# NET Institute*

www.NETinst.org

Working Paper #08-43

November 2008

**Do Social Networks Solve Information Problems for Peer-to-Peer Lending? Evidence from Prosper.com**

Seth Freedman
University of Maryland

Ginger Zhe Jin
University of Maryland & NBER

* The Networks, Electronic Commerce, and Telecommunications ("NET") Institute, http://www.NETinst.org, is a non-profit institution devoted to research on network industries, electronic commerce, telecommunications, the Internet, "virtual networks" comprised of computers that share the same technical standard or operating system, and on network issues in general.

SCHOOL OF PUBLIC AND ENVIRONMENTAL AFFAIRS
INDIANA UNIVERSITY

Research Paper No. 2008-11-06

# Do Social Networks Solve Information Problems for Peer-to-Peer Lending? Evidence from Prosper.com

Seth Freedman

Ginger Zhe Jin

# Do Social Networks Solve Information Problems for Peer-to-Peer Lending? Evidence from Prosper.com*

Seth Freedman
University of Maryland

Ginger Zhe Jin
University of Maryland & NBER

November 14, 2008

**Warning:** This is an *academic* study using Prosper data from June 1, 2006 through July 31, 2008. Readers should *not* use it as an investment guide. Because none of the Prosper loans have reached their regular maturity, the loan performance reported in this paper is up to data availability as of August 1, 2008 (our data download date). Consequently, the estimated rate of return entails a number of assumptions. Any conclusion drawn from our study is subject to the validity of these assumptions.

JEL: D45, D53, D8, L81

*Seth Freedman, Department of Economics, University of Maryland, College Park. Phone: 301-405-3266, Email: freedman-s@econ.umd.edu. Ginger Zhe Jin, Department of Economics, University of Maryland, College Park. Phone: 301-405-3484, Fax: 301-405-3542, Email: jin@econ.umd.edu. We received constructive comments from Larry Ausubel, Robert Hampshire, John Haltiwanger, Anton Korinek, Haim Mendelson and Phillip Leslie. Special thanks to Chris Larsen, Kirk Inglis, Nancy Satoda, Reagan Murray, Anurag Malik, and other Prosper personnel for providing us detailed information about prosper.com, to Jim Bruene for helping us understand the lending industry in general, and to Adam Weyeneth and other prosper lenders for sharing with us their experience on prosper.com. We are grateful to the UMD Department of Economics, the Kauffman Foundation, and the Net Institute (www.netinst.org) for their generous financial support. An earlier draft has been circulated under the title "Dynamic Learning and Selection." In comparison, this draft has updated the data from December 2007 to July 2008 and corrected several mistakes in the data work. All the remaining errors are our own. 

**Abstract**

This paper studies peer-to-peer (p2p) lending on the Internet. Prosper.com, the first p2p lending website in the US, matches individual lenders and borrowers for unsecured consumer loans. Using transaction data from June 1, 2006 to July 31, 2008, we examine what information problems exist on Prosper and whether social networks help alleviate the information problems.

As we expect, data identifies three information problems on Prosper.com. First, Prosper lenders face extra adverse selection because they observe categories of credit grades rather than the actual credit scores. This selection is partially offset when Prosper posts more detailed credit information on the website. Second, many Prosper lenders have made mistakes in loan selection but they learn vigorously over time. Third, as Stiglitz and Weiss (1981) predict, a higher interest rate can imply lower rate of return because higher interest attracts lower quality borrowers.

Micro-finance theories argue that social networks may identify good risks either because friends and colleagues observe the intrinsic type of borrowers ex ante or because the monitoring within social networks provides a stronger incentive to pay off loans ex post. We find evidence both for and against this argument. For example, loans with friend endorsements and friend bids have fewer missed payments and yield significantly higher rates of return than other loans. On the other hand, the estimated returns of group loans are significantly lower than those of non-group loans. That being said, the return gap between group and non-group loans is closing over time. This convergence is partially due to lender learning and partially due to Prosper eliminating group leader rewards which motivated leaders to fund lower quality loans in order to earn the rewards.

# 1 Introduction

The idea of using the Internet as a platform for peer-to-peer (p2p) transactions has extended to job search, dating, social networks, and other every day interaction. A relatively new example is finance. The past three years have witnessed 12 new consumer lending websites opening around the world, all aiming to link individual borrowers with individual lenders without financial institutions as an intermediary. What kind of credit risks are listed and funded on these platforms? On what grounds will p2p lending differ from and compete with traditional banks? How do individual borrowers and lenders behave in p2p lending? Will P2P lending define the future of consumer finance, or is it a fad to wane over time? Answers to these questions are not only important for the long-run viability of p2p platforms, but will deepen the understanding of social interactions and help reshape policies that target the functionality of financial markets.

This paper is the first attempt to address these questions using transaction level data from Prosper.com.[1] As the first P2P lending website in the US[2], Prosper.com has attracted 750,000 members and originated loans of over 160 million dollars in 2.5 years. Aside from operation style[3], Prosper.com differs from a traditional lending market in two ways.

First, although Prosper lenders face a traditional information imperfection in assessing borrower risk, anonymous online interaction presents new challenges that do not apply to traditional banks. For instance, Prosper only posts a categorical credit grade for each borrower, so the lender never observes the borrowers exact credit score. Furthermore, individual lenders, by definition smaller and less professional than financial institutions, may not have the expertise to predict and screen risks. Even if they can, most loans are funded by multiple lenders (for the purpose of risk diversification), and therefore each individual lender may lack the incentive to gather information before funding and monitor performance after funding.[4]

[1] Hampshire (2008) has studied lender perception of group variables on Prosper, but he focuses on group listings only and does not analyze loan performance.

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

[3] Prosper.com automates the borrower-lender match via real-time auctions. With sufficient scale, this format may generate significant savings in operation costs, implying lower interest rates for individual borrowers and better returns for individual lenders. Unfortunately, we do not have sufficient data to measure the cost difference.

[4] In the recent subprime mortgage crisis, a similar argument may apply to those traditional lenders that initiate high risk loans, repackage them in securities, and spread the risk to the rest of the market. In this sense, it is unclear whether p2p lenders have more or less incentives to care about the loan performance as compared to traditional lenders.

The second difference between p2p and traditional lending is the formers ability to utilize social networks. Prosper.com encourages borrowers and lenders to form online groups and establish friendships with other members. It allows group leaders and friends to offer endorsements for a specific listing and highlights bids from group members, endorsing group leaders, and endorsing friends. Like other micro-finance approaches, it is hoped that p2p lending can better utilize the social ties among its individual members. Coupled with the potential for the Internet to facilitate information flow among borrowers and lenders, the "soft" information conveyed via social networks may compensate for the lack of "hard" information on Prosper. However, unlike group lending in the Grameen Bank (Yunus 2003), the social networks permitted on Prosper do not impose joint liability within the network. That being said, social networks, especially those with offline ties, may still identify good risks if friends and colleagues observe the intrinsic type of borrowers ex ante or the monitoring within social networks provides a stronger incentive to pay back ex post (Stiglitz 1990, Arnott and Stiglitz 1991, Besley, Coate and Loury 1993, Besley and Coate 1995). Whether these features hold in reality is an empirical question.

Aware of these issues, Prosper.com has implemented a series of policies to minimize its disadvantage in information access and strengthen its advantage in social networks. The first and foremost policy is information transparency: before listing a loan request, Prosper.com authenticates the identity of each borrower (by checking her social security number), extracts the borrower's credit history from a third party credit bureau (Experian), and posts credit grades and historical credit information in the borrower's listing.[5] In addition, Prosper.com posts all of the up-to-date Prosper activities, from listing to loan performance, on its website.[6] In theory, every potential lender can look at the complete collection of prosper "books" before lending. As detailed in Section 2, both the extent of transparency and the nature of Prosper networks have evolved over time.

Using transaction data from June 1, 2006 to July 31, 2008, we present evidence of three information problems on Prosper: first, Prosper lenders face extra adverse selection because they observe categories of credit grades rather than the actual credit scores. We show that, although the overall Prosper market has moved towards better credit grades, over time there are more listings and more loans towards the lower end of each grade. This selection is partially offset by increasing interest rates in these intervals when Prosper begins to post more detailed

[5] If a borrower defaults, she is not allowed to borrow any more from Prosper.com and the default is reported to the credit bureau.

[6] In fact, the transparency policy has spawned a number of user-generated websites that summarize the Prosper statistics in real time.

credit information on the website. Second, many Prosper lenders make mistakes in loan selection and therefore have a negative rate of return on their portfolios, but they learn vigorously and the learning speeds up over time. Third, as Stiglitz and Weiss (1981) predict (for traditional lending), a higher interest rate may imply a lower (financial) rate of return because higher interest attracts lower quality borrowers. We show that, the estimated internal rate of return (IRR) is a non-monotone function of interest rate reaching a peak when the interest rate is 8-9% and then decreasing until the interest rate is above 28%.

While abundant evidence points to information problems on Propser.com, a key question is whether social networks help alleviate the problems. We find evidence that social networks do help identify quality borrowers when a borrower's listing is endorsed by her friend *and* this friend bids on the listing. In fact, loans with friend endorsement and friend bids tend to have less missed payments and yield significantly higher rates of return than other loans. This result suggests that the market may under-estimate the positive signaling effect of friend endorsement plus bid. In contrast, loans with friend endorsement but no bid generate a lower rate of return than the loans without endorsements, implying that the market does not discount the negative signal of friend endorsement alone to the full extent.

On average Prosper groups do not succeed in identifying high quality borrowers. The estimated rate of return is significantly lower for group loans; however, the gap has been closing over time. This convergence is partially due to lender learning and partially due to Prosper eliminating group leader rewards which motivated leaders to fund lower quality loans in order to earn the rewards.

Additionally, there is a large amount of heterogeneity among group loans: we observe better performance and higher returns if a group borrower is endorsed by the group leader but receives no bid from the leader, if the group borrower belongs to a group that is small and less borrower-concentrated, if the loan attracts a greater percent of funding from its own group members, and if the group is formed based on alumni or other tangible connections. Overall, these results suggest that Prosper groups have the potential to clear some information hurdles if the group is designed with the correct incentives.

Our work contributes to a number of literatures. As Stiglitz and Weiss (1981) point out, the information asymmetry between lenders and borrowers leads to credit rationing. While many papers using offline data have found evidence of credit rationing (e.g. Jaffee 1971, Cox and Japelli 1990, Berger and Udell 1992, Voridis 1993) and liquidity constraints (e.g. Souleles

1999, Parker 1999, Gross and Souleles 2002, Adam, Einov and Levin 2007), we have a rare opportunity to directly test the non-monotonic relationship between rate of return and interest rate. As the loan performance unravels and Prosper lenders learn from mistakes, we observe a dynamic evolution toward credit rationing based on the "hard" information in the borrower's credit profile.

Our paper also relates to the literature of informal lending and micro-finance. Previous researchers have argued that informal lenders and micro-finance institutions 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). We show evidence both for and against this argument. It seems some social networks permitted on Prosper can clear information hurdles if they face the right incentives. If well understood by the market, "soft" information provided by social networks could contribute to an alleviation of credit rationing.

Finally, as a fresh example of an online marketplace, the experience of Prosper highlights the role that information and social relationships can play in the rise of e-commerce. Unlike previous studies that document the segmentation between online and offline markets (Jin and Kato 2007, Hendal, Nevo and Ortalo-Magne 2008), we show that Prosper is converging with the traditional market except for the positive signals contained in some social network variables.

The rest of the paper is organized as follows. Section 2 describes the background of Prosper.com and its major competitors in traditional lending. Section 3 describes the data, defines the sample, and provides a simple summary of the Prosper population over time. Section 4 presents evidence for three types of information problems. Section 5 lists the potential roles of social networks and tests them in the data. A short conclusion is offered in Section 6.

## 2 Background

After two years of development, Prosper officially opened to the public on February 13, 2006. The launch attracted significant media coverage including features in Business Week, the Wall Street Journal, and ABC's World News Tonight. As of August 1, 2008, Prosper had registered 750,000 members and originated 26,273 loans that total over 164 million US dollars. The quick expansion of Prosper has coincided with a number of similar new p2p lending sites in the US.[7]

[7] The best known examples are Kiva.org (incorporated November 05), Smava (launched in February 2007), Lending Club (open May 24, 2007 as part of Facebook), MyC4 (launched in May 2007), Globefunder (launched

In this section we describe the specifics of the Prosper market place, policy changes that have occurred since its inception, and the parameters of Prosper's social networks. Finally we discuss Prosper's competition from traditional credit markets and the changes in the macroeconomic environment that coincide with our study period.

## 2.1 Market Setup

All Prosper loans are fixed rate, unsecured, three-year, and fully amortized with simple interest. Loan can range from $1,000 to $25,000. There is no penalty for early payment. As of today, the loans are not tradable in any financial market[8], which means a lender that funds a loan is tied up with the 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.

Before listing on Prosper, a potential borrower must file a short application so that Prosper can authenticate 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.[9] If the credit score falls into an allowable range, the borrower may post an eBay-style listing specifying the maximum interest rate she is willing to pay, the requested loan amount, the duration of the auction (3-10 days)[10], 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, the city of residence, how she intends to repay the loan, and any other information (including an image) that she feels may help fund the loan. In the same listing, Prosper will post the borrower's credit grade (computed based on credit score), home ownership status, debt-to-income ratio, and other credit history information.[11]

Like borrowers, a potential lender must provide a social security number and bank information for Prosper to verify identity. Lenders can browse listing pages which include all of the

in Oct. 2, 2007), and Zopa US (us.zopa.com, open December 4, 2007).

[8] In October of 2008, Prosper began the process of registering with the appropriate securities authorities in order to offer a secondary market.

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

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

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

information described above, plus information about bids placed, the percent funded, and the listings current prevailing interest rate. To view historical market data a lender can download a snapshot of all Prosper records from Prosper.com, use a Prosper tool to query desired statistics, or visit a third party website that summarizes 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 (so long as it is below the borrower's specified maximum rate) and the amount of dollars he would like to contribute (any amount above $50). Most lenders bid a small amount on each loan in order to diversify their Prosper portfolio. A listing is fully funded if the total amount bid exceeds the borrower's request. If the borrower chooses the autofunding option, the auction will end immediately and the borrower's maximum interest rate applies. Otherwise, the listing remains open and new bids will compete down the interest rate. Lenders with the lowest specified minimum interest rate will fund the loan and the prevailing rate is set as the minimum interest rate specified by the first lender excluded from funding the loan. We will refer to the resulting interest rate as the contract rate.

Prosper charges fees to both borrowers and lenders. These fees have changed over time, but in general borrowers pay a closing fee when their loan originates ranging from 1% to 3% depending on credit grade (there is no fee for posting a listing). If a borrower's monthly payment is 15 days late, a late fee is charged to the borrower and transferred to lenders in the full amount. Prosper does not acquire anything in this process. Lenders are charged an annual servicing fee based on the current outstanding loan principal[12]. The lender fee has ranged from 0.5% to 1% depending on credit grade.

In legal terms, Prosper loans are first issued by Prosper and then sold to individual lenders. Prior to April 15, 2008, Prosper was subject to state usury laws which specify the maximum interest rate a lender could charge. The binding law was that of the borrower's state of residence, and within each state regulations depended on whether Prosper held a consumer loan license in that state. The interest rate caps varied from 6% to 36% across states. On April 15, 2008, Prosper became a partner of WebBank, a Utah-chartered industrial bank, which allows the site to circumvent most state usury laws. Following this partnership, the interest rate cap became a universal Prosper implemented 36% (except for Texas and South Dakota).

[12]This fee is accrued the same way that regular interest is accrued on the loan.

## 2.2 Information Policies

Prosper has continually changed the information that it provides lenders. The policy changes are listed in Table 1 and highlighted here. Originally, the only credit information posted on Prosper was debt-to-income ratio and credit grade. Credit grades are reported in categories, where grade AA is 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. The numerical credit score is never available to lenders. On April 19, 2006, Prosper started to post whether the borrower has a verified bank account at the time of listing and whether the borrower owns a home.

On May 30, 2006 further credit history information about delinquencies, credit lines, public records, and credit inquires were reported followed by even more detailed credit information, self reported income, employment and occupation on February 12, 2007. On this date, lenders were also allowed to begin asking borrowers questions and the borrowers had the option to post the Q&A on the listing page. Additionally, Prosper tightened the definition of credit grade E from 540-599 to 560-599 and grade HR from less than 540 to 520-559 eliminating borrowers who do not have a credit score (NC) or have a score below 520 from borrowing on the site. The February 12, 2007 policy changes are likely to particularly impact risk selection on Prosper as we discuss in Section 4.

The next information change occurred on October 30, 2007, when Prosper began to display a Prosper-estimated rate of return on the bidding page (bidder guidance). Before the change, a lender had to visit a separate page to look for the historical performance of similar loans. Prosper also introduced portfolio plans on October 30, 2007, which allow lenders to specify a criterion regarding what types of listings they would like to fund and Prosper will place their bids automatically. These portfolio plans simplified the previously existing standing orders.

## 2.3 Social Networks on Prosper

A unique feature of Prosper is its 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 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. The imbalance between member recruiting and performance monitoring prompted Prosper to discontinue the group leader reward on September 12, 2007. We will consider these changing incentives when analyzing the role of groups in the Prosper marketplace.

Starting February 12, 2007, Prosper members could begin to invite their offline 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 begin including aspects such as friend endorsements and bids from friends as criteria in their listing searches.

### 2.4 Who Competes With Prosper in the Traditional Market?

The main competitors Prosper face in the traditional market are credit card issuers. Up to our observation date (August 1, 2008), 36% of all previous Prosper listings have mentioned credit card consolidation, which is higher than the mention of business (23%), mortgage (14%),

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

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

education (21%), and family purposes (18%) such as weddings.[15]

According to the Federal Reserve, the total consumer credit outstanding (excluding mortgages) was valued at $2.54 trillion in February 2008.[16] Within this category, $0.95 trillion was revolving debts primarily borrowed in the form of credit cards. The rest ($1.58 trillion) were non-revolving debts including loans for cars, mobile homes, education, boats, trailers, vacations, etc. By definition, credit card borrowing is not secured by any tangible asset. In contrast, a large proportion of the non-revolving debt is collateralized by the goods purchased via the loan, and therefore carries a lower interest rate than credit cards.[17] Commercial banks also issue unsecured personal loans, at an average interest rate of 11.40%. Most Prosper loans carry an interest rate much higher than the average rate of credit cards, but since we do not know the credit grade composition of credit card accounts, we are not able to make the comparison conditional on the same observable attributes. We will revisit this issue in Section 4.

Roughly 6% of Prosper listings mention that the Prosper loan, if funded, will be used to pay off payday loans in the offline market. Compared to the APR of 528% that Caskey(2005) reports for payday loans, one may argue Prosper could provide a much better alternative to payday loans, given the 3-year duration of Prosper loans and the interest rate cap no higher than 36%. However, lenders must consider the credit risk they face on Prosper. If a payday lender must charge an annual interest rate of 500% to survive competition (Skiba and Tobachman 2007), it is unclear why Prosper lenders would be willing to support this pool of borrowers with a much lower interest rate.

### 2.5 Changes in Macro Environments

The years 2007 and 2008 have witnessed dramatic changes in consumer lending as shown in Figure 1. Before the subprime mortgage crisis began to grab headlines in August 2007, the financial market was relatively calm with stable monetary policy. Starting August 9, 2007, the major indices such as the London Interbank Offered Rate (LIBOR), jumbo mortgage spread, and the yields of asset-backed commercial paper (ABCP) have all shown abrupt change and increased

[15] 69% of listings mention cars, but this is likely a result of borrowers listing their car payments as a monthly expense.

[16] Source: Federal Reserve G.19 Statistical Release as of April 7, 2008. Based on the Quinquennial Finance Company Survey 2005, see more details at http://www.federalreserve.gov/releases/g19/ (accessed at April 9, 2008).

[17] e.g. 7.27% for 4-year new-car loans vs. 13.71% for credit card accounts that have assessed interest.

volatility. The Senior Loan Officer Survey (conducted quarterly by the Federal Reserve) also reveals progressive tightening of credit standards on a wide variety of loans, including prime and subprime mortgages, commercial & industrial loans, and credit cards. In response, the Fed funds rate has fallen from 5.41% (August 9, 2007) to 2.04% (August 1, 2008). It is clear that the macro environment changes are primarily driven by the subprime mortgage crisis, and the crisis spills over to other types of lending and investment.

Given the drastic changes in the macro environment during our study period, our analysis controls for a number of macroeconomic variables. At the daily level we include the bank prime rate, which tracks the Fed funds rate with a 0.99 correlation, the TED spread (the difference between 3-month LIBOR and 3-month Treasury bills), the yield difference between corporate bonds rated AAA and BAA, and S&P 500 closing quotes. According to Greenlaw et al. (2008), the middle two are the strongest indicators of the subprime mortgage crisis. 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, and 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.

In addition, we 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. The first two variables intend to capture the overall traffic on Prosper, which may vary by media coverage, word of mouth, or the mood of borrowers and lenders. The percent ever late intends to capture the ex-post performance of the Prosper market as a whole, so as to track the performance evolution that lenders may observe on Prosper over time. Because the financial turmoil observed in the macro environment is rooted in the subprime mortgage crisis, we control for the interaction of the OFHEO foreclosure rate and the borrower's home owner status and consumer loan easing and tightening with whether the borrower has a credit grade of E or HR. It is worth noting that most of the time-series variables, except for those specific to day, state or credit grade, will be absorbed in year-week fixed effects. Whenever possible, we estimate specifications with and without these fixed effects for robustness.

# 3 Data

In addition to macroeconomic indicators described above, our study utilizes data publicly available for download from Prosper's website and a private data set provided to us by Prosper.

The main data set is downloaded on August 1, 2008. This data set 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 extracted from 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 the full payment history up to the download date. For each Prosper member we observe their group affiliation and their network of friends.[18] Finally, we observe data on all Prosper bids allowing us to construct each lender's portfolio on any given day.

We also utilize a private data set obtained from Prosper that includes the number of listings, number of loans, average contact interest rate, percent late at 6 months, and percent late at 12 months by state, month and credit score interval. These credit score intervals are finer than the publicly posted credit grades. For comparison, it also includes Experian data on historical loan performance in these finer credit intervals for offline consumer loans.

Our sample includes 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. We exclude the few loans that were suspects of identity theft and as a result repurchased by Prosper. Table 2 summarizes listings and loans by quarter for this sample. This sample 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 have 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. This difference is preliminary evidence of credit rationing. It appears that lenders are wary of listings requesting larger loans and view this as a signal of higher risk. The average listing lists a maximum borrower rate of 19.19% while the average contract rate is 17.90%.[19]

[18]The data dump reflects information about groups and 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.

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

In terms of social networks, Table 2 suggests that being a group member and having a friend endorsement increases the likelihood of funding. Both variables have larger representation in loans than in listings. However, it is striking that the proportion of listings and loans with group affiliation has decreased drastically from 60% and 70% to 7.5% and 10%, respectively. When friend and group leader endorsements became available, the percent of listings and loans with endorsements initially grew but have decreased since the middle of 2007. The only exception is the percent with friend endorsements plus bids. These patterns call into question the importance and effectiveness of social networks which we will explore in detail in Section 5.

Table 2 also summarizes the percent of default as observed on August 1, 2008. We define a loan as in "default" if it is four or more months late or labeled default by Prosper due to bankruptcy.[20] About 30% of loans originating in 2006 have defaulted by August 1, 2008, which makes it clear that lenders observe negative performance in their portfolios and the overall market. Note that the proportion of loans in the 2007 and 2008 cohorts that have defaulted are much lower than in the earlier cohorts as a result of the life cycle of loans.

# 4 Information Problems

This section presents evidence for three information problems on Prosper.com: (1) adverse selection due to less credit information on Prosper; (2) lender misinterpretation of listing attributes because they do not have expertise in consumer lending; and (3) a non-monotone relationship between rate of return and interest rate because lenders have imperfect information about borrower risk (Stiglitz and Weiss 1981). The last problem is common to all lending, but the first two are likely unique to p2p lending.

## 4.1 Adverse selection due to less information on Prosper

The most compelling example for the information difference between traditional and Prosper lenders is that traditional lenders observe a borrower's actual credit score but Prosper lenders only observe a credit grade. Consider two borrowers, one with a credit score of 601 and the other

[20]Once a loan is four months late, Prosper considers it eligible for debt sale, and once it is sold it is considered to be in default. However, because debt buyers only purchase packages of loans, a four month late loan will not be considered "default" immediately. Loans can thus be labeled "4+ months late" for long periods of time. Our default definition overcomes this mechanical ambiguity.

639. Traditional lenders observe the exact scores and treat the two differently. But since Prosper categorizes both as credit grade D, they look identical to Prosper lenders if the other observable information is the same. According to Akerlof (1970), this will drive the D- borrowers towards Prosper more often than those with a grade of D+, because Prosper lenders cannot price these categories differentially. Using the confidential data from Prosper, we observe the distribution of D- and D+ and its evolution over time.

More specifically, we focus on summary statistics by census division, month, and "half grade." Except for the ends of the score distribution (300-900), most half grades are defined as a 20-point interval of credit scores, for instance, 600-619 (referred to as D-) and 620-639 (D+). In total, we have 20 half grades, which is much more detailed than the 8 credit grades posted on Prosper.com.[21] Not only does this data allow us to identify adverse selection in the whole sample of Prosper, we can also test whether such adverse selection is alleviated when Prosper reveals more detailed credit information or exacerbated when traditional lenders tighten credit in general.

Table 3 presents the funding rate, interest rate, the percent late, and the percent 3-months late or worse (as of August 1, 2008) by the 8 credit grades observable to Prosper lenders. As expected, a better grade means a higher funding rate, lower interest rate, and better loan performance. The last two columns attempt to compare Prosper loan performance to all the Experian accounts that have a new credit line approved in September 2003. Since the performance of Experian accounts are observed as of September 2005, we summarize the observed 2-year performance for the Prosper loans that were originated in July 2006. While the time horizon of Prosper and Experian loans are not exactly the same, it is clear that Prosper loans perform much worse than the traditional Experian accounts.[22] One potential explanation is that Prosper loan composition is worse than the Experian accounts *within* each credit grade because Prosper attracts more borrowers towards the lower end of the grade.

To better reflect the composition difference, Figure 2 compares the c.d.f. of Prosper listings, Prosper loans, the Experian population, and Experian new accounts across the 20 half grades. By Experian population, we mean all the accounts that have a score by the Experian ScorexPLUS

[21] The precise definition of the 20 half grades are 300-479, 480-499, 500-519, 520-539 (HR-), 540-559 (HR+), 560-579 (E-), 580-599 (E+), 600-619 (D-), 620-639 (D+), 640-659 (C-), 660-679 (C+), 680-699 (B-), 700-719 (B+), 720-739 (A-), 740-759 (A+), 760-779 (AA-), 780-799 (AA+), 800-819, 820-839, 840-900.

[22] According to the Federal Researve, the credit card charge-off rate has increased from 4.3% in the third quarter of 2005 to 5.5% in the second quarter of 2008. If we had grade-specific performance data in 2008, the comparison between traditional and Prosper loans would be less stark.

model in December 2003.[23] This comparison imperfect because a person may have a record in Experian but does not demand credit. The Experian new accounts are defined as above, where the credit could be secured (such as a mortgage) or unsecured (such as a credit card). Even though the Prosper vs. Experian comparison is imperfect,[24] there is no doubt that Propser listings have much greater concentration on lower credit intervals. Prosper lenders are able to select better risks from the listing pool, but the overall distribution of Prosper loans is still worse than that of Experian accounts.

Figures 3 and 4 present the p.d.f. of Prosper listings and Prosper loans by the 20 half grades and across time. The loan distribution is also compared with the p.d.f. of Experian new accounts as defined above. Not surprisingly, Prosper attracts listings towards the lowest end of the credit score distribution (Figure 3) while the traditional lenders tend to focus on the highest end (Figure 4). These two facts are probably linked – because traditional lenders cannot satisfy the credit demand of near or subprime risk (due to credit rationing), these risks find Prosper an attractive alternative.

More interestingly, the Prosper loan distribution is much jumpier than the Experian accounts. As Figure 4 shows we see a higher frequency at D- than D+, C- than C+, etc. in the Prosper loans (but not in the Experian accounts), suggesting adverse selection with more Prosper borrowers appearing in the lower half of each grade. Of course, this evidence is only suggestive because loans reflect both borrower selection and lender decisions. Given the fact that the Prosper listing distribution leans toward the very low tail of credit scores, the decline of listing frequency from the lower end to higher end of each grade could be due to adverse selection or the skewness itself. Note that the jumpiness of Prosper loans does not disappear over time. The listing and loan distributions are both moving towards the right, which could be due to the credit crunch in traditional lending (which forces near prime and prime risks to seek credit on Prosper), Prosper revealing more information hence discouraging subprime risks, or Prosper lenders learning to avoid subprime risks.

The imperfect comparison of Experian accounts and the Prosper population motivates us to explore the discontinuity of credit grade definitions in a more sophisticated way. For a "half-

[23] "Redeveloped Experian/Fair, Issac Risk Model" (December 2003) accessed at www.chasecredit.com/news/expficov2.pdf on September 5, 2008

[24] Given the stability of credit markets before the subprime crisis and the credit crunch after August 2007, the Experian distribution is likely to overestimate the traditional credit access in 2006-2008 and therefore constitutes a conservative comparison group against Prosper.

grade" interval $i$ in census division[25] $c$ and month $t$, we estimate the following two specifications:

$$\begin{aligned} Y_{ict} &= 1_{minusgrade} \cdot \beta_1 + MonthCount_t \cdot 1_{minusgrade} \cdot \beta_2 \\ &\quad + MonthCount_t \cdot 1_{nearprime} \cdot \beta_3 + MonthCount_t \cdot 1_{subprime} \cdot \beta_4 \\ &\quad + \mu_c + \mu_t + \mu_{grade} + \epsilon_{ict} \end{aligned}$$

$$\begin{aligned} Y_{ict} &= 1_{minusgrade} \cdot \beta_1 + Macro_{ct} \cdot 1_{minusgrade} \cdot \beta_{2m} \\ &\quad + Macro_{ct} \cdot 1_{nearprime} \cdot \beta_{3m} + Macro_{ct} \cdot 1_{subprime} \cdot \beta_{4m} \\ &\quad + ProsperPolicy_t \cdot 1_{minusgrade} \cdot \beta_{2p} + ProsperPolicy_t \cdot 1_{nearprime} \cdot \beta_{3p} \\ &\quad + ProsperPolicy_t \cdot 1_{subprime} \cdot \beta_{4p} + \mu_c + \mu_t + \mu_{grade} + \epsilon_{ict} \end{aligned}$$

In both specifications, we adopt six dependent variables: (1) the number of Prosper listings, (2) the number of Prosper loans, (3) the funding rate,[26] (4) the average interest rate of loans, (5) the percent late in 6 month, and (6) the percent late in 12 month. In principle, all six outcomes can be driven by borrower behavior, lender behavior, or both. Both specifications control for a full set of year-month dummies, a set of credit grade dummies (i.e one dummy for AA, one for A, etc.), and a set of dummies for census division. The coefficient on the dummy of minus grade tells us how minus grades differs from plus grades *within* the same grade. Standard errors are clustered by census division.

With no explicit control for Prosper policy changes or the macro environments, the first specification intends to describe how Prosper populations have changed across credit intervals and over time. In the second specification, we relate the over-time population change with various macro variables and the major Prosper policies. Since most macro and Prosper policy variables are simple time-series, it is difficult to tell them apart from the general time trend. As a result, we interact the macro/policy variables with whether the credit interval refers to a minus grade, whether the interval falls into the near prime range defined by Experian (600-679), or whether the interval belongs to the subprime range (below 600). These interactions capture the co-movement of the Prosper population and the overall environment, but do not represent causal effects.

Table 4-1 presents the regression results for the first specification, with two columns for each dependent variable. Because the February 2007 Prosper policy disallowed any listing with

[25] We have state level data but some states have too few observations in the count of listings or loans. Aggregation into census division alleviates this problem. We have also tried aggregation into census regions, results are similar.

[26] Which is literally the number of loans divided by the number of listings in each cell.

credit score below 520, to facilitate comparison the regression sample excludes credit scores below 520.[27] The odd numbered columns suggest significant adverse selection: compared to plus grades, minus grades have on average 11 more listings and 2 more loans per division-grade-month. Both numbers imply a significant density towards minus grades as there are only 30 listings and 6 loans in each division-month-interval on average. As the theory predicts, the minus grade loans perform significantly worse. The fact that Prosper lenders do not observe credit scores explains why the funding rate is no different between minus and plus grades after we control for the fixed effects of month, grade and division. However conditional on funding, lenders charge 0.4 percentage point higher interest rates on the minus grades, which suggests that they may have some clue as to which loans are minus grades and which are not. The even numbered columns include the interactions of month count (since June 2006) with minus grade, near prime, and subprime. Over time we observe more near and subprime listings relative to prime, but less subprime loans. Note this is slightly different from what is seen in Figures 3 and 4, because these regressions describe the absolute number of listings and loans in each interval as opposed to the relative distribution. While the overall risk composition has improved, the adverse selection towards minus grades increases through time at a speed of 0.55 more minus grade listings and 0.18 more minus grade loans per month.

Table 4-2 replaces the month count interactions with those that involve macro variables and Prosper policy changes. While we have included all the major macro variables (bank prime rate, state-specific unemployment rate, and state-specific foreclosure rate) in the interactions, we only report those of bank prime rates because they are most related to the credit crunch.[28] As shown in column 1, changes in the listing population is clearly correlated with the macro environment. However, when we include the interaction of Prosper policies (column 3), the coefficients of the bank prime rate interactions have all switched sign from negative to positive. Thus, it is unclear whether the credit crunch has contributed to more or fewer non-prime borrowers (relative to prime).

The coefficients on the policy interactions are much more stable: data suggests that, for both the number of loans and listings, the concentration towards minus grades has increased after Feburary 2007 and April 2008. Interestingly, Prosper lenders do not demand a higher interest rate on a minus grade loan until February 2007. We suspect this occurs because the extra

[27] Results using all the "half-grade" intervals are very similar to the presented results except for the chop-off of the scores below 520 after February 2007.

[28] The correlation between bank prime rate and the fraction of banks that reported credit tightening of consumer loans is -0.92.

credit information that Prosper provided since February 2007 has helped lenders distinguish risks within a grade. One may argue that Prosper introduced friend endorsement in February 2007 as well and that could contribute to lenders charging higher interest rates. We cannot test this explicitly because the half-grade data is aggregated. But as shown in Table 2, friend endorsements account for only 20-30% of the Prosper population and these percentages are declining sharply over time. These facts do not explain why the increased interest rate for the minus grade loans appears abruptly in Feburary 2007 and stays stable afterwards. Turning to the interaction of Prosper policies and sub prime, the results suggest that Prosper policies, especially the bidder guidance introduced in October 2007, may have helped lenders better understand the true meaning of sub prime and therefore motivate them to shift towards better grades. This result will be further confirmed in Section 4.3.

Above all, we argue that the crude definition of credit grade has resulted in adverse selection towards the lower end of each grade. While the macro environment and the Prosper policies may have contributed to the shift towards better grades, the adverse selection towards minus grades has increased over time. The market is aware of the problem, as the adverse selection is partially offset by higher interest rates when Prosper began posting more credit information in February 2007.

### 4.2 Funding rate, interest rate and loan performance

The second information problem is probably specific to p2p lending: because most individual lenders are amateurs in consumer lending, they may not understand the true risk underlying a specific attribute. If the misunderstanding exists in a systematic way, we may observe a listing attribute that signals higher default but has a higher funding probability or a lower interest rate. However, mismatch alone does not necessarily imply lender mistakes, especially if some lenders have charity motives towards the listing attribute or other incentives.[29]

To detect mismatch, we run three descriptive regressions that correlate observable listing

[29] A third explanation is omitted variables that lenders observe but we do not. Examples include the attractiveness of the image or the way in which the borrower answers a lender question privately. But for the omitted variables to explain the mismatch, they must be correlated with the observables in a systematic way and overturn the initial signal embodied in the observable attributes. For instance, if most low grade borrowers are more responsive to lender questions and this attitude dominates the effect of credit grade on default risk, that may explain the mismatch. But we believe such events are unlikely and no data allow us to justify it one way or the other.

attributes to the probability of being funded ($1_{funded}$), the interest rate if funded ($InterestRate$), and whether the loan is default or late as of August 1, 2008 ($1_{defaultorlate}$). In all three, we include year-week fixed effects ($FE_{yw}$) to control for the changing environment on and off Prosper. In the third equation, we also control for a full set of monthly loan age dummies ($FE_a$) to control for the life cycle of loan performance. Table 5 summarizes the listing attributes we use in these regressions. The funding rate and performance regressions are estimated by probits and the interest rate regression is estimated by OLS.

$$\begin{aligned}
1_{funded,i} &= f_1(ListingAttributes_i, macro, FE_{yw}) + e_{1it} \\
InterestRate_i &= f_2(ListingAttributes, macro, FE_{yw}) + e_{2it} \\
1_{defaultorlate,it} &= f_3(ListingAttributes, macroFE_{yw}, FE_a) + e_{3it}.
\end{aligned}$$

According to the regression results reported in Table 6, the consistency between funding rate, interest rate and loan performance holds for most but not all listing attributes. For example, the probability of being default or late increases by credit grade, and in response, interest rate increases and the funding probability decreases. Similarly, lenders understand that the more a borrower requests to borrow, the higher the risk of misperformance, and therefore deserves a lower funding probability and a higher interest rate.[30]

The consistency between interest rate and loan performance is easier to interpret because they are based on the same sample of Prosper loans. For instance, conditional on being funded, a listing with an image on average enjoys a lower interest rate (0.1 percentage points) than a seemingly equivalent listing without an image. However, the two listings do not show any significant difference in loan performance. These two findings imply that the expected rate of return is lower for listings with an image.[31] The impact of an image on the funding rate is harder to interpret. While having an image increases the funding rate, one explanation is that having an image is meaningless but lenders misinterpret it as a positive signal. Another possibility is that loans without an image are better in other attributes (in a non-linear way) and the borrowers of these loans feel it is unnecessary to post an image. As a result, loans with and without images perform the same but the listings that do not get funded due to lack of an image could perform worse than the funded loans.

We observe both consistency and inconsistency for the social network variables. Compared with others, borrowers that belong to a group are 0.4 percentage points more likely to get

[30] Loan size is a typical method of credit rationing.

[31] Ravina (2007) and Pope and Sydnor (2008) present more details on the impact of the race, gender, age and beauty contents of the images in Prosper listings.

funded, enjoy a 0.4 percentage point lower interest rate, but are 0.5 percentage points more likely (though statistically insignificant) to be default or late. Similar inconsistency occurs for a group loan that receives an endorsement and bid from the group leader. These results imply that group loans, especially those that receive an endorsement and bid from the group leader, may generate lower returns than the non-group loans. How much lower the rate of return is and why lenders are willing to support lower-return loans are the questions we will examine next.

In comparison, having a friend endorsing and bidding on the listing shows more consistency: it has a large effect on the funding rate (9.6 percentage points), and conditional on being funded, the interest rate is 0.7 percentage points lower and the probability of default or late is 4.1 percentage points lower. Whether the favorable interest rate has over- or under-compensated the better loan performance is an empirical question.

### 4.3 Expected Rate of Return

To better understand loan performance, we follow two principles to compute the internal rate of return (IRR) that a sophisticated lender should expect from a Prosper loan: the lender considers all the information at the time of listing, and he projects the risk of late and default throughout the 36-month loan life. We define IRR as the annual discount factor that equalizes the loan amount to the present value of all the predicted monthly payments. We believe this method reflects the rate of return that a lender *expects* to earn at the start of the loan if he can perfectly predict the statistical distribution of loan performance. The step-by-step algorithm is described in the Appendix.

Our method is more comprehensive than the ones used by Prosper and LendingStats.[32] Specifically, when we predict misperformance in a specific month, we regress observed loan-month performance on all listing attributes posted online, their interactions with each credit grade, and a set of loan age dummies (in months). This method utilizes more listing information than Prosper's grade-specific predictions.[33] Unlike LendingStats, we consider the fact that every

[32]LendingStats is a popular independent website that tracks Prosper activities in real time.

[33]For a given portfolio, Prosper assumes that roll rates from one loan status to another are revealed in the historical performance of each grade. For example, a 1-month-late AA loan has a 42% probability of becoming 2-months late, and a 2-months-late AA loan has a 71% probability of becoming 3-months-late. Prosper also makes assumptions on the probability of early payment-in-full (3.5% for AA, 0.5% for HR) and the probability of loss recovery if default. These assumptions enter the calculation of monthly returns. Annualizing this figure and averaging it across the whole life of the loan results in an overall rate of return.

loan has a positive risk at the time of origination even if ex post it is paid in full.[34] In this sense, we capture the return *expected* at the time of origination, not the return that is realized ex post.

We use three dummies to measure loan performance: default, default or late, and missed payment. Located between the most optimistic (default) and the most pessimistic (default or late), the dummy of missed payment is defined as one if the loan's payment history indicates that the borrower has missed the payment in a specific month. If the borrower misses the payment at month $t$ but makes it up in a later month, we count it as not missing the payment. To reflect the actual cash flow as much as possible, we treat loans that are paid off early in two ways. One counts these loans as on-time in all months following the early pay off, and the other counts the early pay off as a bulk of cash flow in the actual month of payment and zero afterwards. In the present value framework, the former effectively assumes that the early payoff is reinvested in a loan that is always on time, while the latter assumes that the early payoff is reinvested into a loan that is identical to the loan under study. For both versions, we predict the probability of missed payment and early payoff for each loan and each month using the full history from June 1, 2006 to July 31, 2008. Since Prosper added new credit information in February 2007, our full-sample prediction only uses the variables that are always available.[35]

Because all Prosper loans are three years, the majority of them are still ongoing at our observation date unless they were paid early or have already defaulted. As a result, we do not have information for loan performance in months 25-36 if we use the full sample to predict risk. Instead of using arbitrary roll over rates, we report two sets of IRR estimates: one assumes that the cumulative misperformance remains constant after month 24 (referred to as "flat IRR"), and the other assumes that the misperformance rate will follow a linear projection after month 24 ("linear IRR").[36] Our prediction regressions suggest that misperformance does not have a statistically significant increase after month 18. While this concavity may be driven by fewer observations towards the later loan life, the raw Prosper performance depicted in Figure 5 does confirm that misperformance is more likely to occur in the earlier part of the loan life, as typically

[34] Compared to Prosper, LendingStats uses more pessimistic roll rate assumptions but puts more emphasis on actual performance than predicted performance. In particular, it takes the current status of a loan as given, and does not project its future risk until it is late. In that case, it is assumed that a 1-month-late loan will default with a 50% probability and loans that are more than 1 month late will default for sure.

[35] As a robustness check, we rerun the prediction regression for the post-Feb-2007 sample only. For this sample, including or excluding the new credit information makes very little difference (less than 0.2%) in the final IRR estimates. From this we conclude that not using the new credit information does not bias our IRR estimates.

[36] More specifically, linear projection for the full sample means that the predicted misperformance rate at month x (where $x \geq 25$) is equal to [predicted risk at month 24 + (x-24)*(predicted risk at month 24-predicted risk at month 23)].

observed in the industry. Based on this observation, we believe the truth is somewhere between the flat and linear IRRs. More details of the potential bias in our IRR calculation are discussed in the Appendix.

Table 7 summarizes 12 IRR estimates for each loan depending on which performance measure we use, how we treat early payoffs, and whether we assume a flat or linear projection in the unobserved loan life. Because the performance prediction is probabilistic and the present value function may be non-smooth[37], we cannot achieve convergence for every IRR estimate. As reported in Table 7, each of the 12 IRR estimates has a convergence rate close to or above 90%. In the simplest version where we measure performance by default and treat early payoff as on-time payments, the convergence rate is higher than 97%.

Conditional on the converged IRRs, the average estimates are consistent with expectation. Treating early payoff as an early cash flow yields a lower rate of return because the reinvestment of the early payoff faces a positive risk of misperformance. Additionally, flat IRRs are 2-3 percentage points higher than linear IRRs because the latter is more pessimistic about the unobserved loan life. Within flat IRRs, the average return based on missed payments (IRR2, -0.45%) is bounded between those based on default (IRR1, 3.02%) and default or late (IRR3, -0.99%). For comparison, the average annual yields of 3-year Treasury Bill and S&P 500 are 3.97% and -0.66% in the same period (June 1, 2006 to July 31, 2008). As shown below, the seemingly low average IRRs of Prosper loans masks the fact that IRRs of newer loans are significantly higher (and positive) than the reported average because lenders have learned over time.

In all 12 IRR estimates, we find large heterogeneity across loans, ranging from nearly -60% to +34%. To describe how the IRRs differ across different types of loans, the tables and figures discussed below utilize IRR2, which is computed based on the risk of missed payment, counts early payoff as early cash flows, and assumes a flat projection into the unobserved loan life. Using the other IRR estimates generates very similar comparisons across loans, which suggests that the relatively low convergence rate on IRR2 does not imply significant bias in the understanding of loan heterogeneity.[38]

The first IRR heterogeneity we explore is testing an important prediction from Stiglitz and

[37] Due to the fact that Prosper does not charge lender service fees if the borrower makes no payment

[38] We also check that the difference in the reported IRR averages are not driven by the different samples of converged loans.

Weiss (1981): because lenders have imperfect information about borrower risk (due to either adverse selection or moral hazard), the willingness to pay for a higher interest rate may signal higher risk. This implies that a higher interest rate may yield lower financial returns because it attracts worse risk. As a result, Stiglitz and Weiss argue that there exists a non-monotonic relationship between rate of return and interest rate and this non-monotonicity motivates credit rationing. To test this prediction, Figure 6 plots IRR2 against the contract rate.[39] The curve suggests that IRR2 first increases and then decreases after the interest rate reaches 8-9%. The final uptick suggests that an increase of interest rate does not fully compensate the increased risk until 30-31%. According to the 5 and 95 percentiles shown in the same figure, we have more noise at the two ends due to smaller numbers of observations. Over all, Figure 6 confirms the argument that higher interest rates may attract riskier borrowers leading to lower IRRs.

Figure 7 presents the kernel density of IRR2 by credit grade. On average, grades AA-A have the highest average rate of return (3.89%) as compared to the other categories (1.54% B-D and -8.35% E-HR). AA-A also has a tighter distribution and less variability than B-D and E-HR. As one would expect, E-HR has the longest left tail and the lowest return on average. The negative IRRs suggest that some lenders are not experienced enough to foresee a negative return, or they have specific incentives to fund lower-quality loans. As shown below, both explanations hold to some extent.

Turning to social loans, we compare the kernel density of IRR2 by group status in Figure 8 and endorsement status in Figure 9. As shown in Figure 8, group loans perform worse than the non-group loans. This result is against the intuition that group members may have better "soft" information to signal a "good type" all else equal. In contrast, friend endorsements show a different pattern. On average, loans that have friend endorsements and friend bids perform better than the loans without friend endorsements. However, loans with friend endorsements only perform worse. Combined with the descriptive regressions reported in Table 6, this suggests that friend endorsements may not provide any positive signal about borrower risk until the endorsing friend is willing to certify the "soft" information with a bid of their own. Section 5 will revisit this argument and present evidence in greater detail.

Figure 10 plots the average IRR2, contract rate, and the predicted risk of missed payment as a function of loan origination month. It is clear that the estimated IRR2 increases steadily over time, which is attributed to a significant decline in missed payments and a relatively smaller decline in interest rate. These trends are consistent with the fact that the market is moving

[39] Interest rates are rounded by percentage points in Figure 6.

towards better credit grades over time, partly a result of lender learning as shown below. The two vertical lines drawn on this picture represent Prosper information policies in February 2007 and October 2007. While we do not know whether the policy changes have a causal effect on the increase of IRR2, they definitely coincide with the trend towards improving returns: the average IRR2s before February 2007, between February and October 2007, and after October 2007 are -3.63%, -1.60%, and 2.13% respectively.

### 4.4 Lender Learning

As we have shown in the previous section, some lenders have chosen loans whose observables predict poor performance. We are interested in understanding whether these choices are caused by lenders making mistakes or lenders choosing risky loans as a form of charity or due to other incentives. Assuming a lender's charity preference remains fixed over his life as a Prosper lender, if we observe that lenders learn, we can infer that at least a portion of these choices resulted from "mistakes."

To identify the extent to which lenders learn from their own mistakes, we estimate a series of regressions describing how a lender's behavior changes in response to late or default loans in his portfolio. We estimate three types of regressions at the lender-week level. These regressions describe a particular behavior of lender $i$ in week $t$ as a function of lender $i$'s age at time $t$ and characteristics and performance of the lender's portfolio up through week $t-1$. The outcome behaviors that we look at are whether or not a lender funds at least one loan in a given week, and conditional on funding a loan in a given week, the investment amount and the portion of new loans in various categories. The following three equations describe these regressions:

$$\begin{aligned}
FundedALoan_{it} &= g_1(LenderAge_{it}, PortChar_{it-1}, PortLate_{it-1}) + \mu_{1i} + \gamma_{1t} + \epsilon_{1it} \\
AmountFunded_{it} &= g_2(LenderAge_{it}, PortChar_{it-1}, PortLate_{it-1}) + \mu_{2i} + \gamma_{2t} + \epsilon_{2it} \\
PortComp_{it} &= g_3(LenderAge_{it}, PortChar_{it-1}, AtoAALate_{it-1}, BtoDLate_{it-1}, \\
&\quad EtoHRLate_{it-1}, NCLate_{it-1}) + \mu_{3i} + \gamma_{3t} + \epsilon_{3it}
\end{aligned}$$

The $FundedALoan$ regression is a linear probability model[40] of an indicator that a lender funded at least one loan in a given week. The other two equations only include the sample of lenders who funded at least one loan in week $t$. In the $AmountFunded$ equation, $AmountFunded_{it}$ is

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

the dollar amount invested by an active lender in week $t$. The $PortComp$ Equation is estimated for various $PortComp_{it}$ variables which specify the percentage of an active lender's investment in AA to A, B to D, and E to HR loans in week $t$.

$LenderAge_{it}$ includes indicators of lender $i$ being in his first month and second through sixth month on Prosper at week $t$.[41] $PortChar_{it-1}$ includes lender $i$'s portfolio HHI and portfolio size through the previous week. $PortLate_{it-1}$ reflects the percentage of lender $i$'s portfolio that has ever been late as of the previous week. $AtoAALate_{it-1}$, $BtoDLate_{it-1}$, $EtoHRLate_{it-1}$ are the percentage of lender $i$'s portfolio through the previous week that has ever been late in each of the three respective credit grade categories[42].

$\gamma_{jt}$ is a set of year-week fixed effects allowing us to control for changes in the macro environment and the Prosper market.[43] $\mu_{ji}$ is a set of lender fixed effects. With these fixed effects the coefficients on the ever late variables are identified by *within* lender changes in portfolio performance and investment decisions. In other words, we can interpret these coefficients as within lender learning from the performance of their past investments. In all of the results presented here, we cluster standard errors at the lender level.

The results of these regressions are reported in Table 8. The first two columns show a very pronounced age profile as lenders are less likely to invest and invest less when active as they age. The sample mean probability of funding a loan in a week is 0.382, so the coefficient on the month 1 indicator of 0.350 in column 1 implies that lenders are 92% more likely to fund a loan in a week in their first month on Prosper as compared to weeks in months 7 and higher. Lenders also show strong responses to poorly performing loans in their portfolios. On average, a ten percentage point increase in the proportion of their portfolio that has ever been late decreases their probability of funding a loan by 2.5 percentage points and decreases the amount they invest in an active week by $78.

The next 3 columns display the coefficients from the different versions of the $PortComp$ regressions. Controlling for the performance of lenders' portfolios in each grade category, lenders are more likely to fund AA to A and E to HR loans in their first month on Prosper than in later months. As lenders age, they move away from these two extremes and toward B to D loans.

[41] We count a lender as joining Prosper when he funds his first loan

[42] We have also tried specifications using the percent of a lender's portfolio (in total or in various categories) that is currently late or in default and the results are very similar.

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

As lenders observe late loans, they tend to decrease their funding of loans in the grade with the adverse shock and increase their funding of higher quality grades.[44] These results indicate strong evidence of learning. The high late and default rates of E and HR loans have driven lenders away from these loans and toward higher credit grades as lenders have learned about the dangers of investing in these lower credit grades.[45]

To further explore details of lender learning we run similar regressions as above but interact the ever late variables with dummies indicating different Prosper policy regimes. In results not shown here we find that the magnitude of these coefficients increase over time. We cannot identify if this change is attributable to Prosper's information policies or a natural acceleration of learning over time, but in general, Prosper lenders learn more strongly from their "mistakes."

We also directly test whether lenders shift toward loans with higher rates of return in response to late loans in their portfolio. Figure 11 plots the average lender's IRR2 for loans he funds in a given week by lender cohort. As lender's age, they clearly fund loans with a higher rate of return. Interestingly, new cohorts pick up the market trend, perhaps responding to information that was not available when older lenders joined Prosper. In the final column of Table 8 we present results of a regression as above with IRR2 as the dependent variable and the percent of the lender's portfolio that has ever been late as the key explanatory variable. As lenders see more late loans in their portfolios, subsequent loans that they fund do in fact have a higher rate of return. The coefficient implies that when the average lender sees a ten percentage point increase in the portion of his portfolio that has been late, his newly funded loan will have a 1.69 percentage point higher rate of return.

Lenders clearly respond to the realization of bad outcomes in their portfolios by adjusting the characteristics of loans they choose to fund. The presence of this learning suggests lenders fund observably risky loans partially as a result of not fully understanding the relationship between observable characteristics and loan performance.

[44] Note that when lenders observe late AA to A loans, they do show slight substitution towards the lower credit grade loans.

[45] In results not shown here, coefficients from regressions describing the propensity to fund loans in other categories including autofunded loans and loans of various sizes as a function of late loans in these categories show similar patterns.

## 5 Analysis specific to social networks

This section focuses on social networks on Prosper.com. We first describe four potential roles of social networks and then look for evidence for or against each explanation.

### 5.1 Potential roles of social networks

First, having a social tie may be a good signal of on-time payment. For example, kins, friends and colleagues who are familiar with the borrower in their daily lives may have private information as to whether the borrower has good repayment prospects in the future even if she has a poor or no credit history. If so, the soft information conveyed in friend endorsements could alleviate adverse selection. Alternatively, kins, friends and colleagues may have the opportunity to closely monitor the borrower after the loan is approved, which could mitigate moral hazard (Arnott and Stiglitz 1991). Members of a social network may also impose social sanctions on the borrower, thus reducing the incentive to default (Besley and Coate 1995). In the cases such as alumni connections, even if alumni do not know each other in person, an alumni group that verifies the alumni status could serve as a credible signal of the borrower's education. To the extent that higher education represents better risk, belonging to an alumni group could have a positive signaling effect. All of these channels can ensure a higher probability of repayment all else equal. Since Prosper broadcasts social ties to *all* lenders, the signaling effect of social ties should imply a higher funding rate and equal financial return. More specifically, because we can only compare loan performance among the *funded* listings, the selective and competitive funding process implies that a loan with social ties may have better performance and lower interest rate than a non-social loan, or worse performance and a higher interest rate. Either way, the financial return should be equal if lenders understand the signaling effect of social networks correctly.

The separating equilibrium described above will not occur unless the social ties lead to incentives to gather and/or reveal the true type of borrowers, and the bad type cannot mimic the good type. Both conditions do not necessarily hold on Prosper. Group leaders are expected to do the leg work for a listing of a group member but the financial return is no more than a small group leader reward ($12 per new loan) plus the interest if the leader funds a portion of the loan. Since group leaders do not co-sign the loan and there is a natural lag between funding and repayment, the group leader reward could provide a perverse incentive for group leaders to recruit as many borrowers as possible, endorse/bid on the groups listings to ensure funding, but engage in no leg work at all.[46] Even if the group leader completes the leg work, the information gathered is broadcast only via a group leader endorsement. As a result, the 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 a cost advantage in information access and imposes stringent screening before inviting a new borrower to join the group. This could happen if the group is based on close off-line ties, which we test below. Similar logic applies to friend endorsements: if it is easy for a bad borrower to obtain favorable endorsements from a dishonest friend, friend endorsement cannot separate good types from bad types and therefore loses its signaling value.

The second role of social networks lies in the potential to facilitate within-network charity. Sociologists have argued that network members may do favors to each other due to reciprocity, or make charity giving in a single direction because the giver enjoys non-financial returns from the giving process (see the survey article of Portes 1998). The non-financial returns may be approval and status within the network, future benefits from the network as a whole, or satisfaction of helping people within the same network. In short, the charity role of networks implies that social loans should have a higher funding rate but lower financial returns.

One unique feature of within-network charity is the distinction between insiders and outsiders. In the simplest case where everyone that should belong to the network is in the network (e.g. every Harvard alumni that joins Prosper is in the Harvard alumni group), we should observe all the social loans being funded inside the network. To the extent that a Harvard graduate may not join the Harvard group but still has a charity motive for any listing from the Harvard group, he may fund the listing despite the low financial return. This implies that social loans may be funded by both insiders and outsiders, but so long as the network affiliation reflects charity motives, we should observe lower financial returns as the amount of inside funding increases.

The third possibility is that social networks represent meaningless cheap talk. If every borrower can have some social ties with little cost, the pooling means that social networks will not convey any information. In theory, cheap talk may still be informative if the message sender has full incentives to reveal the truth (Farrell and Rabin 1996). This condition is unlikely to hold on Prosper: if lenders are more willing to lend to borrowers with certain social ties, both good and bad borrowers would like to have those ties. In other words, assuming lenders interpret the cheap talk correctly, social loans should have the same funding rate and same financial return

[46] To give credit to Prosper, it held back part of the $12 group leader reward until the loan had some payment history.

as non-social loans.

The last possibility is lenders misinterpret social ties as a signal of good risk when it is actually not. In this case, we could have a misalignment in funding rate and financial returns: the misinterpretation may lead to a higher funding rate on social loans, but these loans yield lower financial returns. On this front, the prediction is similar to that of within-network charity. However, the two explanations can be distinguished if mistaken lenders learn over time. All of the predictions discussed above are summarized in Table 9.

### 5.2 Data summary on social networks

Table 10 presents a detailed summary of social variables. As we saw in Table 5, 28.8% of listings have some group affiliation, 19.1% have friends, 3.2% have an endorsement from a group leader (2.2% with a leader bid), and 3.2% receives friend endorsement (1% with a friend bid). All these fractions have increased substantially in the loan sample, indicating that social loans are more likely to be funded than the listings that have no group affiliation or friend ties.

Conditional on a borrower being in a group, on average the borrower belongs to a group with 1800 members in which 1083 (or 63%) are borrowers. More specifically, borrowers' group membership is almost evenly distributed between groups with 1-100, 101-500, 501-1000 and above 1000 borrower members. But because larger groups have a larger number of borrowers, they contribute more to the average. In terms of group types, 2.3% of group borrowers belong to an alumni group, 1.9% to a military group, 1.7% to a group with employment, local or personal connections (in combination referred to as other connection), and 2.5% to a loose connection such as common religion or common ethnicity. All the other group borrowers are not classified. Since alumni groups account for 9% of the group count, this implies that most alumni groups are smaller than an average group. The same observation is true for military group and other connections, but not for the groups with loose connections. Only 34.1% of borrowers belong to groups that require borrower review (by the group leader) before listing. After Prosper introduced group ratings in October 2006, we observe 41.4% of group members belonging to low rated groups (1-3 stars), 32.3% to high rated groups (4-5 stars), and 26.1% to the groups that do not have sufficient data to be rated at the time of listing (referred to as unrated).

The rest of Table 10 documents the extent to which social loans are funded within the borrower's network. For an average group borrower (whose listing gets funded), 3.2% (or $130.8) comes from the group leader and 1.7% (or $95.7) of the loan amount comes from other members of the group. For an average borrower that has any endorsement and is funded at the end of the listing auction, the endorsing friends contribute to an average 12.7% (or $775) of the loan amount. In comparison, endorsing group leaders contribute to an average 6.8% (or $323). These numbers suggest that while social ties contribute positively to the final funding of social loans, most funding comes from stranger lenders.

Table 11 reports what types of borrowers are more likely to have social ties. Given the importance of credit grade in summarizing borrower risk, we present the grade composition conditional on group borrowers, endorsed borrowers, and the whole Prosper market. At the listing level, it is clear that group borrowers are more likely to have lower credit grades, especially E and HR. This observation does not hold at the loan level though group affiliation does help funding within each credit grade at or below D. For the endorsed loans, we focus on the borrower population after February 12, 2007 because friends are not allowed to make endorsement until then. Unlike group listings, the grade composition of endorsed listings is very similar to that of the whole market. Judging from the grade composition, friend endorsement seems to help funding in grades at or below D, a phenomenon similar to that of group loans.

### 5.3 IRR analysis by social variables

According to Table 9, the key difference among the four potential roles of social networks lies in the effect of social ties on the funding rate and the financial rate of return. Based on both the summary statistics in Table 11 and the regression results of the funding equation in Table 6 (the latter controls for other listing attributes), we have no doubt that having a social tie increases the funding rate. This fact excludes the cheap talk explanation of social networks if we assume lenders have interpreted the meaning of social ties correctly. For the other three explanations – signaling good risk, within-network charity/other incentives, and lender misinterpretation – we turn to analyze the estimated IRR2 as a proxy for the financial rate of return.

Conditional on the funded loans that have a valid estimate of IRR2, Table 12 reports regressions of the estimated IRR2 on different functions of social variables. Because the calculation of IRR2 has already taken into account all the observable listing attributes, the contracted interest rate, and the predicted loan performance at each loan age, this regression does not control for listing attributes other than social variables. In this sense, it already accounts for the selection of social ties by observable attributes.

$$IRR2 \quad = \quad f_4(socialvariables) + \epsilon_4$$

Column 1 confirms the results of Figure 8 that group loans have a lower IRR2 than non-group loans. In particular, an average group loan (with no endorsement) yields a statistically significant 4.7 percentage point lower return than the non-group loans, which is a large difference considering the average IRR2 is -0.45%. The distinction between endorsed and non-endorsed loans is more complicated: having an endorsement but no bid from a group leader implies a 3.4 percentage point higher IRR2, but group leader endorsement plus bid does not make a difference (as compared to other group loans). In contrast, friend endorsements plus bid implies a 5.4 percentage point higher IRR2, but friend endorsement with no bid means 2.1 percentage points lower, both compared to non-friend endorsed loans.

These significant coefficients reject the most stringent form of the signaling effect: if these social variables are valuable signals and lenders understand their meanings to the full extent, we should not observe significant rate of return heterogeneity across different types of social loans. One possible explanation for the positive coefficients of leader endorsements without bids and friend endorsements with bids is that these social variables provide positive signals but lenders under estimate these signals. Similarly, the negative coefficients for group loans, group leader endorsements with bids, and friend endorsements without bids may imply that they are negative signals but lenders do not account for it fully in the interest rate. We will examine these possibilities in Table 13 when we look at the impact of social variables on interest rate and loan performance separately. But before doing that, we would like to check basic evidence for the remaining stories, that is, charity motives/other incentives or lender misinterpretation.

If charity is the main explanation we expect to see that group members do not learn from lower returns within their own group. We also expect that returns will be lower if a higher portion of the loan is funded within the borrowers network. Figure 12 plots IRR2 for group and non-group loans and shows that the IRR gap has partially closed as the IRR of group loans has increased more than the IRR of non-group loans. We also know from Table 2 that the fraction of loans to group members has fallen drastically. Together this suggests that group loans were perceived as unattractive due to the lower IRR and became less prevalent in the listing and loan population over time. In results not shown here, we run learning regressions similar to section 4.4 and it is clear that group lenders substitute away from own group loans when they observe late own group loans in their portfolios suggesting within group charity is not a large factor.

Turning to friend endorsements without bids, Figure 13 shows that the IRR of these loans remains lower through time. As we saw in Table 2, the population of friend endorsed listings and loans without bids has decreased and the population of friend endorsed listings and loans with bids has increased over time. In learning regressions not reported, lenders show expected substitution patterns between these two categories and loans with no friend endorsements. These results indicate that the market has reacted to the performance of these types of loans on the funding margin, but interest rates have not adjusted accordingly.

To test how the IRR varies as a function of the amount of in network funding, Column 2 of Table 12 includes the percentage of funding that comes from the group leader, group members and friends. These results show that returns are higher when a larger portion of the loan is funded group members and friends, but returns are lower when a larger portion is funded by the group leader. Because of this discrepancy we cannot yet rule out charity or other incentives for group loans.

Because of the nature of group incentives early on and the changing incentives when group leader rewards are eliminated, we statistically test how the IRR gap between group and non-group loans and the effect of the funding portion by group leaders has changed since group ratings were removed. These results are presented in Columns 3 and 4 of Table 12. The initial gap between group and non-group loans was a statistically significant 4.9 percentage points, increased slightly when ratings were adopted, but decreased by 3.7 percentage points after leader rewards were eliminated. Column 4 shows that when we let the effect of the portion of funds from the group leader change after the elimination of leader rewards, the negative impact is mostly driven by the period with group leader rewards.

One explanation is that before the removal of rewards, group leaders may have been motivated to endorse and bid on a group members listing in order to earn group leader rewards. The ex post performance indicates that group leader endorsement plus bid constituted a signal of worse risk. But to the extent that the market does not fully understand the true meaning of this signal, group leader endorsement plus bid could increase the funding probability and be profitable for the leader. After the removal of rewards, group leader manipulation may have decreased as seen in the drastic decrease in the number of listings with group leader endorsement plus bid (4.1% in the third quarter of 2007 to 0.84% in the fourth quarter of 2007).

While it appears that lenders have misinterpreted group loans as a positive signal on average, it is possible that certain types of group loans do provide signals of lower risk. Table 13 adds variables that describe group size, percentage of a group made up of borrowers, group rating, whether a group is based on alumni, military, other or loose connections, and whether the group requires review before listing to the regressions discussed above. The "group loan" dummy is dropped because we include a complete list of dummies for group ratings that includes no rating before rating was introduced, unrated due to insufficient data, low rating, and high rating. If we believe lenders correctly interpret the meaning of different ratings, there should not be any rate of return difference by rating categories - with sufficient competition, interest rates will fully adjust. This prediction is confirmed in the regression: high rating does not imply higher rate of return than low or no ratings. If anything, the coefficients suggest the opposite relationship. While the worst performance seems to come from the unrated groups, the group rating dummies suggest that group loans are universally worse than the non-group loans.

Compared to groups with 1000 or more borrowers, smaller the groups and groups with fewer members that are borrowers have a higher rate of return. Compared to the unclassified groups, we find IRR2 is significantly higher in alumni groups or groups with employment, local or personal connections. In contrast, military groups have significantly lower IRR2s.

To ensure the connection between positive rate of return and positive signaling effect, we need to decompose the heterogeneity of IRR2 by interest rate and loan performance. Columns 2 and 3 of Table 13 replace the dependent variable with these two measures. All of the factors that associate with higher IRR2 – endorsement plus bid from friends, endorsement but no bid from group leader, percent funds from group members, percent funds from friends, small and less borrower-concentrated groups, and groups based on alumni and other tangible connections – show less likelihood of missed payment and lower interest rate. In an unreported table, we show that these relationships continue to hold if we control for the other observable listing attributes.

Over all, these results suggest that some social variables have a positive signaling effect for "good" risk and the market tends to under-estimate this effect and not fully adjust interest rates. Similarly, factors that correlate with worse performance – such as group affiliation, friend endorsement without bid, group leader endorsement plus bid – are not fully compensated in the interest rate and therefore generate significantly lower IRR2s. We present evidence that some of the negative signaling effect of group affiliation is due to the perverse incentives of group leader rewards. Once Prosper removes the leader rewards the percent of funds from the group leader is less of a negative signal. This phenomenon, combined with strong learning of group lenders suggests that charity is not a big factor contributing to the lower returns of group loans.

## 6 Conclusion

The most fundamental question facing p2p lending is how it differs from and competes with traditional banks. We show that the basic information problem faced by traditional banks – that higher interest rate tends to attract worse borrowers – also exists in p2p lending. This implies that p2p lenders should exercise similar credit rationing if they do not have other hard information and pursue financial returns like traditional banks. This prediction has already been confirmed in the data: the market of Prosper.com has evolved towards better credit grades, which effectively rations credit to the lower grades. The evolution also suggests that most of the Prosper market will compete head to head with traditional banks in the near future.

We identify two more information problems that are unique to p2p lending: Prosper lenders face increased adverse selection because they do not observe the actual credit score, and many lenders have made mistakes in their loan selection. The latter is gradually improved by lender learning, and the former is partially offset by lenders charging higher interest rates on minus grade loans when Prosper posts more detailed credit information on the website. One way to further reduce the adverse selection would be for Prosper to post the actual credit score on each listing, or at least allow borrowers to voluntarily post a certified score. According to the unraveling theory (Grossman 1981, Milgrom 1981), these two methods should yield the same results because borrowers would have full incentive to disclose a score that they know privately with zero cost.[47]

One dimension that p2p lending could differ from traditional banks is by utilizing social networks. Our results suggest that some social network variables may convey "soft" information about borrower risk and therefore has a potential to compensate the lack of "hard" information on Prosper.com. In this sense social networks utilized in p2p lending could alleviate credit rationing, if they are implemented with the right incentives. That being said, our data suggest that the market does not fully understand the signaling effect of social networks, resulting in significantly higher returns for loans with the positive signals and lower returns for loans with the negative signals.

Overall, the past two years have seen substantial changes in the nature of p2p lending. Although the estimated rate of return to Prosper loans is still on average lower than alternative investment vehicles such as CDs and T-bills, both the degree of lender learning and the distinctive

[47]The theory could break down if there is serious concern about privacy or identity theft based on the credit score.

effects of social networks point towards an optimistic future. Whether p2p lending leads to welfare enhancements or simply to a redistribution of wealth is a question to be answered in the future.

# 7 Appendix: IRR algorithm and potential bias

For each loan funded in our sample period, we use the following algorithm to compute the expected internal rate of return (IRR):

- Given a loan amount and the interest rate of the loan, calculate the amortized monthly payment ($MonthlyPay$) and the proportion that goes into the payment of principal ($MonthlyPrincipalPay$). Specifically, we define $MonthlyPay = [(InterestRate/12) * LoanSize*(1+InterestRate/12)^{36}]/[(1+InsterestRate/12)^{36}-1]$. $MonthlyPrincipalPay_t = (MonthlyPay - InterestRate * LoanSize/12) * (1 + InterestRate/12)^{(t-1)}$.

- Regress the observed monthly performance of each loan (which includes four dummies that indicates default, default or late, miss payment and paid off)[48] on an exhaustive set of loan age dummies plus all the listing variables available since June 1, 2006. To be comprehensive, we also interact all the listing variables with each credit grade. These four prediction regressions yield the predicted probability of the four outcomes by loan-month for each loan that was originated on Prosper between June 1, 2006 and July 31, 2008. Because we do not observe any loans older than 24 months we have to make assumptions about the performance in months 25 through 36. In one version we assume that the cumulative misperformance remains constant after month 24 (referred to as "flat IRR"). The other version assumes that the misperformance rate will follow a linear projection after month 24 ("linear IRR"). In this version the predicted misperformance rate at month x (where $x \geq 25$) is equal to [predicted risk at month 24 + (x-24)*(predicted risk at month 24-predicted risk at month 23)]. In both versions, we assume no new early payoff occurs after month 24.

- For loan $i$ at month $t$, define $PrincipalRemain_{it}$ as the remaining principal after considering the possibility of misperformance or early payoff in that month. This is calculated iteratively. In the first month of the loan, $PrincipalRemain_{i1} = LoanSize$. For the other

[48] If a loan is defaulted at month $t$, it is counted as default in all months after $t$.

months, $PrincipalRemain_{it} = PrincipalRemain_{it-1} - MonthlyPay * (1 - Prob_{it}(nopay) - Prob_{it}(paidoff))$.

- For loan $i$ and month $t$, define $NetMonthlyReturn_{it}$ as the difference between the expected payment and lender service fees, where the expected monthly payment is set equal to $PrincipalRemain * (1 + InterestRate/12) * Prob(paidoffinthismonth) + MonthlyPay * (1 - Prob_{it}(nopay) - Prob_{it}(paidoff))$ and the monthly lender service fee is set equal to $LenderFee/12 * PrincipalRemain_{it}$.

- Solve for the IRR that equalizes LoanSize to the sum of the present value of $NetMonthlyReturn$ from month 1 to month 36, while using IRR as the discount factor.

The algorithm described above are subject to potential bias in both directions. On the one hand, our IRR estimates may be downward biased because we try to be conservative in the calculation of cash flows. Specifically, 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 of 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. Lastly, our IRR estimates are based on the average loan performance observed from June 1, 2006 to July 31, 2008, a period that stretches from the end of a boom to the beginning of a recession. If the recession prolongs and worsens over time, the reported IRR will overestimate the actual rate of return.

# 8 References

Adam, William; Liran Einav and Jonathan Levin (2007): "Liquidity Constraints and Imperfect Information in Subprime Lending" *American Economic Review forthcoming.*

Akerlof, George A. (1970): "The Market for 'Lemons': Quality Uncertainty and the Market Mechanism" *Quarterly Journal of Economics* 84(3): 488-500.

Arnott, Richard and Joseph E. Stiglitz (1991) "Moral Hazard and Nonmarket Institutions: Dysfunctional Crowding Out or Peer Monitoring?" *The American Economic Review* March 1991, 179-190.

Berger, Allen N. and Gregory F. Udell (1992): "Some Evidence on the Empirical Significance of Credit Rationing" *The Journal of Political Economy* 100(5): 1047-1077.

Besley, Timothy; Stephen Coate and Glenn Loury (1993) "The Economics of Rotating Savings and Credit Associations" *The American Economic Review* September 1993, 792-810.

Besley, Timothy and Stephen Coate (1995) "Group Lending, Repayment Incentives and Social Collateral" *Journal of Development Economics* Vol. 46, 1-18.

Caskey, John P. (2005): "Fringe Banking and the Rise of Payday Lending", Chapter 2 of *Credit Markets for the Poor*, Russell Sage Foundation, New York.

Cox, Donald and Tullio Japelli (1990) "Credit Rationing and Private Transfers: Evidence from Survey Data" *The Review of Economics and Statistics* 72(3): 445-454.

Farrell, Joseph and Matthew Rabin (1996) "Cheap Talk" *Journal of Economic Perspectives* Summer 1996, 10:3, 103-118.

Greenlaw, David; Jan Hatzius; Anil Kashyap, Hyun Song Shin (2008) : "Leveraged Losses: Lessons from the Mortgage Market Meltdown", mimeo, accessed at http://www.chicagogsb.edu/usmpf/docs/usmpf2008confdraft.pdf.

Gross, David B. and Nicholas S. Souleles (2002) "Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior: Evidence from Credit Card Data" *Quarterly Journal of Economics* 117(1): 149-185.

Grossman, S. (1981) The informational Role of Warranties and Private Disclosure about Product Quality, *Journal of Law and Economics* Vol. 24 (1981), pp. 461-489.

Hampshire, Robert (2008) "Group Reputation Effects in Peer-to-Peer Lending Markets: An Empirical Analysis from a Principle-Agent Perspective" *mimeo.*

Hendal, Igal; Aviv Nevo and Francois Ortalo-Magne (2008) "The Relative Performance of Real Estate Marketing Platforms: MLS versus FSBOMadison.com" *mimeo.*

Hoff, Karla and Joseph E. Stiglitz "Introduction: Imperfect Information and Rural Credit Markets – Puzzles and Policy Perspectives" *the World Bank Economic Review* 4(3): 235-250.

Jaffee, Dwight M. (1971) *Credit Rationing and the Commercial Loan Market* New York: Wiley.

Jin, Ginger Z. and Andrew Kato (2007) "Dividing Online and Offline: A Case Study" *Review of Economic Studies* July 2007.

La Ferrara, Eliana (2003) "Kin Groups and Reciprocity: A Model of Credit Transactions in Ghaha" *American Economic Review* 93(5): 1730-1751.

Madajewicz, Malgosia (2005) "Can Microcredit Reduce Poverty? The Effect of the Loan Contract on Loan Size" Chapter 9 of *Credit Markets for the Poor*, Russell Sage Foundation, New York.

Mendelson, Haim (2006) "Prosper.com: A People-to-People Lending Marketplace" mimeo.

Milgrom, Paul (1981) Good News and Bad News: Representation Theorems and Applications, *The Bell Journal of Economics* Vol. 12 (1981), pp. 380-391.

Parker, Jonathan A. (1999) "The Reaction of Household Consumption to Predictable Changes in Social Security Taxes" *American Economic Review* 89(4): 959-973.

Pope, Devin and Justin R. Sydnor (2008) "What's in a Picture? Evidence of Discrimination from Prosper.com" *mimeo.*

Portes, Alejandro (1998) "Social Capital: Its Origins and Applications in Modern Sociology" *Annual Reviews of Sociology* 24: 1-24.

Ravina, Enrichetta "Love & Loans: The Effect of Beauty and Personal Characteristics in Credit Markets", Available at SSRN: http://ssrn.com/abstract=972801.

Skiba, Paige and Jeremy Tobacman (2007) "Profitability of Payday Loans" Working paper available at http://www.law.vanderbilt.edu/faculty/faculty-personal-sites/paige-skiba/index.aspx.

Souleles, Nicholas S. (1999) "The Response of Household Consumption to Income Tax Refunds" *American Economic Review* 89(4): 947-958.

Stiglitz, Joseph E. (1990) "Peer Monitoring and Credit Markets" *The World Bank Economic Review* 4:3 351-366.

Stiglitz, Joseph E. and Andrew Weiss (1981): "Credit Rationing in Markets with Imperfect Information" *American Economic Review* 71(3): 393-410.

Udry, Cristopher (1994): "Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria" *Review of Economic Studies* July 1994, 61(3): 495-526.

Voridis, Hercules (1993): "Ceilings on Interest Rates and Investment: The Example of Greece" *The Review of Economics and Statistics* 75(2): 276-283.

Yunus, Muhammad (2003): *BANKER TO THE POOR: Micro-Lending and the Battle Against World Poverty* PublicAffairs, New York, 2003. ISBN 978-1-58648-198-8.

**Table 1: Evolution of Prosper Policies**

| Date initiated | Policy |
|---|---|
| Always | History updated online every day, Allow groups |
| May 30, 2006 | Reveal more credit info, home ownership status, and bank account status |
| Oct. 19, 2006 | Start group rating based on past loan performance |
| Feb. 12, 2007 | Disallow borrowers with score<520<br>Reveal more credit info (e.g. amount delinquent) |
| Feb. 12, 2007 | Allow friend endorsements |
| Sept. 12, 2007 | Eliminate group leader rewards ($4/new borrower) |
| Oct. 30, 2007 | Add bidder guidance |
| Feb. 23, 2008 | Allow search by friend bids and endorsements |
| Apr. 15, 2008 | Raise interest rate cap to 36% except for TX (10%) and SD (N/A) |

Note: Gray rows indicate social network policies. White rows indicate information and other policies.

**Table 2: Summary of Listings and Loans by Quarter**

Listings:

| Quarter | Number | Total Amount Requested ($100,000) | Mean Amount Requested ($) | Mean Borrower Max Interest Rate | % in a Group | % endorse no bid by group leader | % endorse with bid by group leader | % endorse no bid by friends | % endorse with bid by friends | Funding rate |
|---|---|---|---|---|---|---|---|---|---|---|
| 20062 | 5375 | 26.65 | 4,957.22 | 16.86% | 58.59% | 0.00% | 0.00% | 0.00% | 0.00% | 10.01% |
| 20063 | 19771 | 107.25 | 5,424.63 | 18.15% | 61.84% | 0.42% | 0.71% | 0.00% | 0.00% | 9.94% |
| 20064 | 31629 | 196.57 | 6,214.85 | 17.45% | 53.57% | 1.33% | 2.04% | 0.00% | 0.00% | 7.98% |
| 20071 | 31373 | 263.22 | 8,389.94 | 16.72% | 48.24% | 1.42% | 3.46% | 11.04% | 0.58% | 10.14% |
| 20072 | 37505 | 331.62 | 8,841.98 | 17.51% | 34.09% | 1.07% | 5.68% | 20.86% | 0.97% | 8.07% |
| 20073 | 39353 | 328.79 | 8,355.00 | 18.06% | 23.64% | 1.01% | 4.10% | 19.93% | 1.14% | 6.71% |
| 20074 | 41585 | 334.23 | 8,037.29 | 18.41% | 16.08% | 1.42% | 0.84% | 16.48% | 1.33% | 6.32% |
| 20081 | 33485 | 250.14 | 7,470.30 | 19.24% | 12.77% | 0.70% | 0.75% | 12.91% | 1.86% | 9.46% |
| 20082 | 43371 | 318.53 | 7,344.20 | 24.50% | 7.83% | 0.54% | 0.64% | 9.36% | 1.58% | 10.08% |
| 20083 | 10361 | 73.48 | 7,092.42 | 26.40% | 7.53% | 0.53% | 0.61% | 8.98% | 1.89% | 9.31% |
| Total | 293808 | 2230.48 | 7,591.62 | 19.19% | 28.82% | 0.98% | 2.23% | 12.01% | 1.04% | 8.51% |

Loans:

| Quarter | Number | Total Amount Funded ($100,000) | Mean Amount Funded ($) | Mean Contract Interest Rate | % in a Group | % endorse no bid by group leader | % endorse with bid by group leader | % endorse no bid by friends | % endorse with bid by friends | % default |
|---|---|---|---|---|---|---|---|---|---|---|
| 20062 | 385 | 1.47 | 3,822.17 | 19.03% | 67.01% | 0.00% | 0.00% | 0.00% | 0.00% | 30.39% |
| 20063 | 1934 | 9.37 | 4,844.63 | 19.41% | 71.30% | 1.14% | 3.10% | 0.00% | 0.00% | 28.54% |
| 20064 | 2403 | 11.54 | 4,804.05 | 18.97% | 70.20% | 4.04% | 12.82% | 0.00% | 0.00% | 29.09% |
| 20071 | 3079 | 19.93 | 6,472.60 | 17.37% | 67.49% | 4.38% | 17.93% | 10.91% | 2.24% | 23.74% |
| 20072 | 3118 | 23.47 | 7,527.98 | 17.42% | 63.28% | 4.36% | 29.76% | 27.77% | 4.62% | 17.54% |
| 20073 | 2671 | 18.43 | 6,900.12 | 17.31% | 44.85% | 4.64% | 23.40% | 26.21% | 5.13% | 9.21% |
| 20074 | 2593 | 18.98 | 7,320.17 | 17.11% | 23.95% | 2.70% | 6.44% | 22.33% | 6.56% | 4.09% |
| 20081 | 3074 | 20.47 | 6,658.94 | 17.37% | 19.00% | 0.81% | 3.81% | 17.99% | 5.50% | 0.46% |
| 20082 | 4344 | 26.33 | 6,061.10 | 17.98% | 13.54% | 1.31% | 3.06% | 14.11% | 5.62% | 0.00% |
| 20083 | 1407 | 8.27 | 5,877.70 | 19.39% | 10.80% | 0.78% | 2.70% | 12.30% | 6.54% | 0.00% |
| Total | 25008 | 158.27 | 6,328.65 | 17.90% | 42.06% | 2.71% | 11.71% | 15.28% | 4.10% | 12.04% |

## Table 3: Summary of Listings and Loans by Credit Grade

| Credit Grade | Prosper Listings: Number of listings | Prosper Listings: Mean Borrower Maximum Interest Rate | Prosper Listings: Funding Rate | Prosper Loans: Number of loans | Prosper Loans: Mean Contract Interest Rate | Prosper Loans observed on 8/1/2008: % Late | Prosper Loans observed on 8/1/2008: % Default | Prosper Loans observed on 8/1/2008: % 3m late or worse | Prosper Loans observed on 8/1/2008: % 3m late or worse (if loan life = 2 years) | Experian Accounts opened in Sept. 2003, observed on 9/2005: % 3m late or worse (loan life = 2 years) |
|---|---|---|---|---|---|---|---|---|---|---|
| 2A | 9321 | 11.57% | 32.08% | 2990 | 9.70% | 1.07% | 1.64% | 1.91% | 2.27% | 0.89% |
| A | 11099 | 14.05% | 25.45% | 2825 | 12.29% | 2.90% | 3.58% | 4.04% | 4.08% | 3.33% |
| B | 17211 | 16.47% | 21.88% | 3766 | 15.00% | 3.90% | 5.50% | 6.27% | 12.24% | 6.04% |
| C | 30843 | 18.57% | 15.76% | 4862 | 17.49% | 5.29% | 8.97% | 10.24% | 22.73% | 9.44% |
| D | 43282 | 20.08% | 10.35% | 4479 | 20.66% | 5.20% | 11.23% | 12.30% | 23.08% | 15.29% |
| E | 52000 | 20.65% | 5.56% | 2891 | 24.82% | 7.06% | 21.27% | 22.79% | 43.64% | 24.25% |
| HR | 128633 | 19.83% | 2.39% | 3077 | 24.52% | 7.12% | 33.67% | 35.36% | 48.18% | 34.40% |
| NC | 1419 | 17.66% | 8.32% | 118 | 22.06% | 4.24% | 55.08% | 56.78% | | |

## Table 4-1: Half Grade Regressions: include month counts since June 2006

Unit of observation = census division by month by half-grade interval
Sample: the half-grade intervals that have credit scores at or above 520

| | # of listings | | # of loans | | Funding rate | | Average contract interest rate | | % late in 6m | | % late in 12m | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dummy of minus grade | 11.381* | 4.351* | 1.908* | -0.006 | 0.006 | 0.022 | 0.004* | -0.000 | 0.014** | 0.012 | 0.023* | 0.024 |
| | (4.962) | (3.791) | (4.124) | (-0.024) | (0.671) | (0.877) | (2.989) | (-0.216) | (2.213) | (1.073) | (2.825) | (1.008) |
| Monthcount * nearprime | | 1.614* | | 0.090 | | -0.004* | | 0.000 | | 0.001 | | 0.001 |
| | | (5.996) | | (1.525) | | (-2.589) | | (0.750) | | (0.524) | | (0.277) |
| Monthcount * subprime | | 1.416* | | -0.227* | | -0.004* | | 0.001* | | 0.001 | | -0.002 |
| | | (6.100) | | (-3.121) | | (-2.643) | | (3.995) | | (0.425) | | (-0.622) |
| Monthcount * minus grade | | 0.547* | | 0.183* | | -0.001 | | 0.000 | | 0.000 | | 0.000 |
| | | (5.384) | | (4.143) | | (-0.926) | | (0.941) | | (0.233) | | (0.116) |
| N | 3,978 | 3,978 | 3,978 | 3,978 | 3,779 | 3,779 | 3,357 | 3,357 | 2,776 | 2,776 | 2,006 | 2,006 |
| R2 | 0.679 | 0.700 | 0.552 | 0.581 | 0.269 | 0.271 | 0.795 | 0.801 | 0.145 | 0.144 | 0.208 | 0.207 |

T-statistics are in parenthesis. * $p<0.01$, ** $p<0.05$, *** $p<0.1$. All regressions control for credit grade FE, year-month FE, and census-division FE, standard errors clustered by census division.

## Table 4-2: Half Grade Regressions: use macro and Prosper policy variables instead of month counts

| | | # of listings | | # of loans | Funding rate | Avg Contract Interest Rate | % late in 6m | % late in 12m |
|---|---|---|---|---|---|---|---|---|
| Dummy of minus grade | 11.381* | 4.087* | 3.876* | 0.262 | 0.008 | 0.002 | 0.015 | 0.043 |
| | (5.012) | (4.202) | (3.353) | (1.115) | (0.324) | (0.871) | (1.001) | (0.680) |
| Bankprimerate*nearprime | -7.264* | | 9.331* | -1.839* | -0.024 | 0.003 | -0.027** | -0.124 |
| | (-3.279) | | (5.739) | (-2.931) | (-0.692) | (0.719) | (-2.318) | (-0.447) |
| Bankprimerate*subprime | -1.714 | | 7.319* | 0.562 | -0.018 | -0.014*** | -0.037* | -0.015 |
| | (-0.578) | | (3.854) | (0.907) | (-0.508) | (-1.924) | (-2.645) | (-0.061) |
| Bankprimerate*minus grade | -2.557* | | 0.473 | -0.467*** | 0.010 | -0.001 | -0.015 | -0.053 |
| | (-2.885) | | (0.773) | (-1.655) | (0.338) | (-0.289) | (-0.871) | (-0.485) |
| AftNewInfo(Feb07)*nearprime | | 19.909* | 20.443* | 3.079** | -0.089** | -0.004 | 0.012 | 0.041 |
| | | (5.372) | (5.256) | (2.431) | (-2.355) | (-1.043) | (1.058) | (1.466) |
| AftBidguide(Oct07)*nearprime | | 0.550 | 11.532* | -3.966* | -0.049 | 0.003 | -0.023 | NA |
| | | (0.400) | (4.231) | (-3.705) | (-0.924) | (0.562) | (-0.560) | . |
| AftRateCap(Apr08)*nearprime | | 14.167* | 25.559* | 2.459 | 0.041 | 0.015 | NA | NA |
| | | (4.933) | (3.891) | (1.225) | (0.736) | (1.432) | . | . |
| AftNewInfo(Feb07)*subprime | | 29.864* | 32.004* | -0.783 | -0.093* | -0.005 | 0.023 | -0.051 |
| | | (5.492) | (5.862) | (-0.771) | (-2.659) | (-0.893) | (1.041) | (-1.589) |
| AftBidguide(Oct07)*subprime | | -15.964* | -8.817* | -2.707* | -0.010 | 0.002 | -0.066* | NA |
| | | (-5.123) | (-3.220) | (-4.490) | (-0.248) | (0.207) | (-3.249) | . |
| AftRateCap(Apr08)*subprime | | 10.511* | 14.600*** | 0.042 | -0.016 | 0.023 | NA | NA |
| | | (5.195) | (1.851) | (0.064) | (-0.286) | (1.259) | . | . |
| AftNewInfo(Feb07)*minus grade | | 1.589* | 1.841* | 3.023* | -0.009 | 0.006* | 0.015 | 0.018 |
| | | (2.724) | (2.768) | (3.569) | (-0.433) | (5.048) | (0.928) | (0.789) |
| AftBidguide(Oct07)*minus grade | | -0.205 | 0.337 | -0.411 | -0.010 | -0.003 | -0.028 | NA |
| | | (-0.727) | (0.442) | (-1.617) | (-0.346) | (-0.658) | (-0.920) | . |
| AftRateCap(Apr08)*minus grade | | 3.876* | 4.246** | 1.554*** | 0.053 | -0.004 | NA | NA |
| | | (5.370) | (2.511) | (1.783) | (0.925) | (-0.943) | . | . |
| AftNewInfo(Feb07)*HR*minus grade | | 61.338* | 60.991* | -2.199* | 0.001 | -0.008*** | 0.019 | 0.069*** |
| | | (4.944) | (4.890) | (-3.200) | (0.091) | (-1.904) | (0.726) | (1.675) |
| N | 3,978 | 3,978 | 3,978 | 3,978 | 3,779 | 3,357 | 2,776 | 2,006 |
| r2_a | 0.695 | 0.771 | 0.775 | 0.640 | 0.275 | 0.812 | 0.146 | 0.215 |

T-statistics are in parenthesis. * p<0.01, ** p<0.05, *** p<0.1. All regressions control for credit grade FE, year-month FE, census-division FE, all macro variables, and nearprime, subprime and minus-grade interacting with unemployment rate and foreclosure rate. Standard errors clustered by census division.

**Table 5: Summary Statistics of Listing Attributes (June 1, 2006 – July 31, 2008)**

| | Listings | | | Loans | | |
|---|---|---|---|---|---|---|
| | Mean | STD | N | Mean | STD | N |
| **Information available before Feb. 12, 2007** | | | | | | |
| Grade=AA | 0.032 | 0.175 | 293808 | 0.120 | 0.324 | 25008 |
| Grade=A | 0.038 | 0.191 | 293808 | 0.113 | 0.317 | 25008 |
| Grade=B | 0.059 | 0.235 | 293808 | 0.151 | 0.358 | 25008 |
| Grade=C | 0.105 | 0.307 | 293808 | 0.194 | 0.396 | 25008 |
| Grade=D | 0.147 | 0.354 | 293808 | 0.179 | 0.383 | 25008 |
| Grade=E | 0.177 | 0.382 | 293808 | 0.116 | 0.320 | 25008 |
| Grade=HR | 0.438 | 0.496 | 293808 | 0.123 | 0.328 | 25008 |
| Grade=NC | 0.005 | 0.069 | 293808 | 0.005 | 0.069 | 25008 |
| amountrequested | 7592 | 6388 | 293808 | 6329 | 5679 | 25008 |
| autofunded | 0.311 | 0.463 | 293808 | 0.263 | 0.441 | 25008 |
| borrowermaximumrate | 0.192 | 0.084 | 293808 | 0.209 | 0.074 | 25008 |
| yeshomeowner | 0.327 | 0.469 | 293808 | 0.441 | 0.497 | 25008 |
| debt-to-income (DTI) ratio | 0.505 | 1.359 | 293808 | 0.330 | 0.978 | 25008 |
| missing DTI | 0.068 | 0.251 | 293808 | 0.035 | 0.183 | 25008 |
| DTI topcoded if DTI>=10 | 0.083 | 0.275 | 293808 | 0.044 | 0.205 | 25008 |
| have image | 0.515 | 0.500 | 293808 | 0.659 | 0.474 | 25008 |
| length of listing desc (in chars) | 1058 | 772 | 293808 | 1295 | 866 | 25008 |
| mention debt consolidation | 0.358 | 0.480 | 293808 | 0.375 | 0.484 | 25008 |
| mention business loan | 0.231 | 0.421 | 293808 | 0.271 | 0.444 | 25008 |
| mention car | 0.689 | 0.463 | 293808 | 0.626 | 0.484 | 25008 |
| mention mortgage | 0.139 | 0.346 | 293808 | 0.187 | 0.390 | 25008 |
| mention health | 0.721 | 0.449 | 293808 | 0.790 | 0.407 | 25008 |
| mention education | 0.211 | 0.408 | 293808 | 0.248 | 0.432 | 25008 |
| mention family | 0.179 | 0.383 | 293808 | 0.189 | 0.392 | 25008 |
| mention retirement | 0.030 | 0.171 | 293808 | 0.041 | 0.199 | 25008 |
| mention pay-day loan | 0.057 | 0.233 | 293808 | 0.057 | 0.231 | 25008 |
| concede relisting | 0.008 | 0.089 | 293808 | 0.021 | 0.144 | 25008 |
| # of listings (incld current one) | 2.811 | 3.361 | 293808 | 2.912 | 2.863 | 25008 |
| interest rate cap | 0.243 | 0.093 | 293808 | 0.273 | 0.082 | 25008 |
| borrower fee | 1.800 | 0.794 | 293808 | 1.548 | 0.781 | 25008 |
| lender fee | 0.852 | 0.231 | 293808 | 0.790 | 0.258 | 25008 |
| amountdelinquent ($) | 3516 | 12374 | 221618 | 1176 | 6257 | 18618 |
| missing amountdelinquent | 0.004 | 0.066 | 221618 | 0.001 | 0.037 | 18618 |
| currentdelinquency | 3.833 | 5.303 | 293808 | 1.454 | 3.400 | 25008 |
| delinquency in 7yrs | 11.022 | 16.450 | 293808 | 5.800 | 12.356 | 25008 |
| lengthcredithistory (in days) | 152.208 | 84.472 | 293808 | 158.049 | 87.107 | 25008 |
| totalcreditlines | 24.354 | 14.393 | 293808 | 23.964 | 14.424 | 25008 |
| in public records in past 10 years | 0.657 | 1.395 | 293808 | 0.405 | 0.936 | 25008 |
| # of inquiries in past 6 months | 4.153 | 4.959 | 293808 | 2.927 | 3.979 | 25008 |

## Table 5 Continued: Summary Statistics of Listing Attributes (June 1, 2006 – July 31, 2008)

| | Listings | | | Loans | | |
|---|---|---|---|---|---|---|
| | Mean | STD | N | Mean | STD | N |
| **Credit info added after Feb. 12, 2007** | | | | | | |
| currentcreditlines | 8.230 | 6.001 | 221618 | 9.566 | 5.931 | 18618 |
| opencreditlines | 7.224 | 5.303 | 221618 | 8.165 | 5.223 | 18618 |
| band card utilization rate | 0.629 | 0.431 | 221618 | 0.547 | 0.373 | 18618 |
| revolving balance ($) | 12087 | 31802 | 221618 | 16326 | 39388 | 18618 |
| in publice records in past 1 year | 0.075 | 0.346 | 221618 | 0.040 | 0.237 | 18618 |
| working full time | 0.821 | 0.383 | 221618 | 0.859 | 0.348 | 18618 |
| working part time | 0.040 | 0.196 | 221618 | 0.038 | 0.192 | 18618 |
| income 25-75 K | 0.670 | 0.470 | 202271 | 0.651 | 0.477 | 17782 |
| income > 75K | 0.144 | 0.351 | 202271 | 0.220 | 0.415 | 17782 |
| missing income | 0.297 | 0.457 | 293808 | 0.284 | 0.451 | 25008 |
| no employment or income reported | 0.014 | 0.119 | 293808 | 0.005 | 0.072 | 25008 |
| missing new credit info posted after 2/07 | 0.000 | 0.013 | 293808 | 0.000 | 0.018 | 25008 |
| missing credit info posted bef 2/07 | 0.008 | 0.087 | 293808 | 0.004 | 0.062 | 25008 |
| **Social network variables (more details in Table 10)** | | | | | | |
| borrower in a group | 0.288 | 0.453 | 293808 | 0.421 | 0.494 | 25008 |
| borrower having any friend | 0.191 | 0.393 | 293808 | 0.249 | 0.432 | 25008 |
| listing with endorsement+nobid by group leader | 0.010 | 0.098 | 293808 | 0.027 | 0.162 | 25008 |
| listing with endorsement+nobid by friend | 0.120 | 0.325 | 293808 | 0.153 | 0.360 | 25008 |
| listing with endorsement+bid by group leader | 0.022 | 0.148 | 293808 | 0.117 | 0.322 | 25008 |
| listing with endorsement+bid by friend | 0.010 | 0.101 | 293808 | 0.041 | 0.198 | 25008 |

**Table 6: fund rate, interest rate and default or late (June 1, 2006 – July 31, 2008)**

| | Funded? | Contract interest rate | Default or late as of 8/1/2008 |
|---|---|---|---|
| | Probit (marginal effects) | OLS | Probit (marginal effects) |
| **Listing attributes available before Feb 2007** | | | |
| Grade=AA | 0.696* | -0.032* | -0.134* |
| | (21.041) | (-8.258) | (-17.371) |
| Grade=A | 0.409* | -0.026* | -0.118* |
| | (14.144) | (-8.326) | (-14.290) |
| Grade=B | 0.252* | -0.021* | -0.122* |
| | (11.146) | (-6.855) | (-11.878) |
| Grade=C | 0.095* | -0.016* | -0.121* |
| | (8.135) | (-5.175) | (-9.000) |
| Grade=D | 0.033* | -0.008* | -0.115* |
| | (6.020) | (-2.597) | (-9.295) |
| Grade=E | 0.001 | -0.003 | -0.089* |
| | (0.578) | (-0.889) | (-7.667) |
| Grade=HR | -0.005* | -0.003 | -0.048** |
| | (-2.711) | (-1.068) | (-2.370) |
| amountrequested | -0.000* | 0.000* | 0.000* |
| | (-32.188) | (17.345) | (11.306) |
| autofunded | 0.011* | 0.036* | 0.047* |
| | (20.910) | (90.511) | (9.190) |
| borrowermaximumrate | 0.702* | 0.458* | 1.732* |
| | (38.743) | (17.009) | (6.271) |
| borrowermaximumrate2 | -1.161* | 0.484* | -2.308* |
| | (-34.968) | (7.978) | (-3.871) |
| yeshomeowner | 0.001*** | 0.001 | -0.060* |
| | (1.729) | (0.608) | (-5.085) |
| Debt to income ratio | -0.017* | 0.004* | 0.015* |
| | (-15.799) | (5.433) | (2.822) |
| debt-to-income * homeowner | 0.001** | -0.000 | 0.004 |
| | (2.156) | (-0.711) | (1.205) |
| having an image | 0.005* | -0.001* | -0.003 |
| | (16.152) | (-3.449) | (-0.582) |
| length of description | 0.000* | -0.000* | -0.000* |
| | (18.177) | (-5.380) | (-2.987) |
| mention debtconsolidation | 0.001** | 0.000 | -0.010** |
| | (2.372) | (0.174) | (-2.493) |
| mention business | -0.001* | 0.000 | 0.021* |
| | (-3.199) | (1.062) | (4.359) |
| mention car | -0.000 | 0.001** | 0.011** |
| | (-1.207) | (2.524) | (2.244) |
| mention mortgage | 0.000 | 0.000 | 0.008 |
| | (0.315) | (0.026) | (1.514) |
| mention health | 0.001* | 0.001** | 0.008 |
| | (2.647) | (1.997) | (1.563) |

| | | | |
|---|---|---|---|
| mention education | 0.000 | -0.000 | -0.008*** |
| | (0.016) | (-0.132) | (-1.782) |
| mention family | 0.001* | 0.001** | 0.014* |
| | (2.887) | (2.054) | (2.846) |
| mention retirement | -0.001** | -0.001 | -0.004 |
| | (-2.053) | (-1.343) | (-0.455) |
| mention pay-day loan | 0.003* | 0.003* | 0.025* |
| | (5.157) | (3.113) | (2.884) |
| saidrelisting | 0.008* | 0.002 | 0.009 |
| | (4.951) | (1.570) | (0.695) |
| count of relisting | -0.000* | 0.001* | 0.002* |
| | (-5.666) | (6.828) | (3.225) |
| currentdelinquencies | -0.001* | 0.000* | 0.008* |
| | (-18.347) | (4.454) | (10.886) |
| delinquencies in passt 7 yrs | -0.000* | 0.000* | -0.000** |
| | (-11.790) | (6.091) | (-2.317) |
| length of credit history | -0.000* | 0.000* | -0.000*** |
| | (-7.724) | (3.973) | (-1.660) |
| totalcreditlines | 0.000 | 0.000** | -0.001* |
| | (0.438) | (2.171) | (-4.257) |
| In public records in past 10 yrs | -0.001* | 0.000 | 0.002 |
| | (-8.563) | (0.126) | (1.350) |
| # of inquiries in past 6m | -0.001* | 0.000* | 0.007* |
| | (-13.047) | (6.197) | (12.927) |
| missing credit info | 0.002 | -0.005 | 0.032 |
| | (0.957) | (-1.359) | (0.843) |
| **Social network variables** | | | |
| in_a_grp_borrower | 0.004* | -0.004* | 0.005 |
| | (10.464) | (-9.299) | (0.988) |
| have endorsement + nobid by group leader | 0.017* | -0.003* | -0.000 |
| | (8.118) | (-2.798) | (-0.011) |
| have endorsement + bid by group leader | 0.096* | -0.005* | 0.005 |
| | (21.708) | (-7.294) | (0.772) |
| have endorsement + nobid by friend | 0.002* | 0.001** | 0.009 |
| | (5.304) | (2.367) | (1.435) |
| have endorsement + bid by friend | 0.050* | -0.007* | -0.041* |
| | (12.454) | (-6.150) | (-4.830) |
| **Prosper environment** | | | |
| interest rate cap (by state) | 0.035* | 0.014** | -0.048 |
| | (9.015) | (2.299) | (-0.567) |
| borrowerfee (by grade) | 0.001*** | -0.004* | 0.019*** |
| | (1.854) | (-4.826) | (1.717) |
| lenderfee (by grade) | -0.005* | 0.001 | 0.024 |
| | (-3.953) | (1.092) | (1.012) |
| Total $ requested by grade | -0.000* | 0.000 | 0.000 |
| | (-9.636) | (1.186) | (0.401) |
| Total $ amount bid by grade | 0.000* | -0.000** | 0.000 |
| | (8.428) | (-2.428) | (1.118) |
| percent_EverLate by grade | -0.016* | 0.023* | -0.429* |
| | (-4.311) | (2.691) | (-3.838) |

| | | | |
|---|---|---|---|
| **Micro environment** | | | |
| ofheo_index | 0.000 | 0.000 | 0.000 |
| | (0.784) | (1.528) | (0.793) |
| homeowner_ofheoindex | 0.000*** | -0.000** | 0.000* |
| | (1.893) | (-1.981) | (6.079) |
| foreclosure rate in state | -0.000 | 0.000 | 0.000 |
| | (-0.944) | (0.019) | (1.040) |
| missing foreclosure rate | -0.008** | -0.011*** | -0.096* |
| | (-2.030) | (-1.862) | (-31.548) |
| homeowner_foreclose | -0.000 | 0.000 | -0.000 |
| | (-0.660) | (0.332) | (-0.387) |
| bls unemploy rate (by state) | -0.000 | -0.001*** | 0.005 |
| | (-1.214) | (-1.798) | (0.518) |
| bankprimerate | 0.008** | -0.001 | -0.055 |
| | (2.253) | (-0.233) | (-0.796) |
| tedspread | -0.000 | -0.001 | 0.057** |
| | (-0.168) | (-0.451) | (2.495) |
| diff_baa_aaa | -0.012*** | -0.001 | 0.089 |
| | (-1.676) | (-0.056) | (0.728) |
| s_p_500_close | 0.000 | -0.000 | 0.000 |
| | (1.249) | (-1.587) | (1.310) |
| % banks report consumer loan tightened | -0.007 | 0.002 | -0.050 |
| | (-1.620) | (0.617) | (-0.742) |
| consumer loan tightened * EHR | 0.000* | 0.001* | 0.002*** |
| | (7.848) | (7.584) | (1.882) |
| % banks report consumer loan eased | 0.001 | -0.000 | 0.007 |
| | (1.134) | (-0.421) | (0.535) |
| consumer loan eased * EHR | -0.000 | 0.000 | -0.001 |
| | (-0.716) | (1.618) | (-0.710) |
| Year-week FE | Yes | Yes | Yes |
| N | 293,802 | 25,008 | 23,344 |
| Adjusted R2 | 0.375 | 0.855 | 0.269 |

The sample includes all the listings and loans between June 1, 2006 and July 31, 2008. T-statistics are in parenthesis. * p<0.01, ** p<0.05, *** p<0.1. All regressions control for state dummies, year-week FE, duration of auction, and indicators for missing debt-to-income ratio and other credit attributes. All regressions do not include the new credit variables added after Feb. 12, 2007. In an unreported table, we show that regressions including these variables and condition on the post-Feb-2007 sample generate similar results.

Table 7: IRR Summary

| | Outcome to predict | Treatment of early payoff | % converged | Conditional on convergence | | | |
|---|---|---|---|---|---|---|---|
| | | | | mean | STD | min | max |
| **Flat projection: assume cumulative risk remains constant after month 24** | | | | | | | |
| IRR1 | default | as early cash flow | 89.14% | 3.02% | 10.55% | -58.78% | 34.00% |
| IRR2 | miss payment | as early cash flow | 89.09% | -0.45% | 10.90% | -54.91% | 34.00% |
| IRR3 | default or late | as early cash flow | 88.89% | -0.99% | 10.81% | -57.01% | 33.29% |
| IRR4 | default | as on-time | 98.18% | 4.33% | 9.20% | -38.42% | 34.00% |
| IRR5 | miss payment | as on-time | 91.02% | 2.33% | 10.10% | -35.71% | 31.19% |
| IRR6 | default or late | as on-time | 96.67% | 0.65% | 9.76% | -34.74% | 33.29% |
| **Linear projection: assume cumulative risks grow linearly after month 24** | | | | | | | |
| IRR7 | default | as early cash flow | 89.33% | -0.47% | 12.42% | -58.78% | 34.00% |
| IRR8 | miss payment | as early cash flow | 88.98% | -1.15% | 11.20% | -54.91% | 34.00% |
| IRR9 | default or late | as early cash flow | 88.82% | -1.29% | 10.93% | -56.77% | 33.27% |
| IRR10 | default | as on-time | 97.47% | 1.57% | 10.69% | -44.09% | 34.00% |
| IRR11 | miss payment | as on-time | 91.03% | 1.74% | 10.33% | -36.37% | 30.94% |
| IRR12 | default or late | as on-time | 96.50% | 0.41% | 9.84% | -35.11% | 33.27% |

**Table 8: Lender Responses to Ever Late Loans**

| | | Conditional on Funding a Loan in Week t | | | | |
|---|---|---|---|---|---|---|
| | Funded A Loan | Amount Funded | % of Investment in: | | | |
| | | | AA to A | B to D | E to HR | IRR2 |
| | coef/t | coef/t | coef/t | coef/t | coef/t | coef/t |
| Month 1 | 0.350* | 136.862* | 0.038* | -0.049* | 0.010* | 0.002* |
| | (133.127) | (9.610) | (9.870) | (-12.239) | (4.566) | (2.799) |
| Month 2 to 6 | 0.019* | 26.674** | -0.001 | -0.014* | 0.015* | -0.001* |
| | (9.939) | (2.321) | (-0.487) | (-4.673) | (9.191) | (-2.684) |
| HHI | -0.256* | 14.710* | 0.008* | -0.001 | -0.007* | -0.002** |
| | (-78.535) | (2.716) | (2.664) | (-0.302) | (-3.568) | (-2.500) |
| Portfolio Size | 0.001 | -152.696* | 0.001 | -0.002** | 0.001*** | 0.000*** |
| | (1.154) | (-3.728) | (1.288) | (-2.166) | (1.805) | (1.919) |
| % of Portfolio Ever Late | -0.250* | -777.338* | | | | 0.169* |
| | (-22.881) | (-11.275) | | | | (41.143) |
| % of NC Loans Ever Late | | | 0.065* | 0.042* | -0.076* | |
| | | | (5.919) | (3.145) | (-8.499) | |
| % of E to HR Loans Ever Late | | | 0.164* | 0.047* | -0.211* | |
| | | | (18.135) | (4.865) | (-30.915) | |
| % of B to D Loans Ever Late | | | 0.488* | -0.426* | -0.063* | |
| | | | (24.713) | (-21.666) | (-6.543) | |
| % of A to AA Loans Ever Late | | | -0.144* | 0.085* | 0.059* | |
| | | | (-10.609) | (5.474) | (5.412) | |
| N | 1,448,939 | 553,117 | 553,117 | 553,117 | 553,117 | 541,998 |

T-statistics are in parenthesis. * p<0.01, ** p<0.05, *** p<0.1. Column 1 is a linear probability model and all other columns are OLS regressions. Standard errors are clustered at the lender level.

**Table 9: Potential roles of Social Networks on Prosper.com**

| Potential roles of social network | Predictions | | |
|---|---|---|---|
| | Funding rate | IRR conditional on funded | Others |
| Signal good risk | + | 0 | |
| Within-network charity | + | - | (1) Lower IRR if more funds come from within-network (2) No or less learning over time, especially for listings within the network |
| Cheap talk (interpreted correctly) | 0 | 0 | |
| Lender misinterpretation | + | - | Learn over time |

**Table 10: 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 |
| % of Members that are Lenders | 0.138 | 0.116 | 84,377 | 0.202 | 0.169 | 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 Connection | 0.017 | 0.128 | 84,680 | 0.022 | 0.145 | 10,518 |
| Loose Connection | 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 Members | | | | 95.818 | 553.280 | 10,518 |
| % Funded by Group Leader | | | | 0.032 | 0.124 | 10,518 |
| $ Funded by Group Leader | | | | 131.042 | 605.746 | 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 |
| NUnrated 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 | 6,205 |
| $ Funded by Friends | | | | 190.498 | 1109.441 | 6,205 |
| **Conditional on a borrower that has endorsement(s):** | | | | | | |
| % Funded by Endorsing Friends | | | | 0.127 | 0.247 | 1,022 |
| $ Funded by Endorsing Friends | | | | 775.496 | 2040.419 | 1,022 |
| % Funded by Endorsing Group Leader | | | | 0.068 | 0.165 | 2,903 |
| $ Funded by Endorsing Group Leader | | | | 322.991 | 907.019 | 2,903 |

**Table 11: Credit Grade Composition of Social Network Loans**

**Groups:**

| Grade | Group Listings | All Listings | Group Loans | All Loans |
|---|---|---|---|---|
| A | 2.84% | 3.78% | 8.10% | 11.30% |
| AA | 2.18% | 3.17% | 7.70% | 11.96% |
| 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% |

**Friend Endorsements (Listings & Loans after Feb 12, 2007):**

| Grade | Endorsed Listings | Endorsed + Bid Listings | All Listings | Endorsed Loans | Endorsed + Bid Loans | All Loans |
|---|---|---|---|---|---|---|
| A | 3.96% | 9.27% | 4.35% | 10.27% | 12.82% | 12.61% |
| AA | 2.87% | 8.84% | 3.49% | 9.50% | 14.97% | 13.23% |
| 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% | 11.20% | 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% |

**Table 12: Regressions of IRR2 on Social Variables**

| | IRR2<br>(1) | IRR2<br>(2) | IRR2<br>(3) | IRR2<br>(4) |
|---|---|---|---|---|
| Borrower in a group | -0.047* | -0.047* | -0.049* | -0.048* |
| | (-25.638) | (-25.398) | (-15.184) | (-14.637) |
| Borrower in a group * no group leader reward | | | 0.037* | 0.036* |
| | | | (11.897) | (11.395) |
| Borrower in a group * group rating adopted | | | -0.007*** | -0.009** |
| | | | (-1.894) | (-2.265) |
| Have endorsement no bid from group leader | 0.034* | | 0.033* | |
| | (7.352) | | (7.038) | |
| Have endorsement + bid from group leader | 0.003 | | 0.006*** | |
| | (0.956) | | (1.914) | |
| Have endorsement no bid from friends | -0.019* | | -0.022* | |
| | (-9.480) | | (-10.539) | |
| Have endorsement + bid from friends | 0.053* | | 0.048* | |
| | (14.204) | | (13.141) | |
| Have any endorsement from friends | | -0.009* | | -0.012* |
| | | (-4.862) | | (-6.116) |
| Have any endorsement from group leader | | 0.010* | | 0.012* |
| | | (3.983) | | (4.551) |
| % funds from friends | | 0.096* | | 0.090* |
| | | (10.277) | | (9.875) |
| % funds from group members | | 0.125* | | 0.121* |
| | | (6.937) | | (6.901) |
| % funds from group leader | | -0.112* | | -0.152* |
| | | (-9.305) | | (-5.951) |
| % funds from group leader * no group leader reward | | | | 0.077* |
| | | | | (2.667) |
| % funds from group leader * group rating adopted | | | | 0.039 |
| | | | | (1.317) |
| N | 22,155 | 22,155 | 22,155 | 22,155 |
| Adjusted R2 | 0.057 | 0.053 | 0.064 | 0.061 |

**Table 13: Detailed Regressions of IRR2, Interest Rate and Loan Performance on Social Variables**

| | IRR2<br>(1) | Contract Interest Rate<br>(2) | Miss Payment at 6m<br>(3) |
|---|---|---|---|
| Borrower in a group * group rating not available | -0.073* | 0.026* | 0.048* |
| | (-15.835) | (11.532) | (16.252) |
| Borrower in an unrated group after group rating adopted | -0.108* | 0.015* | 0.060* |
| | (-20.572) | (5.942) | (17.952) |
| Borrower in a low rate group (1-3 stars) | -0.075* | 0.018* | 0.045* |
| | (-15.700) | (7.320) | (14.766) |
| Borrower in a high rate group (4-5 stars) | -0.087* | 0.008* | 0.044* |
| | (-18.473) | (3.442) | (14.706) |
| Have any endorsement from friends | -0.011* | 0.005* | 0.009* |
| | (-5.956) | (4.268) | (7.586) |
| Have any endorsement from group leader | 0.014* | -0.004* | -0.007* |
| | (4.595) | (-2.648) | (-3.554) |
| % funds from friends | 0.086* | -0.069* | -0.065* |
| | (9.705) | (-12.108) | (-17.159) |
| % funds from group members | 0.100* | 0.000 | -0.044* |
| | (5.703) | (0.016) | (-4.179) |
| % funds from group leader | -0.120* | -0.032* | 0.047* |
| | (-9.711) | (-5.024) | (6.251) |
| % funds from group leader * no group leader reward | 0.067** | -0.003 | -0.038** |
| | (2.523) | (-0.218) | (-2.307) |
| Borrower in a group * no group leader reward | 0.022* | 0.011* | -0.006* |
| | (6.530) | (5.634) | (-2.785) |
| Group leader requires review of new group member | 0.003 | -0.001 | -0.003 |
| | (1.108) | (-0.414) | (-1.306) |
| Borrower in a group that has <100 borrowers | 0.030* | -0.006** | -0.015* |
| | (7.142) | (-2.496) | (-5.578) |
| Borrower in a group that has 101-500 borrowers | 0.008** | -0.007* | -0.005** |
| | (2.114) | (-3.339) | (-2.140) |
| Borrower in a group that has 501-1000 borrowers | 0.008*** | -0.002 | -0.002 |
| | (1.864) | (-0.889) | (-0.775) |
| Borrower in a group with <25% members being borrowers | 0.079* | -0.024* | -0.050* |
| | (9.616) | (-4.090) | (-10.196) |
| Borrower in a group with 25-50% members being borrowers | 0.047* | -0.015* | -0.028* |
| | (12.208) | (-7.403) | (-11.224) |
| Borrower in a group with 50-75% members being borrowers | 0.015* | -0.005* | -0.009* |
| | (4.605) | (-3.110) | (-4.177) |
| Alumni group | 0.082* | -0.007*** | -0.040* |
| | (14.630) | (-1.672) | (-11.761) |
| Military group | -0.053* | -0.008 | 0.020* |
| | (-5.311) | (-1.429) | (2.999) |
| Group based on local, personal or employment connections | 0.050* | -0.010** | -0.031* |
| | (7.289) | (-2.342) | (-7.385) |
| Group based on common religion or common ethnicity | 0.023* | 0.004 | -0.011** |
| | (2.795) | (0.766) | (-2.098) |
| N | 22,155 | 22,155 | 22,155 |
| Adjusted R2 | 0.089 | 0.020 | 0.070 |

T-statistics are in parenthesis. * p<0.01, ** p<0.05, ***p<0.1. The dummy of groups with more than 1000 borrowers and the dummy of groups with more than 75% of borrowers are dropped due to colinearity.

**Figure 1: Macro Economic Indicators (2005 – June 2008)**

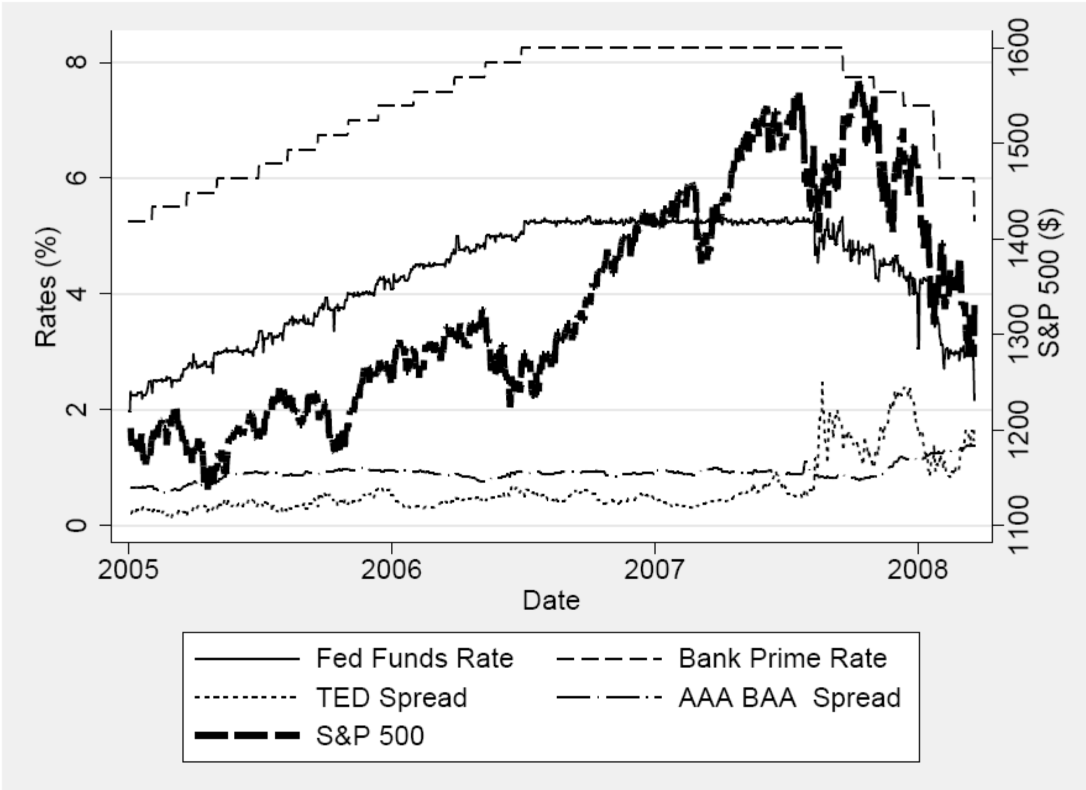



**Figure 2: CDF of Prosper and Experian Listings**

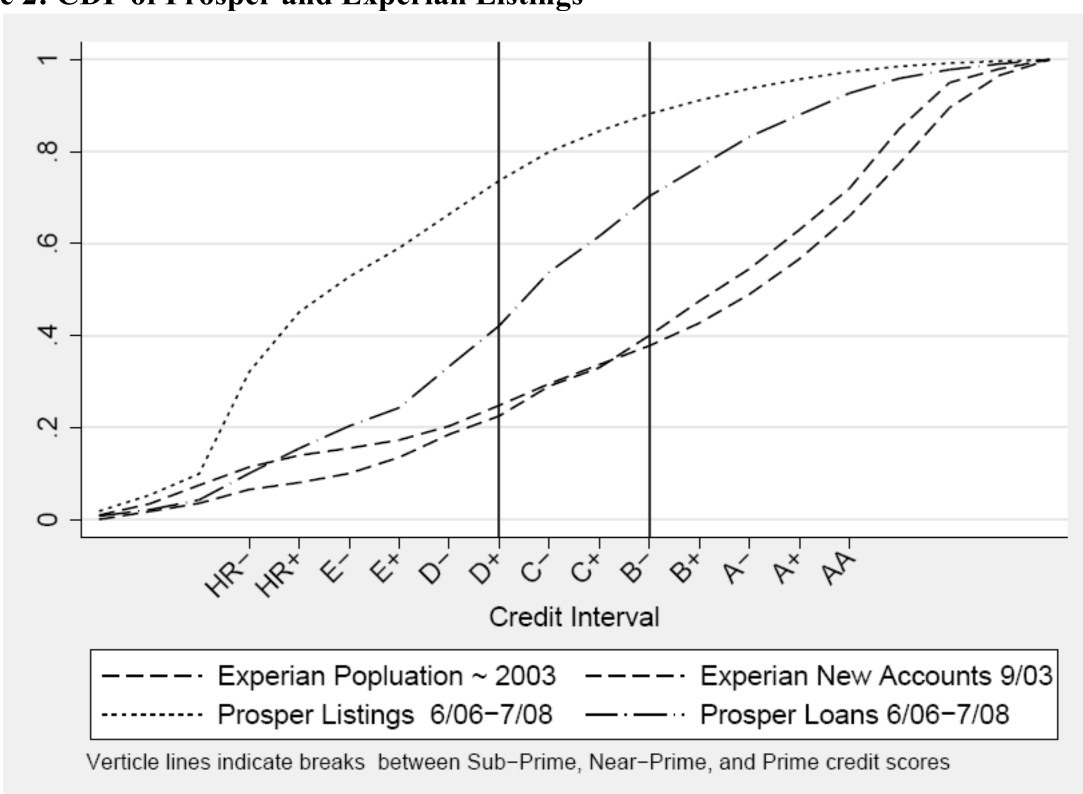


**Figure 3: PDF of Prosper Listings by Time**

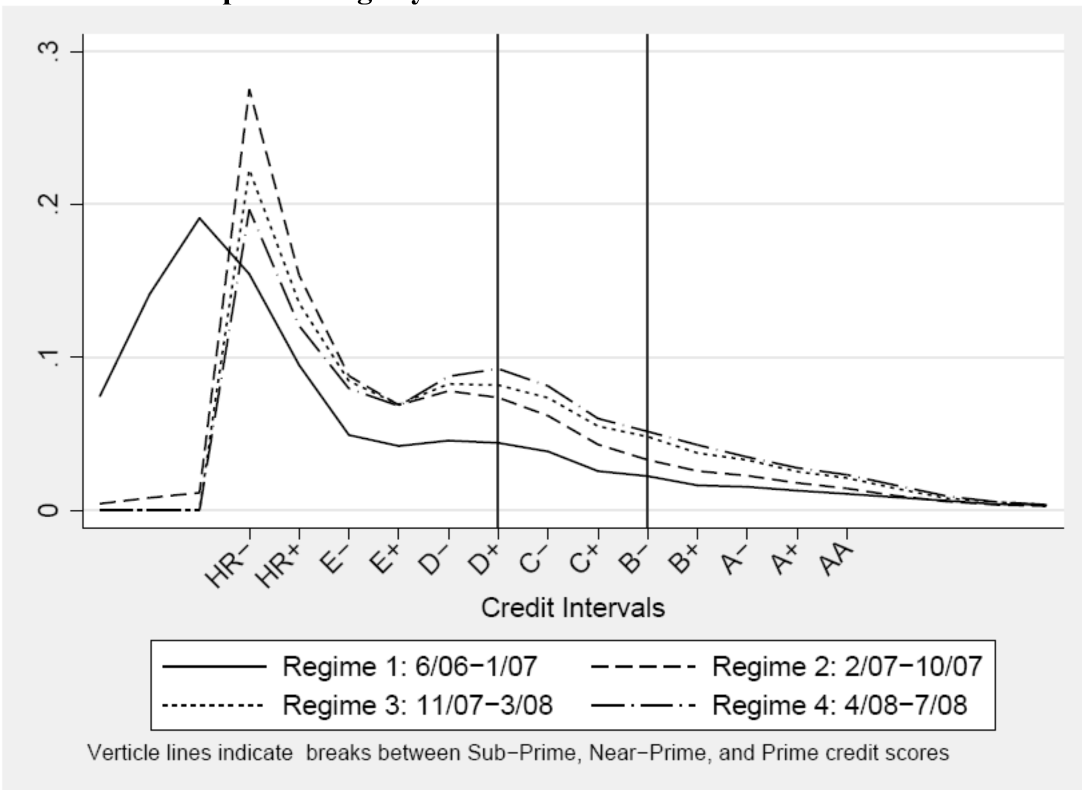



**Figure 4: PDF of Prosper and Experian Loans by Time**

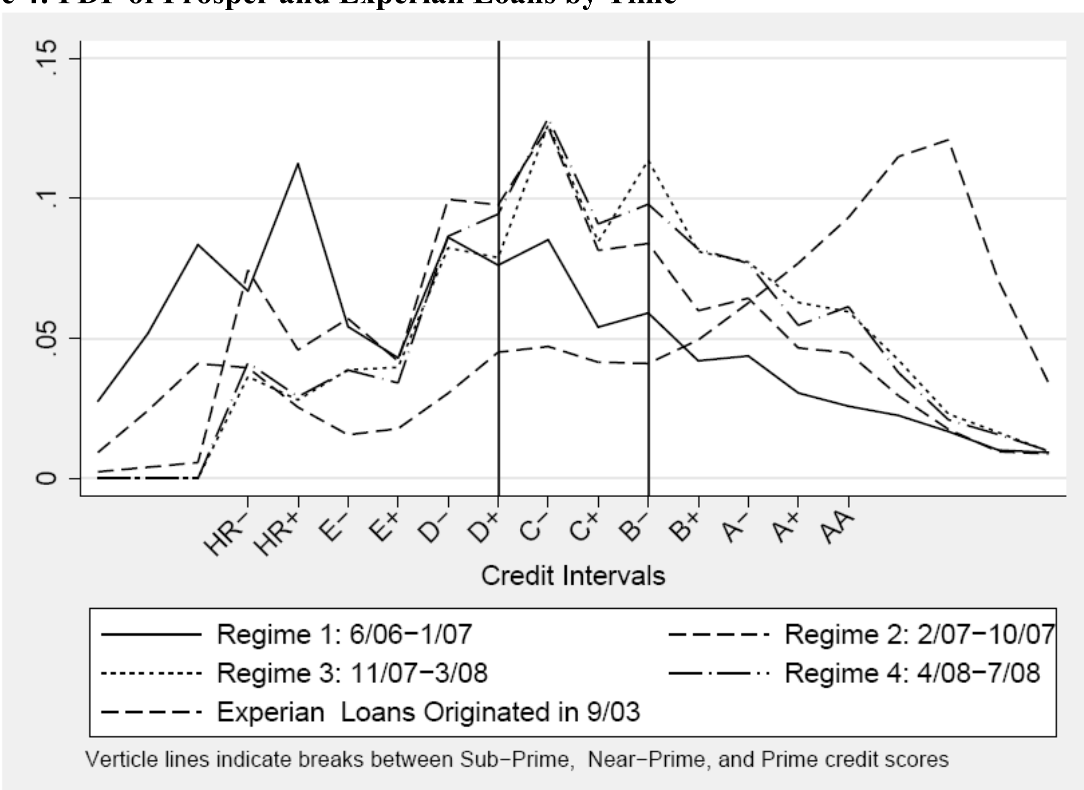


**Figure 5: Observed Loan Performance by Loan Age (cumulative)**

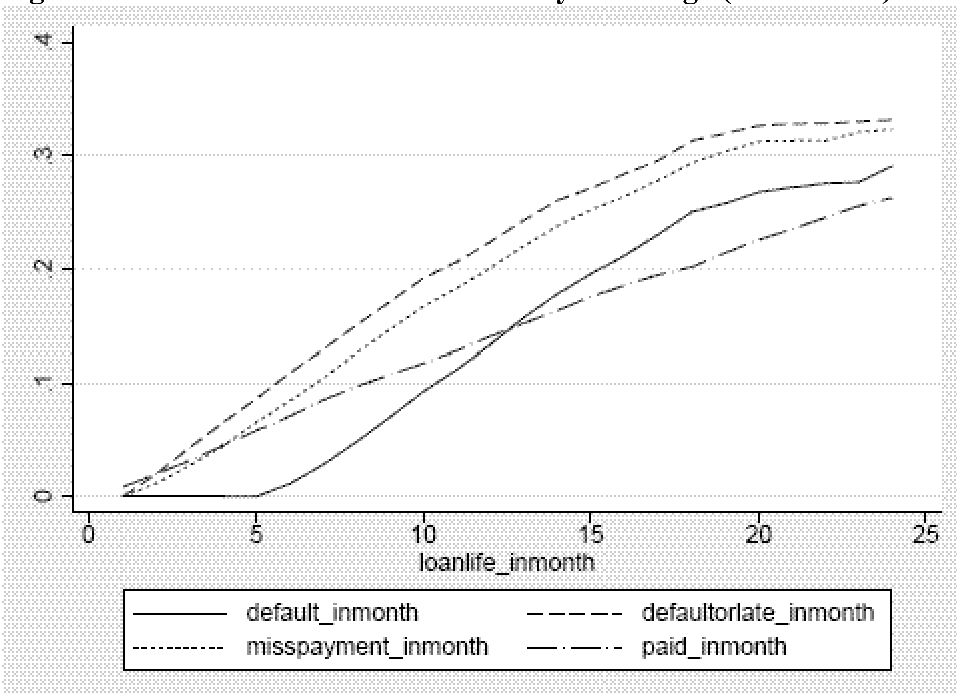



**Figure 6: IRR2 by Contract Interest Rate**

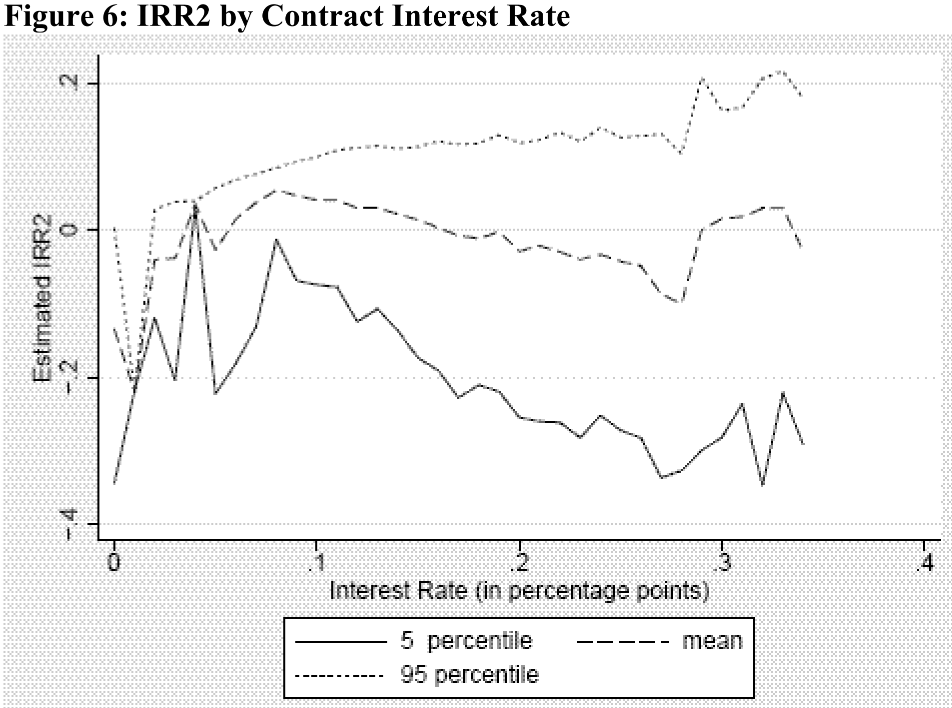


**Figure 7: Density of IRR2 by Credit Grade**

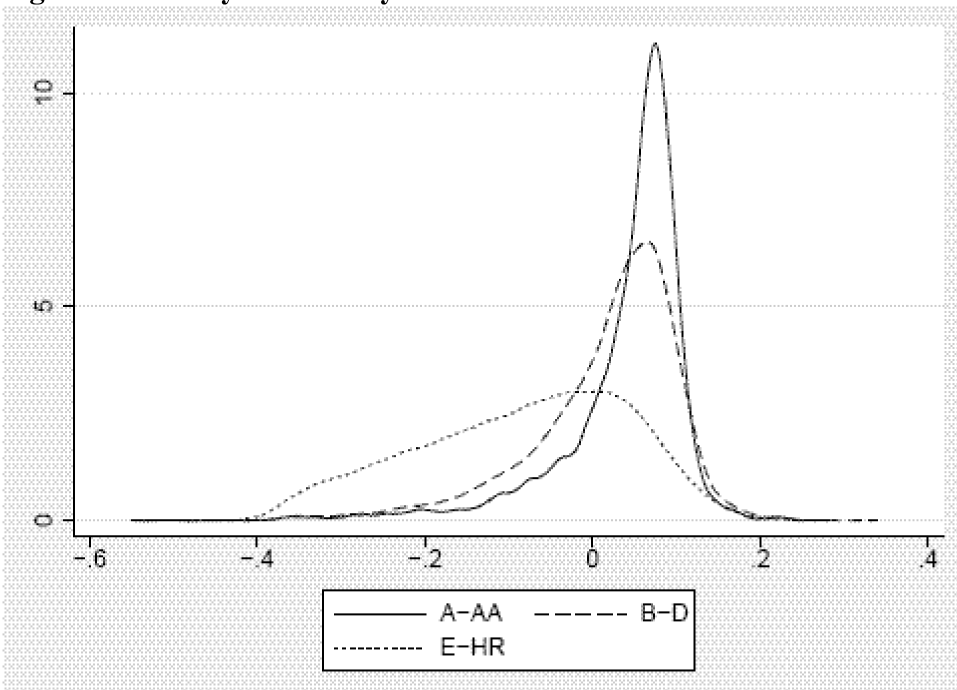



**Figure 8: Density of IRR2 by borrower's group affilation**

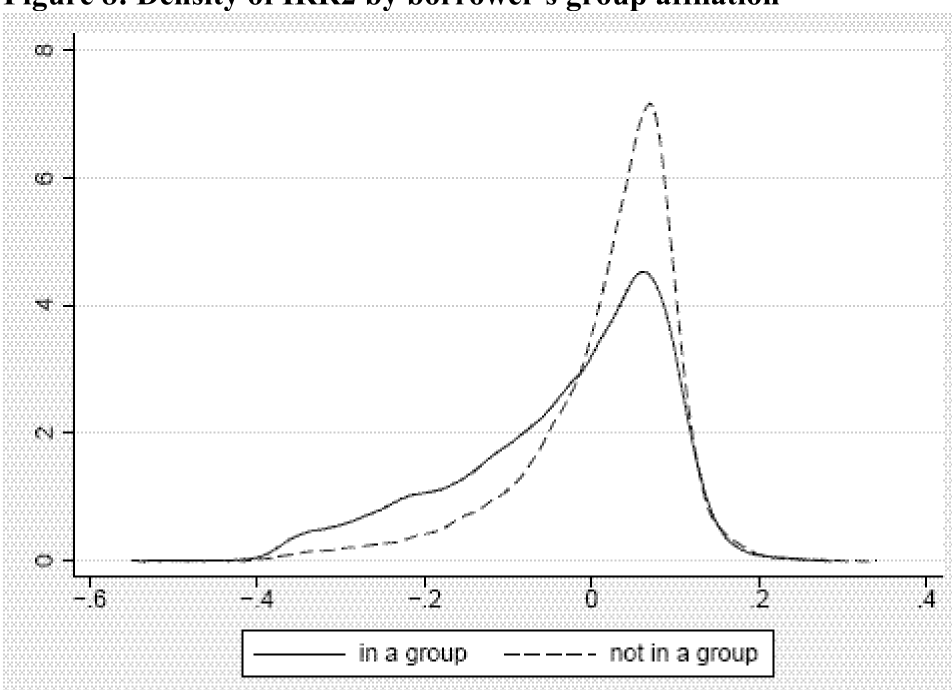


**Figure 9: Density of IRR2 by friend endorsement**

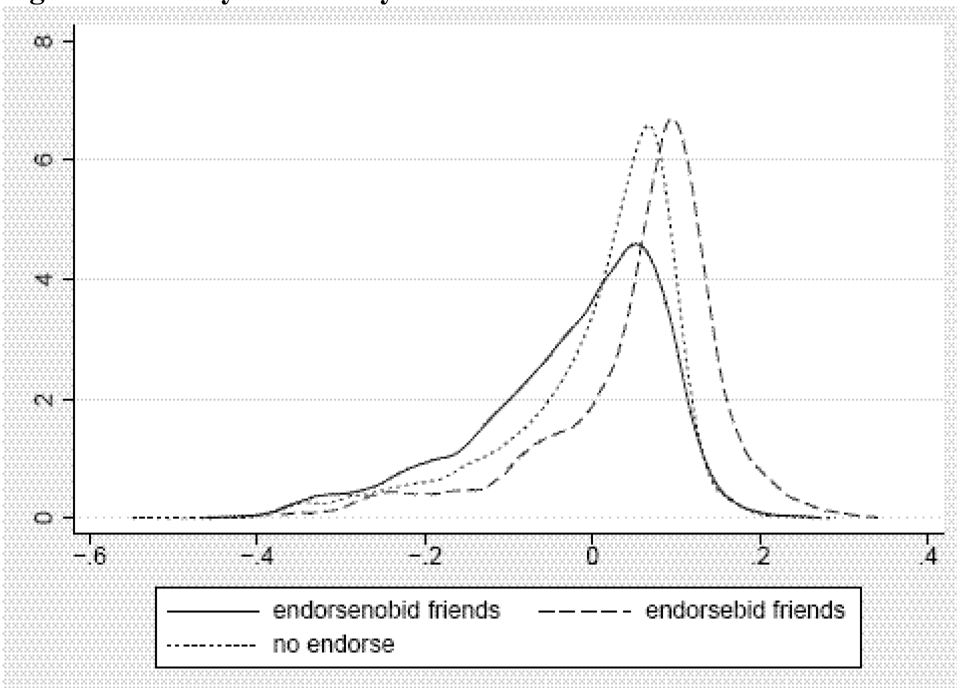
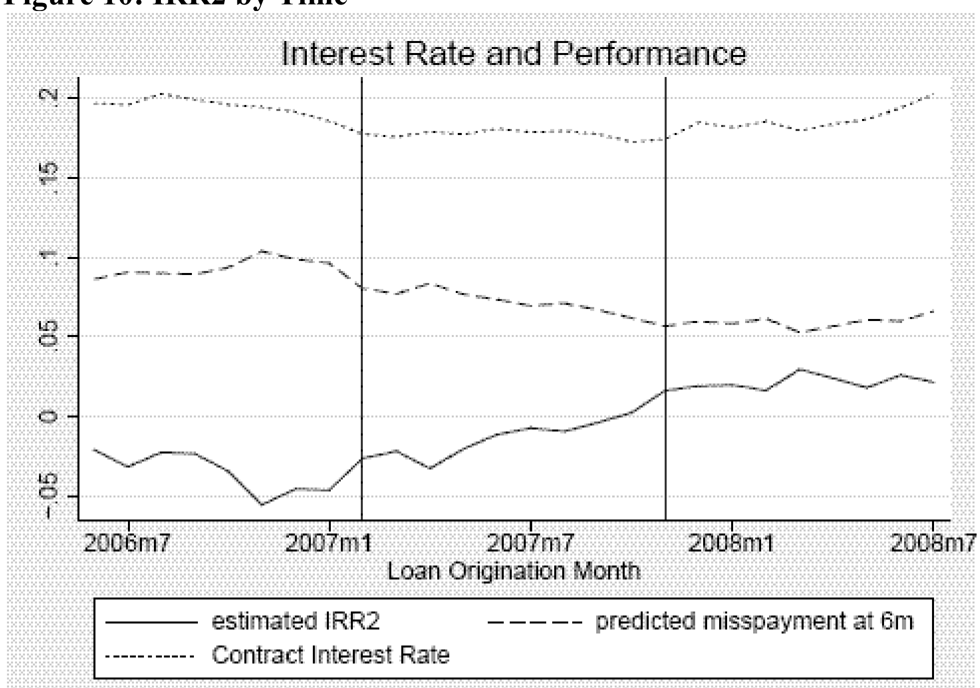



**Figure 10: IRR2 by Time**




**Vertical lines indicate Prosper's Feb. 12, 2007 policy of redefining E and HR plus posting more credit information and Oct. 30, 2007 introduction of bidder guidance.**

**Figure 11: Average IRR2 of New Investments by Investment Date and Lender**

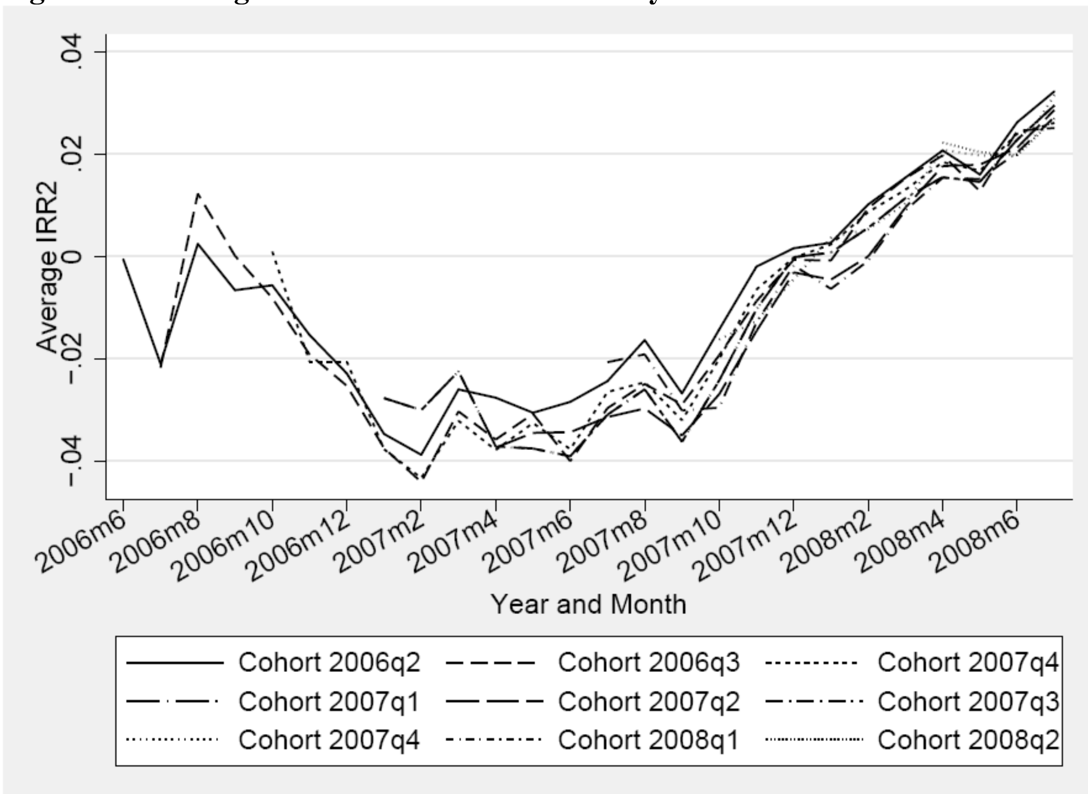
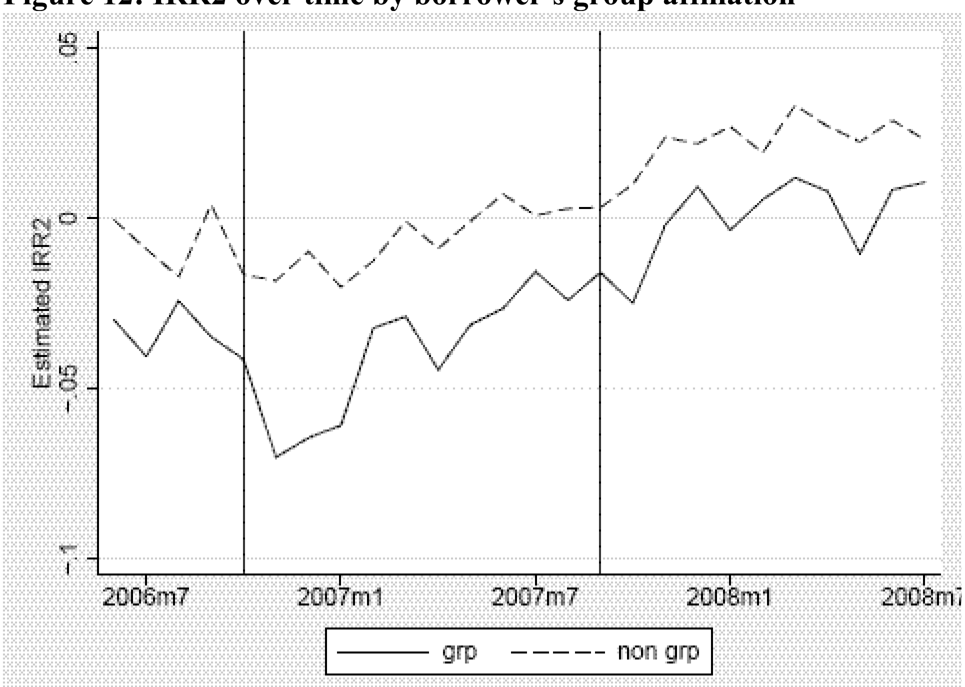
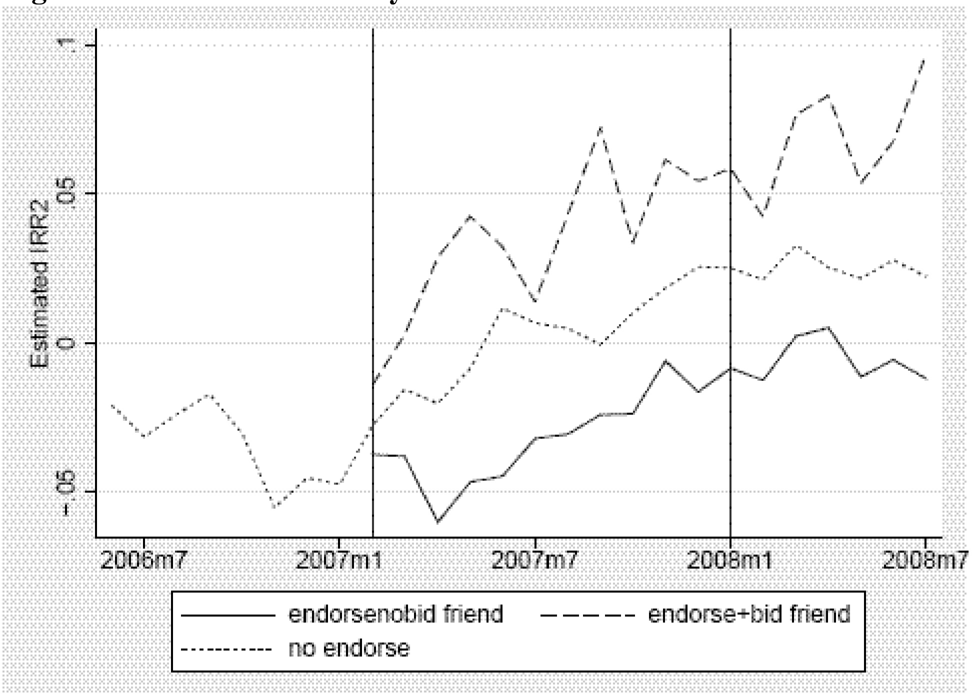



**Figure 12: IRR2 over time by borrower's group affiliation**




**Vertical lines indicate Prosper's Oct. 19, 2006 introduction of group ratings and Sept. 12, 2007 elimination of group leader reward.**

**Figure 13: IRR2 over time by friend endorsement**




**Vertical lines indicate Prosper's Feb. 12, 2007 introduction of friend endorsements and Feb. 23, 2008 change on search of listings by friend endorsements.**