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THE SIGNALING 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. Borrowers with social ties are consistently more likely to have their loans funded and receive lower interest rates. However, most social loans do not perform better ex post, except for loans with endorsements from friends contributing to the loan or loans with group characteristics most likely to provide screening and monitoring. 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 (p2p) consumer lending platform in the US¹ – 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. Hence social networking may merely act as a signaling device initiated by a borrower; its signaling value depends on how lenders interpret it and whether lender interpretation is eventually backed up by *ex post* loan performance.

Given the lack of legal responsibility, the meaning of social networking is not straightforward. On one hand, friends and group leaders may certify aspects of

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

a borrower's payment ability not illustrated by other available information. This signaling may be passive to the extent that belonging to certain types of groups, such as alumni or employment groups, certifies a characteristic of the borrower. Or this signaling could be active if the social network is able to credibly convey screening and monitoring of the borrower. If these mechanisms are effective, online social networking could be an innovative way for lenders to discover diamonds in the rough.

On the other hand, some social networks may 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 illusive and non-sustainable in the long run.

We examine these possibilities using loan application and performance data from Prosper.com. 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. On average, most categories of social loans generate an unconditional *lower* rate of return *ex post* than non-social loans, because social networking is more likely to be utilized by high-risk borrowers. Even conditional on credit grade and other observables, 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. This suggests that if return-maximizing lenders are determined to fund high-risk borrowers, they need to be careful in interpreting social ties within

this risky pool.

Since borrower-initiated social networking does not necessarily entail verifiable information, it is 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 other's loan without a reciprocating endorsement and bid. Over time however, lenders learn to avoid listings with misleading social network signals, especially when loans with such signals in the lender's past portfolio perform poorly. That said, lender learning is gradual and part of the overall rate-of-return gap between social and non-social loans persists over time, suggesting that financial rate of return may not be the only reason for lenders to fund social loans.

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 p2p lending is worth studying itself, even if there is no legal or social intervention from lenders. If borrowers' social networking activities deliver a meaningful signal 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.²

Our paper also contributes to a growing literature on p2p 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 p2p 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 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 2006); 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.

²Gomez 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.

Section 5 examines the effect of borrower social ties on funding probability, interest rate, *ex post* performance and an estimated internal rate of return. Section 6 explores how lenders respond to the previous performance of social network associated loans and the extent to which lenders learn from other lenders in their social groups. A short conclusion is offered in Section 7.

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.³ During this time period the loans are not tradable in any financial market,⁴ 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 authenticates 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.⁵ 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

³The quick expansion of Prosper has coincided with a number of similar new P2P 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).

⁴In 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.

⁵The 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.

of the auction (3-10 days),⁶ 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,⁷ and other credit history information.

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 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.⁸ 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

⁶As of April 15, 2008 all listings have a duration of 7 days.

⁷The 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.

⁸If 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.

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.⁹ The actual numerical credit score is not available to lenders partly because of privacy protection for borrowers¹⁰ 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.¹¹ 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.¹² 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 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

⁹Prosper has refined credit grade definitions since its registration with the SEC in July 2009.

¹⁰If a borrower volunteers personal-identifiable information in the listing, Prosper personnel will remove such information before posting the listing.

¹¹On 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.

¹²Prosper 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.

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.¹³

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.¹⁴ 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 dispropor-

¹³Groups must have at least 15 loan cycles billed before they are rated, otherwise they are “not yet rated.”

¹⁴Group leaders do not have access to the borrower’s credit report prior to listing.

tionately used by borrowers. In our sample, 28.8% of borrowers belong to a group, 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 how the market extracts information from a borrower's social network affiliation. In this section we discuss conceptually the roles that social networks may play on Prosper and make empirical predictions to distinguish 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. For such a signal to be credible, there must be a separating equilibrium such that borrowers with a specific piece of information are able to join a specific network, while other borrowers find it difficult to mimic. In this signaling equilibrium, social network affiliation may send a positive or negative signal of borrower risk for several reasons that we list below. That said, the Prosper market may have not reached such a separating equilibrium, in which case the positive benefits of social networks may not be fully capitalized by lenders, or these network affiliations may have additional negative effects on performance beyond lender expectation.

Passive Signals. On the positive side, in a separating equilibrium social network affiliation can be a passive signal of better risk. It may simply verify a certain borrower attribute but involve no active screening or monitoring by other network members. 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 members' employment.¹⁵

¹⁵These passive signals are not as applicable to having friends or friend endorsements unless simply being more social is a signal of certain borrower characteristics.

Active Signals. Social network affiliation in a separating equilibrium can also signal better 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).

It 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.

Distinguishing Passive and Active Signals. Both mechanisms – passive signaling or active screening/monitoring – imply that borrowers with certain social network affiliations would be more likely to get funded on Prosper and, if funded, receive a lower interest rate and perform better in loan repayment as compared to those without such affiliation. Theoretically, if the market fully understands these signals, rates of return between social and non-social loans should be competed to the same level. That said, if not all lenders recognize the difference or competition is too thin, these positive signals can be associated with higher rates of return. Since both active and passive signals lead to similar predictions, it is difficult to distinguish the two.

That being said, there are additional network attributes that may help distinguish these two stories. If group affiliation is merely a passive signal, its signaling value should depend on the review requirement of the group (whether or not the leader reviews all listings prior to posting) but not on group characteristics such as the number of members or the lender/borrower composition of the group. In contrast, if we assume members of large social networks interact less with each other, it is conceivable that smaller groups are more effective in screening and monitoring group members. Additionally, if friends or group leaders act on the additional information from their screening and monitoring behaviors, we would expect the size of the financial investment by the friends or members of the borrower's group to predict better loan performance.

Perverse Incentives & Gaming. As discussed above, some social incentives may be perverse and may allow low risk borrowers to mimic high risk borrowers through the selection of social networking attributes. 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 If lenders do not understand this perverse incentive, this mechanism encourages free-riding and diminishes the incentives to gather new information. These arguments suggest that group affiliation and group leader endorsements do not necessarily certify good risks unless the group leader has sufficient incentives to gather and share borrower information. In addition to examining the effect of group cohesion as discussed above, we also directly examine how the performance of group loans changed before and after group leader rewards were removed.

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

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

always separate good types from bad types. However, for such gaming to exist, some lenders must perceive friend endorsement as a positive signal of borrower risk. We show how lenders perceive friend endorsement empirically and examine mutual endorsement between two borrowers as a potential form of gaming.

Charity Lending. Even if gaming and mimicking were not possible and a separating equilibrium prevailed, social network affiliation could be associated with *worse* borrower risk if some 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). The charity role of social networks implies that social loans should have a higher funding rate, lower interest rate, but lower repayment rates and lower financial returns.

Lender Misinterpretation. Even in the absence of charity lending, it would be possible to observe social attributes leading to higher funding rates but worse performance if lenders misinterpret social network affiliation as a positive signal of borrower risk when it is actually a negative signal. We argue that charity and this out of equilibrium 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.

To summarize, a borrower’s social network affiliation may indicate better or worse risk for Prosper lenders. On the positive side, listings with social networks may be associated with a higher funding rate, lower interest rate and better repayment if social network affiliation is a passive signal of desirable attributes, or the affiliation reveals any active role that members of the same social network may play in screening or monitoring borrower risk. On the negative side, social loans could perform worse than non-social loans if social loans target charity lenders, if some

lenders misinterpret the negative signal of social networks (thus attracting worse risks), or if financial incentives encourage gaming. Unless the Prosper market has fully understood the true meaning of social network affiliation, the realized rate of return may differ by a borrower's tie with specific social networks.

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,

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

including the bank prime rate, the TED spread, the yield difference between corporate 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 signaling value of borrower social networking 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

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

¹⁹To 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.

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

– 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, 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 1 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 1 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, 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 2 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

²¹The 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.

²²To 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.

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 2 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.

Table 3 reports what types of borrowers are more likely to have social ties. Given the importance of credit grade in summarizing borrower risk,²³ we present the grade composition of group borrowers, endorsed borrowers, and the whole Prosper market. At the listing level, it is clear that group borrowers, as compared to the whole population of borrowers, are more likely to have lower credit grades, especially E and HR. This observation holds at the loan level, but the proportion of grades at D or below is less in group loans than in group listings. For the friend-endorsed loans, we focus on the borrower population after February 12, 2007 because friends are not allowed to make endorsement until this time. Unlike group listings, the grade composition of endorsed listings is very similar to that of the whole market, mostly because listings with friend endorsements and bids are less likely to be of E or HR. This implies that borrowers with friend endorsements but no bids are more likely to have lower grades, as with group borrowers. However, compared to the full loan population, loans with friend endorsements are more likely to be D or below, suggesting that friend endorsement is more helpful in funding lower credit grade borrowers.

These summary statistics suggest that on average lenders are more likely to fund

²³Freedman and Jin (2010) show that funding rate increases monotonically with credit grade, interest rate declines with credit grade, and *ex post* performance is significantly worse for lower credit grades.

loans with social networking attributes, but there is important heterogeneity by type of network and over time. Additionally, on average borrowers with most social networking characteristics are of lower credit grades than other borrowers. Turning to financial returns, Figures 1 through 3 compare the IRR density and mean IRR over time for borrowers with and without social networking attributes. In Figure 1A it is clear that there is important heterogeneity in group borrowers and 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. In particular, 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. This is not surprising given the relationship between social networking characteristics and credit grade. 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. To disentangle the roles of social networks, we ask whether social networking attributes signal higher quality borrowers *conditional* on all other

loan attributes. In other words, while unconditionally they may perform worse, within a group of similar loans, do borrowers with social network ties perform better?

Empirically we examine how social networking attributes impact the likelihood a listing is funded, and for funded loans how these attributes impact the contract interest rate, 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 or signal of the borrowers 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.

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

$$\begin{aligned}
 (1) \quad 1(Funded)_{it} &= f_1(SocialVar_i, ListingAttributes_i, macro_{it}, YW_t) + \varepsilon_{1it} \\
 (2) \quad ContractRate_{lt} &= f_2(SocialVar_l, ListingAttributes_l, macro_{lt}, YW_t) + \varepsilon_{2lt} \\
 (3) \quad 1(Perform)_{lta} &= f_3(SocialVar_l, ListingAttributes_l, macro_{lt}, YW_t, Age_a) + \varepsilon_{3lta} \\
 (4) \quad IRR_{lt} &= f_4(SocialVar_l, ListingAttributes_l, YW_t) + \varepsilon_{4lt}
 \end{aligned}$$

Equation 1 includes the full sample of listings and describes whether or not listing i created at time t is funded or not ($1(Funded)_{it}$). Equations 2 and 4 include the listings of fully funded loans and describe the contract interest rate ($ContractRate_{lt}$) 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 ($macro_{it}$) 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).²⁴ 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 variables 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.²⁵

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

²⁴We 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.

²⁵Note, the sample sizes in the contract rate and IRR regressions are slightly smaller than the full sample of loans available to us. For 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.

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, enjoy a 0.4 percentage point lower contract rate, but are 0.6 percentage points more likely to be default or late in a given month. However, these group affiliated listings are also less likely to be paid off early, allowing lenders to gather interest over a longer payment period if the loan remains current. Summarizing performance and interest rate in IRR, group loans have a 1.8 percentage point lower expected rate of return than non-group loans conditional on the other listing attributes, consistent with with the unconditional comparisons in Figures 1A and 1B.²⁶

Within group listings, some receive an endorsement from the group leader and some receive a group leader bid in addition to the endorsement. Table 4 shows that group leader endorsement, regardless of group leader bidding, further increases the probability of funding and further decreases the contract rate if the listing is funded. The funding effect is much larger when a bid is present as group leader endorsed and bid on loans are 6 percentage points more likely to be funded than group member loans without leader endorsements, and group leader endorsed loans without bids are 1 percentage point more likely to be funded. The effect of group leader endorsement on loan performance is also dependent on whether the group 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 group members 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 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.²⁷ These results suggest group leader endorsement is a positive signal of good credit risk when the leader does not bid on the loan but a negative signal when the leader has bid on the loan. We explore this counterintuitive finding below by examining how the effects of these variables change

²⁶This is a large difference as the average IRR is -7.50% across all the loans in our sample.

²⁷Note 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.

after the elimination of group leader reward.

The distinction between friend endorsements with and without bids is more stark. 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 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%.²⁸ 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 signals additional borrower quality that has not been priced by the market.

To this point, our estimates suggest that some social networking attributes signal better loan performance after conditioning on observable selection. However, these estimates represent an overall average, and it may be the case that these results are driven by particular types of loans. For example, it may be the case that these attributes help lenders find “diamonds in the rough” from the pool of lower credit

²⁸As 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.

grade borrowers. On the other hand, it may be the case that social networking helps lower risk borrowers appear even more attractive. To explore this we rerun Specifications (1), (2), (3) and (4) and estimate the effect of social networking variables separately for three credit grade categories: A-AA, B-D and E-HR. The results are presented in Table 5. Looking first at the two attributes with positive effects on IRR overall, friend endorsement with bid and group leader endorsement without bid, the IRR effect is positive and statistically significant for all credit grades, but is largest among the lowest credit grade loans. This translates to a similar gradient in the effect of friend endorsement and bid on whether a listing is funded; although, the funding effect of group leader endorsement is the largest for the grade B-D group. The differential effects on other social network variables are less clear. The negative impact of group membership on IRR is actually largest among lower credit grade loans, while group membership equally increases funding probability for all grades. Group leader and friend endorsements without a bid actually has a similar sized negative impact on IRR for all grades and increases funding probability the most for lower grades. This suggests that friend endorsement alone might mislead lenders to invest in subprime borrowers, but friend endorsement coupled with a bid indicates effective risk screening or monitoring.

5.3 Active or Passive Signals?

To this point, we have found evidence that some forms of social network affiliation can signal lower risk borrowers, particularly friend endorsement with accompanying bids. In this section we attempt to disentangle whether these are passive signals verifying particular borrower attributes associated with their network affiliation such as employment or education, or if these effects occur because social networks provide risk screening and monitoring of their borrowers.

First, we examine whether the amount of within-network investment in a borrower leads to better performance. To the extent that lenders in the social network of the borrower may know more about the borrower *ex ante* and/or have more ability to monitor the borrower *ex post*, we expect that more funding from the borrower's social network will signal better payment ability. Table 6 adds the percent of the

loan funded by group members, by the group leader, and by friends, to the loan-level regressions of contract rate, default or late and IRR.²⁹ The estimates imply that more funding from group members and friends is correlated with less default or late and higher IRR; although, more funding from group leaders indicates the opposite. This suggests that more funding from group members and friends indicates better screening or monitoring from these social ties, but more funding from group leaders is indicative of worse borrower risk. This may be associated with group leaders having greater charity motives or assisting in loan funding in order to receive rewards, which we examine in more detail below.

Table 7 considers the sample of group member listings and tests whether various attributes of groups are associated with better loan performance. In particular we add measures of group ratings, group size, group composition, group type, and whether the leader reviews listings.³⁰ If groups function as a screening or monitoring device, we 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 7 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 active signaling or monitoring. Compared to loans affiliated with groups

²⁹Note, we do not examine the funded margin because we are only considering the fraction of the total loan amount funded by a borrowers social ties.

³⁰Variables 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.

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 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.

We also attempt to classify groups by their type of connection. While some of these group types may be associated with passive signals, particularly alumni groups, 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 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 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 veteran status as an indicator of higher risk. Lastly, loans affiliated with a group that requires member reviews are more likely to be funded and less likely to be default or late if funded, though their contract rates are slightly higher and IRRs are statistically similar to those without review requirement. Lenders respond to this signal of screening, and lower default rates appear to be competed away and returns are equalized.

5.4 Incentives and Gaming

While most social networking characteristics appear to signal information about a borrower's unobserved quality, there are some incentives in the Prosper market place to use social networks to game the system. Here we consider two types of gaming that may partially mitigate the signaling 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 8 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 8 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.

6 Lender Dynamics

While we have found that social networks can signal higher return loans conditional on other observable characteristics, some social loans, especially group loans, on average deliver lower unconditional IRRs. 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.” 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 $t - 1$:

$$(5) \text{ FundedALoan}_{it} = g_1(\text{PortChar}_{it-1}, \text{SocialLate}_{it-1}) + a_{1it} + \mu_{1i} + \gamma_{1t} + \epsilon_{1it}$$

$$(6) \text{ AmountFunded}_{it} = g_2(\text{PortChar}_{it-1}, \text{SocialLate}_{it-1}) + a_{2it} + \mu_{2i} + \gamma_{2t} + \epsilon_{2it}$$

$$(7) \quad \text{ AvgIRR}_{it} = g_3(\text{PortChar}_{it-1}, \text{SocialLate}_{it-1}) + a_{3it} + \mu_{3i} + \gamma_{3t} + \epsilon_{3it}$$

$$(8) \quad \text{ PortComp}_{it} = g_4(\text{PortChar}_{it-1}, \text{SocialLate}_{it-1}) + a_{4it} + \mu_{4i} + \gamma_{4t} + \epsilon_{4it}$$

Equation 5 is a linear probability model of an indicator that a lender funded at least one loan in a given week.³¹ 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 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 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

³¹Because we will use a large number of fixed effects, we choose a linear probability model over a probit model for this set of regressions,

been late, fraction of previously funded group loans that have ever been late, etc. $PortChar_{it-1}$ includes lender i 's portfolio HHI and portfolio size through the previous week to control for time varying lender characteristics.

All regressions include lender, week, and lender age fixed effects, with standard errors clustered by lender. With lender fixed effects (μ_{ji}) the coefficients on the ever late variables are identified by *within* lender changes in portfolio performance and investment decisions.³² Year-week fixed effects (γ_{jt}) controls for changes in the macroeconomic environment and the Prosper market.³³ Monthly lender age fixed effects (a_{jit}) capture any general pattern in lenders' choices as they age.³⁴

Regression results are reported in Table 9. When previous loans of any type 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. In addition, the overall effect of these substitution patterns is to fund 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 9, 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.

³²Note, these regressions reflect how lenders respond to both late and on-time performance because on-time payment (or early payoff) is by definition the opposite of default or late.

³³Results of identical regressions with controls for macro variables and Prosper supply, demand, and market performance instead of week fixed effects are very similar.

³⁴We 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.

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 9 the coefficient on this group portfolio performance measure is negative and statistically significant in the funding regression, but small and not statistically significant in the regressions describing the amount funded and IRR of funded loans. 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 on the extensive margin (i.e. propensity to fund new loans) from the performance of loans funded by other members of his group, but conditional on funding, does not change the types of loans funded.

7 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 signaling device.

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 signal 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 signals and unobserved borrower quality and 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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9 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:

$$1(\text{payoff})_{la}^* = \alpha_{1a} + \beta_1 \cdot \text{ListingAttributes}_l + \gamma_1 \cdot \text{macro}_{lt} + \epsilon_{1lt}$$

$$1(\text{misperformance})_{la}^* = \alpha_{2a} + \beta_2 \cdot \text{ListingAttributes}_l + \gamma_2 \cdot \text{macro}_{lt} + \epsilon_{2lt}.$$

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 $\hat{h}(Y)|_{\text{realmacro}}$) and macro variables as of June 1, 2006 (denoted as $\hat{h}(Y)|_{\text{fixedmacro}}$). 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 $\hat{h}(Y)|_{\text{realmacro}}$ closely tracks the average hazard risk of loan performance in the real data.³⁵

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

$$\hat{p}\text{rob}(\text{payoff}_{la}) = \hat{h}(\text{payoff}_{la}) \cdot \prod_{t=1}^{a-1} (1 - \hat{h}(\text{payoff}_{ft}) - \hat{h}(\text{misperform}_{lt}))$$

$$\hat{p}\text{rob}(\text{misperform}_{la}) = \hat{h}(\text{misperform}_{la}) \cdot \prod_{t=1}^{a-1} (1 - \hat{h}(\text{payoff}_{ft}) - \hat{h}(\text{misperform}_{lt}))$$

$$\hat{p}\text{rob}(\text{current}_{la}) = 1 - \hat{h}(\text{payoff}_{la}) - \hat{h}(\text{misperform}_{la}).$$

³⁵We have estimated IRR with different degrees of $\text{macro} \cdot \text{ListingAttributes}$. 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:

$$IRR_l = \underset{r_l}{\operatorname{argmin}} \left\{ -M_l + \sum_{a=1}^{36} [\widehat{\text{cashflow}}_{la} / (1 + r_l)^a] \right\}^2$$

where the predicted cash flow is defined as:

$$\widehat{\text{cashflow}}_{la} = \widehat{\text{prob}}(\text{payoff}_{la}) \cdot M_{la}^{\text{payoff}} + \widehat{\text{prob}}(\text{current}_{la}) \cdot M_{la}^{\text{current}} - \text{ProsperFee}_{la}$$

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).³⁶

³⁶By definition, the only difference between misspay and default is misspay counting three more

Potential bias and limitation This paper aims to detect the signaling 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 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.

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.

Table 1: Summary of Listings and Loans by Quarter

A: Listings										
Quarter	Total Market		Mean Listing Characteristics			Percent of Listings by Social Network Characteristics				
	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										
Quarter	Total Market		Mean Loan Characteristics			Percent of Loans by Social Network Characteristics				
	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 2: 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 3: Credit Grade Composition of Social Network Loans

Panel A: Groups				
Grade	Group Listings	All Listings	Group Loans	All Loans
AA	2.18%	3.17%	7.70%	11.96%
A	2.84%	3.78%	8.10%	11.30%
B	4.76%	5.86%	11.62%	15.06%
C	9.16%	10.50%	17.83%	19.44%
D	13.10%	14.73%	18.42%	17.91%
E	19.20%	17.70%	15.61%	11.56%
HR	47.96%	43.78%	19.95%	12.30%
NC	0.81%	0.48%	0.78%	0.47%

Panel B: Friend Endorsements (Listings & Loans after Feb 12, 2007)						
Grade	Endorsed	Endorsed	All	Endorsed	Endorsed	All Loans
	Listings	+ Bid Listings	Listings	Loans	+ Bid Loans	
AA	2.87%	8.84%	3.49%	9.50%	14.97%	13.23%
A	3.96%	9.27%	4.35%	10.27%	12.82%	12.61%
B	6.13%	11.96%	6.80%	14.89%	16.24%	16.82%
C	12.03%	16.20%	12.14%	20.98%	16.54%	21.30%
D	16.58%	19.49%	16.91%	19.93%	17.91%	18.55%
E	17.43%	11.30%	17.22%	10.79%	8.41%	8.64%
HR	41.00%	22.91%	39.08%	13.65%	13.11%	8.86%
NC	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%

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

	Contract		I(Default or Late)	I(Paid Off)	IRR
	I(Funded)	Interest Rate			
	Probit (marg. eff.)	OLS	Probit (marg. eff.)	Probit (marg. eff.)	OLS
In a Group	0.002*** (0.0002)	-0.004*** (0.0004)	0.006*** (0.001)	-0.004*** (0.001)	-0.018*** (0.001)
Group Leader Endorsement & No Bid	0.010*** (0.001)	-0.003** (0.001)	-0.001 (0.002)	-0.028*** (0.002)	0.019*** (0.002)
Group Leader Endorsement & Bid	0.062*** (0.004)	-0.004*** (0.001)	0.007*** (0.001)	-0.029*** (0.001)	-0.013*** (0.001)
Friend Endorsement & No Bid	0.001*** (0.0002)	0.001** (0.001)	0.004*** (0.001)	-0.012*** (0.001)	-0.008*** (0.001)
Friend Endorsement & Bid	0.034*** (0.004)	-0.006*** (0.001)	-0.041*** (0.002)	0.006*** (0.002)	0.060*** (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: Effects of Basic Social Variables by Grade

	I(Funded)		Contract Interest Rate	
	Probit (marg. eff.)	OLS	I(Default or Late) Probit (marg. eff.)	IRR OLS
In A Group				
X Grade= AA or A	0.002*** (0.001)	-0.003*** (0.001)	-0.027*** (0.002)	-0.004*** (0.001)
X Grade = B, C or D	0.002*** (0.000)	-0.004*** (0.001)	0.003* (0.001)	-0.015*** (0.001)
X Grade = E, HR, or NC	0.003*** (0.000)	-0.006*** (0.001)	0.024*** (0.002)	-0.036*** (0.002)
Group Leader Endorsement & No Bid				
X Grade= AA or A	0.004** (0.002)	0.002 (0.002)	-0.012** (0.006)	0.004* (0.002)
X Grade = B, C or D	0.013*** (0.002)	-0.006*** (0.002)	0.006** (0.003)	0.012*** (0.003)
X Grade = E, HR, or NC	0.008*** (0.002)	-0.002 (0.002)	-0.005 (0.004)	0.045*** (0.006)
Group Leader Endorsement & Bid				
X Grade= AA or A	0.024*** (0.005)	-0.004*** (0.001)	0.058*** (0.005)	-0.014*** (0.002)
X Grade = B, C or D	0.056*** (0.005)	-0.004*** (0.001)	-0.001 (0.002)	-0.013*** (0.002)
X Grade = E, HR, or NC	0.079*** (0.006)	-0.005*** (0.001)	0.006*** (0.002)	-0.011*** (0.002)
Friend Endorsement & No Bid				
X Grade= AA or A	0.001 (0.000)	0.001 (0.001)	-0.010*** (0.003)	-0.006*** (0.001)
X Grade = B, C or D	0.001*** (0.000)	0.001 (0.001)	0.007*** (0.001)	-0.007*** (0.001)
X Grade = E, HR, or NC	0.002*** (0.000)	0.001 (0.001)	0.006*** (0.002)	-0.009*** (0.002)
Friend Endorsement & Bid				
X Grade= AA or A	0.012*** (0.003)	-0.005*** (0.001)	-0.048*** (0.004)	0.029*** (0.002)
X Grade = B, C or D	0.025*** (0.003)	-0.006*** (0.001)	-0.037*** (0.003)	0.060*** (0.002)
X Grade = E, HR, or NC	0.094*** (0.012)	-0.008*** (0.003)	-0.040*** (0.003)	0.101*** (0.004)
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.

Table 6: Within Network Funding

	Contract		
	Interest Rate	I(Default or Late)	IRR
	OLS	Probit (marg. eff.)	OLS
Basic Social Variables			
In a Group	-0.004*** (0.000)	0.006*** (0.001)	-0.017*** (0.001)
Group Leader Endorsement & No Bid	-0.003*** (0.001)	-0.0003 (0.002)	0.018*** (0.002)
Group Leader Endorsement & Bid	-0.004*** (0.001)	0.006*** (0.001)	-0.009*** (0.001)
Friend Endorsement & No Bid	0.001* (0.001)	0.004*** (0.001)	-0.008*** (0.001)
Friend Endorsement & Bid	-0.004*** (0.001)	-0.034*** (0.002)	0.054*** (0.002)
Within Network Funding			
% Funds from Group Members	0.005 (0.005)	-0.112*** (0.011)	0.044*** (0.010)
% Funds from Group Leader	-0.004 (0.003)	0.034*** (0.005)	-0.095*** (0.007)
% Funds from Friends	-0.019*** (0.003)	-0.053*** (0.007)	0.038*** (0.007)
N	23,863	859,068	23,863
Year-week FE	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 and 3 are at the loan level, and Column 2 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 2 also control for monthly loan age fixed effects and the loan's contract interest rate.

Table 7: 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** (0.004)	-0.001 (0.005)	0.021* (0.013)	-0.016 (0.010)
Low Rating (1-3 stars)	-0.008* (0.005)	0.003 (0.005)	-0.001 (0.012)	0.044*** (0.010)
High Rating (4-5 stars)	-0.003 (0.005)	0.000 (0.005)	0.003 (0.012)	0.026*** (0.010)
Size and Composition				
1-100 borrowers	0.009*** (0.001)	-0.004*** (0.001)	-0.020*** (0.003)	0.034*** (0.002)
101-500 borrowers	0.005*** (0.001)	-0.005*** (0.001)	-0.003 (0.002)	-0.009*** (0.001)
501-1000 borrowers	-0.002** (0.001)	-0.003*** (0.001)	-0.006*** (0.002)	-0.003** (0.001)
% of borrowers <25%	-0.007*** (0.002)	0.003 (0.002)	-0.088*** (0.010)	0.102*** (0.006)
% of borrowers betw 25% and 50%	0.000 (0.001)	0.001 (0.001)	-0.043*** (0.004)	0.045*** (0.002)
% of borrowers betw 50% and 75%	0.002*** (0.001)	0.001* (0.001)	-0.024*** (0.003)	0.012*** (0.001)
Type				
Alumni	0.003 (0.002)	0.002 (0.001)	-0.037*** (0.005)	0.031*** (0.004)
Military	-0.007*** (0.002)	0.001 (0.002)	0.014** (0.006)	-0.035*** (0.004)
Other Connections (Employment, Local, Personal)	0.000 (0.002)	0.001 (0.001)	-0.047*** (0.006)	0.039*** (0.003)
Loose Connection (Common Religion or Ethnicity)	-0.003 (0.002)	-0.005** (0.002)	-0.007 (0.005)	0.026*** (0.004)
Leader Review				
Group Leader Review Requirement	0.005*** (0.001)	0.002** (0.001)	-0.004*** (0.002)	-0.000 (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.

Table 8: Potential Gaming

	I(Funded)		Contract Interest Rate	
	Probit (marg. eff.)	OLS	Probit (marg. eff.)	IRR OLS
Basic Social Variables				
In a Group	0.002* (0.000)	-0.005* (0.000)	0.019* (0.001)	-0.023* (0.001)
Group Leader Endorsement & No Bid	0.013* (0.002)	-0.001 (0.001)	-0.013* (0.002)	0.021* (0.003)
Group Leader Endorsement & Bid	0.062* (0.004)	-0.003* (0.001)	0.006* (0.001)	-0.012* (0.001)
Friend Endorsement & No Bid	0.001* (0.000)	0.001** (0.001)	0.005* (0.001)	-0.008* (0.001)
Friend Endorsement & Bid	0.032* (0.004)	-0.006* (0.001)	-0.036* (0.002)	0.061* (0.002)
Gaming				
In a Group after Leader Rewards Removed	-0.000 (0.000)	0.004* (0.001)	-0.032* (0.002)	0.013* (0.002)
Group Leader Endorsement & No Bid After Leader Rewards Removed	-0.002* (0.001)	-0.008* (0.003)	0.058* (0.007)	-0.010** (0.004)
Group Leader Endorsement & Bid After Leader Rewards Removed	-0.000 (0.001)	-0.006* (0.002)	-0.004 (0.003)	0.000 (0.003)
Mutual Friend Endorsement & No Bid	0.002* (0.001)	-0.001 (0.001)	-0.001 (0.002)	-0.001 (0.002)
Mutual Friend Endorsement & Bid	0.001 (0.002)	-0.003 (0.005)	-0.065* (0.006)	-0.012*** (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 9: 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	-0.139*** (0.004)	-189.368*** (19.060)	-0.053*** (0.009)	0.013** (0.006)	0.039*** (0.010)	0.063*** (0.003)
% of Endorsed w/ Bid Loans Ever Late	-0.126*** (0.006)	-56.446*** (15.314)	0.011 (0.008)	-0.029*** (0.005)	0.018** (0.009)	0.033*** (0.003)
% Not Endorsed Loans Ever Late	-0.076*** (0.004)	-438.120*** (44.482)	-0.078*** (0.014)	0.048*** (0.008)	0.030* (0.016)	0.160*** (0.006)
N	2,293,731	471,470	471,470	471,470	471,470	456,332
B: By Group Status						
	Funded A Loan	Amount Funded	% In Group	% Not in Group		Mean IRR
% of Group Loans Ever Late	-0.080*** (0.004)	-361.753*** (37.552)	-0.136*** (0.013)	0.136*** (0.013)		0.146*** (0.004)
% of Non-Group Loans Ever Late	-0.142*** (0.005)	-391.985*** (40.913)	0.245*** (0.014)	-0.245*** (0.014)		0.075*** (0.005)
N	2,518,945	553,117	553,117	553,117		534,836
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	-0.083*** (0.013)	-88.425* (45.399)	-0.119*** (0.015)	0.041 (0.027)	0.079*** (0.024)	0.020*** (0.007)
% of Other Group Loans Ever Late	-0.061*** (0.008)	-261.558*** (50.752)	0.036** (0.016)	-0.105*** (0.031)	0.069** (0.031)	0.154*** (0.010)
% of No Group Loans Ever Late	-0.129*** (0.011)	-263.908*** (45.533)	0.069*** (0.015)	0.190*** (0.031)	-0.258*** (0.031)	0.055*** (0.011)
N	499,575	82,387	82,387	82,387	82,387	79,451
D: Response to Group Performance						
	Funded A Loan	Amount Funded				Mean IRR
% of Group Portfolio Ever Late	-0.101*** (0.024)		-27.157 (133.394)			0.004 (0.018)
% of Own Portfolio Ever Late	-0.031*** (0.009)		-617.450*** (99.570)			0.240*** (0.013)
N	499,575		81,394			78,513

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

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

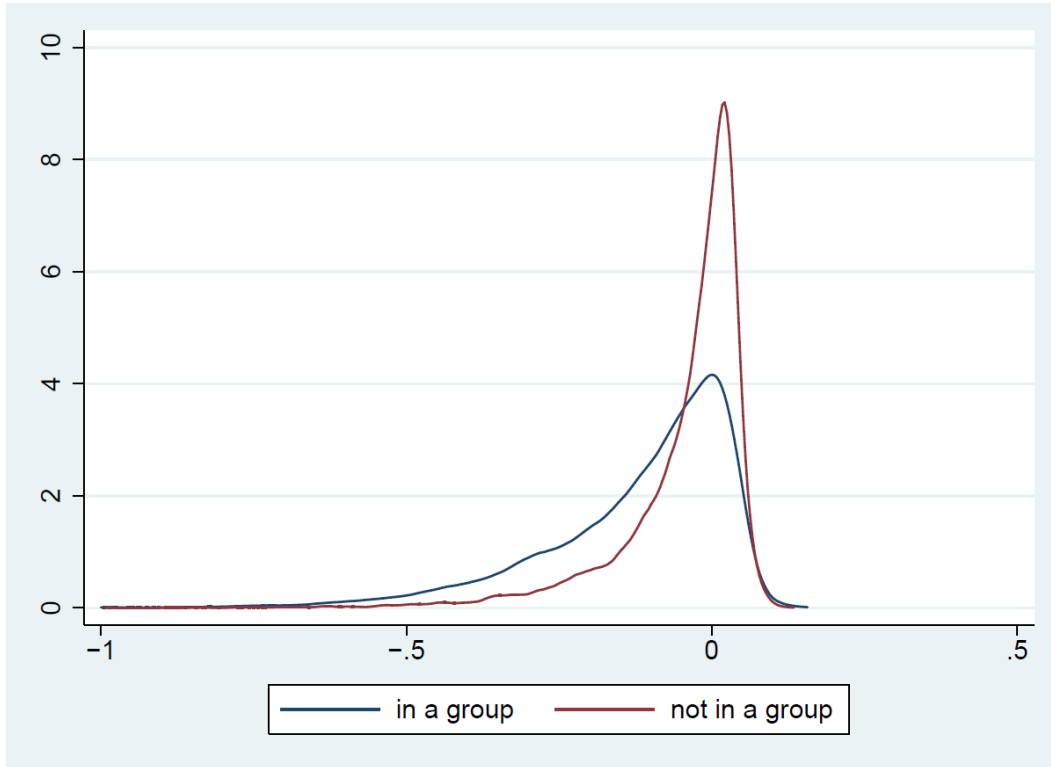


Figure 1B: Mean Loan Level IRR by Borrower's Group Affiliation Over Time



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

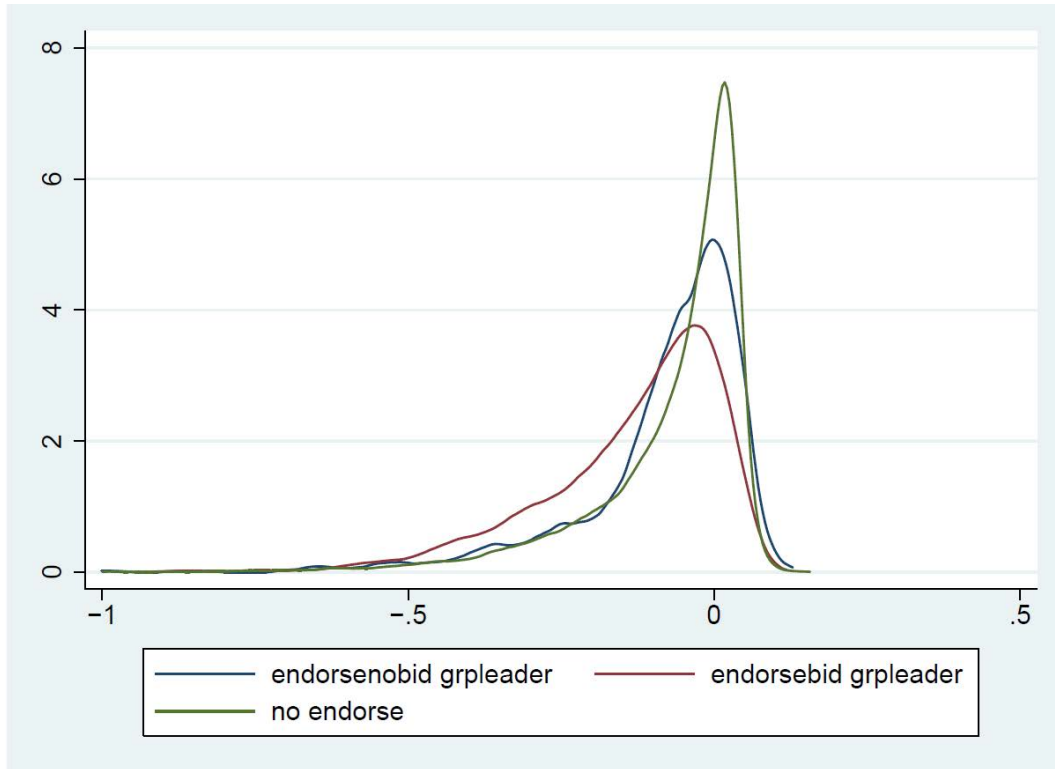


Figure 2B: Mean of Loan Level IRR by Borrower's Group Leader Endorsement Status Over Time

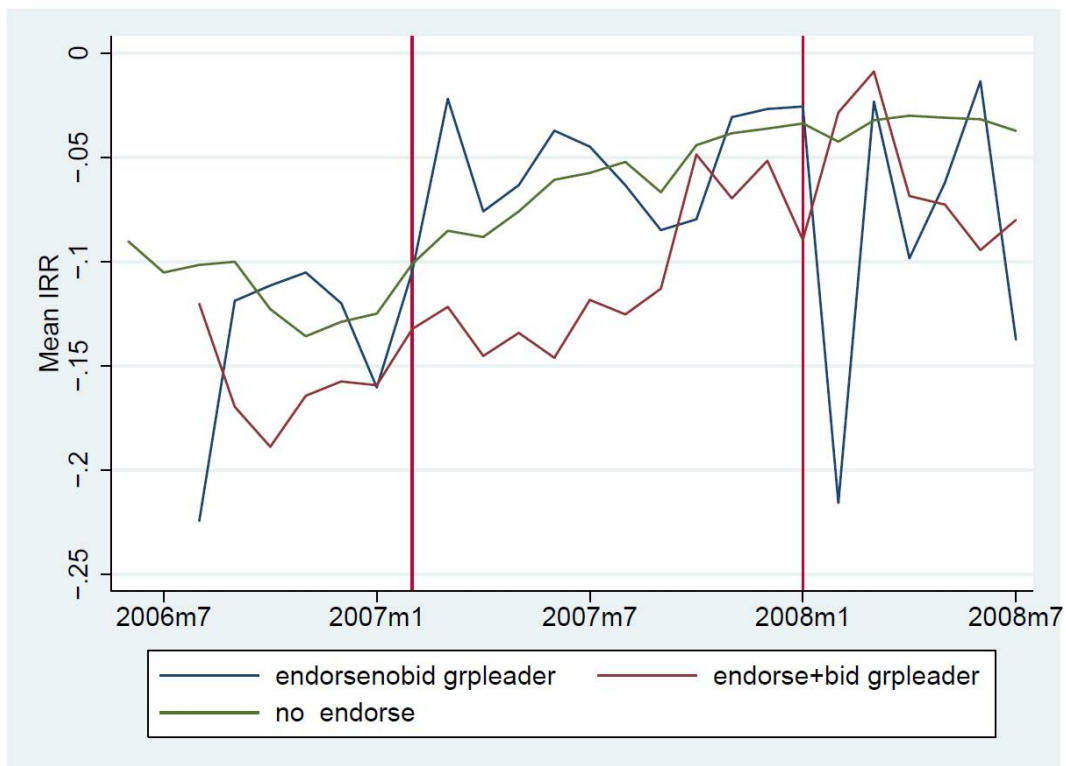


Figure 3A: Density of Loan Level IRR by Borrower's Friend Endorsement Status

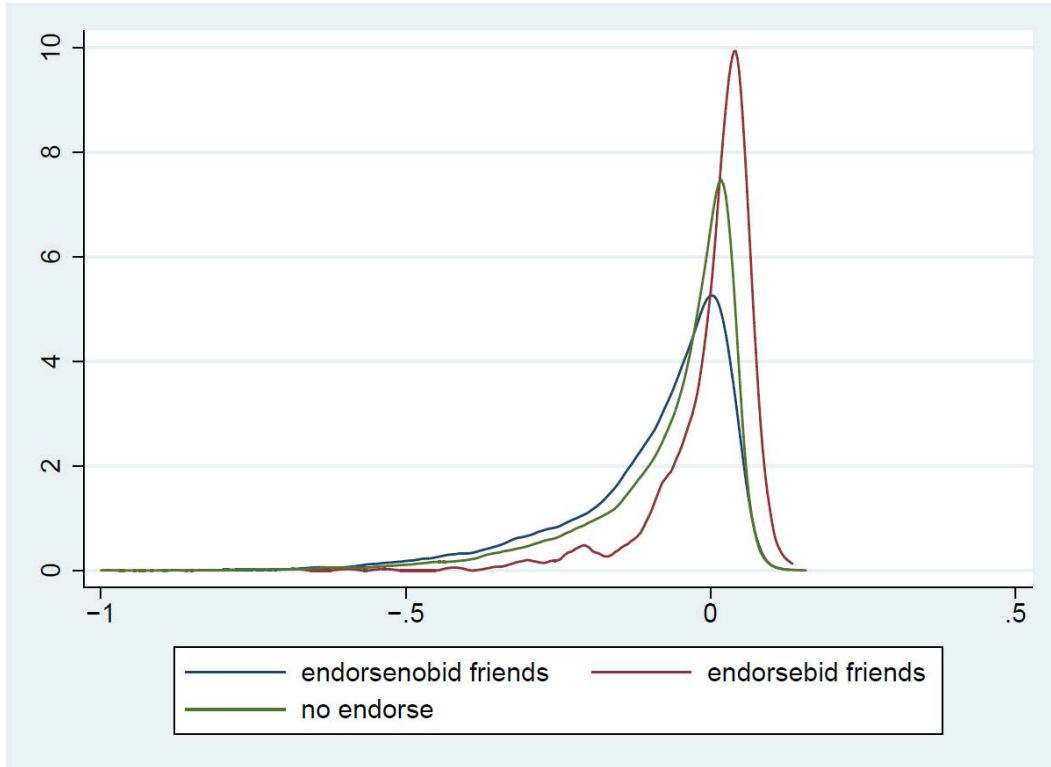
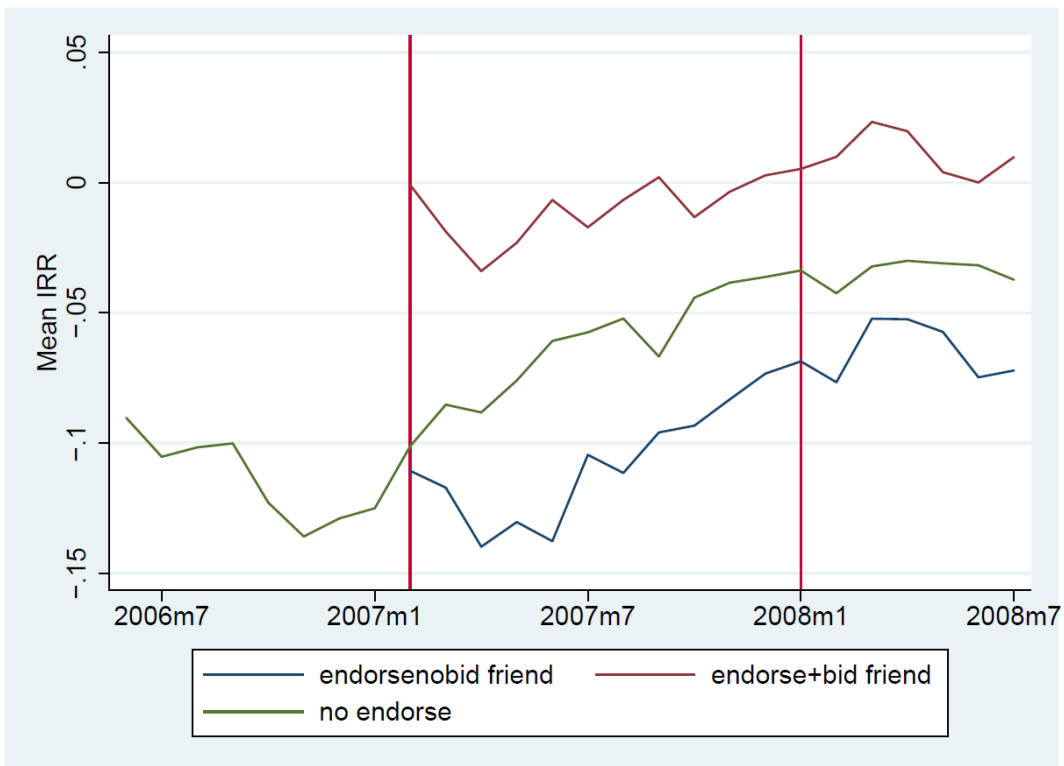


Figure 3A: Mean of Loan Level IRR by Borrower's Friend Endorsement Status Over Time



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.