the economic agents engaged in decision making. In our study, loans are funded by aggregated contributions from many small lenders, virtually all of whom are strangers with no private information about the creditworthiness of the borrowers.[12] We have access to the complete vector of information that a potential lender sees about a borrower. Thus, if a variable is unobservable to us, it is also unobservable to potential lenders. This identification strategy is consistent with Angrist (1998, p. 251), who writes that he has access to information about "most of the characteristics used by the military to screen applicants," and thus can eliminate bias due to unobservables. We have a similar or an even stronger setting as we observe (and control) for all information available to potential lenders. As Jackson (2010, p. 519) writes, this strategy is justifiable in studies of networks if we "...observe all of the relevant factors affecting behavior."

Our additional tests further mitigate concerns about unobservables. Most importantly, our empirical strategy does not rely on friendships alone, but also on friendship types, which identify economic effects by exploiting the differences among friendships based on friends' roles and identities. We also consider several nonstandard controls based on information available to potential lenders, but not included in conventional studies of credit markets. These include images and descriptive texts contained in many Prosper.com listings. As these variables are self-reported and thus cheap talk, it is not clear that they could subsume

Table 2 Estimated Models

Model	Variable set 1	2	3	4	5	6
Funding probability	Spec. P1	Spec. P2	Spec. P3	Spec. P4	Spec. P5	
Interest rate	Spec. H1	Spec. H2	Spec. H3	Spec. H4	Spec. H5	Spec. H6
Loan default	Spec. C1	Spec. C2	Spec. C3	Spec. C4	Spec. C5	Spec. C6

Note: The sets of variables used in each model are described in Table 3.

friendship or particularly grades of friendships based on their roles. Nevertheless, we consider them in multiple ways. We analyze listings with or without images. We also examine and encode the descriptive text in listings using methods derived from computational linguistics. Our friendship results remain robust.

6. Results

Our sample has 205,132 listings seeking an average of \$6,973. We find that 56,584 (27.58%) listings report friends. Listings showing friends are spread across credit grades. For instance, of the 6,523 AA listings, 1,881 or 28.84% have friends, whereas 9,462 of the 33,068 D grade listings (28.61%) show friends. In the HR category, 22,556 (26.39%) of 62,904 listings show friends. Listings in which borrowers have no friends have mean debt-to-income ratios of 58%, whereas those with friends have debt-to-income ratios of 57%. Borrowers with no friends have about 4.17 credit inquiries in the six-month period before the listing date against 4.22 inquiries for borrowers with friends.[13] In our data, 16,500 (8.04%) listings attract full funding. For the sample of borrowers with no friends, 10,410 of 148,548 listings, or 7.04%, are successfully funded. By contrast, the success rate for listings with friends is 10.76%.

We explore loan funding probability, interest rates and loan default in multivariate specifications. Table 1 provides a full list of the explanatory variables. Tables 2 and 3 describe the different models that we report in the paper and the set of variables used in each specification. For instance, specification P1 is a model of funding probability that uses variable set 1 (Table 3). From Table 3 we can see that variable set 1 corresponds to the root level of the friendship hierarchy and uses ttlfriends, or the number of friends, plus the common variables listed in Table 1 as explanatory variables. Section 6.1 reports the ex ante outcomes, funding probability, and interest rates. Section 6.2 models the probability of default. Each of these sections focuses on the friendship variables, and §6.3 discusses the coefficients for control variables.

[11] Prosper.com also explicitly disallows borrowers to reveal personally identifiable information in loan requests. This includes email addresses, which are necessary to create friendship ties. In unreported robustness tests, we obtain highly consistent findings on friendship variables after either excluding borrowers who had loans before our sampling time frame, or adding a variable indicating the number of loans that they obtained before our time frame.

[12] In more than 95% of the listings associated with friends, contributions from friends account for less than 4.4% of the funds that borrowers receive. In other words, more than 95% of funds for over 95% of listings come from lenders who are strangers to the borrower.

[13] These are credit applications to banks or credit card companies, and do not include loan requests made on Prosper.com.

Table 3 Variable Sets Used in the Models

Variable sets	Corresponding level of the friendship hierarchy	Common variables	Additional variables
1	Root level		*ttlFriends*
2	1	Hard credit information	*ttlNoRole, ttlRole*
3	2		*ttlNoRole, ttlPureBorrow, ttlLend*
4	3	Auction characteristics	*ttlNoRole, ttlPureBorrow, ttlPotentLend, ttlRealLend*
5	4	Social network information—Groups	*ttlNoRole, ttlPureBorrow, ttlPotentLend, ttlRealNoBid, ttlRealBid*
6	5	Additional control variables	*ttlNoRole, ttlPureBorrow, ttlPotentLend, ttlRealNoBid, ttlRealBidWin, ttlRealBidLose*

6.1. Funding Probability and Interest Rates

Table 4 reports estimates of a Probit model for the probability that a listing is successfully funded.[14] If x is a vector of information about a listing, we estimate

$$Probability(Funded=1\,|\,x) = \Phi(\alpha_1 Hard\ Credit+\alpha_2 Friendship\ Ties+\alpha_3 Controls), \quad (1)$$

where Φ denotes the standard cumulative normal distribution. Specification P1 in Table 4 shows that the number of friends is positively related to the probability of successful funding and is significant at 1%. However as we discuss below, this relation reflects a more extensive relation based on the roles and identities of the friends.[15] Specification P2 in Table 4 distinguishes friends according to whether their identities are verified on Prosper.com. This process effectively decomposes a borrower's number of friends into two orthogonal pieces, friends who are verified and those who are not. We find that unverified connections, i.e., connections that merely signify a valid email address, represent insignificant cheap talk or even negative signals at the 10% significance level. In contrast, ttlrole, which denotes friends with verified roles, has a positive coefficient that is significant at 1%. These results constitute the first evidence that roles and identities, or the nature of the company that borrowers keep, matter.

We next categorize friends based on their roles on Prosper.com. To this end, we decompose the verified friends into orthogonal and additive pieces: friends with roles as borrowers and those with roles as lenders, both adding up to the total number of friends with roles. We also include the total number of friends with no roles. Specification P3 gives the results. Friends with no verified roles have negative effects as before. Connections to borrowers have insignificant effects while having friends with roles as lenders increases the probability of the loan being funded.

Specification P4 further differentiates between *real* lender-friends, who have made loans on Prosper.com to other borrowers before the current listing, and *potential* lender-friends who have not yet made loans on Prosper.com before the start of the current listing. We continue to include other friendship variables, including all friends with no roles, and friends who are borrowers but not lenders, as control variables. There is a continued gradation of the friendship effects. Having lender-friends matters only to the extent that the friends are real lenders who have already lent to other borrowers. The coefficient almost doubles relative to that for the total number of lender-friends, and remains statistically significant at the 1% level. Holding all other variables at their median, we find that those with one real lender-friend have an estimated funding probability of 3% versus 1.4% for those with no real lender-friends. The funding probability has more than doubled.

Specification P5 decomposes real lender-friends into those who bid on the specific borrower's listing and those who do not. At this level, it is also possible that a potential lender who has not lent in the past now chooses to initiate bidding with the current loan. Thus, we decompose both potential lenders and real (past) lenders into those who bid on the current listing and those who do not. We find positive and significant effects for potential lenders who bid on the current listing. Interestingly, borrowers whose real or potential lender-friends do not bid are less likely to

[14] We obtain similar results with a logit model.

[15] In the literature on social networks, this simple count of friends is the degree centrality of a borrower. Other network metrics include coreness, effective size of network, eigenvector centrality, and efficiency (Hanneman and Riddle 2005). These notions have limited relevance in our context due to the fragmented nature of the network with several disconnected components. We discuss this issue further in the robustness tests.

Table 4 Probability of Funding

	Spec. P1	Spec. P2	Spec. P3	Spec. P4	Spec. P5
# Friends	0.033***				
	(0.008)				
# Friends who are neither borrowers nor lenders		−0.020*	−0.020**	−0.017*	−0.017
		(0.010)	(0.010)	(0.010)	(0.010)
# Friends who are either borrowers or lenders		0.106***			
		(0.017)			
# Pure borrower-friends			−0.006	−0.002	0.018
			(0.023)	(0.021)	(0.018)
# Lender-friends			0.170***		
			(0.023)		
# Potential lender-friends				0.025	
				(0.022)	
# Real lender-friends				0.312***	
				(0.055)	
# Potential lender-friends who did not bid					−0.062**
					(0.028)
# Potential lender-friends who bid					0.325***
					(0.050)
# Real lender-friends who bid					0.849***
					(0.044)
# Real lender-friends who did not bid					−0.148***
					(0.022)
Credit grade – A (dummy)	−0.375***	−0.372***	−0.372***	−0.373***	−0.381***
	(0.037)	(0.037)	(0.037)	(0.037)	(0.036)
Credit grade – B (dummy)	−0.806***	−0.805***	−0.805***	−0.805***	−0.814***
	(0.062)	(0.061)	(0.061)	(0.061)	(0.063)
Credit grade – C (dummy)	−1.457***	−1.455***	−1.456***	−1.457***	−1.470***
	(0.056)	(0.056)	(0.056)	(0.056)	(0.057)
Credit grade – D (dummy)	−2.105***	−2.102***	−2.107***	−2.109***	−2.133***
	(0.094)	(0.094)	(0.093)	(0.094)	(0.094)
Credit grade – E (dummy)	−2.831***	−2.825***	−2.833***	−2.837***	−2.867***
	(0.139)	(0.138)	(0.138)	(0.139)	(0.139)
Credit grade – HR (dummy)	−3.310***	−3.304***	−3.312***	−3.318***	−3.354***
	(0.132)	(0.131)	(0.131)	(0.131)	(0.131)
Debt-to-income ratio	−0.102***	−0.102***	−0.102***	−0.103***	−0.106***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Group leader is rewarded (dummy)	0.141***	0.145***	0.146***	0.145***	0.141***
	(0.026)	(0.025)	(0.025)	(0.025)	(0.025)
(Other controls)			(Included in estimation)		
N	205,131	205,131	205,131	205,131	205,131

Notes. This table reports estimates of a probit specification in which the dependent variable is 1 if a listing on Prosper.com is funded and 0 otherwise. The explanatory variables include a borrower's hard credit variables, social network variables, group affiliation, and other characteristics of the loan, the loan domicile, and the borrower plus quarterly time period fixed effects. For brevity, some covariates are not shown. Table 1 gives the detailed definitions of the variables. Robust standard errors are in parentheses.

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

get funded.[16] In contrast, having real lender-friends bid on a listing elevates the chances of a successful funding. We do not further decompose real bidders into those who win or lose as the bid status is not known to lenders, but only observable after the outcome is known.

We next examine the price effects of friendship, i.e., whether it lowers interest rates. We regress interest rates on hard credit variables, controls, and friendship ties for loans that are successfully funded using Heckman's (1979) familiar two-step method:

$$E(r \mid x, funded=1) = \gamma_1 Hard\ Credit + \gamma_2 Friendship\ Ties + \gamma_3 Controls + \lambda(x;\hat{\alpha}), \qquad (2)$$

[16] Bidders seem wary of passive friends with no roles or those who do not participate in bidding, consistent with our main point that the types and actions of friends matter more than friends per se. We remain cautious, however, because of the mixed significance of the passive friend variables and their insignificance in the default models of Table 6. We instead stress the significant and consistent results for lender-friends, particularly those who bid and win in the hierarchy of Figure 1.

Table 5 Interest Rate on Funded Listings

	Spec. H1	Spec. H2	Spec. H3	Spec. H4	Spec. H5	Spec. H6
# Friends	−0.002*** (0.001)					
# Friends who are neither borrowers nor lenders		0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
# Friends who are either borrowers or lenders		−0.005*** (0.001)				
# Pure borrower-friends			0.000 (0.001)	−0.000 (0.001)	−0.001 (0.001)	−0.001 (0.001)
# Lender-friends			−0.006*** (0.001)			
# Potential lender-friends				−0.001 (0.001)		
# Real lender-friends				−0.007*** (0.001)		
# Potential lender-friends who did not bid					0.002** (0.001)	0.002** (0.001)
# Potential lender-friends who bid					−0.008*** (0.001)	−0.008*** (0.001)
# Real lender-friends who bid					−0.007*** (0.001)	
# Real lender-friends who did not bid					0.002 (0.001)	0.001 (0.001)
# Real lender-friends who bid and won						−0.006*** (0.001)
# Real lender-friends who bid but lost						−0.006*** (0.002)
(Other controls)	(Included in estimation)					
Inverse mills ratio	−0.081*** (0.007)	−0.073*** (0.006)	−0.064*** (0.005)	−0.047*** (0.003)	−0.016*** (0.002)	−0.013*** (0.002)
Selection equation: All variables used but not reported for conciseness						
Spikedays	−0.050** (0.020)	−0.053*** (0.020)	−0.053*** (0.020)	−0.054*** (0.020)	−0.052*** (0.020)	−0.051** (0.020)
N	205,132	205,132	205,132	205,132	205,132	205,132

Notes. This table reports two-stage estimates of a model in which the dependent variable is the interest rate on Prosper.com listings that are successfully funded. The probit selection equation models the probability of a listing being successfully funded. The explanatory variables include a borrower's hard credit variables, social network variables, group affiliation, and other characteristics of the loan, the loan domicile, and the borrower plus quarterly time period fixed effects. Because of page limits, we only report results on the main variables and do not report the first-stage probit equation estimates, which are consistent with the estimates in Table 4. Robust standard errors are in parentheses.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

where r is the interest rate at which the loan is funded. The the inverse Mills ratio $\lambda(x;\hat{\alpha})$, based on Probit estimates $\hat{\alpha}$ from Equation (1), accounts for the fact that interest rates are only observed when listings are successfully funded. Because $\lambda(\cdot)$ is a nonlinear function, Equation (2) can be identified without exclusion restrictions (e.g., Overby and Jap 2009, Uzzi 1999). Alternatively or additionally, one could have an exclusion restriction with a variable in the Probit step not included in the interest rate regression. We estimated the model using both methods and the results are similar.[17]

The interest rate results in Table 5 are remarkably consistent with those for funding probability. The coefficients for the friend types show direction and gradation consistent with the results for funding probability. Connections to friends not verified

[17] For the exclusion restriction, we consider a variable, Spikedays. We download the relative scaling results for the search volume on Google Trends for "Prosper.com." Spikedays is a dummy variable for whether the listing started in a week when the search volume was above the 75th percentile in our sample period (3.55). When Spikedays is high, Prosper.com traffic volumes increase and borrowing activities increase, but lenders adjust slower because of delays due to bank verification and funds transfer, and because old bids cannot be withdrawn as they are firm commitments. We find that Spikedays has a negative coefficient with F-statistic of 50, well above the cutoff of 10 for the Staiger and Stock (1997) criterion for a strong instrument.

Table 6 Time-to-Default of Successful Listings

	Spec. C1	Spec. C2	Spec. C3	Spec. C4	Spec. C5	Spec. C6
# Friends	1.017					
	(0.021)					
# Friends who are neither borrowers nor lenders		1.048	1.048	1.047	1.047	1.047
		(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
# Friends who are either borrowers or lenders		0.968				
		(0.027)				
# Pure borrower-friends			1.061	1.061	1.058	1.055
			(0.055)	(0.055)	(0.055)	(0.053)
# Lender-friends			0.912**			
			(0.034)			
# Potential lender-friends				0.950		
				(0.061)		
# Real lender-friends				0.877***		
				(0.044)		
# Potential lender-friends who did not bid					0.964	0.964
					(0.073)	(0.071)
# Potential lender-friends who bid					0.910	0.916
					(0.150)	(0.150)
# Real lender-friends who bid					0.856**	
					(0.052)	
# Real lender-friends who did not bid					0.938	0.938
					(0.113)	(0.113)
# Real lender-friends who bid and won						0.791***
						(0.062)
# Real lender-friends who bid but lost						1.086
						(0.146)
(Other controls)			(Included in estimation)			

Notes. This table reports hazards ratio estimates of a Cox proportional hazards model of the time to default for borrower listings that are successfully funded on Prosper.com. The explanatory variables include a borrower's hard credit variables, social network variables, group affiliation, and other characteristics of the loan, the loan domicile, and the borrower plus quarterly time period fixed effects. Because of page limits, we only report results on the main variables. Table 1 gives the detailed definitions of the variables. The table reports the exponentiated coefficients (hazards ratio), where values greater than 1 indicate that a higher value of the explanatory variable increases the risk of default. Robust standard errors are in parentheses.

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

by Prosper.com tend to increase interest rates, as reflected by the coefficient for the variable *ttlNoRole*: On average, an additional unverified friend increases the interest rate by 20 basis points (or 0.20%). More important, friends with lender roles have the opposite effect: Having a lender-friend decreases the interest rate by about 60 basis points. Interest rates fall the most when real lender-friends who have participated in past loans on Prosper.com also participate in the current listings. These effects are significant regardless of whether they win in the listing.

6.2. Loan Defaults

Prosper.com records the status of loans in each month, or payment cycle. Loans are current if repayments occur on time. Otherwise, loans can be "late," "one month late," "two months late," and so on. We model a default as occurring if a payment is late by at least two months. We follow the consumer finance literature (e.g., Gross and Souleles 2002) and model the time-to-default using a Cox proportional hazards specification (e.g., Grover et al. 1997, Bhattacharjee et al. 2007). In this model, the hazard $h(t)$ is specified as

$$h(t \mid x) = h_0(t)\exp(x\beta) \tag{3}$$

where $h_0(t)$ is a baseline hazard rate, and x denotes a vector of covariates. For each covariate x_j in the Cox model, we report the exponentiated form of the coefficient β, which is called the *hazards ratio*, whose standard error is obtained using the Delta method. A hazards ratio greater than 1.0 for variable x_j indicates that it is positively associated with the probability of default, whereas a ratio less than 1.0 indicates that x_j is negatively associated with the probability of default.

Table 6 reports the Cox model estimates in odds ratios. We use coefficients β to construct a baseline hazard function (Kalbfleisch and Prentice 2002), which increases initially, peaks at about 10 months, and then slowly wears off. This pattern is remarkably consistent with consumer lending delinquencies analyzed in Gross and Souleles (2002). In specification C1, the total number of friends is insignificant as a predictor of default. Specification C2 decomposes friends into those with verified identities as lenders or borrowers and friends with no verification. Having more unverified friends is associated with an increased odds of default, as indicated by a hazards ratio of 1.05, and having friends with verified identity is associated with lower odds of default. However, neither variable is statistically significant. Specification C3 shows statistically significant effects for Prosper.com verified friends who are lenders. The exponentiated hazards ratio of 0.91 shows that borrowers with a lender-friend are about 9% $(1-0.91)$ less likely to default than those without.

Specification C4 includes the number of lender-friends, but controls for whether they actually participated in lending before the borrower's listing. The hazards ratio for real lender-friends is 0.88, indicating that having real lender-friends is associated with lower probabilities of default. Likewise, the hazards ratio is 0.86 when we consider lender-friends who bid on the borrower's listing. Both coefficients are significant at 1%. The hazards ratio for friends who bid on and win a listing is 0.79 and is significant at 1%. Thus, the odds of default are significantly lower when lender-friends bid and win on the borrower's listing.

The result for the real lenders who bid indicate that financial stakes taken by friends are strong signals for outside lenders that a borrower is creditworthy. An alternative explanation may be that borrowers have better repayment histories because the loans are essentially funded by friends. The data suggest that this is not a first-order force because in more than 95% of all loan requests associated with friends, funds from friends account for less than 4.4% of the amount that the borrowers receive. The results are more consistent with the hypothesis that investors are not misled by relying on friends, especially friend types at the root level of the hierarchy in Figure 1, as informational cues about borrower credit quality.

6.3. Controls

Whereas friendships are the primary focus of our study, we also include an exhaustive set of controls. We briefly review and comment on the key controls. Hard credit variables have the expected signs in all specifications. Lower rated listings, as well as those with more credit inquiries and higher debt-to-income ratios are less likely to be funded, attract higher interest rates, and are more likely to default. Bank card utilization has a positive coefficient, whereas its square has a negative coefficient. Some card utilization is beneficial as it signals creditworthiness, but excessive usage is not as it likely signals borrowers who are financially stretched. An interesting variable is the number of years since a borrower's first credit line, a proxy for the borrower's age and credit experience. It has small effects on funding probability and interest rate and no effect on default.

Auctions that close upon funding can encourage aggressive early bidding, but also higher interest rates as there are fewer opportunities for lenders to bid down the interest rate. The results in Tables 4 and 5 support this view: Closed auctions result in higher funding probability, but higher interest rates. We also examine loan purpose. Specifying some purpose appears to lend credibility to listings as it increases overall probability of funding and lowers interest rates. Business loans appear to be more risky. They are less likely to be funded, attract higher interest rates, and are about 24% more likely to default at a 10% significance level. Debt consolidation loans are more likely to be funded than other loans at lower interest rates. Lenders value the fact that borrowers are using Prosper.com to shop interest rates or limit credit card debt. These loans are about as likely to default as other loans.

Borrowers willing to pay low rates may be less profitable to lenders and may be less likely to be funded. However, in the spirit of credit rationing theories (Stiglitz and Weiss 1981), high rates may signal risky borrowers and deter bidding. Our results support this view. The linear term has a positive coefficient and the quadratic term has a negative sign. While rationing theories argue for linear and quadratic terms in the funding probability equation, it is less obvious that there is a similar implication for funded loans. The linear term is negative in four specifications and positive in two others, whereas the squared term is consistently positive in all models. In unreported results, we estimated models with the linear term alone, and obtained a positive and significant coefficient.

Finally, we consider group affiliations. Any member on Prosper.com can propose a group and members are admitted based on eligibility criteria. Some groups, such as employee or university alumni groups require verification of the qualifying criteria, whereas others have looser joining criteria. An individual can be a member of only one group at a time. Whereas borrowers cannot leave or change groups until loan repayment, entry or exit into other groups is free. We manually code all groups that have at least three members and create dummy variables based on membership criteria such as religious affiliation. We also control for group size.

There are 4,139 groups in our sample; 59,978 loan requests representing 29% of loan requests, indicate a group affiliation. Group variables explain funding probability; 7.09% of listings not affiliated with a group are successfully funded, whereas 10.36% of listings with a group affiliation are funded. Groups with a religious motif enjoy lower interest rates by between 70 and 200 basis points, perhaps reflecting taste-based discrimination (Becker 1971) because these groups do not default less. Geography-based groups matter in models H1–H4, but not in models H5 and H6. Groups based on company or university alumni, which are verifiable criteria, enjoy lower interest rates (about 120 basis points), but only 451 of the over 200,000 requests in our sample are associated with such groups. In terms of ex post default, Table 6 shows that only two types matter for loan performance: alumni groups and geography-based groups. Members of these groups are less likely to default.

We also include a dummy variable for whether a leader of a group is rewarded for group member listings that are funded. Among all listings affiliated with groups, 28,006 (46.63%) are associated with a leader incentive structure. We find that the presence of group leader incentives leads to a greater likelihood of funding and lower interest rates, but these listings are in fact more likely to default. Thus, group rewards create incentives similar to the originate-sell model of intermediaries held responsible for the 2008 financial crisis (Hildebrand et al. 2010). This is partly the reason that such incentives were discontinued by Prosper.com. The important finding is, however, that including group variables does not affect the results friendship or friendship type in any of our specifications.

6.4. Alternative Specifications

We estimate several alternative specifications to assess the robustness of our friendship results. All results not reported here are available from the authors.

One potential concern is that friend-lenders may be driving the results in the funding probability. If the majority of funds for a loan comes from a friend-lender, there will be information unobservable to researchers, and our models may produce biased results even though, for 95% of the loans, friends provide less than 4.4% of the requested amount. To address this concern, we study the number of bids from strangers (lenders who are not friends with the borrower) as a function of the same covariates in the probit models.[18] We use a negative binomial model to account for overdispersion. Our results across all levels of the friendship hierarchy remain highly consistent as well.[19]

We re-estimate the funding probability model using a logit model and find consistent results. We consider the correlation induced by borrowers who re-list after a failed initial listing by constructing a panel data set, with each member as a unit and each listing as a time period. The panel is unbalanced as 53% of members post only one listing. We estimate a random effects model and also consider a fixed effect logit model; both yield consistent results and support the role of friendships. We also consider survival specifications that model the number of listings that a borrower must post before getting funded for the first time. Our primary results remain robust to this specification. We also analyze and find similar results for borrowers who only have one loan, mitigating the reverse causality concern that friendships may manifest previous loan outcomes on Prosper.com.[20] We also include binary indicators for all friendship variables in the hierarchy in Figure 1 instead of their counts, and obtain consistent results. Finally, while Prosper.com defines success as 100% funding of loans, we also estimated a Tobit model with the extent of funding as a dependent variable rather than the funding probability. The friendship results are consistent.

We further consider whether structural measures of networks, which deal with node positions and network topologies rather than roles and identities, matter. They have little effect on the results for friendships. This is unsurprising. We find that the friendship networks on Prosper.com have many disjoint, star-shaped components. Because Prosper.com friendship networks are formed offline and then revealed on the platform—rather formed on the platform due to identity-shielding—the network has a low degree of closure.[21] This strengthens the case for looking at the roles and identities of friends. We also consider the number of endorsements received by borrowers. This variable is cheap talk and unsurprisingly, it is insignificant. One variable that does matter is the number of friends' defaults in a borrower's neighborhood (the ego network in the network analysis literature). We find that a higher number of defaults in a neighborhood of a borrower is associated with higher risk of the ego's loan (Cohen-Cole and Duygan-Bump 2008), though inclusion of this variable does not meaningfully alter our main results.

7. Images and Text

Individuals seeking funding on Prosper.com can upload images and add descriptive text to their listings. A priori, it is not clear why these data should subsume friendship. The image and text data are self-reported by borrowers and are not authenticated by

[18] We thank the associate editor for this suggestion.

[19] These results are available from the authors.

[20] Borrowers who default are not allowed to borrow again, mitigating the concern that past defaults influence current outcomes.

[21] See Coleman (1988) or Burt (2005) for details. As an example, A, B, and C are members on Prosper.com and are only identified by random user names. A and B both have a friendship tie with C, but A and B are not directly connected. Then, A and B still cannot tell or recognize the real identity of each other, reducing the probability of a closure in C's ego network.

Prosper.com. However, images or text could act as a channel by which friendships matter. For instance, borrowers with better quality friends may leverage the friendships to post more persuasive text or images that might do a better job at attracting funding. Whether images or text subsume friendships becomes an empirical issue that we turn to next. For conciseness, we focus only on the coefficients for the friendship variables. The full results are available from the authors.

7.1. Images

Many listings on Prosper.com either post no images or simply use the boilerplate images provided by Prosper.com. As a starting point, we consider the role of friendship variables in the no-image subsample. All key variables—friends, friends who are potential lenders, real lenders, or real lenders who bid on listings—remain significant in this subsample.

We next consider sample listings that include images. Automatic image processing software yield unreliable results due to varying photo quality and content. We instead manually code the data. Because of the high costs of coding the entire sample, we work with a 10% random subsample of listings. To ensure representativeness, we preserve the proportions of successful listings, credit grades, and the degrees of relations depicted in Figure 1. We also consider a second subsample comprising all 16,500 funded listings. In the 10% random sample of 20,513 listings, 15,928 post images, of which 7,986 contain images of adult humans. In the sample of 16,500 funded loans, 10,198 listings have images, of which 8,279 listings contain images of adult humans. We hire assistants to code objective aspects of images such as race, age, and gender. We implement extensive screens to ensure output quality. Details are available to readers on request.

About 14.55% of the random 10% subsample of all listings have images of blacks, whereas the proportion of blacks in the funded loans is only about 8.79%. Thus, blacks are less likely to be funded, as in Pope and Sydnor (2011) and Ravina (2008). The differences for other minority racial groups are less significant; 6.20% of listings are Asian and 4.75% are Hispanic, while these populations represent 6.91% and 4.21% of loans funded, respectively. Females form 30% of the listings, but 37% of all funded loans, suggesting that women are more likely to attract funding. Young people below 25 form 23% of all listings, but 19.33% of all funded loans. Older people of age 50+ form 6.65% of the listings, but only 6.24% of the funded loans.

We consider multivariate specifications that incorporate image data jointly with friendships. We find that listings with images of older people of age 50+ and those with images of black adults are less likely to be funded at the 5% and the 10% levels, respectively.[22] Blacks pay between 40 and 50 basis points more in interest rates compared to the point estimate of 60–80 basis points reported in Pope and Sydnor (2011). Our estimate is not significant. As in Pope and Sydnor, we find that blacks are significantly more likely to default with a hazards ratio of 1.20 that is significant at 1%. We find that the key coefficients for friendships are similar and show similar gradation along friend roles and identities as in the full sample.

7.2. Text

We next examine whether descriptive text provided by borrowers explains some of the content of the friendship ties. Following Tetlock (2007), we use a disambiguation routine to classify text. We use the program Linguistics Inquiry and Word Count (LIWC), which classifies words into five broad categories and 80 further (overlapping) subcategories such as long words or punctuation marks as well as complex psychological, social, and personal categories. The classification is based on an extensively validated and updated dictionary of words from psychology and linguistics (Slatcher and Pennebaker 2006).

We experiment with and settle on a set of 12 LIWC categories that represent a nontrivial fraction of the word count and that seem most relevant to lending outcomes. On average, funded listings have more words per listing, shorter sentences, use more numerals, more words in the money subcategory, positive emotion words, more words of certainty, and fewer tentative words. Most variables, however, do not show consistent results across three outcome variables. For instance, money words are more likely to result in funding and lead to lower interest rates, but they are insignificant in default models. Conversely, quantifiers such as few or many lower defaults, and certainty words matter in defaults but not in the funding equation. No text variable shows the consistency of the friendship variables across the funding probability, interest rate, and default specifications. Thus, the friendship results remain robust to text. This is not intended to be a comprehensive verdict on the role of linguistic content in determining economic outcomes. Although LIWC and General Inquirer are accepted state-of-the-art text mining programs, they may not capture all of the subtle nuances of text or their complementarity to the other listing data. Furthermore, these data are self-reported and unlikely to be processed as evenly and rationally as credible signals with more economic content that are subject to extensive authentication by Prosper.com.

[22] Despite our extensive set of controls, it remains possible that variations about race may be due to other demographic factors such as education and occupation. Therefore, the results on race should be interpreted conservatively (we thank the associate editor for this insight).

7.3. Quantitative Valuation of Friendship Signal

The previous results show that loans to borrowers with friends are made at lower rates. We assess whether the reduction in interest rates due to friendship is reasonable relative to its effect on defaults. To motivate our approach, we note that the loan interest rate equals the risk-free rate plus compensation for a borrower's default risk. Thus, to assess how the friendship signal is valued we compare the effect of friendship on default rates to its effect on default risk. A higher number would indicate that investors value the friendship signal more, whereas a low number suggests that the P2P market offers conservative adjustments for friendships relative to its ex post effect on defaults. To benchmark the findings, compare the friendship results to those for hard credit variables.

Empirically, the adjustments in interest rates for friendship variables are modest ranging from 22 to 45 basis points. The most informative comparison is how friendship fares relative to hard credit variables. Relative to AA borrowers (the omitted category) in our specifications, the raw credit spreads for A and B borrowers are 80 and 190 basis points, and escalate to 660 basis points for E credits. Scaled for their effects on the default hazard, the spreads are 47, 94, and 132 basis points, respectively. These adjustments are higher relative to those for the friendship variables. Thus, investors use the friendship information conservatively, offering conservative rate adjustments relative to the ex post effect of friendship on default rates. Consistent with the view of Pope and Sydnor (2011), markets do not appear to make sufficient adjustments for race effects.

8. Conclusions and Implications

We study the online market for P2P lending, where individual lenders make unsecured microloans to individual borrowers. We show that borrowers with online friends on the Prosper.com platform have better ex ante outcomes. The results are consistent with the joint hypothesis that friendship ties act as a signal of credit quality, and that individual investors understand this relationship and incorporate it into their lending decisions. To further understand why friendships matter, we examine whether friendships are related to ex post loan outcomes. We find that borrowers with friends, especially of the sort that are more likely to be credible signals of credit quality, are less likely to default. Our results are more pronounced when friends have roles and identities that are more likely to signal better credit quality.

Our findings are of interest from a number of viewpoints. One perspective is that our study represents data from an emerging online credit market in which there is an especially severe problem of adverse selection. An interesting question is what mechanisms individual agents use to adapt. The mechanism by which agents adapt is interesting given that they lack the sophisticated risk assessment methodologies or scale economies of banks. Individual agents also lack the soft information in lending from a broader vector of financial relationships that is available to traditional intermediaries such as banks. However, agents adapt precisely as predicted by the economic theories of signaling. The results are particularly interesting because of the context, which features a rather subtle signal, arm's-length loans, and individual agents putting small sums of money to work. Yet, the results line up surprisingly well with the predictions of economic theory.

We also shed light on the role of soft information in credit markets. Extensive work in economics and finance argues that credit markets suffer from a problem of adverse selection. The literature traditionally views financial intermediaries as a solution because they can produce soft information about borrowers. As financial markets undergo disintermediation driven by information technology, a natural concern is that the soft information produced by intermediaries is lost, adversely affecting credit flows. Additionally, while digital technology widens the reach of credit markets, it can exacerbate asymmetric information because borrowers become more anonymous. Our results highlight how these concerns are at least partially mitigated. Information technology could supplant some sources of soft information, but it could also increase its supply by developing new sources of soft information, hardening it, and permitting its self-organization and availability to lenders. The use of friendship may be seen as one manifestation of such an effect.

Our study can also be viewed as new evidence on whether social capital facilitates economic exchange, a question of growing interest in information systems, economics, and management. The P2P lending marketplace offers microlevel data on this issue with two significant empirical advantages. It identifies social capital, which is a key challenge in the literature. In many studies, it is hard to identify the social relationships formed outside the economic context being studied. The P2P loan marketplace offers relatively well-defined, objective measures of social capital through friendships that are formed outside the lending context. It provides additional granularity based on the roles and identities of the friends. The marketplace also provides well-defined measures of transactional outcomes, viz., funding, interest rates, and default.

Finally, our results have specific implications for new businesses based on emerging Web 2.0 technologies, such as other electronic commerce sites.

Much of the potential in these new businesses comes from the new sources of information about users and the ability to harness this information in new business models. Our study suggests that such businesses could facilitate the creation of online relationships and incorporate them into their business models, which could result in economic benefits for end-users. This is particularly true when such relationships are self-organizing and impose little cost to the marketplace,[23] as we document in this study. The realization of such benefits, however, depends on the ability of the platform to make the new information credible and enrich the vector of economic attributes of the people forming the relationships. For instance, in our study, friendships matter. However, this is not a quantity effect that scales with the number of friends, but depends on the roles and identities of the friends and the nature of their social and economic relations. Ties that are more difficult to form and more likely to lead to social stigma in case of default create stronger incentives to repay, and are also more credible signals of creditworthiness.

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