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CAN SOCIAL NETWORKS HELP MITIGATE INFORMATION ASYMMETRY IN ONLINE MARKETS?

Completed Research Paper

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Abstract

This study examines whether online social networks can help mitigate information asymmetry in online markets, and if so, what aspects of these networks generate value for market participants. Using a comprehensive dataset on transactions and social network information in an online peer-to-peer lending market, Prosper.com, we empirically study the linkage between borrowers' social network positions and their transactional outcomes. Our results highlight the distinction between the structural and relational dimensions of social networks. Stronger ties, where social and economic relations intertwine with each other, create value by both exerting peer pressures and increasing the verifiability of network ties, thereby alleviating the information asymmetry between borrowers and lenders. Our findings contribute to the growing IS literature on the economics of social networks as well as to the study of online quality signaling mechanisms.

Keywords: P2P Lending, Information Asymmetry, Online Social Networks, Econometric Analyses

Introduction

The evolution of online social networks is one of the most exciting phenomena in online commerce in the past few years. A large number of social networking sites such as Facebook and LinkedIn have emerged with the specific goal of connecting users. More recently, online retailers such as Amazon.com have also begun to implement social networking features on their websites. A general perception among researchers and practitioners is that connecting users can help create value, yet the details of how such value is generated and what its sources are is not clear. The goal of this study is to empirically investigate if and how online social networks create value.

Drawing on literature from sociology and economics, we propose that one potential role of online social networks is to help alleviate information asymmetry issues that plague online commerce. To test such a proposition, an ideal context is the online peer-to-peer (P2P) lending marketplaces, where individuals make unsecured microloans to other individual borrowers. This market was virtually non-existent prior to 2005, yet we have seen many such sites rapidly gaining popularity over the last few years. The most prominent of them is Prosper.com, which has logged over 200,000 loan requests seeking about \$1 billion since its inception.

Prosper.com is ideal to our investigation for a number of reasons. First, members create and maintain social networks in this marketplace, which provides objective measures of their network positions as well as information about all "nodes" on the network. There are friendship networks as well as group affiliation networks, providing an opportunity to contrast their effectiveness. Secondly, as a financial lending marketplace, Prosper.com provides detailed objective information regarding all transactional outcomes, giving us a unique opportunity to explore the link between online social networks and economic outcomes. The transactional outcomes that we study include all major events in the life cycle of loans: (1) the probability that a borrower's loan is funded; (2) the interest rate of loans; and (3) the ex post performance of loans. Last but not the least, financial lending is the ideal context to study issues of information asymmetry and trust. As Guiso et al (2004) suggest, "Financial contracts are the ultimate trust-intensive contracts". The issue of information asymmetry is only heightened by the decentralized nature of the P2P market, as each individual lender decides whom to lend and how much to lend, in a disaggregated manner.

We draw on the literature in social networks that differentiate between structural and relational aspects of these networks. Relational aspects of the network can be further classified as either "arm's length" or "strongly embedded" depending on the extent to which economic relationships are intertwined into the social network. While both forms of social relationships have the potential to create value, they operate in different ways (Granovetter, 1972; 2005). Weaker arm's length relationships create value via access to diverse and heterogeneous information or resources; stronger embedded relationships create value by facilitating the sharing and transfer of private resources and promote self-enforcing governance such as norms. Whether the structural or the relational aspects of online social networks matter in online P2P lending markets, and further, whether arm's length relationships are more valuable than embedded ones in influencing positive lending outcomes, are the empirical questions that we seek to address in this study.

We gather data on transactions as well as the social networks created by participants on Prosper.com to address the following research questions:

- (1) *Does the social network position of borrowers affect their probability of funding, interest rate of loans, and loan performance?*
- (2) *How do the structural and relational aspects of online social networks impact transactional outcomes?*

Our empirical analysis shows that the relational aspects online social networks can indeed create value by mitigating the information asymmetry between borrowers and lenders. The relational aspects create value by not only exerting peer pressure through network ties, but also increasing the verifiability and credibility of the ties themselves. By contrast, structural aspects of the social networks, measured through a variety of network metrics, have limited to no significance in explaining the transactional outcomes.

Our findings have implications for both IS research and practice. While it is widely accepted in economics and sociology that networks matter, especially to the sets of individuals forming the networks and the organizations that employ them, our study quantifies its value and places boundary conditions to the claim. Secondly, our study emphasizes the issue of *verifiability* in the online context. While we empirically support the relevance of the "relational embeddedness" dimension of social capital (Granovetter 1972), such relational embeddedness has to be visible and verifiable to outsiders, such as lenders, in order to unleash its value.

Literature Review

We draw on the following streams of literature: prior research on social networks, information asymmetry and trust in online environments, as well as microfinance.

Social Networks

The relation between social networks and economic outcomes has been the subject of much attention for researchers in sociology and economics; and “social capital” is usually denoted as the resource that accrues to an agent because of his or her position in a social network. For instance Granovetter (2005) reviews applications in areas such as employment, innovation, and entrepreneurship. Burt (1992, page 9) describes an individual’s social capital as “friends, colleagues, and more general contacts through whom you receive opportunities to use your financial and human capital.” The focus of our paper is to study the effectiveness of social capital on economic transactions.

Theorists differentiate between two dimensions of social capital (e.g. Granovetter 1992; Moran 2005; Tsai and Ghoshal 1998). The first dimension, structural embeddedness, refers to the position of an actor in the network. Relational embeddedness, on the other hand, refers to the quality of the relationship among actors in the network. Studies have shown that on a given network, the position of an agent can often reflect his or her resources. Some positions in a network endow control over the flow of information and other resources through the network, e.g., individuals who are in a “hub” position (Granovetter 1972; Constant et al 1996), or those occupying “structural holes” (Burt 1992). Examples of studies on relational embeddedness include Grewal et al. (2006), who study open software projects and Cowan et al. (2007), who examine embeddedness in a network of collaborators on innovation. In management studies, papers such as Rodan and Galunic (2004) show that it is not just the network structure that matters, but also the content of the network. Whether structural or relational aspects of networks matter in P2P lending remains open questions. It is of special interest given the decentralized nature of the network with independent lending decisions made by small investors on an arms-length basis to borrowers, and the fact that even if friends lend to borrowers, their stakes only account for a small portion of the loan amount.

Researchers have identified various pathways through which peers on a social network can influence the perceptions and behavior of an individual. Social psychologists suggest two channels: informational influence and normative influence (Cialdini and Goldstein 2004; Rashotte 2007; Manstead and Hewstone 1995; Campbell and Fairey 1989). The idea of informational influence is comparable to the theory of informational cascading in economics (Bikhchandani et al 1992), where individuals follow the action of another agent due to the belief that others’ behaviors contain important information about the market. Normative influence, on the other hand, is more subjective: it is the “conformity to the positive expectations of others, motivated by the desire for approval and to avoid rejection” (Manstead and Hewstone 1995).

Explicit economic incentives represent another channel for peer influence. A case in point is the group lending programs in microfinance (Morduch 1999), where if one member defaults on his loan, all other members will be denied access to future loans. Alternatively, peer influence can arise out of the indirect economic effects. Karlan (2007) argues that the pressure to repay microloans can come from a desire to “protect their social connections ... and avoid any repercussions” such as “reduced trading partners for one’s business” (Karlan 2007, page F58). This is echoed by Granovetter, who proposes that “individuals with whom one has a continuing relation have an economic incentive to be trustworthy, so as not to discourage future transactions” (Granovetter 1985). These economic incentives can further be intertwined with social norms, which “carries strong expectations of trust and abstention from opportunism” (Granovetter 1985, page 490). Therefore, economic and social motivations, both related to the presence and action of others, combine to discourage what Granovetter calls “malfeasance” (1985) or opportunistic behaviors. Furthermore, Latane (1981) and Latane et al (1995) argue that stronger degrees of mutuality and interdependence lead to greater levels of normative influence and economic incentives – the stronger the tie, the greater the strength of the peer influence.

The existence of social capital per se, however, does not ensure better lending outcomes. It needs to be visible to and verifiable by potential lenders to become part of their information set. Additionally, given the ease of formation of online networks, they may not be credible in reducing opportunistic behavior by borrowers, so verifiability is important. As noted by Rosenthal (1971), a message “must be testable by means independent of its source and available to its receiver” to be verifiable. This applies to online social networks as well, since a user’s social network is fundamentally a signal that he or she is trying to send to others.

Information Asymmetry and Trust

Information asymmetry generally refers to the incomplete information among market participants, which further leads to adverse selection and moral hazard. Akerlof (1979) showed that such information asymmetry could potentially lead to the demise of an entire market, in the absence of sufficient signaling and reputation mechanisms. In the context of electronic commerce, information asymmetry is a particularly problematic issue due to the anonymity and lack of accountability. IS scholars have accumulated a significant body of literature on trust and reputation mechanisms in the online world (e.g. Dellarocas et al, forthcoming). To the best of our knowledge, however, there has been no research on role of online social networks in mitigating information asymmetry. Our study seeks to fill this gap.

Microfinance

Grameen Bank is arguably the most popular example of a microfinance institution. Unlike typical banks however, microfinance institutions are often faced with poor or "ultrapoor" borrowers, and consequently, much higher levels of information asymmetry. Social networks often serve as "soft collateral" in microfinance. One such soft collateral is "group lending", where borrowers borrow as a group, and if one member defaults, none of the other members in that group can borrow again. This mechanism leverages "peer pressure" as collateral for lending. Online P2P lending, on the other hand, does not (yet) explicitly offer such "soft collaterals". But as we argue, even though a borrower's network does not directly offer financial guarantees regarding the borrowers' trustworthiness, there still exist various types of pressure (on the ego) from the alters. The authenticity of such pressures, in turn, depends on the degree of verifiability of these ties.

Background and Data Description

Our data is collected from a major online peer-to-peer lending website, Prosper.com. It was first created in 2005 and opened to public in 2006. Due to the changes in website policies in its early years, our analysis uses loan request and performance data between January 2007 and May 2008. In what follows, we first describe the social networks on Prosper.com, and then outline the process through which loans are generated.

Members join Prosper.com using an email address. Once the email address is verified, members can create or join a social network. We consider two types of social networks: the friendship network and groups. In a friendship network, a member can be a friend with other members who already have a valid user ID on Prosper.com. Alternatively, the member can ask offline friends to join Prosper.com and become an online friend on Prosper.com. A member's friendship network is visible on the profile page or a listing page.

Another type of social network on Prosper.com is a group. Any member can create a group, and a member can typically join any group whose membership criteria are met. However, each individual can be a member of only one group at a time; if a borrower is a member of a group when requesting a loan, the borrower cannot leave the group or join any other group until the outstanding loan is repaid in full. The leader of each group can determine the rules regarding who can become group members and how others may join. Some groups, such as alumni groups, typically require verification. Other groups require little verification.

Borrowers who wish to request loans do so by setting up a listing on Prosper.com once their identities are verified. They are, however, required to verify their true identity by providing social security numbers (SSNs), drivers license numbers, and so on. Only people with a FICO score above 520 are allowed to borrow, and their credit report information will be made available to potential lenders. In the listings, borrowers specify the amount that they would like to borrow, the maximum interest rate they are willing to pay for the loan, as well as other information such as the duration of loans and the format of auction (close versus open). A close-format auction is one in which the auction closes as soon as the amount requested has been fulfilled, whereas an open-format auction allows the bidding process to go on so that the borrower can receive a lower rate. In addition, the listing also displays hard credit information from the borrower's credit report, including number of credit inquiries, his debt-to-income ratio, and a letter credit grade, which is a coarse version of the borrower's FICO score. Purpose of a loan is also specified in listings and could be a business loan, or an auto loan, mortgage, a student loan, and so on. We control for the loan purpose in our models. We also include the total amount of text included in a listing in our analysis. The listing also

contains information about the borrower's friends and groups to which he belongs. These variables are an important part of our analysis and are discussed separately next.

A lender interested in a borrower's listing can bid an amount that she's willing to lend and specify the minimum interest rate. The actual bidding process uses a "proxy bidding" mechanism. That is, if the loan has not yet been funded 100%, the ongoing interest rate will be the borrower's asking rate, even if the lenders' "minimum rate" is lower. Once 100% of the requested funding has been reached and the format of the auction is "open", the ongoing rate decreases as the lender with the highest rate-bid is competed out. In a sense the auction is similar to a second-price auction. All bids are committed, and no withdrawals are 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. From a borrower's perspective, a loan is either fully funded or not, in which case the auction is deemed to have failed and no funds are transferred.

When the auction process ends, the listing will be processed by website staff for further verifications; during this process, the borrower could be asked to provide further documentation. Once the loan is approved, the loan originates, and the funds will be transferred from the lenders to the borrower. There will be 1-2% service fee to maintain the website, depending on the credit grade of borrowers. After that, the loan will be managed by Prosper, and lenders are paid each month automatically. Borrowers who defaulted will be reported to credit bureaus and collection agencies, and will not be allowed to borrow from the site again.

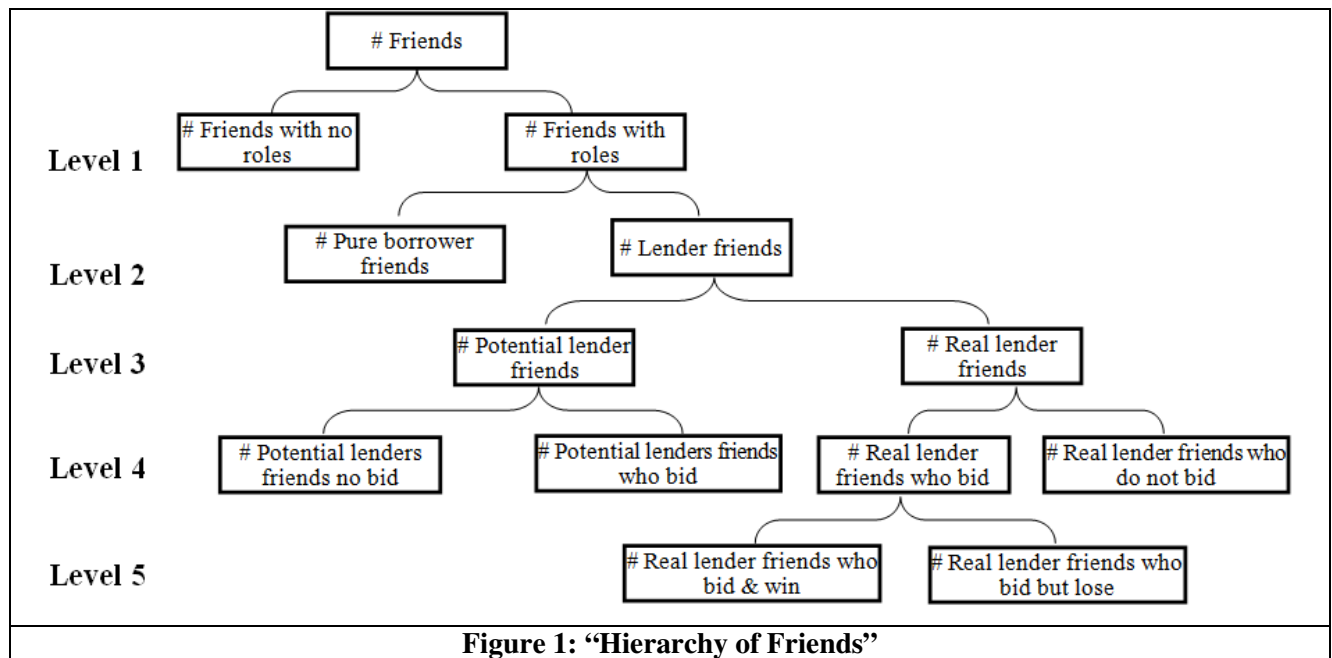
A major advantage of our dataset is that the majority of information received by lenders at the time of the auction is captured, allowing us to control for potential confounding factors. Our dataset contains information regarding borrower's credit history, their unique identifiers (not their social security numbers), their position in the online social network, features of their auctions, outcome of their loan listings, and the current status of their loans. In particular, we obtained detailed credit profile information of the borrowers at the time of listing. Our dataset contains information about loans originated between Jan 1st, 2007 and May 20th, 2008. In what follows, we describe the "hard credit information" and "social network information" used in our models. It should be noted that our sample includes borrowers and lenders who do not have any friends; for these borrowers, their "friendship" variables are recorded as zero. Twenty-one percent of the loan requests in the data set are from individuals with friends, and the borrowers of 29% funded loans have friends.

- **Hard credit information:** including credit grades, debt-to-income ratio, bank card utilization, number of credit inquiries in the past 6 months¹, record of bankruptcy, and so on. When borrowers apply for loans at banks, these are typically requested by banks to evaluate their riskiness and probability of repayment.
- **Social network metrics:**
 - **Friendship network:**
 - **Structural:** To measure the structural aspect of the borrower's friendship network, we use social network software Pajek and UCINET to calculate a number of frequently used network metrics, including degree centrality, closeness centrality, betweenness centrality, power, eigenvector centrality, coreness, and clustering coefficients, for each individual borrower (cf. Hanneman et al 2005). Due to the size of the network, we use Pajek to extract individual components and then import the components into UCINET to derive the above metrics.
 - **Relational:** The relational social network measures emphasize roles and identities of members in the network. Figure 1 discusses the hierarchy underlying our empirical strategy. In Level 1, we distinguish friends according to whether their identities are verified on Prosper, i.e., individuals who have elected to undergo verification of identities and bank accounts versus individuals who have merely registered and are thus little more than persons with a verifiable email address. In level 2, we categorize the friends of borrowers based on their roles – whether these friends are borrowers or lenders. Lenders are individuals with extra financial capital while borrowers are likely to be facing financial constraints. On the other hand, borrowers are subject to greater scrutiny as they have assigned credit grades that form a backbone of their listings. Level 3 further differentiates between "real lender" friends – those who have lent prior to the current listing; and "potential lender" friends – those who have provided enough information to Prosper to be listed as lenders but have yet to

¹ "Number of credit inquiries" refer to credit applications at financial institutions, and do not include loan requests on Prosper.com.

participate in a loan. Level 4 differentiates real lender friends according to whether they bid on the specific borrower’s listing or not. Here, we can have two effects. Having friends who participate can enhance lending outcomes. However, having several friends who do *not* participate in a borrower’s auction can send negative signals about the borrower, which can potentially lead to negative outcomes if “inaction” is interpreted by other lenders as a negative signal. Level 5 is the finest classification. Here, we distinguish further between lender friends who bid on the borrower’s listing and won (i.e. actually lent money to the borrower), and those who bid but did not win. Overall, as we progress from higher to lower levels of this friendship hierarchy, the relationship between the borrower and lender becomes more actionable, verifiable and more strongly embedded.

- **Groups:** Members can choose to create or join groups on any basis: geographic proximity, common interest, alumni, or any other possible commonality. However, once they create a loan while a member of a group, they are not allowed to change their affiliation until the loan is repaid in full. In our analysis, we manually coded all groups associated with loans and have 6 or more members, according to their descriptions and names.
- **Auction Characteristics:** These include the duration of listing, the format of auction, the maximum interest rate (similar to the starting bid in auctions), purpose of the loan, and the amount requested. We mainly incorporate these variables in the model as controls.
- **Additional variables.** We also obtained or calculated the following variables for our analysis:
 - A dummy variable for whether the borrower comes from a state with interest rate caps (or “usury laws”).
 - Outside interest rate. We purchased a proprietary dataset from a professional company that collects data on interest rates in different US markets. This is the average interest rate for borrowers in each credit grade, in each regional market, for a given month. The term of loans is of the same length as Prosper loans (36 months). In our analysis, it serves as a proxy for the “outside option” of borrowers; it is also intended to subsume geographical or seasonal variations in macroeconomic conditions.



Models and Results

Probit Model of Funding Probability

Our first model examines the probability that a listing is funded using a probit model:

$$\text{Probability (funding)} = \alpha_1 \text{ HardInfo} + \alpha_2 \text{ SocialNetwork} + \alpha_3 \text{ Other Variables} + \varepsilon_i \quad (1)$$

To control for unobserved changes in Prosper.com policies, we include quarterly fixed effects. We report six sets of results that vary based on how they specify the social network variables (see Table 1 and Table 2 for details). All six specifications include a common set of variables and controls. In addition, these results do not change when we use a Logit setup; here we use a Probit model because it allows us to compare with the results from the Heckman model on interest rates, since the first stage of Heckman model is a Probit specification.

Hard credit information

The first set of variables in our model represents hard credit information, including credit grade, number of credit inquiries, and so on. All hard credit variables are significant and have the expected signs. For instance, worse credit rated borrowers are less likely to be funded. Other hard credit variables such as number of public records tend to be highly collinear with these variables; adding them does not affect our results.

Social network Variables – Friendship network

Our main focus is on the social network variables. We start with structural measures of networks. The degree centrality measures a borrower's position in the friendship network. Specification P1 shows that degree centrality is positively related to the probability of being funded. As discussed below, this relation masks a more extensive relation caused by the roles and identities of the members of the friendship network. We included other structural network measures such as coreness, effective size of network, and efficiency but none of these alternative metrics have any significant effects on the probability of funding. It should be noted that we add these metrics sequentially to test for their significance, not simultaneously, since they could be correlated with one another.

We then distinguish friends according to whether their identities are verified on Prosper or not. If a borrower is connected to friends who are not verified, the loan is less likely to be funded. Lenders apparently view the presence of friends who do not choose to initiate verifiable roles in Prosper.com as a negative signal, so connections that merely verify email addresses have no economic value. In contrast, that having friends with roles on Prosper is positive and significant at 1%. These results constitute the first evidence that it is not numbers alone, but rather the roles and identities that matter.

Next, we further decompose the total number of friends into two orthogonal and additive pieces: the friends with roles as borrowers and roles as lenders, so that the total adds up to the total number of friends with roles. In addition to these two components of friendship, we also include the total number of friends with no roles. The number of friends with no roles continues to have a negative coefficient, as before. We find that being connected to borrowers has no impact. However, having additional "lender" friends increases the probability of the loan being funded.

We then further differentiate between "real lender" friends – those who have lent prior to the current listing; and "potential lender" friends – those who are yet to lend prior to the start of the current listing, and the real and potential lender friends add up to the total number of lender friends. There is a continued gradation of the friendship effects based on the nature of a friend's role and its verifiability and visibility to outside lenders. Having just potential lender friends has little effect. Our results show that having "potential lender" friends does not have a significant impact on any of the transactional outcomes. In contrast, having "real lender" friends increases the probability of the loan being funded and the coefficient almost doubles relative to that for the total number of lender friends.

At the next level, we differentiate real lender friends further according to whether they bid on the specific borrower's listing or not. We find that if a borrower has more potential lender friends who do not bid, the borrower is less likely to generate funding for a listing. On the other hand, the greater the potential lender friends who bid, the more likely is the listing to get funded. We see similar and even stronger effects for friends who are real (past)

lenders. A greater number of real lender friends who bid on a listing make the listing more likely to be a success. More strikingly, if the borrower has a real lender friend but this friend chooses not to lend to this particular borrower, this “inaction” is interpreted by other lenders as a negative signal, thereby decreasing the probability of the loan being funded.

At the finest level of role and identity is whether a real lender friend who bid actually won or lost in the listing. Real lender friends who win a bid not only signal their willingness to lend to the friend but also signal their willingness to compete and win in the auction. This type of behavior may serve as a more positive signal to outside lenders to participate in the loan listing aggressively. We find that the number of real lenders bidding on a friend’s loan listing has beneficial effects on the funding probability both when the friends win and do not win in the auction, although the coefficient for winners is about twice that of the coefficient for lenders who do not win. Other coefficients in the specification are not affected.

In sum, our results establish that social capital matters in attracting outside financial capital. Furthermore, the structural aspects of the social network are not necessarily the critical variables for successful listings. Rather, the role and identity of the members of a social network matter. In this context, verifiability is critical. Social capital that is verifiable and visible to outside lenders has the capacity to influence outside lender behavior, even in a setting in which these outside lenders are atomistic individuals participating in arms-length transactions with the individuals possessing the social capital.

Social network variables – Group Affiliation

Our hypothesis that verifiability matters applies to groups as well. We specifically consider the group characteristics. Here, we again draw a distinction between group memberships that are less or more verifiable based on the criteria imposed for joining a group. We find two categories of groups where there is a relatively high bar on verifiability: alumni memberships based on university or former or current employers, and geography based groups. For both variables, group membership results in a greater chance of listings being funded in all six specifications. Interestingly, being affiliated with religious groups also matters. In a later section, we test these (and other) hypothesis by examining ex-post default rates on loans.

Survival Model of Loan Performance

Prosper.com records the status of loans in each month, or payment cycle. If the borrower pays off the monthly amount due, the loan status is listed as “current” for that month. Otherwise, the loans can be “late”, “1 month late”, “2 month late”, etc. We create a dummy variable “defaulted” if a loan is late for 2 months or more, consistent with the Prosper.com policies that once a loan is 2 months late or more, it is considered to be in default and sent to a collection agency. In this section, we model the default hazard as a function of hard and soft credit variables as explanatory variables, an approach taken, for instance, by Gross and Souleles (2002) in modeling consumer loan defaults.

Probit or logit models are inappropriate to model loan performance because of the nature of data: loan performance data is highly censored; it is not reasonable to compare the current status between loans that were generated a year ago to others that were generated a month ago.

The key dependent variable in the survival model is the time-to-default, or the number of payment cycles after which a loan defaults. Survival models estimate the hazard function, or the probability of surviving for the next instant of time given that a subject has survived until time T . The hazard function $h(t)$ is defined as

$$h(t) = \Pr(t \leq T \leq t + \Delta t \mid t \geq T) \tag{2}$$

Different survival models vary based on how they specify the survival function. Preliminary diagnostics indicate that the baseline hazard increases and then decreases at a slower rate over time, suggesting that either a parametric log logistic model or a Cox model is appropriate. We employ the Cox model (see, e.g., Cleves et al., 2008), which specifies the hazard as

$$h(t \mid x_j) = h_0(t) \exp(x_j \beta_x) \tag{3}$$

where $h_0(t)$ is a baseline hazard rate, and x_j represents the explanatory variables. For easier interpretation, the results we report for each covariate x_j in the Cox model is not the coefficient β_j , but rather its exponential form, which is called the “hazards ratio.” The significance of this hazards ratio must be gauged by comparing it to 1.0 rather than zero. The standard error of the exponentiated coefficients are obtained by applying the Delta method to standard errors of the coefficients (Cleves et al 2008, page 133). This allows direct and intuitive interpretation of the results. For instance, if we have a dummy variable of whether the borrower is from a usury state, and the hazards ratio is 1.2, it means that people from the usury states are 20% more likely to default than those from a state without the usury law.

Hard credit variables all affect loan performance in expected directions. For instance, more credit inquiries and higher debt to income ratios have hazard ratios exceeding 1, so they increase the probability of default. Hazards ratio on credit card inquiries is 1.037, indicating that one additional credit inquiry is associated with an average of 3.7% increase in the loan default rate.

Our focus is still the social network variables. We find that the total number of friends is insignificant as a predictor of default. However, when we decompose the friends into those with verified identities on Prosper, i.e., those who classify themselves as lenders or borrowers, and friends with no verification, we find a consistent pattern. Other things equal, having more friends without verified identities actually increases the odds of default with a hazards ratio of 1.05, while friends with verified identity decrease the odds of default. Neither variable is significant. In specification C3, we find sharper effects for the number of Prosper verified friends who are potential lenders. Having lender friends decreases default risk, with a hazards ratio of 0.91 significant at 1%, while having borrower friends (with similar financial needs) is insignificant.

Specification C4 includes the number of lender friends but this time controlling for whether they actually participate in lending. Having real lender friends further decreases the hazards ratio to 0.88, indicating even lower probability of default, and the hazards ratio decreases to 0.86 when we consider friends who bid on a listing. The coefficients are significant at 1%. Similarly, friends who bid on and win a listing; these types of listings have still lower hazard rates of 0.79, significant at 1%. The odds of default are significantly reduced when friends have a personal stake. Financial stakes taken by friends appear to be the strongest information signal for outside lenders that a borrower is credit worthy. Alternatively or additionally, peer pressure is generated when friends take stakes in a borrower’s listing, generating a positive externality to not default on loans.

In terms of group characteristics, Table 8 shows that two matter for loan performance: alumni groups and geography-based groups. Interestingly, of the various groups considered in our study, only these two groups contain verifiable information about members: borrowers need to prove that they were actually part of the relevant organization before they can join alumni groups (such as universities or companies), and geography information is verified during the registration process. Being members of these two groups increases the probability of the loan being funded and decreases the risk of default. None of the other groups have an impact on the risk of default. Controlling for the type of the group, we find that group size does not affect the loan performance or the interest rate of funded loans.

Heckman Model of Interest Rate Effects

We further examine the interest rate at which a loan is funded. The motivation for this model is straightforward. Our results show that social network variables increase the likelihood of loans being funded, and are associated with lower default rates. The question is whether social network variables have complementary price effects for borrowers. We examine this issue by regressing interest rate spreads on loans on social network variables plus controls, using a Heckman selection model.

An Ordinary Least Squares (OLS) model of interest rate is not appropriate in this context due to selectivity bias. More specifically, interest rates of loans are not available unless they are funded. We account for selectivity by using the Heckman (1979) model that specifies an equation for the probability of being funded as a function of observables and an unobserved error, and a second equation for the interest rate, which is observed only if a listing is successful.

We use the two step method of Heckman (1979) to estimate the coefficients. The model can be identified through exclusion restrictions or non-linearity intrinsic to selection models, the latter effectively identifying the model

through functional form. We obtain substantively similar results through both methods. We implement the exclusion restriction by using SPIKEDAYS in the probit model as an instrument that affects probability of funding but not the interest rate. SPIKEDAYS is the volume of search for “prosper.com” on Google Trends, a proxy for traffic to Prosper.com. This variable passes the strong instrument test of Staiger and Stock (1997). Its F-statistic exceeds 50, well above the strong instrument cutoff of 10 suggested by Stock and Staiger. The results with the instrument included are reported in Table 9. Results on hard credit variables are still in expected directions, but our focus is still the social network variables, which we shall discuss next.

None of the structural variables including centrality, coreness, effective size, and efficiency affect loan interest rates. On the other hand, the variables reflecting role and identity matter, with direction and gradation consistent with the results for funding probability and ex-post default. Connections to unverified friends increase interest rates, reflecting “negative” social capital (Portes 1998). Connections to lender friends decrease interest rates by 60 basis points, while connections to borrower friends have no effect. Both connections to real lenders and those to potential lenders matter, and the real lender coefficient results in a greater decrease in interest rates to a 70 basis point effect. These effects and their significance remain quantitatively similar when we consider real lenders who win or lose on the specific borrower auction. Interestingly, having potential lender-friends who do not bid on a borrower’s listing hurts, increasing loan spreads by about 20 basis points. In sum, we obtain consistent gradation effects as before.

The group variables also explain interest rates in a fashion largely consistent with the funding probability model. Belonging to a group that has a religious motif lowers the interest rate on loans significantly, although it has no effect on default rates. Business or university alumni affiliation groups show an even stronger effect, lowering interest rates by close to 120 basis points, consistent with the lower ex-post default rates for such loans. Geography based groups have insignificant interest rate effects and about a 10% significance in ex-post loan defaults.

Robustness and Additional Tests

We conduct extensive robustness check for the above results, and results are all consistent with them. More specifically, our robustness check includes the following: (1) panel data for funding probability, to account for multiple listings by the same borrower; (2) a survival model for “time to first time funded; (3) a Tobit model on the percentage of funding, which is censored at 0 and 100%; (4) additional hard credit variables such as number of public records and amount of delinquencies; (5) potential endogeneity of the choice of auction format, using a bivariate Probit model. Details about these tests are available upon request.

We also test and find that having endorsements has no impact on loan performance. This result holds for both having/not-having endorsements as well as for the number of endorsements received, which is consistent with the verifiability argument since endorsements are largely subjective.

Another potential confounding factor in our analysis is that borrowers themselves, or their friends who are borrowers, could already have a borrowing history, and the repayment of those loans could affect later loan requests. We found that controlling for this has no impact in our results, since all loans on Prosper.com are 3-year loans, and borrowers are not allowed to have more than 2 outstanding loans. Hence borrowers with a history on Prosper is a small fraction, and do not bias our results. We also found that controlling for other factors, amount of bids from lenders in the borrower’s group do not have an impact on the riskiness of loans. Furthermore, although we are able to incorporate most, if not all, borrower characteristics that the lenders have access to at the time of lending, cautions should be used when making causal inferences.

In addition, as pointed out by one of the reviewers, our results on funding probability and interest rate should hold only if potential lenders have access to both the borrower’s social networks, and whether any bids came from their friends. This is indeed the case in our sample, as Prosper.com displays an icon next to a bid if it comes from a friend. And the borrower’s social network is easily accessible on the page of their loan requests. But more surprisingly, even though Prosper.com does not show all the intermediary levels of the “friendship hierarchy” in figure 1, the gradation effect across these levels are evident from the analysis.

Discussions and Conclusions

Web 2.0 technology and its successors are continuing to transform how businesses and consumers interact with each other. As more entrepreneurs and investors jump on the “social networking” bandwagon, our study suggests that

social networks, especially online social networks, do not automatically and always create value to stakeholders. In fact, our results show that online social networks can be sometimes associated with negative outcomes. Our study shows that it is the relational aspects of the social network that mitigates information asymmetry: Borrowers can use the social network as a viable signaling mechanism for their trustworthiness, since as we move down the friendship hierarchy (Figure 1), the cost of signaling increases. Meanwhile, lenders can positively reward borrowers with higher chances of funding and lower interest rate, since they are less risky than others.

Borrower signaling is an important reason that the relational aspect of the networks matters more than the structural aspect in online P2P lending. Structural metrics matter in other contexts because they reflect ties that offer access to resources or information. Even if two members are not directly connected to each other, information and resources can still flow. In the context of peer-to-peer lending, the main function of ties is signaling, and signaling would work only when the tie can reasonably influence the behavior of borrowers. Hence, those who are not directly connected are much less likely to exert social pressure to repay, especially when those “distant” nodes are unverified members and there is not perceivable social contact with the borrower. In addition, as pointed out by economists such as Spence (1973), a signal is effective only when it is costly to send, such as an education. Given the “virtual” nature of this marketplace, the cost of creating online networks is very low: it is cheap to expand one’s online social networks structurally. If such networks – no matter how cheap they are – can benefit borrowers, all borrowers would have a large number of “friends”, which can be as cheap as email addresses. This, in turn, will render the signal worthless. As we have seen in our results, only the relational aspect of the social network can create a separating equilibrium that distinguishes good borrowers and bad borrowers.

Therefore for practitioners, an important implication of our study is the need to carefully understand the heterogeneity of social network ties. Specifically in decentralized marketplaces, a value-added service would be incorporating relation-specific network metrics as additional search criteria. This promises to increase the efficiency of matching among market participants. In addition, despite the popularity of many social networking websites, our study suggests that a proper valuation of these websites should not simply depend on the number of users, but rather how these users and connections can actually create tangible values.

Our study also contributes to the growing IS literature on the economic value of online social networks, as well as the literature on trust and reputation. We find that even though social networks can create value, there is a critical boundary condition: it is the relational aspect that matters. In addition, the "online" nature of these networks requires that their value can be realized only to the extent that they are verifiable to other stakeholders. These findings should have significant implications for trust and reputation mechanisms of electronic markets in general.

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Appendices

Table 1: Estimated models and their different specifications

	Variable set 1	Variable set 2	Variable set 3	Variable set 4	Variable set 5	Variable set 6
Probit Model	Spec. P1	Spec. P2	Spec. P3	Spec. P4	Spec. P5	Spec. P6
Heckman model	Spec. H1	Spec. H2	Spec. H3	Spec. H4	Spec. H5	Spec. H6
Cox model	Spec. C1	Spec. C2	Spec. C3	Spec. C4	Spec. C5	Spec. C6

Table 2: Variable sets used in different specifications of the models

Variable sets	Corresponding level in the friendship hierarchy	Common variables	Additional variables
1	Root level (degree centrality)	• Hard credit	ttlFriends
2	1		ttlNoRole, ttlRole

3	2	information; • Auction characteristics; • Social network info – Groups; • Quarterly Fixed Effects • Additional control variables	ttlNoRole, ttlPureBorrow, ttlLend
4	3		ttlNoRole, ttlPureBorrow, ttlPotentLend, ttlRealLend
5	4		ttlNoRole, ttlPureBorrow, ttlPotentLend, ttlRealNoBid, ttlRealBid
6	5		ttlNoRole, ttlPureBorrow, ttlPotentLend, ttlRealNoBid, ttlRealBidWin, ttlRealBidLose

Tables 1 and 2 explain the specifications of the main models that we use. For instance, the first specification of the Probit model is P1, and it uses variable set 1 in a Probit setup. The contents of variable set 1 can be found in the first row (root level) of Table 2, which includes common variables (the shaded column in Table 2) and the variable “ttlFriends” for the total number of friends. Other variables sets are similarly defined.

Table 3: Probability of funding (Probit model)

Table 3 reports the estimates of probit models, where 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, plus quarterly time period fixed effects. Robust standard errors are in parentheses. Results on controls are available upon request. (* p<0.1, ** p<0.05, *** p<0.01)

	Spec. P1	Spec. P2	Spec. P3	Spec. P4	Spec. P5	Spec. P6
ttlFriends	0.033*** (0.008)					
ttlNoRole		-0.020* (0.010)	-0.020** (0.010)	-0.017* (0.010)	-0.017 (0.010)	-0.017* (0.010)
ttlRole		0.106*** (0.017)				
ttlPureBorrow			-0.006 (0.023)	-0.002 (0.021)	0.018 (0.018)	0.018 (0.018)
ttlLend			0.170*** (0.023)			
ttlPotentLend				0.025 (0.022)		
ttlRealLend				0.312*** (0.055)		
ttlPotentNobid					-0.062** (0.028)	-0.063** (0.029)
ttlPotentBid					0.325*** (0.050)	0.329*** (0.050)
ttlRealBid					0.849*** (0.044)	
ttlrealnobid					-0.148*** (0.022)	-0.151*** (0.023)
ttlRealBidWin						0.782*** (0.047)
ttlRealBidLose						1.628*** (0.185)
creditgrdA	-0.375*** (0.037)	-0.372*** (0.037)	-0.372*** (0.037)	-0.373*** (0.037)	-0.381*** (0.036)	-0.381*** (0.036)
creditgrdB	-0.806*** (0.062)	-0.805*** (0.061)	-0.805*** (0.061)	-0.805*** (0.061)	-0.814*** (0.063)	-0.812*** (0.062)
creditgrdC	-1.457*** (0.056)	-1.455*** (0.056)	-1.456*** (0.056)	-1.457*** (0.056)	-1.470*** (0.057)	-1.466*** (0.057)
creditgrdD	-2.105***	-2.102***	-2.107***	-2.109***	-2.133***	-2.127***

	(0.094)	(0.094)	(0.093)	(0.094)	(0.094)	(0.094)
creditgrdE	-2.831***	-2.825***	-2.833***	-2.837***	-2.867***	-2.859***
	(0.139)	(0.138)	(0.138)	(0.139)	(0.139)	(0.139)
creditgrdHR	-3.310***	-3.304***	-3.312***	-3.318***	-3.354***	-3.346***
	(0.132)	(0.131)	(0.131)	(0.131)	(0.131)	(0.130)
bankCardUtilization	0.359***	0.356***	0.357***	0.355***	0.357***	0.358***
	(0.105)	(0.104)	(0.103)	(0.103)	(0.102)	(0.103)
BankCardUtilization²	-0.203**	-0.201**	-0.200**	-0.200**	-0.199**	-0.199**
	(0.096)	(0.096)	(0.095)	(0.096)	(0.095)	(0.095)
inquiriesLast6months	-0.020***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
debttoincomeratio	-0.102***	-0.102***	-0.102***	-0.103***	-0.106***	-0.106***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log(amountReq)	-0.706***	-0.707***	-0.708***	-0.709***	-0.714***	-0.713***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
BorrowerMaximumRate	24.308***	24.307***	24.406***	24.558***	24.844***	24.760***
	(1.099)	(1.095)	(1.093)	(1.094)	(1.092)	(1.093)
Borrowermaxrate²	-37.911***	-37.904***	-38.057***	-38.357***	-38.849***	-38.708***
	(2.234)	(2.220)	(2.212)	(2.217)	(2.220)	(2.223)
auctionformat	0.122***	0.125***	0.126***	0.127***	0.133***	0.134***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.018)
_ReligionGroup	0.280***	0.287***	0.283***	0.273***	0.246***	0.246***
	(0.089)	(0.088)	(0.087)	(0.085)	(0.084)	(0.083)
_GeographyGroup	0.572**	0.536**	0.512**	0.467***	0.411**	0.419***
	(0.241)	(0.220)	(0.200)	(0.176)	(0.161)	(0.163)
_AlumniGroup	0.529***	0.526***	0.519***	0.519***	0.527***	0.529***
	(0.098)	(0.096)	(0.098)	(0.097)	(0.100)	(0.099)
_cons	2.494***	2.473***	2.474***	2.458***	2.528***	2.522***
	(0.192)	(0.190)	(0.192)	(0.193)	(0.190)	(0.189)
N	205131	205131	205131	205131	205131	205131
pseudo R-sq	0.322	0.323	0.324	0.325	0.331	0.331

Table 4: Time to default of successful listings (Cox model)

Table 4 reports the estimates of a Cox proportional hazards model on the time-to-default of loans successfully funded on Prosper.com. Robust standard errors are in parentheses. The table reports the exponentiated coefficients, or the hazards ratio. Values greater than 1 suggest that risks increase as covariates increase, and vice versa.

	Spec. C1	Spec. C2	Spec. C3	Spec. C4	Spec. C5	Spec. C6
ttlFriends	1.017					
	(0.021)					
ttlNoRole		1.048	1.048	1.047	1.047	1.047
		(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
ttlRole		0.968				
		(0.027)				
ttlPureBorrow			1.061	1.061	1.058	1.055
			(0.055)	(0.055)	(0.055)	(0.053)
ttlLend			0.912**			
			(0.034)			
ttlPotentLend				0.950		
				(0.061)		
ttlRealLend				0.877***		
				(0.044)		
ttlPotentNobid					0.964	0.964

					(0.073)	(0.071)
ttlPotentBid					0.910	0.916
					(0.150)	(0.150)
ttlRealBid					0.856**	
					(0.052)	
ttlrealnobid					0.938	0.938
					(0.113)	(0.113)
ttlRealBidWin						0.791***
						(0.062)
ttlRealBidLose						1.086
						(0.146)
inquirieslast6months	1.037***	1.037***	1.037***	1.037***	1.037***	1.037***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Debt-to-incomeRatio*10	1.004***	1.004***	1.004***	1.004***	1.004***	1.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Interest Rate	1.088***	1.088***	1.087***	1.087***	1.087***	1.087***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)
auctionformat	1.073	1.070	1.069	1.069	1.069	1.072
	(0.074)	(0.074)	(0.074)	(0.074)	(0.074)	(0.075)
GroupLeaderRewarded	1.152***	1.151***	1.152***	1.153***	1.153***	1.148***
	(0.047)	(0.047)	(0.047)	(0.047)	(0.047)	(0.046)
_ReligionGroup	0.758	0.760	0.766	0.768	0.769	0.767
	(0.180)	(0.181)	(0.182)	(0.182)	(0.182)	(0.185)
_GeographyGroup	0.404**	0.416**	0.426**	0.430**	0.430**	0.433**
	(0.166)	(0.166)	(0.170)	(0.171)	(0.170)	(0.170)
_AlumniGroup	0.406***	0.407***	0.408***	0.409***	0.408***	0.409***
	(0.120)	(0.120)	(0.122)	(0.123)	(0.122)	(0.123)
creditgrdA	1.696***	1.692***	1.692***	1.692***	1.694***	1.691***
	(0.204)	(0.204)	(0.205)	(0.205)	(0.205)	(0.205)
creditgrdB	2.009***	2.009***	2.007***	2.005***	2.009***	2.008***
	(0.233)	(0.233)	(0.233)	(0.233)	(0.235)	(0.235)
creditgrdC	2.329***	2.330***	2.333***	2.334***	2.341***	2.342***
	(0.333)	(0.336)	(0.337)	(0.337)	(0.338)	(0.338)
creditgrdD	2.461***	2.463***	2.476***	2.479***	2.489***	2.496***
	(0.466)	(0.465)	(0.468)	(0.467)	(0.470)	(0.472)
creditgrdE	3.055***	3.064***	3.097***	3.106***	3.122***	3.139***
	(0.896)	(0.895)	(0.902)	(0.903)	(0.908)	(0.911)
creditgrdHR	4.550***	4.567***	4.638***	4.655***	4.685***	4.710***
	(1.394)	(1.393)	(1.408)	(1.408)	(1.421)	(1.427)
BIC	45998.573	46007.992	46016.797	46028.312	46052.031	46061.700
Log lik.	-2.28e+04	-2.28e+04	-2.28e+04	-2.28e+04	-2.28e+04	-2.28e+04

Table 5: Interest rate on funded listings (Heckman model)

Table 5 (please see next page) reports the estimates of a Heckman selection model. The dependent variable of the outcome equation is the interest rate for successful listings. The selection equation is a probit specification that models the probability of a listing being successfully funded. We report all estimated coefficients for the interest rate equation but suppress coefficients for all probit variables included in Table 3 since they are very consistent. Robust standard errors are shown in parentheses. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$)

	Spec. H1	Spec. H2	Spec. H3	Spec. H4	Spec. H5	Spec. H6
<i>Borrower Rate (Outcome)</i>						
ttlFriends	-0.002***					
	(0.001)					
ttlNoRole		0.002***	0.002***	0.002***	0.001***	0.001***
		(0.001)	(0.001)	(0.000)	(0.000)	(0.000)

ttlRole		-0.005***				
		(0.001)				
ttlPureBorrow			0.000	-0.000	-0.001	-0.001
			(0.001)	(0.001)	(0.001)	(0.001)
ttlLend			-0.006***			
			(0.001)			
ttlPotentLend				-0.001		
				(0.001)		
ttlRealLend				-0.007***		
				(0.001)		
ttlPotentNobid					0.002**	0.002**
					(0.001)	(0.001)
ttlPotentBid					-0.008***	-0.008***
					(0.001)	(0.001)
ttlRealBid					-0.007***	
					(0.001)	
ttlrealnobid					0.002	0.001
					(0.001)	(0.001)
ttlRealBidWin						-0.006***
						(0.001)
ttlRealBidLose						-0.006***
						(0.002)
bankrate	0.104*	0.106**	0.102**	0.102***	0.100***	0.099***
	(0.053)	(0.048)	(0.042)	(0.032)	(0.027)	(0.027)
Log(Loan Amount)	0.047***	0.043***	0.038***	0.030***	0.014***	0.012***
	(0.004)	(0.003)	(0.003)	(0.002)	(0.001)	(0.001)
borrowermaximumrate	-1.008***	-0.854***	-0.688***	-0.368***	0.206***	0.255***
	(0.135)	(0.119)	(0.102)	(0.071)	(0.038)	(0.036)
BorrowermaxRate²	2.749***	2.507***	2.246***	1.746***	0.846***	0.769***
	(0.221)	(0.195)	(0.167)	(0.117)	(0.068)	(0.064)
auctionformat	0.030***	0.031***	0.031***	0.033***	0.035***	0.036***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
grpleaderrewarded	-0.005***	-0.004***	-0.003***	-0.002*	0.002**	0.002**
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
_ReligionGroup	-0.020***	-0.019***	-0.017***	-0.014***	-0.007***	-0.007***
	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)	(0.002)
_GeographyGroup	-0.031***	-0.026***	-0.021***	-0.014***	-0.002	-0.001
	(0.008)	(0.007)	(0.006)	(0.004)	(0.003)	(0.003)
_AlumniGroup	-0.036***	-0.033***	-0.030***	-0.024***	-0.013***	-0.012***
	(0.006)	(0.006)	(0.005)	(0.004)	(0.003)	(0.002)
Inverse Mills Ratio	-0.081***	-0.073***	-0.064***	-0.047***	-0.016***	-0.013***
	(0.007)	(0.006)	(0.005)	(0.003)	(0.002)	(0.002)
_cons	-0.083***	-0.073***	-0.065***	-0.050***	-0.027***	-0.024***
	(0.010)	(0.009)	(0.008)	(0.006)	(0.004)	(0.004)
<i>Selection Equation: All variables used but not reported for conciseness</i>						
spikedays	-0.050**	-0.053***	-0.053***	-0.054***	-0.052***	-0.051**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
N	205,132	205,132	205,132	205,132	205,132	205,132
Chi-squared	20,014	24,575	31,816	56,142	88,973	91,319

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