The Information Value of Online Social Networks: Lessons from Peer-to-Peer Lending*

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Abstract

We examine whether social networks facilitate online markets using data from a leading peer-to-peer lending website. We find that borrowers with social ties are consistently more likely to have their loans funded and receive lower interest rates; however, most borrowers with social ties do not perform better ex post. This finding suggests that lenders do not fully understand the relationship between social ties and unobserved borrower quality. We also find evidence of gaming on borrower participation in social networks. Overall, our findings suggest that return-maximizing lenders should be careful in interpreting social ties within the risky pool of social borrowers.

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1 Introduction

Many online markets provide an infrastructure for anonymous individuals to conduct transactions with each other. To overcome the information asymmetries exaggerated by the anonymity, these markets often allow users to demonstrate social ties with other users on the same or related platforms. However, it is not well understood how effective anonymous social ties can be in helping to solve the information problems. Using transaction level data from Prosper.com – the first and by far the largest peer-to-peer consumer lending platform in the US[1] – this paper examines whether or not informal online social networks can facilitate e-commerce when there are significant information asymmetries.

On Prosper.com individual borrowers and lenders are matched anonymously via real-time auctions. Although part of a borrower's credit history (from Experian) is disclosed to all lenders, online anonymity could exacerbate the classical information problems of consumer lending (Stiglitz and Weiss 1981). In an attempt to overcome some of these information problems, Prosper has instituted social networking features. Prosper members can identify each other as friends and can join groups. Friends and group leaders can endorse a borrower by posting a message on the listing page, and bids from friends and group members are highlighted for other potential lenders to see. Additionally, groups are intended to provide social pressure for their members to repay their loans. However, unlike typical microfinance arrangements (Armendariz and Morduch 2010), endorsement or group membership does *not* entail any co-signing responsibility or require any social interactions after funding.

Some social networks may also fail to solve or even aggravate the information problems. A friend that endorses and bids on a listing may do so for charity purposes, which would confuse the potential positive meaning of the endorsement. During the early portion of our analysis period, group leaders received rewards when their group members were funded, providing incentives for group leaders to endorse risky borrowers in order to earn this reward without performing adequate risk screening. Additionally, a borrower may bribe a friend to endorse and bid on her listing. The danger of gaming and misinterpretation could make social networking elusive and non-sustainable in the long run.

Given borrower self-selection in to social networks, these attributes may convey

[1]Zopa.com (of the UK) was the first peer-to-peer lending website world wide.

positive or negative information about the borrower's true repayment probability, or may simply reflect cheap talk with no additional information beyond other observable characteristics. We use loan application and performance data from Prosper.com to understand what information these social networks convey about a borrower and how lenders tend to interpret these social networking attributes.[2] Evidence suggests that lenders are more likely to fund social network affiliated loans and give them more generous terms. All else equal, listings with group affiliation, group leader endorsements, or friend endorsements are more likely to be funded and enjoy lower interest rates as compared to those without social connections. However, not all social ties imply a higher financial return to lenders. In particular, only endorsements from friends who also contribute money to the loan themselves produce consistently better *ex post* performance as compared to loans without friends. Prosper groups are very heterogeneous and groups with characteristics most likely to provide screening and monitoring demonstrate better *ex post* performance.

Econometrically, one may be concerned that lenders observe some information not included in our data set, for example, gender or race in a borrower-provided image, as previous research has shown that these attributes play some role in funding outcomes (Pope and Sydnor 2011, Duarte et al. 2012). To address this concern, we rerun the analysis based on the subsample of listings without any image. Our findings on social network variables are robust to this sample change, suggesting that our results are unlikely driven by borrower information that lenders observe but we do not. Overall, these findings suggest that some forms of social networking do in fact convey positive information about borrower characteristics, but others do not and are consistently misinterpreted by lenders.

Since borrower-initiated social networking does not necessarily entail verifiable information, it is also subject to gaming. There is evidence that some group leaders have gamed the system to extract group leader rewards from Prosper without adequately screening borrower risk in the group. There are also mutual endorsements and bids among borrowers. Conditional on other observables, loans with mutual endorsement and mutual bids do have lower rates of return than loans in which only one friend has endorsed and bid on the others loan without a reciprocating endorsement and bid.

Despite a great deal of lender misinterpretation and potential overt gaming, over time lenders learn to avoid listings with misleading social network signals, especially when loans with such attributes in the lender's past portfolio perform poorly. That

[2] By loan performance, we mean monthly payment outcomes throughout the life of a loan.

said, lender learning is gradual and part of the overall rate-of-return gap between social and non-social loans persists over time.

Our work contributes to the literature on informal lending, microfinance, and more broadly asymmetric information. Previous researchers have argued that informal and micro lenders have an information advantage over traditional banks because they utilize borrowers' social networks to ensure good risks (e.g. La Ferrara 2003, Udry 1994, Hoff and Stiglitz 1990, Besley and Coate 1995). Most of the microfinance literature focuses on the contractual tools that lenders can use to improve loan performance, such as imposing joint liability among group members, organizing group meetings on a regular basis, or practicing progressive lending based on the borrower's past repayment history (Armendariz and Morduch 2010). While some of these tools are built upon existing social ties, they all introduce *new* incentives to build or harness social capital. Lab and field experiments are designed to randomly assign different contracts to similar borrowers, in order to minimize borrower selection into specific programs (Karlan 2005; Gine and Karlan 2010; Feigenberg, Field and Pande 2010; Bryan, Karlan and Zinman 2010). In contrast, borrower selection in peer-to-peer lending is worth studying itself, even if there is no legal or social intervention from lenders. If borrowers' social networking activities deliver meaningful information to lenders, it constitutes a direct usage of existing social ties and could alleviate information asymmetry without the hefty cost of organizing and enforcing microfinance from the lender's point of view.[3]

Our paper also contributes to a growing literature on peer-to-peer lending itself (Ravina 2007, Pope and Sydnor 2011, Iyer et al. 2009, Rigbi 2011, Hampshire 2008, Freedman and Jin 2010, Lin et al. 2013, Paravisini et al. 2011, Kawai et al. 2013), which focuses on either the relationship between borrower attributes and listing outcomes or lenders' investment decisions. Additionally, Agrawal et al. (2011) find that the internet can reduce the usually important role of spacial proximity in early-stage project investment. However, they also find that offline social networks play an important role, as local investors likely to know the borrower offline typically invest earlier and are followed by more distant investors. In this paper, we aim to provide a balanced view of the role of online social networks in peer-to-peer lending by examining social networks from both the borrower and lender point of view and by contrasting *ex ante* funding outcomes with *ex post* performance throughout the

[3]Gomez and Santor (2003) compare individual and group borrowers in two Canadian microlenders and show that group borrowers tend to have smaller loans and are more likely to be female, Hispanic, immigrant, with lower income, etc. Ahlin (2009) shows that self-selected groups are more homogeneous than randomly assigned groups.

whole life of a loan.

The mixed evidence we have found about social networking on Prosper is consistent with the mixed effects of information on the internet in general. For example, price comparison websites can reduce search costs but obfuscate consumer search at the same time (Ellison and Ellison 2013); seller-provided product information can be a positive signal for seller quality in some eBay transactions (Lewis 2011), but confuse buyers in other situations (Jin and Kato 2007); online reputation can help to distinguish different types of sellers while motivating strategic retaliation (Dellarocas 2003); and social networks can facilitate targeted advertising but raise privacy concerns along the way (Tucker 2011, 2012). All these studies, including ours, suggest that information is a double-edge sword, especially on the anonymous internet.

The rest of the paper is organized as follows. Section 2 describes the background of Prosper.com and its social networking features. Section 3 discusses the potential roles of social networking on Prosper that we will test in our empirical analysis. Section 4 describes the data and summarizes the Prosper population over time. Section 5 examines the effect of borrower social ties on funding probability, interest rate, *ex post* performance and an estimated internal rate of return. A short conclusion is offered in Section 6.

2 Background

2.1 Market Setup

All Prosper loans are fixed rate, unsecured, three-year, and fully amortized with simple interest. Loans can range from $1,000 to $25,000. By the end of our sample period (July 31, 2008), Prosper had attracted 750,000 members and originated loans of over 160 million dollars.[4] During this time period the loans are not tradable in any financial market,[5] so lenders that fund a loan in our sample are tied to that loan until full payment or default. Upon default Prosper hires collection agencies and any money retrieved in collections is returned to the loan's lenders. There is no penalty for early payment.

Before a potential borrower lists a loan application on Prosper, Prosper authen-

[4]The quick expansion of Prosper has coincided with a number of similar new peer-to-peer lending sites in the US. The best known examples are Kiva.org (incorporated November 05), Smava (launched in February 2007), Lending Club (opened May 24, 2007 as part of Facebook), MyC4 (launched in May 2007), Globefunder (launched in October 2, 2007), and Zopa US (us.zopa.com, opened December 4, 2007).

[5]In October 2008, Prosper began the process of registering with the SEC in order to offer a secondary market, which was approved in July 2009 and therefore is outside of our sample period.

ticates the applicant's social security number, driver's license, and address. Prosper also pulls the borrower's credit history from Experian, which includes the borrower's credit score and historical credit information such as total number of delinquencies, current delinquencies, inquiries in the last six months, etc.[6] If the credit score falls into an allowable range, the borrower may post an eBay-style listing specifying the maximum interest rate she is willing to pay, the requested loan amount, the duration of the auction (3-10 days),[7] and whether she wants to close the listing immediately after it is fully funded (called autofunding). In the listing, the borrower may also describe herself, the purpose of the loan, and any other information that she feels may help fund the loan. In the same listing, Prosper posts the borrower's categorical credit grade (computed based on the Experian credit score), home ownership status, debt-to-income ratio,[8] and other credit history information. All of this information is recorded in our data. In addition, the borrower can upload an image in the listing. Our data contains a dummy indicating whether an image exists, but no more details on the content of the image. In reality, lenders may extract information from the image – for example, gender, race, and facial expression – but there is no guarantee that the image reflects the borrower herself or her lifestyle. To address the concern that missing image contents may bias our results, we will conduct robustness check on listings without image and compare them to results from the full sample.

Like borrowers, a potential lender must provide a social security number and bank information for identity confirmation. Lenders can browse listing pages which include all of the information described above, plus information about bids placed, the percent funded to date, and the listing's current prevailing interest rate. To view historical market data, a lender can download a snapshot of all Prosper records from Prosper.com (updated daily), use a Prosper tool to query desired statistics, or visit third party websites that summarize the data. Interviews conducted at the 2008 Prosper Days Conference suggest that there is enormous heterogeneity in lender awareness of the data, ability to process the data, and intent to track the data over time.

The auction process is similar to proxy bidding on eBay. A lender bids on a listing by specifying the lowest interest rate he will accept and the amount of dollars he would like to contribute (any amount above $50). A listing is fully funded if the

[6]The credit score reported uses the Experian ScorePLUS model, which is different from a FICO score, because it intends to better predict risks for new accounts.

[7]As of April 15, 2008 all listings have a duration of 7 days.

[8]The debt information is available from the credit bureau, but income is self-reported. Therefore, the debt-to-income ratio reported in the listing is not fully objective.

total amount of bid exceeds the borrower request loan amount. Lenders with the lowest specified minimum interest rate will fund the loan and the contract interest rate is set as the minimum interest rate specified by the first lender excluded from funding the loan.[9] Prosper charges fees on both sides of the market if a listing is completely funded. Freedman and Jin (2010) discuss additional details of the market operation.

Prosper has continually changed the hard information that it provides lenders. At the beginning of our sample (June 2006), the credit information posted on Prosper includes debt-to-income ratio, credit grade, whether the borrower owns a home and some credit history information about delinquencies, credit lines, public records, and credit inquires. Initially credit grade categories include AA defined as 760 or above, A as 720-759, B as 680-719, C as 640-679, D as 600-639, E as 540-599, HR as less than 540, and NC if no credit score is available.[10] The actual numerical credit score is not available to lenders partly because of privacy protection for borrowers[11] and partly because Prosper has promised to not reveal the numerical credit score in exchange for a deep discount on credit reports from Experian. On February 12, 2007, Prosper began posting more detailed credit information plus self reported income, employment and occupation.[12] Additionally, Prosper tightened the definition of grade E from 540-599 to 560-599 and grade HR from less than 540 to 520-559 eliminating borrowers that have no score or a score below 520. On October 30, 2007, Prosper began to display a Prosper-estimated rate of return on the bidding page (bidder guidance). Before this change, a lender had to visit a separate page to look for the historical performance of similar loans.[13] These important information changes, as well as the changes in the macro environment on and off Prosper will be controlled for by year-week fixed effects and macroeconomic time series to be described below.

2.2 Social Networks

In addition to providing hard information in the form of credit histories, Prosper facilitates the use of social networking through groups and friends. A non-borrowing

[9] If autofunding is chosen by the borrower, the auction ends immediately upon becoming fully funded, and the interest rate is set at the borrower maximum rate.

[10] Prosper has refined credit grade definitions since its registration with the SEC in July 2009.

[11] If a borrower volunteers personal-identifiable information in the listing, Prosper personnel will remove such information before posting the listing.

[12] On this date, lenders were also allowed to begin asking borrowers questions and the borrowers had the option to post the Q&A on the listing page.

[13] Prosper also introduced portfolio plans on October 30, 2007, which allow lenders to specify a criterion regarding what types of listings they would like to fund and Prosper will place their bids automatically. These portfolio plans simplified the previously existing standing orders.

individual may set up a group on Prosper and become a group leader. The group leader is responsible for setting up the group web page, recruiting new borrowers into the group, coaching the borrower members to construct a Prosper listing, and monitoring the performance of the listings and loans within the group. The group leader does not have any legal responsibility. Rather, the group leader is supposed to foster a "community" environment within the group so that the group members feel social pressure to pay the loan on time. Group leaders can also provide an "endorsement" on a member's listing, and bids by group leaders and group members are highlighted on the listing page. Since October 19, 2006, Prosper has posted star ratings (one to five) in order to measure how well groups perform against expected (Experian historical) default rates.[14]

Prosper groups were initiated as a tool to expand the market, and thus Prosper initially rewarded a group leader roughly $12 when a group member had a loan funded (Mendelson 2006). Given the fact that borrowing is immediate but payment does not occur until at least one month later, the group leader reward may have created a perverse incentive to recruit borrowers without careful screening of credit risk. To the extent that the group leader knows the borrower in other contexts (e.g. colleagues, college alumni, military affiliation), she could collect credit-related information via emails, interviews, house visits, employment checks, and other labor-intensive means.[15] However, when a group gets very large (some with over 10,000 members), it becomes difficult if not impossible to closely monitor each loan. This tension between member recruiting and performance monitoring prompted Prosper to discontinue group leader reward on September 12, 2007.

Starting on February 12, 2007, Prosper members could invite their friends to join the website. The inviting friend receives a reward when the new member funds ($25) or borrows her first loan ($50). Existing Prosper members can become friends as well if they know each other's email address but the monetary reward does not apply. Friends can also provide endorsements on each other's listings and a bid by a friend is highlighted on the listing page. Beginning February 23, 2008 lenders could include aspects such as friend endorsements and bids from friends as criteria in their listing searches.

While Prosper-specific social networking is open to all members, it is disproportionately used by borrowers. In our sample, 28.8% of borrowers belong to a group,

[14] Groups must have at least 15 loan cycles billed before they are rated, otherwise they are "not yet rated."

[15] Group leaders do not have access to the borrower's credit report prior to listing.

and 19.1% have friend endorsements and/or friend bids. In comparison, only 18% of lenders who have ever funded a loan have group affiliations and 15.5% have friends on Prosper.

3 Potential Roles of Social Networks

The primary goal of this paper is to examine what information a borrower's social network affiliation conveys and how lenders interpret this information. In this section we discuss conceptually the roles that social networks may play on Prosper and make empirical predictions about the relationship between social ties and observed listing and loan outcomes depending on these roles.

Since a borrower chooses which networks to join on Prosper, the social networking behavior may convey some information that the borrower knows but a generic Prosper lender does not know. All else equal, a borrower with social ties may be of true lower quality or higher quality than a borrower without social ties. Alternatively, joining a social network may be cheap talk that conveys no true information.

On the positive side, social network affiliation may indicate lower risk borrowers for a variety of reasons. Social ties may simply verify a certain borrower attribute. For example, members of a university alumni group may not know each other in person, but group membership certifies the borrower's educational attainment. Similarly, membership in an employment related group, such as the Walmart Employee group, certifies a member's employment status if the group leader verifies employment. Social network affiliation may also be associated with lower borrower risk if the social network engages in active screening and/or monitoring of borrowers. For instance, Prosper group leaders could use their social capital to recruit good borrowers and collect information to screen out bad risks. An endorsement from a group member, group leader, or friend may also signal something about the borrower's unobserved credit-worthiness. This signal may be strengthened if the endorser also bids on the loan, which increases the incentives to actively monitor the borrower or shows that the endorser trusts the borrower enough to take a financial stake. More broadly, a large microfinance literature emphasizes the role that social networks can play in reducing adverse selection and moral hazard in an unsecured credit market (Arnott and Stiglitz 1991, Besley and Coate 1995, see Morduch 1999 and Armendariz and Morduch 2010 for reviews).

Is worth noting that social networks may reduce adverse selection and moral hazard in the Prosper context despite network members not sharing any legal responsibility of loan repayment. Although group liability was the cornerstone of microfinance in the early days of the Grameen Bank, many microfinance institutions have shifted from group liability to individual liability with regular group meetings. In field experiments Gine and Karlan (2010) show no default difference between groups with joint or individual liability. In another field experiment where loan payment is the borrower's individual liability, Feigenberg et al. (2010) find that more frequent group meetings lead to less default.

Some borrowers with social network affiliation could be lower quality, all else equal. This may be particularly true given potentially perverse incentives built into the Prosper market place. While a group leader that lends to same group members or values the group's repayment reputation has incentives to screen and monitor group members, group leader rewards (about $12 per new loan) provide an incentive to forgo active screening and monitoring. Since group leaders do not co-sign the loan and there is a natural lag between funding and repayment, the group leader reward may encourage group leaders to recruit as many borrowers as possible, endorse the group's listings to ensure funding, but engage in no screening or monitoring at all.[16] Similar logic applies to friend endorsements: if it is easy for a bad borrower to obtain favorable endorsements from a dishonest friend, friend endorsement does not always separate good types from bad types.

Regardless of the true information value of social ties, lenders may interpret these social ties as either positive or negative indicators of borrower quality. Lenders may also view these ties as cheap talk that convey no information. Predictions about the impact of social ties on whether a loan is funded, the contract interest rate of a funded loan, and loan performance depend upon the true information value of social ties and how lenders interpret these ties.

Table 1 provides predictions about the impact of social ties on observed outcomes under various scenarios. The rows of this table correspond to the true information content of social ties. The columns correspond to how lenders interpret social ties, with sub-columns reporting our prediction for the relationship between social ties and each outcome. Generally speaking, lender interpretation determines the effect of social ties on the funding rate and the contract interest rate. If lenders expect loans with social ties to perform better, the same, or worse than non-social loans, they will be more, equally, or less likely to fund these loans, respectively. Similarly, they will be willing to fund social loans at lower, similar, or higher interest rates, respectively. True information content determines the effect of social ties on loan performance. All

[16] Prosper did hold back a portion of the $12 group leader reward until the loan had some payment history.

else equal, loans with social ties will perform better than loans without social ties if social ties are associated with positive information about borrower quality. If social ties are cheap talk or provide negative information about borrower quality, they will perform equally to or worse than non-social loans. In our empirical analysis below, we will use our estimates of the effects of social ties on these outcomes to infer the type of information contained in each social tie and whether or not lenders understand this information content.

There are a few caveats to the predictions described in Table 1. First, our empirical analysis will examine multiple measures of performance, including late or default payments, early payoffs, and expected returns. If the Prosper market operates efficiently and lenders correctly interpret social ties, we would expect to find differences in payment outcomes but no difference in returns between social and non-social loans, as any difference in performance would be reflected by different contract rates.

Second, there are alternative potential equilbria beyond this simple characterization in which social ties are associated with homogenous true information content and lenders either homogeneously correctly or incorrectly interpret this true information. In the more likely case that both borrowers and lenders are heterogeneous, our empirical analysis will estimate the average impact of social ties on listing and loan outcomes and will reveal the predominant combination of information content and lender interpretation.

It is worth pointing out a few potential sources of borrower and lender heterogeneity. It may be the case that while high quality borrowers obtain social ties in order to reveal their quality, low quality borrowers may also seek social ties in order to pool with better quality borrowers and obtain the corresponding benefits of increased funding rates and decreased interest rates. Lenders may be heterogeneous in their level of sophistication, as documented by Freedman and Jin (2010), leading some lenders to be more likely to misinterpret social ties. If some lenders are misinformed about distinguishing between high and low quality borrowers, this could increase the incentives for low quality borrowers to seek social ties in order to take advantage of these misinformed lenders.

A third caveat is that social network affiliation could increase funding rates, decreases contract rates, and be associated with worse performance if lenders prefer to give charity within a social network. Sociologists have argued that network members may do favors for each other due to reciprocity or give charity in a single direction, because the giver enjoys non-financial returns from the giving process such as approval of status within the network, future benefits from the network as a whole, or satisfaction of helping people within the same network (Portes 1998). Therefore, if empirical results fall in the lower left corner of Table 1, we cannot fully disentangle if this is a result of lenders mistaking truly negative information as positive or simply charity lending. We argue that charity and this lender misinterpretation can be distinguished because mistaken lenders would learn to avoid funding loans with these characteristics over time. Freedman and Jin (2010) have presented systematic evidence on lender learning, and this paper will focus on whether lenders learn about group affiliation and friend endorsement specifically.

4 Data and Summary Statistics

4.1 Data Sources

Our main data set comes from the data available for download from Prosper's website as of August 18, 2011. Because of changes to the platform that occurred in the second half of 2008, we analyze the sample of all listings that began on or after June 1, 2006 and end on or before July 31, 2008 and the loans that originate from this set of listings.[17] Our data extract includes all of the information available to borrowers and lenders on the website since Prosper's inception. For each listing it contains the credit variables that Prosper posts from the Experian credit reports, the description and image information that the borrower posts, and a list of auction parameters chosen by the borrower. For those listings that become loans, we observe payment through July 31, 2011, which includes the full 36-month history for all loans in our sample. For each Prosper member we observe their group affiliation and network of friends as of the download date. Because these characteristics can change over time, we use monthly downloads beginning in January 2007 to identify these characteristics at the closest possible date to the actual listing. Finally, data on all successful and unsuccessful Prosper bids allow us to construct each lender's portfolio on any given day.

It is worth noting that consumer lending has undergone dramatic changes during our sample period, ranging from a calm market with stable monetary policy before August 2007 to the outbreak of the subprime mortgage crisis on August 9, 2007, followed by gradual spillovers to other types of lending and investment. In light of this, our regression analysis below controls for a number of daily macroeconomic variables, including the bank prime rate, the TED spread, the yield difference between corpo-

[17] We exclude the few loans that were suspects of identity theft and as a result repurchased by Prosper.

rate bonds rated AAA and BAA, and S&P 500 closing quotes.[18] Additionally, we include the unemployment rate reported by the Bureau of Labor Statistics (BLS) by state and month, the housing price index reported by the Office of Federal Housing and Enterprise Oversight (OFHEO) by state and quarter, the quarterly percentage of senior loan officers that have eased or tightened credit standards for consumer loans, and the foreclosure rate reported by Realtytrac.com by state and month.[19] In our analysis, most of the time-series variables, except for those varying at the daily or state level will be absorbed by weekly fixed effects.[20]

4.2 Quantifying Loan Performance

Analysis below examines the relationship between social network attributes and loan performance. Arguably, if the goal of lending on Prosper is to maximize financial returns, a lender should consider interest rate and expected performance together in making lending decisions. To summarize a loan's overall performance accounting for interest rate, we use all available *ex post* performance data to calculate an internal rate of return (IRR) that a sophisticated lender should expect to earn at the start of a loan if he could perfectly predict the statistical relationship between listing attributes and *ex post* loan performance. The effect of borrower social variables on this IRR will capture the difference in performance between social and non-social loans to a sophisticated return-maximizing lender.

One complication is that the macroeconomic environment has changed substantially due to the financial crisis and even the most sophisticated loan officer may not have anticipated this change. To address this problem, we follow a two step algorithm: the first step is estimating how *ex post* loan performance of all Prosper loans – whether to miss a scheduled payment in a month and whether to pay off the whole loan in a month – relates to listing attributes and actual macroeconomic variables at the time of payment. This estimation attempts to isolate the contribution of macroeconomic variables to realized loan performance from the fundamental risk described by listing attributes. The second step predicts performance using the coefficient estimates from the first step but substituting the macroeconomic variables as of June 1,

[18]According to Greenlaw et al. (2008), the middle two are the strongest indicators of the subprime mortgage crisis.

[19]To capture the growth and fluctuation of the Prosper market as a whole, we also control for a number of daily Prosper-specific market characteristics, including the total value of active loan requests by credit grade, the total dollar amount of submitted bids by credit grade, and the percentage of funded loans that have ever been late by credit grade.

[20]Results reported below are robust to excluding these fixed effects and relying on these data series and are available from the authors upon request.

2006 for the real macroeconomic variables. This predicted performance allows us to calculate an internal rate of return (IRR) that the lender should expect to earn from each loan if the macroeconomic environment were unchanged since the beginning of our sample period (June 2006). The detailed algorithm, IRR calculation, and the robustness of this calculation to alternative definitions of IRR are reported in the Appendix.

Note that the calculated IRR differs from raw performance data in several ways: first, it assumes that a sophisticated return-maximizing lender has rational expectation on the statistical relationship between observable macro or borrower attributes and *ex post* loan performance; second, it fixes lender expectation of macro environment as of June 1, 2006 and therefore filters out unexpected macro shocks; third, it considers the timing of every payment outcome. For example a default that occurs in the first month is different from a default in the 36th month because lenders have earned almost all the principal and interests in the latter case. Similarly, an early payoff can imply a lower IRR than a late default. This is because early payoff is counted as cash flow at the time of payoff, which in the IRR calculation implies that the payoff amount is reinvested in a similar loan subject to a new round of risk of default, payoff, etc. As such, the empirical results below on raw performance outcomes and IRR are not always the same, and this highlights the importance of considering all the possible outcomes every month and summarizing them in the IRR.

4.3 Summary Statistics

Table 2 summarizes listings and loans by quarter for our sample, which includes 293,808 listings and 25,008 loans for \$158.27 million. This implies an average funding rate of 8.51%, though this has varied over time ranging from 6.32% to 10.14%. Average listing size and average loan size both increased through the first half of 2007 and have decreased since. Comparing listings and loans, the average listing requests \$7,592 and the average loan is worth \$6,329. The average listing lists a maximum borrower rate of 19.19% while the average contract rate is 17.90%.[21]

In terms of social networks, Table 2 shows that 28.8% of listings have some group affiliation, 3.2% have an endorsement from a group leader (2.2% with a leader bid), and 13.0% receive a friend endorsement (1.0% with a friend bid). All of these fractions increase substantially in the loan sample, indicating that on average social loans are more likely to be funded than the listings that have no social ties. However,

[21] The sharp increase in borrower maximum rates between the first and second quarters of 2008 reflects the April 2008 removal of state specific interest rate caps.

it is striking that the proportion with group affiliation has decreased drastically over time from a peak of 62% to 7.5% for listings and from 71% to 11% for loans. When friend and group leader endorsements became available, the percent of listings and loans with endorsements initially grew but has decreased since the middle of 2007. The only exception is the percent with friend endorsements plus bids.

Interestingly, the percent of listings with group leader endorsement and bid declines sharply from 4.10% in the third quarter of 2007 to 0.84% in the next quarter. Similarly, the percent of loans with group leader endorsement and bid declines sharply from 23.40% to 6.44% in the same time frame. No such declines appear for listings or loans with group leader endorsement but without group leader bid. Combined with the fact that group leader rewards were removed in September 12, 2007, this is potentially consistent with group leader gaming instead of risk screening.

Table 3 summarizes more details of social networking attributes. We classify groups by group size (numbers of total members, both borrowers and lenders), group composition (percent of members who are borrowers), group type (alumni, military, tangible connections such as employment or geographic location, loose connections such as religion or ethnicity),[22] and whether the group leader reviews a borrower's listing before granting her group affiliation. Beginning October 19, 2006, we also observe whether a group borrower is affiliated with a group of low (1-3 stars), high (4-5 stars), or no group ratings. Comparing the samples of listings and loans, it is clear that smaller groups, especially those with fewer borrowers are more likely to be funded. Listings affiliated with high group ratings, alumni groups, groups of tangible connections, or groups with review requirement are more likely to be funded, but listings from military groups or groups of loose connections are less likely to be funded. These comparisons suggest that lenders differentiate between funding different types of groups, and we will explore this further in the regression analysis below. Table 3 also summarizes Prosper loans by source of funding. It is clear that most funding comes from stranger lenders, with friends, group members and group leaders contributing only 1-5% of the total loan amount.

These summary statistics suggest that on average lenders are more likely to fund loans with social networking attributes, but there is important heterogeneity by type of network and over time. Turning to financial returns, Figures 1 through 3 compare the IRR density and mean IRR over time for borrowers with and without social

[22]To classify group type, we read the full description of each group (supplied by group leader when he/she sets up the group) and create indicators if the group description shows clear focus on alumni, military, employment, geographic location, religion or ethnicity.

networking attributes. In Figure 1A it is clear that the IRR distribution of group borrowers has a thicker left tail than that of non-group borrowers. Figure 1B plots mean IRR by group affiliation over time, with mean IRR always being lower for group borrowers. These relationships are less clear when splitting borrowers by whether or not they have a group leader endorsement but no bid, a group leader endorsement and bid, or no group leader endorsement in Figure 2A and 2B. Loans with an endorsement and bid from the group leader appear to have lower IRR's, especially in the earlier time period. Perhaps more clear is the relationship between friend endorsement status and IRR shown in Figure 3A and 3B. On average, borrowers with a friend endorsement and no bid perform worse than borrowers with no friend endorsement, while borrowers with a friend endorsement and bid perform better. These unadjusted mean comparisons suggest that while most social networking attributes are rewarded by lenders in terms of funding rate and interest rate, not all are associated with higher returns. In the next section, we examine whether these relationships change when conditioning on other loan characteristics.

5 Social Networks and Loan Outcomes

5.1 Empirical Approach

Summary statistics suggest that on average borrowers with social networking characteristics are of lower quality, but are still rewarded with higher funding rates by lenders. In this section, we explore these relationships conditional on other borrower observable characteristics.Motivated by the predictions in Table 1, our empirical analysis examines how social networking attributes impact the likelihood a listing is funded, and for funded loans how these attributes impact the contract interest rate and loan performance. To measure loan performance we examine repayment patterns and the overall return.

An important distinction between our empirical approach and previous studies in microfinance is that we are not necessarily attempting to estimate the effect of randomly assigned monitoring/screening networks on performance. Instead we are interested in conditioning on all observable characteristics that the lender sees in a listing and quantifying what additional information social networks convey. This additional information may be correlated with unobservable borrower characteristics, but what we are interested in is how social networks are used as a proxy for the borrower's unobserved quality. One important caveat is that there could be information that is present in the listing that lenders observe and is correlated with social networking status that we are unable to control for in the econometric analysis. These characteristics could include qualitative information in the borrowers picture or text that we cannot quantify in the data. To minimize this concern, we control for the presence of a picture, the length of the text, and whether the text mentions certain loan purposes such as paying for medical bills, starting a business, or purchasing a car. Later, we conduct a robustness check using the subsample of listings that do not post any image.

We estimate the relationship between social networking attributes and loan outcomes with the following four regression equations:

$$
\begin{aligned}
&(1) & 1(\mathit{Funded})_{it} &= f_1(\mathit{SocialVar}_i, \mathit{ListingAttributes}_i, \mathit{macro}_{it}, YW_t) + \varepsilon_{1it} \\
&(2) & \mathit{ContractRate}_{lt} &= f_2(\mathit{SocialVar}_l, \mathit{ListingAttributes}_l, \mathit{macro}_{lt}, YW_t) + \varepsilon_{2lt} \\
&(3) & 1(\mathit{Perform})_{lta} &= f_3(\mathit{SocialVar}_l, \mathit{ListingAttributes}_l, \mathit{macro}_{lt}, YW_t, \mathit{Age}_a) + \varepsilon_{3lta} \\
&(4) & IRR_{lt} &= f_4(\mathit{SocialVar}_l, \mathit{ListingAttributes}_l, YW_t) + \varepsilon_{4lt}
\end{aligned}
$$

Equation 1 includes the full sample of listings and describes whether or not listing i created at time t is funded or not ($1(\mathit{Funded})_{it}$). Equations 2 and 4 include the listings of fully funded loans and describe the contract interest rate ($\mathit{ContractRate}_{lt}$) and the IRR ($IRR_{lt}$) of loan l funded at time t. Regression Equation 3 also includes all funded loans, but it follows the payment history of each loan over its 36 month life span. We run various versions of this regression, measuring *Performance* by whether or not loan l funded at time t at age a is paid off or default/late.

All regressions include year-week fixed effects (YW_t) and, except for Equation 4, macroeconomic conditions that vary by day or by the borrower's state of residence (macro_{lt}) to control for the changing environment on and off Prosper at the time of funding. The *Performance* equations also include a full set of monthly loan age dummies (Age_a) to control for the life cycle of loan performance. *ListingAttributes* include Experian-verified credit history information, borrower-specified loan terms (e.g. amount request and maximum interest rate), borrower self-reported information (e.g. loan purpose, image, description).[23] Summary statistics of these attributes can be found in Appendix Table 1. The listing attributes and the macroeconomic variables are interacted with credit grade dummies to more flexibly control for non-social listing attributes. The parameters of interest are the coefficients on the vari-

[23] We only include observable credit information that was available for our whole sample period and not those new credit variables added after Feb. 12, 2007. Results are similar if we restrict the sample to post February 12, 2007 and include these additional variables and are available from the authors upon request.

ables in *SocialVar*. In the baseline specification these will include indicators for being in a group, having a group leader endorsement with no bid, having a group leader endorsement with a bid, having a friend endorsement without a bid, and having a friend endorsement with a bid. The funding rate and performance regressions are estimated by probit, and the contract rate and IRR regressions are estimated by OLS.[24]

5.2 Overall Effects of Social Network Attributes

Table 4 presents the estimated effects of the social network variables from the above specifications, with coefficient estimates reported for linear regressions and marginal effects for probit estimates. Compared with other listings, listings in which the borrower belongs to a group are 0.2 percentage points more likely to be funded and enjoy a 0.4 percentage point lower contract rate, suggesting that lenders interpret group affiliation as containing positive information about borrower quality. Payment outcomes imply ambiguous performance effects, with group loans being 0.6 percentage points more likely to be in default or late in a given month but 0.4 percentage points less likely to be paid off early, allowing lenders to gather interest over a longer payment period if the loan remains current. When we summarize overall performance, accounting for the contract rate with our measure of IRR,, group loans have a 1.8 percentage point lower expected rate of return than non-group loans. These regression results are similar to the unconditional comparisons in Figures 1A and 1B.[25] Taken together, these results suggest that group membership in fact holds negative information content about borrowers, but lenders incorrectly interpret group membership positively, as in the lower left hand corner of Table 1.

Within group listings, some receive an endorsement from the group leader and some receive a group leader bid in addition to the endorsement. Both types of endorsements appear to be interpreted as additional positive information by lenders with both leading to higher funding rates and lower contract interest rates in the second and third rows of Table 4. Leader endorsements with bids also have a much larger impact on funding rates than those without accompanying bids. The effect of group leader endorsement on loan performance is dependent on whether the group

[24]Note, the sample sizes in the contract rate and IRR regressions are slightly slightly smaller than the full sample of loans available to us. Fort these outcomes and for the monthly performance regressions, we exclude loans for which we are unable to observe the final loan performance outcome, and therefore unable to calculate IRR. See the Appendix describing the IRR calculation for details.

[25]This is a large difference as the average IRR is -7.50% across all the loans in our sample.

leader also bids on the listing: if a group leader endorsement is not accompanied by a bid, the loan has a similar default rate to non-endorsed loans and is less likely to be paid off early, leading to a 1.9 percentage point higher IRR. In contrast, if a loan has both an endorsement and a bid from the group leader, it is more likely to be in default or late, but less likely to pay off early. On net, group leader endorsement with a bid leads to a 1.3 percentage point lower IRR than non-endorsed loans.[26] These results suggest that lenders interpret both types of endorsements as positive information; although, only group leader endorsements without bids actually predict better loan performance. We explore this counterintuitive finding below by examining how the effects of these variables change after the elimination of group leader reward.

The final two rows of Table 4 explore friend endorsements, with and without bids. As with group leader endorsements, friend endorsements increase the likelihood a listing is funded, and the effect is larger when the endorsement is accompanied by a bid. Loans with a friend endorsement alone are 0.1 percentage points more likely to be funded than non-friend endorsed loans, but when the endorsement is accompanied by a bid, the funding probability is 3.4 percentage points higher than non-friend endorsed loans. While either type of friend endorsement relates to a higher funding rate, they do not both correlate with improved performance. Controlling for the other listing attributes, a friend endorsement without a bid is more likely to default. While these loans are also less likely to pay off early and lenders demand a slightly higher interest rate, the net effect on IRR is -0.8 percentage points and statistically significant. In contrast, loans with friend endorsements and accompanying bids are 4.1 percentage points less likely to be in default or late. Lenders appear to recognize this lower risk granting these loans a 0.6 percentage point lower interest rate. However, they do not completely compete away these gains as IRR is 6 percentage points higher than loans without friend endorsements, a very large effect considering the mean IRR of all loans is -7.50%.[27] Interestingly, friend endorsement with a bid is the only social attribute examined thus far that also has an unconditionally higher IRR on average as seen in Figure 3B. In the raw data, these loans perform better due to their concentration of higher grade loans, but even conditioning on observable loan attributes, friend endorsement plus bid conveys additional borrower quality that has

[26]Note that IRR accounts for the exact timing of each event in each loan, while the performance regressions only control for timing via the 36 monthly loan age dummies. Because of this, the impact of a particular loan attribute on IRR is more complicated than the sum or average of the attribute's impact on separate performance measures.

[27]As detailed in the Appendix, the IRR reported in the main text assumes the first default or late in the loan life as an absorbing state of misperformance. This underestimates the magnitude of IRR as compared to what we get if we measure misperformance defined by default or misspay.

not been priced by the market.

To this point, our estimates suggest that, conditional on observed listing and loan characteristics, lenders are more likely to fund and agree to lower interest rates for borrowers with social ties, despite not all social ties being correlated with improved loan performance. These results suggest that most social network characteristics fall in the lower left corner of Table 1 and imply either lenders misinterpret these social ties or exhibit a great deal of charity lending. Two exceptions are group leader endorsement without a bid and friend endorsement with a bid, which fall in the upper left hand corner of Table 1 as positive information of borrower quality that is correctly interpreted by lenders.

5.3 Robustness to Photo Content

Our estimates of the effects of social networking attributes on loan performance would not necessarily be causal if lenders observe some soft information, such as the content of a posted photo, which we cannot include in our analysis. Below we present a robustness check for the subsample of listings without any photo. The robustness of our results suggests that our estimates do capture some, if not all, information value of social networking attributes.

More specifically, our list of control variables includes all hard information observed by lenders and important characteristics of the listing's written description, including the length and the proposed purpose of the loan that the borrower claims. We also control for the presence of an image; however, we do not have any controls for the content of this image. Others have found the content of Prosper pictures to be important determinants of lender funding decisions (Pope & Sydnor 2011, Duarte et al. 2012). In order for the content of these pictures to bias our results, they would have to both be correlated with social networking attributes and be correlated with the error terms in our regression models. In other words, they would have to be correlated with the portion of funding rates, contract rates, and loan performance that we are unable to control for with our other independent variables.

While we cannot verify this assumption directly, we perform a robustness check that suggests our results are not driven by unobserved image content. In Table 5 we present estimation results where we restrict our sample to a set of listings and loans with homogeneous image content – namely those *without* an image. This subsample includes about half of all listings and one-third of all loans. Borrowers without photos are less likely to have social ties. For example, 23% of no-image listings are group members as compared to 29% in our full sample. This negative correlation suggests that borrowers do not consider image a good substitute for social networking in terms of conveying information to lenders. More importantly, the pattern of regression estimates for the no-photo sample in Table 5 are similar to the main results in Table 4. While the coefficient estimate magnitudes are smaller in the funding and contract rate regressions, they are all positive and statistically significant. In terms of payment outcomes, the estimates in Table 5 have the same signs as those in Table 4, except for those related to friend endorsement without bids. However, IRR coefficient estimates are almost identical to the main results for all of our measures of social ties. Interestingly, this seems to suggest that lenders put less weight on social ties for no-photo borrowers, but the social ties end up having a similar relationship with returns, regardless of whether or not a photo is present. Overall these results suggest that not controlling for the content of photos is unlikely to bias our results, since we find similar effects for listings and loans without photos.

5.4 Evidence of Gaming

We have found that some social network characteristics actually hold negative information content while lenders respond as if they have positive information content. Some of this may be due to borrowers and other market participants responding to perverse incentives to use social networks to game the system. Here we consider two types of gaming that may partially impact the effects of social networks. First, we consider the incentives associated with group leader rewards. Recall that before September 12, 2007, a group leader could earn monetary rewards for every loan funded in her group, potentially generating an incentive for the group leader to relax risk evaluation, endorse group member's listing, and get as many listings funded as possible. Such incentive should have been reduced after Prosper eliminated the group leader rewards in September 2007.

The second form of gaming we examine is the potential for borrowers to engage in mutual friend endorsement in order to boost both listings. Two stranger borrowers may agree to endorse each other or even bid on each other's listings with effectively no actual monetary exchange. If lenders do not recognize such mutual endorsements, this could increase the funding rate (or lower the contract rate) for both listings. On average, 11.46% of listings and 16% of loans with a friend endorsement are involved in a mutual endorsement and 6% of listings and loans with an endorsement and bid are involved in a mutual endorsement and bid. For both mutual endorsements with and without bids, the median number of days between the two endorsements is around 30 days, suggesting many occur within a short time window.

Table 6 tests these two types of gaming by adding five variables on the right hand side of Specifications (1)-(4): a dummy of whether the group listing is after the group leader rewards were removed, dummies for whether each type of group endorsement occurred after leader rewards were removed, a dummy of whether the listing has a mutual endorsement but without bids, and a dummy of having a mutual endorsement and mutual bid. Group listings are equally likely to be funded before and after rewards were removed; although, lenders demand higher interest rates from group related loans in the latter period. However, after rewards are removed, group loans have lower default rates and higher IRRs than group loans in the earlier period. This finding combined with the previous findings that the percent of listings and loans associated with groups and with group leader endorsements dropped dramatically in the fourth quarter of 2007 suggests that the removal of group leader rewards reduced gaming by group leaders.

We also interact the group leader endorsement variables with a dummy for loans occurring after leader rewards were removed. The performance advantage of loans with group leader endorsements alone, as compared to group loans with no leader endorsement, is reduced in the post leader reward period, while loans with group leader endorsements and bids see no additional change except for the overall performance improvement of group loans. This suggests that the types of loans that group leaders chose to endorse and/or bid on have changed when leader reward are no longer available.

Turning to mutual endorsements, Table 6 shows that mutual endorsement combined with mutual bidding is associated with little change in funding rate and contract rate, but significantly lower IRRs. Note that the negative coefficient of mutual endorsement and bid on IRR (-1.2 percentage points) is compared to loans with friend endorsement and bid in one direction only. Because loans with friend endorsement and bid are associated with 6.1 percentage points higher IRR than non-social loans, on net loans with mutual friend endorsement and bid still perform significantly better than non-social loans. Interestingly, loans with a mutual endorsement and bid are also associated with a lower probability of being default or late, which suggests that the negative effect on IRR is driven by more of these loans paying off early. In comparison, mutual endorsement without a bid increases the funding rate, but it has no statistically significant effect on other outcomes. Therefore, these mutual endorsements without a bid do not add any additional negative risk beyond friend endorsement without bid on its own. Overall, we conclude that there is evidence of gaming due to group leader reward incentives, but only limited evidence of gaming through mutual friend endorsement and bidding.

5.5 Evidence Against Charity Lending

While we find evidence of gaming, it does not appear to be the only reason why some social ties are rewarded by lenders despite being associated with lower borrower quality. These results are suggestive of lenders misinterpreting the true information content of social ties; however, they would also be consistent with charity motives on behalf of lenders. Freedman and Jin (2010) document that, in addition to social network affiliated loans, lenders invest in many categories of loans that produce lower returns on average. However, additional findings suggest that lenders learn from the poor performance of their initial investments and subsequently target higher return loans. This pattern suggests that lenders learn from their "mistakes" in order to earn higher financial returns as opposed to purposely funding low return loans as a form of "charity."

Since Freedman and Jin (2010) have explored lender learning behavior in detail, here we examine dynamic decisions by lenders specifically related to social loans. Within a social network, lenders may have an even stronger charity motive, so we test if lenders are less responsive to the poor performance of borrowers that belong to the same group as the lenders. We also examine whether or not lenders directly use *their* social ties on Prosper to share information and find better loans.

Specifically, we estimate a series of regressions describing how lender i's choices to fund, amount to fund, and type of loans to fund in week t respond to characteristics and performance of the lender's portfolio up through week $t-1$:

$$\begin{aligned}
(5)\quad FundedALoan_{it} &= g_1(PortChar_{it-1}, SocialLate_{it-1}) + a_{1it} + \mu_{1i} + \gamma_{1t} + \epsilon_{1it} \\
(6)\quad AmountFunded_{it} &= g_2(PortChar_{it-1}, SocialLate_{it-1}) + a_{2it} + \mu_{2i} + \gamma_{2t} + \epsilon_{2it} \\
(7)\quad AvgIRR_{it} &= g_3(PortChar_{it-1}, SocialLate_{it-1}) + a_{3it} + \mu_{3i} + \gamma_{3t} + \epsilon_{3it} \\
(8)\quad PortComp_{it} &= g_4(PortChar_{it-1}, SocialLate_{it-1}) + a_{4it} + \mu_{4i} + \gamma_{4t} + \epsilon_{4it}
\end{aligned}$$

Equation 5 is a linear probability model of an indicator that a lender funded at least one loan in a given week.[28] The other two equations only include the sample of lenders who funded at least one loan in week t. In Equations 6 and 7, $AmountFunded_{it}$ is the dollar amount invested by an active lender in week t, and $AvgIRR_{it}$ is the average IRR of the new loans that lender i invests in during week t. Equation 8

[28] Because we will use a large number of fixed effects, we choose a linear probability model over a probit model for this set of regressions,

is run separately for various $PortComp_{it}$ variables, which specify the percentage of an active lender's investment in loans with certain social variables in week t. For example, in one set of regression, we look at the percentage of a week's investment that are in loans with or without friend endorsement and bids. In another set of regression, we look at the percentage of a week's investment in group or non-group loans.

On the right hand side of these regressions, we use $SocialLate_{it-1}$ to describe corresponding social loan performance history as of the previous week, such as the fraction of previously funded endorsed loans in lender i's portfolio that have ever been late, fraction of previously funded group loans that have ever been late, etc. All regressions include lender fixed effects, thus our identification of the coefficients of the past loan peformance variables is driven by within lender deviations from the mean of these variables. Therefore, there is likely to be a mechanical correlation between current loan characteristics and these deviations since the current loans affect the portfolio's mean performance. To avoid this, all measures of portfolio performance are calculated based solely on the payment histories of loans initiated in the lender's first month on Prosper, and the regressions consider lending decisions that occur after this first month. $PortChar_{it-1}$ includes lender i's portfolio HHI and portfolio size through the previous week to control for time varying lender characteristics.

In addition to lender fixed effects, all regressions include year-week and lender age fixed effects. Year-week fixed effects (γ_{jt}) controls for changes in the macroeconomic environment and the Prosper market.[29] Monthly lender age fixed effects (a_{jit}) capture any general pattern in lenders' choices as they age.[30]

Regression results are reported in Table 7. When previous loans of most types become late, lenders are less likely to fund new loans and invest less when they do fund new loans. Lenders also show expected substitution patterns between loans with friend endorsement without bids, friend endorsements with bids, and no friend endorsements (Panel A), and between group and non-group loans (Panel B). When one type of social loan becomes late, the lender will shy away from new listings with the same social characteristic. Interestingly, the only loan type that does not follow this pattern is friend endorsement with a bid. We do not find any lender response to late loans of this type, which may be due to the fact that these loans generally

[29] Results of identical regressions with controls for macro variables and Prosper supply, demand, and market performance instead of week fixed effects are very similar.

[30] We count a lender as joining Prosper when he funds his first loan, and age is defined as months since joining Prosper. We cannot separately identify weekly age effects with both lender fixed effects and weekly time fixed effects.

perform well. In addition, the overall effect of these substitution patterns is to find new loans with higher returns. This reaction suggests that charity is not the only motivation for funding social loans and lenders attempt to increase their profits in response to their poor performance.

It may be the case that charity lending is more likely to occur if lenders and borrowers belong to the same network (e.g. a university's alumni helping each other). To check this, we run versions of Specifications (5)-(8) to test whether group lenders also substitute away from own group loans when they observe late own group loans in their portfolios. As reported in Panel C of Table 7, lenders who belong to groups fund less own group loans when previous own group loans in their portfolios have been late. This suggests within group charity is not a large factor.

To this point we have mainly focused on social networks of the borrowers. Beyond the charity motive discussed above, lenders may directly utilize social networks to share information with each other. To test this, for lender i at week t, we calculate the percent late for all the loans funded by his group up to week $t-1$ and add this $GroupLate_{g,t-1}$ variable on the right hand side of Equations 5, 6, and 7. In Panel D of Table 7 the coefficient on this group portfolio performance measure is negative and statistically significant in the funding regression and positive and statistically significant in the IRR regression. In addition, the own portfolio percent late has a significantly negative effect on the likelihood to fund future loans and amount to fund, and a significant positive effect on the IRR of funded loans. This suggests that, in addition to the market wide fluctuation (controlled for by weekly fixed effects), an average group lender does learn from the performance of loans funded by other members of his group. Such within-group learning constitutes further evidence against charity lending.

5.6 Heterogeneity within Group Networks

In this section, we attempt to better understand the information conveyed by group networks. While we have found that the average group listing is more likely to be funded but the average group loan results in lower returns, we explore here whether different types of groups convey different information and whether or not lenders are sensitive to these differences. Table 8 considers the sample of group member listings and tests whether various attributes of groups are associated with better loan performance and how lenders respond to these additional attributes. In particular we add measures of group ratings, group size, group composition, group type, and whether the leader reviews listings.[31] If groups provide some level of screening or monitoring, we might expect better borrower risk if the borrower is affiliated with a group with better past loan performance (measured by a higher rating), a smaller group, a group that is composed of a larger concentration of lenders, a group that is indicative of more tangible connections, or a group in which the leader reviews the credential of its borrowers.

The results in Table 8 are mixed. Relative to group listings prior to ratings becoming available, lenders are less likely to fund listings with no rating or a low rating, although ratings do not seem to correlate strongly with subsequent group loan performance. Rated loans do perform better than unrated loans; however, the number of stars itself does not appear to impact performance. Because unrated groups are newer, it suggests that less established groups have lower performing loans.

There are important differences by group size and composition in the direction that suggest borrowers from smaller and less borrower oriented groups perform better. Compared to loans affiliated with groups of more than 1000 borrowers, loans from smaller groups have lower default rates. Groups of 101 to 1000 borrowers do have slightly lower IRRs than groups of more than 1000, but the smallest groups of under 100 borrowers have substantially higher IRRs. These small groups also have the highest funding rates. Compared to loans affiliated with a group in which more than 75% of members are borrowers, loans from less borrower-oriented groups are also much less likely to be in default or late and have much higher IRRs. That said, this characteristic may not be identified by lenders as there is no clear pattern of funding rates by group composition. Lenders appear to respond to the overall size of the group, but not the lender-borrower composition of groups, despite both being correlated with loan performance.

We also attempt to classify groups by their type of connection. It appears that groups that exhibit tangible offline connections perform better. Loans of alumni groups or other offline connections such as common employment, geographic, or other personal connections have lower probability to be in default or late and deliver higher IRRs as a result. Looser connections such as ethnicity or religion have similar effects, but smaller in magnitude. That said, lenders do not appear to respond to these differences in terms of funding rates or interest rates except a slightly lower

[31] Variables for group and friend endorsement are also included in this regression, but excluded from the table to save space. The coefficient estimates on these variables are similar to those in other specifications presented.

interest rate for loosely connected groups. In contrast, military related groups are associated with lower funding rates, higher rates of default or late, and lower IRRs relative to other groups. This suggests that lenders view military connections as an indicator of higher risk.

Lastly, loans affiliated with a group that requires the group leader to review listings are more likely to be funded and less likely to be in default or late if funded, though their contract rates are slightly higher and IRRs are statistically similar to those without review requirement. Lenders appear to interpret reviewed group members as higher quality, and lower default rates appear to be competed away and returns are equalized.

Overall, these results suggest a great deal of heterogeneity among group borrowers. Some types of groups appear to hold more information content than others. While lenders are more likely to fund borrowers from smaller groups, which also appear to perform better, lenders do not tend to differentiate borrowers from most of these different types of groups.

6 Conclusion

The ease of social networking on the Internet has opened opportunities to reduce information asymmetry between anonymous traders. However, online networking does not always imply legal links or social connections off the Internet, casting doubt on its value. Transaction data from Prosper.com suggests that social networking has some value, but is far from a perfect device for conveying information.

In particular, we find that borrowers' social networking activities can be beneficial for both borrowers and lenders. Although high-risk borrowers are more likely to utilize social networks, *some* social ties, conditional on observed characteristics, increase funding probability, decrease interest rate if funded, and can be linked to higher returns than similar loans without such social ties. This suggests that borrower's social ties can be a mechanism for lenders to discover diamonds in the rough. However, some social ties are not associated with better *ex post* performance, and there is evidence suggesting that lenders do not fully understand the relationship between these social network variables and unobserved borrower quality, but learn from their mistakes gradually over time. There is also moderate evidence of gaming on borrower participation in social networks. This evidence, plus the wide distribution of rate of return, suggests that the market is still struggling with the actual meaning of social networking. How to harness the positive potential of social networking with minimal gaming is an important topic for future research.

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8 Appendix: IRR Algorithm and Calculation

This Appendix describes the data cleaning procedure before the IRR calculation, articulates the IRR algorithm, presents robustness checks of the IRR calculation, acknowledges our methodological limitation, and discusses the potential bias of the absolute measure of IRR.

Data Cleaning: Our raw data were downloaded from Prosper.com as of August 18, 2011, which covers the full 36 months of loan age for all loans originated during our analysis sample between June 1, 2006 and July 31, 2011. Because of payment or administrative delays, some loans have performance data beyond month 36. If the last available month of a loan presents a different performance status than month 36, we replace the month 36 performance with the last month's performance. 1,145 loans (4.58% of all loans in our sample) have a terminal status "other," "origination delayed" or "repurchased." To avoid arbitrary interpretation of such codes, we exclude these 1,145 loans from the IRR calculation. For the remaining 23,863 loans, we always define payoff and misperformance as two absorbing states. If a loan's terminal status is "current," "paid," or "pay in progress," it is counted as fully paid at the end of the loan life. If a loan's status is "paid" prior to the last month, the loan is considered paid early and enters the payoff state. For misperformance, we consider three versions separately: default, misspay, and default or late. Default is the most conservative dummy variable of misperformance, which takes the value of one beginning the first month that a loan obtains a status of default. In the raw data, a loan is labeled default if the loan has been more than 3 months late. Misspay ignores lateness that does not lead to default; if default eventually occurs, misspay takes the value of one beginning 3 months before a loan becomes default. Default or late is the most aggressive dummy of misperformance, which takes the value of one beginning the first month a loan is late or default. We calculate IRR for these three definitions of misperformance separately.

IRR Algorithm: Assuming payoff (including early payoff) and misperformance are two absorbing states, a loan's status at month t can be payoff, misperformance or current. If the status is current before the 36th month, it can remain current or enter either the payoff or misperformance state permanently in the next month. This nature of the events best fits a duration model. Because the duration model with competing risks and time-varying explanatory variables is not yet fully developed, we consulted Professor John Ham, who has done extensive research in duration models and suggests the following estimation procedure in our context. Specifically, we use the loan-month data until one of the absorbing outcome events occurs to estimate two separate logit regressions, one for payoff and one for misperformance. For loan l in age a at calendar month t, the two logistic regressions are:

$$1(payoff)^*_{la} = \alpha_{1a} + \beta_1 \cdot ListingAttributes_l + \gamma_1 \cdot macro_{lt} + \epsilon_{1lt}$$
$$1(misperformance)^*_{la} = \alpha_{2a} + \beta_2 \cdot ListingAttributes_l + \gamma_2 \cdot macro_{lt} + \epsilon_{2lt}.$$

These two regressions essentially estimate the hazard risk of a particular outcome in age a conditional on the loan still being current last month. Once we identify the coefficients, we can predict the hazard risk of payoff and misperformance under real macro conditions (denoted as $\hat{h}(Y)|_{realmacro}$) and macro variables as of June 1, 2006 (denoted as $\hat{h}(Y)|_{fixedmacro}$). In theory, we can interact *macro* with *ListingAttributes* extensively; however, when we include the interaction of *macro* and credit grade categories, some interactions are either dropped out completely or carry a coefficient of very large magnitude with very large standard errors. This is because these interactions are driven by very few observations. To avoid misleading predictions of hazard risk, our final estimation does not include these interactions but we include extensive interactions of credit grade categories with major listing attributes so that $\hat{h}(Y)|_{realmacro}$ closely tracks the average hazard risk of loan performance in the real data.[32]

From these predicted hazard risks, we can predict the cumulative risk of payoff, current, and misperformance:

$$p\hat{r}ob(payoff_{la}) = \hat{h}(payoff_{la}) \cdot \prod_{t=1}^{a-1}(1 - \hat{h}(payoff_{lt}) - \hat{h}(misperform_{lt}))$$

$$p\hat{r}ob(misperform_{la}) = \hat{h}(misperform_{la}) \cdot \prod_{t=1}^{a-1}(1 - \hat{h}(payoff_{lt}) - \hat{h}(misperform_{lt}))$$

$$p\hat{r}ob(current_{la}) = 1 - \hat{h}(payoff_{la}) - \hat{h}(misperform_{la}).$$

[32] We have estimated IRR with different degrees of $macro \cdot ListingAttributes$. The cross-sectional variations of these IRR estimates are qualitatively similar to the IRRs reported here, though the absolute magnitude of each IRR estimate usually change by one or a few percentage points.

For loan l, IRR_l is defined as the interest rate r_l that equalizes the loan amount (M_l) to the present value of expected cash flows from the 36 months of loan life:

$$IRR_l = \underset{r_l}{argmin}\{-M_l + \sum_{a=1}^{36}[cash\hat{f}low_{la}/(1+r_l)^a]\}^2$$

where the predicted cash flow is defined as:

$$cash\hat{f}low_{la} = pr\hat{o}b(payoff_{la}) \cdot M_{la}^{payoff} + pr\hat{o}b(current_{la}) \cdot M_{la}^{current} - ProsperFee_{la}$$

with M_{la}^{payoff} defined as the total amount the borrower owes if she pays off the loan in month a, $M_{la}^{current}$ defined as the scheduled monthly payment when the loan is originated, and $ProsperFee_{la}$ defined according to Prosper definition of lender fees. Because cash-flow per month cannot be negative by definition, each loan has a unique solution of IRR_l for a given set of loan terms (principal, interest rate, loan time).

The above algorithm produces six versions of IRR_l, depending on whether we measure misperformance by default, misspay, or default or late, and whether we use real macro or macro variables fixed on June 1, 2006 to predict the hazard risk of payoff and misperformance. Appendix Table 2 summarizes these six versions of IRR_l for all the 23,863 loans that we have enough information to compute loan status each month. The absolute magnitude of IRR varies in expected directions: measuring misperformance by default yields higher IRRs than measuring it by misspay, and measuring it by misspay produces higher IRRs than measuring it by default or late. Calculation under real macro leads to lower IRRs than fixed macro, except when we measure misperformance by default or late. This is probably because the macro changes since June 1, 2006 affect the risk of lateness and default differently. The main text of the paper reports results using IRR6 (default or late, fixed macro). We find similar results when we rerun all regressions using the fixed macro IRR when misperformance is measured in default (IRR2), and the real macro IRR when misperformance is measured by default or default or late (IRR1, IRR5).[33]

Potential bias and limitation This paper aims to detect the information value of social networking and therefore we focus on the relative magnitude of IRR across loans, rather than the absolute magnitude of IRR. There are a couple of limitations

[33]By definition, the only difference between misspay and default is misspay counting three more months of lateness in misperformance right before the month of default. So IRR3 is very similar to IRR1 and IRR4 is very similar to IRR2. This is why our robustness checks focus on the comparison of default versus default or late.

in our algorithm: first, our IRR estimates are based on the average loan performance observed from June 1, 2006 to August 18, 2011, a period that stretches from the end of a boom to slow recovery out of an economy-wide recession. Our model of macro variables may be oversimplified. Second, we estimate the hazard risk of payoff and misperformance separately, assuming that unobservable factors affect the two hazards independently. This assumption can be strong in some situations.

No matter which version of IRR we use, the absolute magnitude of our IRR is subject to potential bias in both directions. On the one hand, our IRR estimates may be downward biased because we are conservative in the calculation of cash flows. Specifically, we treat misperformance as an absorbing state, which can be violated in rare cases (e.g. a late loan can become current, and a default loan can be eventually paid back). Even if a default loan remains default, we assume away any loss recovery from default loans, and we do not account for the late fees that a lender may receive from a late, but non-defaulting borrower. When we count early payoff as a bulk cash flow that arrives in the paid-off month, it effectively assumes that the paid off amount is reinvested in a loan that is identical to the loan under study. This assumption may be conservative because lenders may learn to fund better loans over time. On the other hand, our IRR estimates may have overestimated the return on investment because we do not consider any cost that lenders may incur in processing Prosper information. The time that lenders spend on screening listings and digesting Prosper history could be long and stressful.

Table 1: Predicted Impacts of Social Ties on Listing and Loan Outcomes

True Information Content	Lender Interpretation								
	Positive			Cheap Talk			Negative		
	Funding	Rate	Perf.	Funding	Rate	Perf.	Funding	Rate	Perf.
Positive	+	-	+	0	0	+	-	+	+
Cheap Talk	+	-	0	0	0	0	-	+	0
Negative	+	-	-	0	0	-	-	+	-

Table 2: Summary of Listings and Loans by Quarter

A: Listings	Total Market		Mean Listing Characteristics			Percent of Listings by Social Network Characteristics				
Quarter	Number	Amount Requested ($100,000)	Amount Requested ($)	Borrower Max Interest Rate	Funding rate	In a Group	Group Leader Endorsement w/out Bid	Group Leader Endorsement w/ Bid	Friend Endorsement w/out Bid	Friend Endorsement w/ Bid
20062	5,375	26.65	4,957.22	16.86%	10.01%	58.59%	0.00%	0.00%	0.00%	0.00%
20063	19,771	107.25	5,424.63	18.15%	9.94%	61.84%	0.42%	0.71%	0.00%	0.00%
20064	31,629	196.57	6,214.85	17.45%	7.98%	53.57%	1.33%	2.04%	0.00%	0.00%
20071	31,373	263.22	8,389.94	16.72%	10.14%	48.24%	1.42%	3.46%	11.04%	0.58%
20072	37,505	331.62	8,841.98	17.51%	8.07%	34.09%	1.07%	5.68%	20.86%	0.97%
20073	39,353	328.79	8,355.00	18.06%	6.71%	23.64%	1.01%	4.10%	19.93%	1.14%
20074	41,585	334.23	8,037.29	18.41%	6.32%	16.08%	1.42%	0.84%	16.48%	1.33%
20081	33,485	250.14	7,470.30	19.24%	9.46%	12.77%	0.70%	0.75%	12.91%	1.86%
20082	43,371	318.53	7,344.20	24.50%	10.08%	7.83%	0.54%	0.64%	9.36%	1.58%
20083	10,361	73.48	7,092.42	26.40%	9.31%	7.53%	0.53%	0.61%	8.98%	1.89%
Total	293,808	2,230.48	7,591.62	19.19%	8.51%	28.82%	0.98%	2.23%	12.01%	1.04%

B: Loans	Total Market		Mean Loan Characteristics			Percent of Loans by Social Network Characteristics				
Quarter	Number	Amount Funded ($100,000)	Amount Funded ($)	Contract Interest Rate	Default Rate	In a Group	Group Leader Endorsement w/out Bid	Group Leader Endorsement w/ Bid	Friend Endorsement w/out Bid	Friend Endorsement w/ Bid
20062	385	1.47	3,822.17	19.03%	30.39%	67.01%	0.00%	0.00%	0.00%	0.00%
20063	1,934	9.37	4,844.63	19.41%	28.54%	71.30%	1.14%	3.10%	0.00%	0.00%
20064	2,403	11.54	4,804.05	18.97%	29.09%	70.20%	4.04%	12.82%	0.00%	0.00%
20071	3,079	19.93	6,472.60	17.37%	23.74%	67.49%	4.38%	17.93%	10.91%	2.24%
20072	3,118	23.47	7,527.98	17.42%	17.54%	63.28%	4.36%	29.76%	27.77%	4.62%
20073	2,671	18.43	6,900.12	17.31%	9.21%	44.85%	4.64%	23.40%	26.21%	5.13%
20074	2,593	18.98	7,320.17	17.11%	4.09%	23.95%	2.70%	6.44%	22.33%	6.56%
20081	3,074	20.47	6,658.94	17.37%	0.46%	19.00%	0.81%	3.81%	17.99%	5.50%
20082	4,344	26.33	6,061.10	17.98%	0.00%	13.54%	1.31%	3.06%	14.11%	5.62%
20083	1,407	8.27	5,877.70	19.39%	0.00%	10.80%	0.78%	2.70%	12.30%	6.54%
Total	25,008	158.27	6,328.65	17.90%	12.04%	42.06%	2.71%	11.71%	15.28%	4.10%

Notes: Authors' tabulations from Prosper listing and loan data. Funding rate refers to the percentage of listings that become funded loans. The sample includes all the listings and loans between June 1, 2006 and July 31, 2008.

Table 3: Summary Statistics of Social Network Variables

	Listings			Loans		
	Mean	SD	N	Mean	SD	N
% In a Group	0.288	0.453	293,808	0.421	0.494	25,008
% with Friends	0.191	0.393	293,808	0.249	0.432	25,008
% w/ Group Leader Endorsement no Bid	0.010	0.098	293,808	0.027	0.162	25,008
% w/ Group Leader Endorsement + Bid	0.022	0.148	293,808	0.117	0.322	25,008
% w/ Friend Endorsement no Bid	0.120	0.325	293,808	0.153	0.360	25,008
% w/ Friend Endorsement + Bid	0.010	0.101	293,808	0.041	0.198	25,008
Conditional on a borrower in a group:						
Number of Members	1799.214	2346.502	84,377	1176.963	1872.194	10,512
Number of Borrowers	1082.372	1311.981	84,377	724.992	1070.800	10,512
Number of Lenders	198.860	248.414	84,377	159.373	217.842	10,512
1-100 Borrowers	0.232	0.422	84,680	0.308	0.462	10,518
101-500 Borrowers	0.225	0.418	84,680	0.296	0.457	10,518
501-1000 Borrowers	0.251	0.434	84,680	0.209	0.406	10,518
> 1001 Borrowers	0.288	0.453	84,680	0.186	0.389	10,518
% of Members that are Borrowers	0.627	0.153	84,377	0.651	0.166	10,512
Alumni Group	0.023	0.148	84,680	0.029	0.168	10,518
Military Group	0.019	0.137	84,680	0.014	0.119	10,518
Other Connections (Employment, Local, Personal)	0.017	0.128	84,680	0.022	0.145	10,518
Loose Connection (Common Religion or Ethnicity)	0.025	0.156	84,680	0.016	0.125	10,518
Listing Review Required	0.341	0.474	84,680	0.519	0.500	10,518
% Funded by Group Members				0.017	0.062	10,518
% Funded by Group Leader				0.032	0.124	10,518
Conditional on a borrower in a group & after 10/19/06:						
Low Rated Group	0.414	0.493	66,062	0.275	0.447	8,416
High Rated Group	0.323	0.468	66,062	0.421	0.494	8,416
Nonrated Group	0.261	0.439	66,062	0.301	0.459	8,416
Conditional on a borrower that has friends:						
% Funded by Friends				0.033	0.143	6,229
Conditional on a borrower that has endorsement(s):						
% Funded by Endorsing Friends				0.027	0.126	4,845
% Funded by Endorsing Group Leader				0.055	0.150	3,605

Notes: Authors' tabulations from Prosper listing and loan data. The sample includes all the listings and loans between June 1, 2006 and July 31, 2008.

Table 4: Effects of Basic Social Variables

	I(Funded)	Contract Interest Rate	I(Default or Late)	I(Paid Off)	IRR
	Probit (marg. eff.)	OLS	Probit (marg. eff.)	Probit (marg. eff.)	OLS
In a Group	0.002***	-0.004***	0.006***	-0.004***	-0.018***
	(0.0002)	(0.0004)	(0.001)	(0.001)	(0.001)
Group Leader Endorsement & No Bid	0.010***	-0.003**	-0.001	-0.028***	0.019***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Group Leader Endorsement & Bid	0.062***	-0.004***	0.007***	-0.029***	-0.013***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)
Friend Endorsement & No Bid	0.001***	0.001**	0.004***	-0.012***	-0.008***
	(0.0002)	(0.001)	(0.001)	(0.001)	(0.001)
Friend Endorsement & Bid	0.034***	-0.006***	-0.041***	0.006***	0.060***
	(0.004)	(0.001)	(0.002)	(0.002)	(0.002)
N	293,800	23,863	859,068	858,960	23,863
Year-week FE	X	X	X	X	X
Loan-age FE			X	X	
Contract Rate Control			X	X	

Notes: The sample includes all the listings and loans between June 1, 2006 and July 31, 2008. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 includes all listings while all other columns include only completed loans for which we observe final loan performance status. Columns 1, 2, and 5 are at the listing/loan level, and Columns 3-4 are at the loan-month level. All regressions control for state dummies, year-week FE, macro variables (except for the IRR regression), duration of auction, and posted credit attributes. Columns 3 – 4 also control for monthly loan age fixed effects and the loan's contract interest rate.

Table 5: Robustness to Exclusion of Listings and Loans with Photos

	I(Funded)	Contract Interest Rate	I(Default or Late)	I(Paid Off)	IRR
	Probit (marg. eff.)	OLS	Probit (marg. eff.)	Probit (marg. eff.)	OLS
In a Group	0.001***	-0.005***	0.002	-0.001	-0.019***
	(0.000)	(0.001)	(0.002)	(0.002)	(0.001)
Group Leader Endorsement & No Bid	0.003***	-0.001	-0.003	-0.026***	0.021***
	(0.001)	(0.002)	(0.005)	(0.004)	(0.004)
Group Leader Endorsement & Bid	0.021***	-0.003**	0.016***	-0.037***	-0.014***
	(0.004)	(0.001)	(0.003)	(0.002)	(0.003)
Friend Endorsement & No Bid	0.000**	-0.001	-0.014***	0.006**	-0.008***
	(0.000)	(0.001)	(0.002)	(0.002)	(0.002)
Friend Endorsement & Bid	0.018***	-0.005**	-0.057***	0.030***	0.055***
	(0.005)	(0.002)	(0.005)	(0.005)	(0.004)
N	142,366	8,179	294,048	294,372	8,179
Year-week FE	X	X	X	X	X
Loan-age FE			X	X	
Contract Rate Control			X	X	

Notes: The sample includes all the listings and loans between June 1, 2006 and July 31, 2008. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 includes all listings while all other columns include only completed loans for which we observe final loan performance status. Columns 1, 2, and 5 are at the listing/loan level, and Columns 3-4 are at the loan-month level. All regressions control for state dummies, year-week FE, macro variables (except for the IRR regression), duration of auction, and posted credit attributes. Columns 3 – 4 also control for monthly loan age fixed effects and the loan's contract interest rate.

Table 6: Potential Gaming

	I(Funded)	Contract Interest Rate	I(Default or Late)	IRR
	Probit (marg. eff.)	OLS	Probit (marg. eff.)	OLS
Basic Social Variables				
In a Group	0.002*	-0.005*	0.019*	-0.023*
	(0.000)	(0.000)	(0.001)	(0.001)
Group Leader Endorsement & No Bid	0.013*	-0.001	-0.013*	0.021*
	(0.002)	(0.001)	(0.002)	(0.003)
Group Leader Endorsement & Bid	0.062*	-0.003*	0.006*	-0.012*
	(0.004)	(0.001)	(0.001)	(0.001)
Friend Endorsement & No Bid	0.001*	0.001**	0.005*	-0.008*
	(0.000)	(0.001)	(0.001)	(0.001)
Friend Endorsement & Bid	0.032*	-0.006*	-0.036*	0.061*
	(0.004)	(0.001)	(0.002)	(0.002)
Gaming				
In a Group after Leader Rewards Removed	-0.000	0.004*	-0.032*	0.013*
	(0.000)	(0.001)	(0.002)	(0.002)
Group Leader Endorsement & No Bid	-0.002*	-0.008*	0.058*	-0.010**
After Leader Rewards Removed	(0.001)	(0.003)	(0.007)	(0.004)
Group Leader Endorsement & Bid	-0.000	-0.006*	-0.004	0.000
After Leader Rewards Removed	(0.001)	(0.002)	(0.003)	(0.003)
Mutual Friend Endorsement & No Bid	0.002*	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)
Mutual Friend Endorsement & Bid	0.001	-0.003	-0.065*	-0.012***
	(0.002)	(0.005)	(0.006)	(0.007)
N	293,800	23,863	859,068	23,863
Year-week FE	X	X	X	X
Loan-age FE			X	
Contract Rate Control			X	

Notes: The sample includes all the listings and loans between June 1, 2006 and July 31, 2008. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 includes all listings while all other columns include only completed loans for which we observe final loan performance status. Columns 1, 2, and 4 are at the listing/loan level, and Column 3 is at the loan-month level. All regressions control for state dummies, year-week FE, macro variables (except for the IRR regression), duration of auction, and posted credit attributes. Column 3 also control for monthly loan age fixed effects and the loan's contract interest rate. "Mutual friend endorsement + no bid" includes the cases where (1) neither bids on each other or (2) one bids on the other but not vice versa.

Table 7: Lender response to ever late social loans

A: By Endorsement Status (Conditional on Listing After Feb. 12, 2007)

	Funded A Loan	Amount Funded	% Endorsed No Bid	% Endorsed w/ Bid	% Not Endorsed	Mean IRR
% of Endorsed No Bid Loans Ever Late	-0.050***	-15.382	-0.022***	0.010**	0.013	0.020***
	(0.005)	(19.904)	(0.007)	(0.004)	(0.008)	(0.003)
% of Endorsed w/ Bid Loans Ever Late	-0.056***	6.487	-0.001	0.007	-0.006	0.019***
	(0.009)	(31.688)	(0.009)	(0.005)	(0.010)	(0.003)
% Not Endorsed Loans Ever Late	-0.060***	-73.114***	-0.030***	0.012**	0.018**	0.057***
	(0.005)	(20.746)	(0.008)	(0.005)	(0.009)	(0.003)
N	1,748,185	372,358	372,358	372,358	372,358	359,817

B: By Group Status

	Funded A Loan	Amount Funded	% In Group	% Not in Group	Mean IRR
% of Group Loans Ever Late	-0.054***	-82.880***	-0.028***	0.028***	0.048***
	(0.004)	(21.839)	(0.008)	(0.008)	(0.003)
% of Non-Group Loans Ever Late	-0.067***	-38.824	0.035***	-0.035***	0.032***
	(0.005)	(24.871)	(0.008)	(0.008)	(0.003)
N	1,913,740	421,918	421,918	421,918	407,688

C: By Own Group Status (Conditional on Lender Being a Group Member)

	Funded A Loan	Amount Funded	% In Own Group	% In Other Group	% In No Group	Mean IRR
% of Own Group Loans Ever Late	-0.032**	6.138	-0.077***	0.035	0.042	0.019**
	(0.016)	(44.943)	(0.017)	(0.039)	(0.038)	(0.008)
% of Other Group Loans Ever Late	-0.064***	-50.773	0.003	-0.054**	0.051**	0.047***
	(0.010)	(39.316)	(0.010)	(0.023)	(0.022)	(0.007)
% of No Group Loans Ever Late	-0.070***	-50.566	0.031***	0.032	-0.064***	0.019***
	(0.011)	(31.818)	(0.007)	(0.020)	(0.021)	(0.006)
N	343,524	66,372	66,372	66,372	66,372	64,062

D: Response to Group Performance

	Funded A Loan	Amount Funded	Mean IRR
% of Group Portfolio Ever Late	-0.182***	-188.957	0.084***
	(0.033)	(165.046)	(0.022)
% of Own Portfolio Ever Late	-0.055***	-91.768**	0.064***
	(0.011)	(45.651)	(0.008)
N	343,524	66,216	63,911

Notes: Standard errors clustered at the lender level are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Group Characteristics Conditional on Group Member Listing

	I(Funded)	Contract Interest Rate	I(Default or Late)	IRR
	Probit (marg. eff.)	OLS	Probit (marg. eff.)	OLS
Ratings				
Not Rated (After Ratings Available)	-0.008**	-0.001	0.021*	-0.016
	(0.004)	(0.005)	(0.013)	(0.010)
Low Rating (1-3 stars)	-0.008*	0.003	-0.001	0.044***
	(0.005)	(0.005)	(0.012)	(0.010)
High Rating (4-5 stars)	-0.003	0.000	0.003	0.026***
	(0.005)	(0.005)	(0.012)	(0.010)
Size and Composition				
1-100 borrowers	0.009***	-0.004***	-0.020***	0.034***
	(0.001)	(0.001)	(0.003)	(0.002)
101-500 borrowers	0.005***	-0.005***	-0.003	-0.009***
	(0.001)	(0.001)	(0.002)	(0.001)
501-1000 borrowers	-0.002**	-0.003***	-0.006***	-0.003**
	(0.001)	(0.001)	(0.002)	(0.001)
% of borrowers <25%	-0.007***	0.003	-0.088***	0.102***
	(0.002)	(0.002)	(0.010)	(0.006)
% of borrowers betw 25% and 50%	0.000	0.001	-0.043***	0.045***
	(0.001)	(0.001)	(0.004)	(0.002)
% of borrowers betw 50% and 75%	0.002***	0.001*	-0.024***	0.012***
	(0.001)	(0.001)	(0.003)	(0.001)
Type				
Alumni	0.003	0.002	-0.037***	0.031***
	(0.002)	(0.001)	(0.005)	(0.004)
Other Connections	0.000	0.001	-0.047***	0.039***
(Employment, Local, Personal)	(0.002)	(0.001)	(0.006)	(0.003)
Loose Connection	-0.003	-0.005**	-0.007	0.026***
(Common Religion or Ethnicity)	(0.002)	(0.002)	(0.005)	(0.004)
Military	-0.007***	0.001	0.014**	-0.035***
	(0.002)	(0.002)	(0.006)	(0.004)
Leader Review				
Group Leader Review Requirement	0.005***	0.002**	-0.004***	-0.000
	(0.001)	(0.001)	(0.002)	(0.001)
N	84,676	10,015	360,036	10,015
Year-week FE	X	X	X	X
Loan-age FE			X	
Contract Rate Control			X	

Notes: The sample includes all the listings and loans between June 1, 2006 and July 31, 2008. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1. Columns 1 includes all listings while all other columns include only completed loans for which we observe final loan performance status. Columns 1, 2, and 4 are at the listing/loan level, and Column 3 is at the loan-month level. All regressions control for state dummies, year-week FE, macro variables (except for the IRR regression), duration of auction, and posted credit attributes. Column 3 also control for monthly loan age fixed effects and the loan's contract interest rate. Variables for group and friend endorsements are also included in this regression, but excluded from the table to save space. The coefficient estimates on these variables are similar to those in previous tables.

Figure 1A: Density of Loan Level IRR by Borrower's Group Affilation

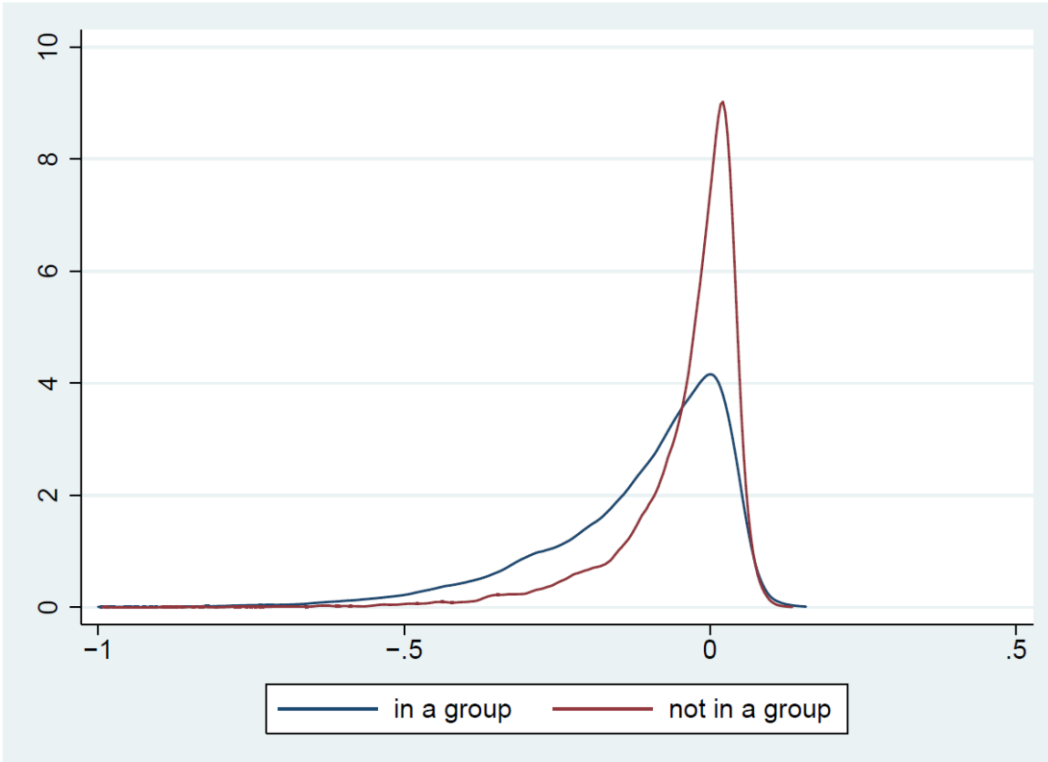


Figure 1B: Mean Loan Level IRR by Borrower’s Group Affiliation Over Time

Figure 2A: Density of Loan Level IRR by Borrower's Group Leader Endorsement Status

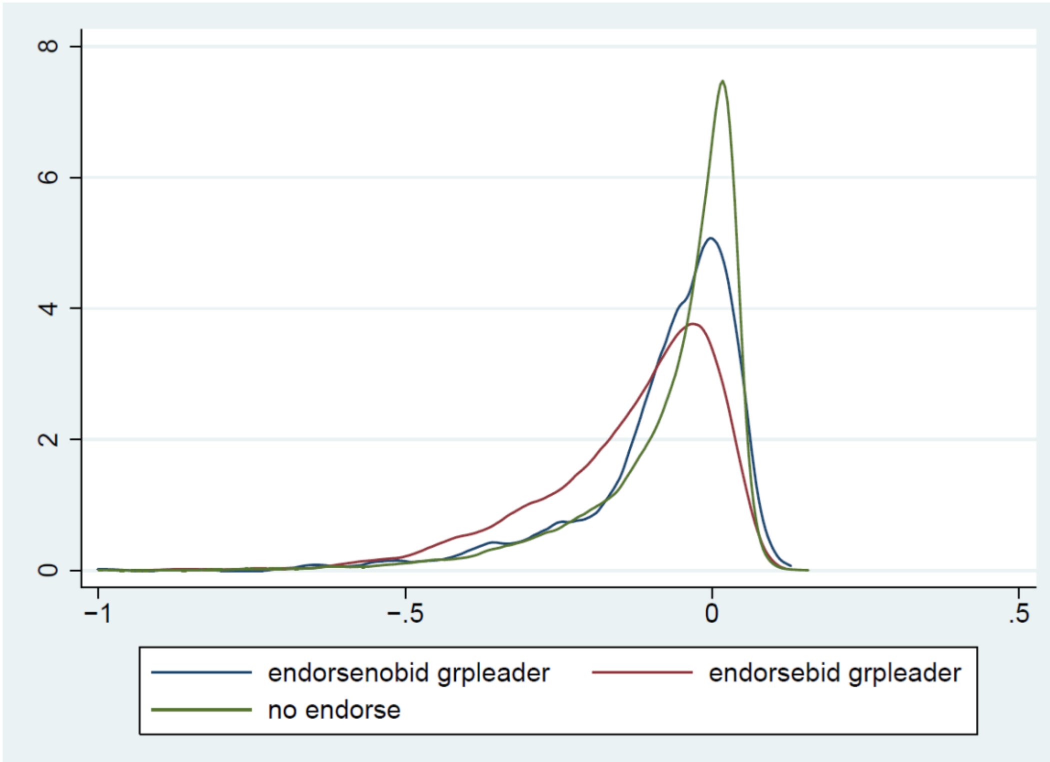


Figure 2B: Mean of Loan Level IRR by Borrower's Group Leader Endorsement Status Over Time

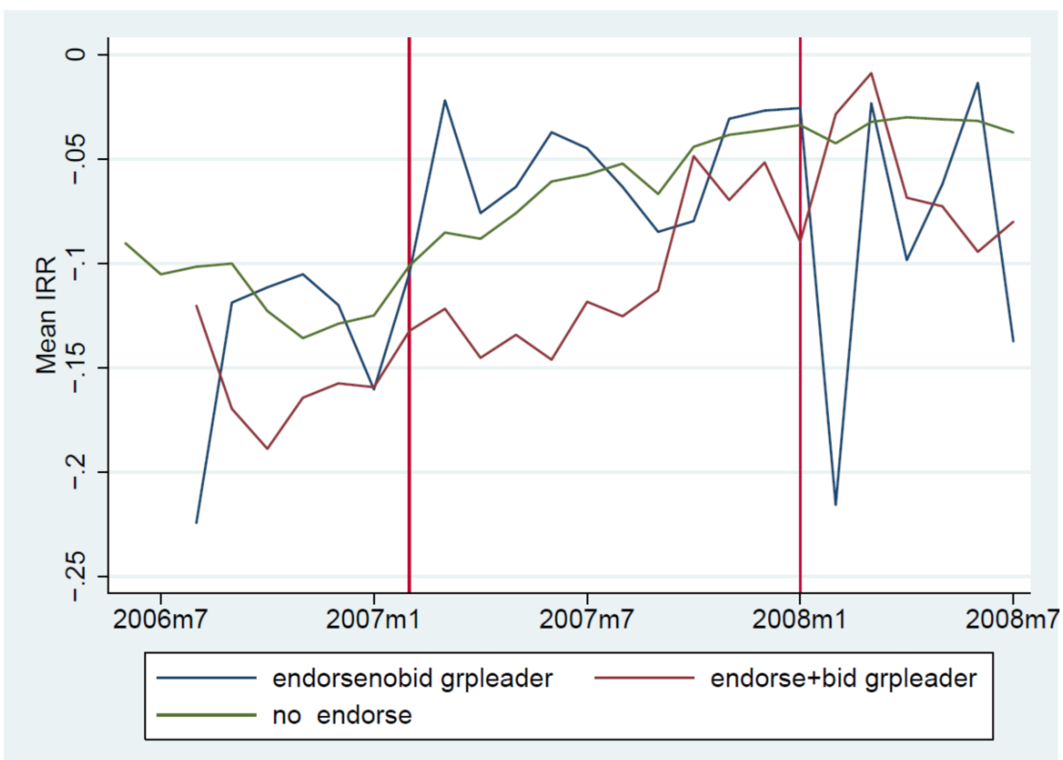


Figure 3A: Density of Loan Level IRR by Borrower's Friend Endorsement Status

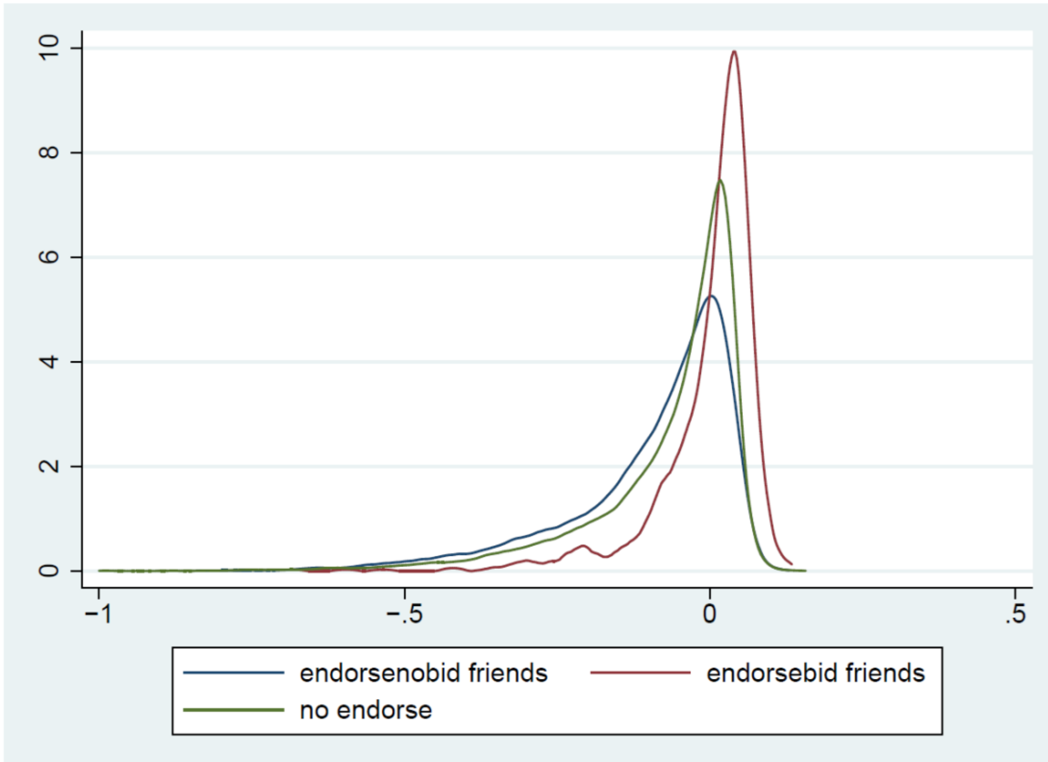
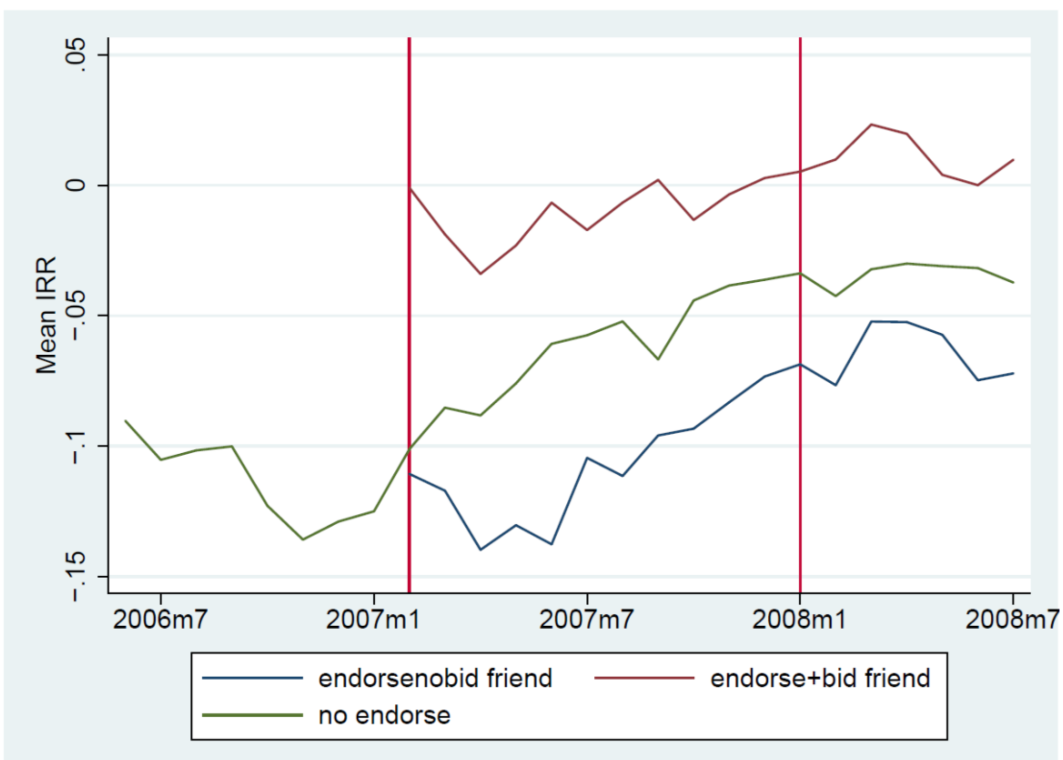


Figure 3A: Mean of Loan Level IRR by Borrower's Friend Endorsement Status Over Time



Appendix Table 1: Summary Statistics of Listing Attributes (June 1, 2006 – July 31, 2008)

	Listings			Loans		
	Mean	STD	N	Mean	STD	N
Grade=AA	0.032	0.175	293,808	0.120	0.324	25,008
Grade=A	0.038	0.191	293,808	0.113	0.317	25,008
Grade=B	0.059	0.235	293,808	0.151	0.358	25,008
Grade=C	0.105	0.307	293,808	0.194	0.396	25,008
Grade=D	0.147	0.354	293,808	0.179	0.383	25,008
Grade=E	0.177	0.382	293,808	0.116	0.320	25,008
Grade=HR	0.438	0.496	293,808	0.123	0.328	25,008
Grade=NC	0.005	0.069	293,808	0.005	0.069	25,008
amountrequested	7592	6388	293,808	6329	5679	25,008
autofunded	0.311	0.463	293,808	0.263	0.441	25,008
borrowermaximumrate	0.192	0.084	293,808	0.209	0.074	25,008
yeshomeowner	0.327	0.469	293,808	0.441	0.497	25,008
debt-to-income (DTI) ratio	0.505	1.359	293,808	0.330	0.978	25,008
missing DTI	0.068	0.251	293,808	0.035	0.183	25,008
DTI topcoded if DTI>=10	0.083	0.275	293,808	0.044	0.205	25,008
have image	0.515	0.500	293,808	0.659	0.474	25,008
length of listing desc (in chars)	1058	772	293,808	1295	866	25,008
mention debt consolidation	0.358	0.480	293,808	0.375	0.484	25,008
mention business loan	0.231	0.421	293,808	0.271	0.444	25,008
mention car	0.689	0.463	293,808	0.626	0.484	25,008
mention mortgage	0.139	0.346	293,808	0.187	0.390	25,008
mention health	0.721	0.449	293,808	0.790	0.407	25,008
mention education	0.211	0.408	293,808	0.248	0.432	25,008
mention family	0.179	0.383	293,808	0.189	0.392	25,008
mention retirement	0.030	0.171	293,808	0.041	0.199	25,008
mention pay-day loan	0.057	0.233	293,808	0.057	0.231	25,008
concede relisting	0.008	0.089	293,808	0.021	0.144	25,008
# of listings (incld current one)	2.811	3.361	293,808	2.912	2.863	25,008
interest rate cap	0.243	0.093	293,808	0.273	0.082	25,008
borrower fee	1.800	0.794	293,808	1.548	0.781	25,008
lender fee	0.852	0.231	293,808	0.790	0.258	25,008
amountdelinquent ($)	3516	12374	293,808	1176	6257	25,008
missing amountdelinquent	0.004	0.066	293,808	0.001	0.037	25,008
currentdelinquency	3.833	5.303	293,808	1.454	3.400	25,008
delinquency in 7yrs	11.022	16.450	293,808	5.800	12.356	25,008
lengthcredithistory (in days)	152.208	84.472	293,808	158.049	87.107	25,008
totalcreditlines	24.354	14.393	293,808	23.964	14.424	25,008
in public records in past 10 years	0.657	1.395	293,808	0.405	0.936	25,008
# of inquiries in past 6 months	4.153	4.959	293,808	2.927	3.979	25,008

Notes: Authors' tabulations from Prosper listing and loan data. The sample includes all the listings and loans between June 1, 2006 and July 31, 2008

Appendix Table 2: Summary of Various IRR Versions

Version	Outcomes predicted	Macro	Mean	Stdev	Minimum	Maximum
IRR1	payoff, default	real	.0525	.0758	-.9804	.2982
IRR2	payoff, default	fixed*	.0997	.0573	-.9594	.3309
IRR3	payoff, misspay	real	.0242	.0908	-.9992	.2792
IRR4	payoff, misspay	fixed*	.1574	.0670	-.9230	.3820
IRR5	payoff, default or late	real	-.0612	.1295	-1.0000	.1713
IRR6	payoff, default or late	fixed*	-.0750	.1331	-1.0000	.1566

*Fixed macro refers to macro variables fixed as of June 1, 2006. Each version of IRR applies to 23,863 loans.