Group Membership, Relationship Banking and Loan Default Risk: The Case of Online Social Lending

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This paper uses a new data source, online social lending (a.k.a. peer-to-peer lending), to help answer the question of what impact borrower-lender information asymmetries have on adverse selection, moral hazard and the hold-up problem. The hold-up problem refers to when lenders with private positive information do not pass long the savings associated with lower borrower risk to the borrower. The results indicate that the hold-up problem is more severe with private lenders than public lenders, and that personal relationships can mitigate the moral hazard problem. This data source has characteristics such as group membership that allow analysis of the public (outsider) versus private (insider) debt choice without some of the endogeneity issues that are present when using other data sources. Each loan contains detailed bidding information from both public and private investors. Thus, a clean distinction can be drawn between public and private debt without the potential problem of unobserved borrower risk characteristics.

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1. Introduction

Over the course of its relationship with the borrower, a financial intermediary will collect a store of private positive information about the borrower (Black, 1975; Fama, 1985). This allows the bank to more correctly assess credit risk and, in an efficient market, will allow the private relationship bank to offer more favorable interest rates to the borrower.

There is, however, a growing body of evidence in the financial intermediation literature that relationship lenders use private, soft information to extract monopoly economic rents in the form of higher interest rates. Borrowers experiencing this "hold-up" problem cannot easily switch lenders since the private information proving that the borrower is not a lemon is kept confidential by the borrower's existing relationship bank (Rajan, 1992; Petersen and Rajan, 1994; Houston and James, 1996).

Measurement of the magnitude of the reduction in lending costs resulting from private banking relationships, as well as measurement of the increases in interest rates due to the hold-up problem, has proven problematic due to issues such as a lack of good measures for relationships and because of endogeneity problems. For example, loan terms certainly affect the loan interest rate, but they are also jointly determined *with* the interest rate, based upon borrower risk characteristics.

This paper uses data from Prosper.com. At the time the data for this paper was collected, Prosper was the largest peer-to-peer lending organization (a.k.a. online social lending) in the United States. It was essentially an online Dutch auction[1] for loans, removing the need for an intermediary between borrower and investor. Peer-to-peer lending data have unique characteristics that shed new light on adverse selection issues, such as the hold-up problem, while avoiding some of the common endogeneity problems. This data source also provides new insight into the resolution of moral hazard through monitoring. This is a contribution to the literature that is possible because the Prosper lending business model incorporated peer monitoring.

Peer monitoring is a concept adopted from microfinance, which is most prevalent in the developing world. In most microfinance programs borrowers are members of a lending group. The members of the group monitor each other and thus repayment rates remain high, even without explicit monitoring by a professional financial intermediary. Groups help improve selection through private information and also mitigate moral hazard via informal enforcement mechanisms such as shame and ostracism.

Group membership is an optional feature in the Prosper.com online peer-to-peer lending communities. This provides the opportunity to test whether or not the risk mitigating impacts of membership in a lending group in the developing world have corresponding impacts in online peer-to-peer lending. If group membership has similar effects in both microfinance and the online world, then we should find a negative relationship between online group membership and default rate. I find that this is indeed the case for certain types of groups. For example, if a borrower is a member of a group with personal relationships, that membership is associated with substantially reduced default rates. In turn, lower default rates are, by definition, associated with lower loan costs.

In this paper I assume that deals between the borrower and fellow members of the same group are analogous to relationship banking or private debt. Both are characterized by the potential presence of private, soft information. Likewise, deals between the borrower and unaffiliated investors in the auction are analogous to public debt auctions, where the information asymmetries are assumed to be more pronounced.

The choice between public and private debt is fundamentally an endogenous one for firms, and thus a robust econometric analysis must somehow exogenize this

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[1] At the time of the original research for this project Prosper.com operated as a Dutch auction. Since then, their business model has changed and is now less relevant to the hypotheses of this paper. Thus, the data used in this paper is only from Prosper's Dutch auction period.

choice. Just as the risk characteristics of the borrower are a key determinant of the ultimate rate spread on the debt, the debt terms are not exogenous and can simultaneously impact the risk profile of the borrower. The precise measurement of the hold-up problem is thus difficult to accomplish. Previous research has either assumed that the nature of the banking relationship is exogenous (Houston and James, 1996) or has addressed the endogeneity issue econometrically. The latter has been done with instrumental variables (Santos and Winton, 2008) or by exogenizing the public/private debt choice via samples that are matched using propensity scoring (Hale and Santos, 2009). Unfortunately, between the samples, there still may be unobserved risk characteristics that drive the public vs. private debt choice.

In peer-to-peer lending, both insider (private) investors and outsider (public) investors actively bid on the loans so the exercise of finding matching sets of borrowers in order to exogenize the public vs. private debt choice is unnecessary. Each loan contains detailed bidding records from both public and private investors. Thus, a clean distinction can be drawn between public and private debt choice without the potential problem of the presence (between loans) of unobserved risk characteristics that drive the decision.

This paper also contributes to the literature by providing contrasting evidence on the impact of certain borrower characteristics on two outcomes: default rate and interest rate spread. The borrower characteristic that I focus on is group membership within peer-to-peer lending. I hypothesize that group membership is related to adverse selection and moral hazard mitigation capabilities and thus its impact on default rate and spread can be empirically tested. The ability to distinguish between informed and uninformed pricing *within a single loan* appears to be unique to this paper, allowing for relatively unambiguous examination of the effects of private soft information. Thus, it also provides a potentially cleaner measurement and pricing of information monopolies. The data support the idea that group membership is negatively and significantly associated with default rate when the group has a potential for personal relationships. I also find evidence of a hold-up problem with a magnitude of between fourteen and thirty-eight basis points that prevents cost reductions from being efficiently passed down to the borrower.

This paper proceeds as follow: Section 2 explores the relevant literature and background information regarding peer-to-peer lending and the hold-up problem. Section 3 discusses the sources of data and methodology. Section 4 presents the empirical results, and Section 5 concludes.

2. Related Literature

2.1. Peer-to-Peer Lending

Since online social lending is still a relatively new phenomenon, this section provides a brief summary of how the online borrowing and lending processes function. For the purposes of this paper I will describe only the lending processes of Prosper.com, which is my source of loan data. There are many social lending internet sites, each operated in a slightly different way. Since Prosper.com is the largest U.S. peer-to-peer lending site, it has attracted the most media interest and thus its description provides a relevant introduction to the basics of social lending.

The process begins when a borrower creates a listing that includes the loan amount requested, the maximum interest rate they are willing to pay, personal data such as income and occupation, and a detailed description of the purpose of the loan. The borrower is always an individual, even for business loans. Loan amounts are limited to $25,000 (USD), which imposes a type of credit rationing that can lower overall default rates (Jaffee and Russell, 1976). Simply the threat of future credit rationing can mitigate moral hazard problems (Stiglitz and Weiss, 1981).

Once the listing is submitted, Prosper.com pulls a credit report for the borrower and appends the salient credit report information onto the loan listing. The credit report information includes credit score, delinquency history, number of credit lines, credit line utilization, and other pertinent information. The borrower's bank account information is also verified. When the listing is approved, it appears on the website. Lenders, who are simply individual investors who have signed up on the site and have also had their bank accounts verified, are then permitted to bid on loans. Lenders can bid as little as $50 (USD) toward any listing and can bid any interest rate less than or equal to the borrower's maximum rate.

The process then works like a Dutch auction. The loan stays in "unfunded" status until enough bids are submitted to add up to the full amount of the loan requested. At that point, additional bids at lower interest rates can continue to be submitted, crowding out the bids at higher rates. The winning lenders are the collection of lenders who have bid the lowest interest rates and whose cumulative bid amounts add up to at least the loan request amount. The ultimate interest rate to the borrower is 0.05% less than the lowest rate that was bid among the losing bidders.

Borrowers have the option of joining a "group." The presence of lending groups is a concept borrowed from microfinance and is unique to Prosper.com in the U.S. online social lending market. Group leaders can impose additional information requirements as a condition for joining. Employment verification, for example, is a common condition imposed by some groups, but is not required by Prosper.com itself. This is the source of private information that can exist for group lenders. Borrowers often join a group after they have been unsuccessful in previous individual peer-to-peer loan attempts. Thus, these borrowers may be subject to particularly severe information asymmetry problems.

Borrowers can be members of only one group at a time. In order to join a different group, the borrower must first resign from their current group, which cannot be done if the borrower has any open loans. The borrower must first pay off all current loans before being allowed to leave the group.

For borrowers who have opted to become members of a group, the winning list of bidders will typically consist of both members of their own group (a.k.a. insider, relationship, or private investors) as well as non-members (a.k.a. outsider, arm's-length, transactional, or public investors). This fact becomes important in drawing the parallels between the social lending market and the traditional public and private debt markets.

Each loan auction stays open for seven to ten days. Bidders are notified by email whenever they have been outbid and therefore no longer one of the potential winners. Lenders then have the option of updating their bid to a lower interest rate. At the end of the auction period, if the loan receives enough bids to be funded, the loan is initiated and the funds are withdrawn from the lenders' bank accounts, and the loan proceeds are deposited to the borrower's account. The website charges an origination fee to the borrower equal to one percent of the loan principal, as well as a small monthly servicing fee to the lenders. Prosper.com then services the three-year loan on an ongoing basis, doing automatic withdrawals from the borrower's account and proportional deposits to lenders' accounts each month.

After the loan is originated, monthly email messages are sent to the borrower a few days before the loan payment debit is made from his/her bank account. The standard enforcement mechanisms for repayment are the imposition of additional fees in the case of insufficient funds, adverse credit report postings for past due accounts, and key derogatory credit report information and referral to a collection agency in the case of default.

If the borrower is a member of a group, then there may be additional informal enforcement mechanisms. Lending groups are the foundation of microfinance, and the moral hazard mitigation mechanisms available to a traditional lending group are shared risk, peer monitoring, and peer enforcement (Brau and Woller, 2004). In online social lending, on the other hand, late payments and defaults will affect the group's "star" rating, which can impact the ability of groups to attract new members, as well as the ability of existing group members to get new loans. This is the only shared risk, since members are not responsible for the repayment of fellow members' loans. Additionally, group members can monitor the status of loans borrowed by other members of their group. If a late payment is reported, they can exert pressure on the delinquent borrower via email messages. This constitutes a peer monitoring and enforcement mechanism, albeit a potentially weak one that has no explicit sanctions.

Table 1 lists the pioneers of online social lending by their dates of inception. It is evident that this is a rapidly developing phenomenon with the number of new players accelerating over time to satisfy the growing worldwide demand for unsecured business and personal loans. Returns to lenders appear to be consistent with conventional lending. A complete list of variable definitions is shown in Table 2. In Table 3, summary statistics show that interest rate spreads (above LIBOR) are between 4.2% (for loans to borrowers with a credit score of 760 and above) and 18.5%

(for the lowest scoring borrowers). The overall default rate, when also including "E" rated borrowers and unrated borrowers (no credit history), is approximately 7.5%. The overall default rate (Table 4) is 38%, but only if defaults that occurred prior to the financial crisis are counted (using a break date of November 1, 2008), the default rate is only 7.5%, which is similar to the default rates of other types of debt. For example, the average default rate on corporate bonds between 1982 and 2001 was 4.19% (Altman et al, 2005). The default rate for small business loans (source: SBA) during a similar time frame was approximately 11%. Market interest rates during the sample period (May 31, 2006 to Nov 6, 2007) were reasonably stable until the summer of 2007 when mortgage-backed securities began to be downgraded.

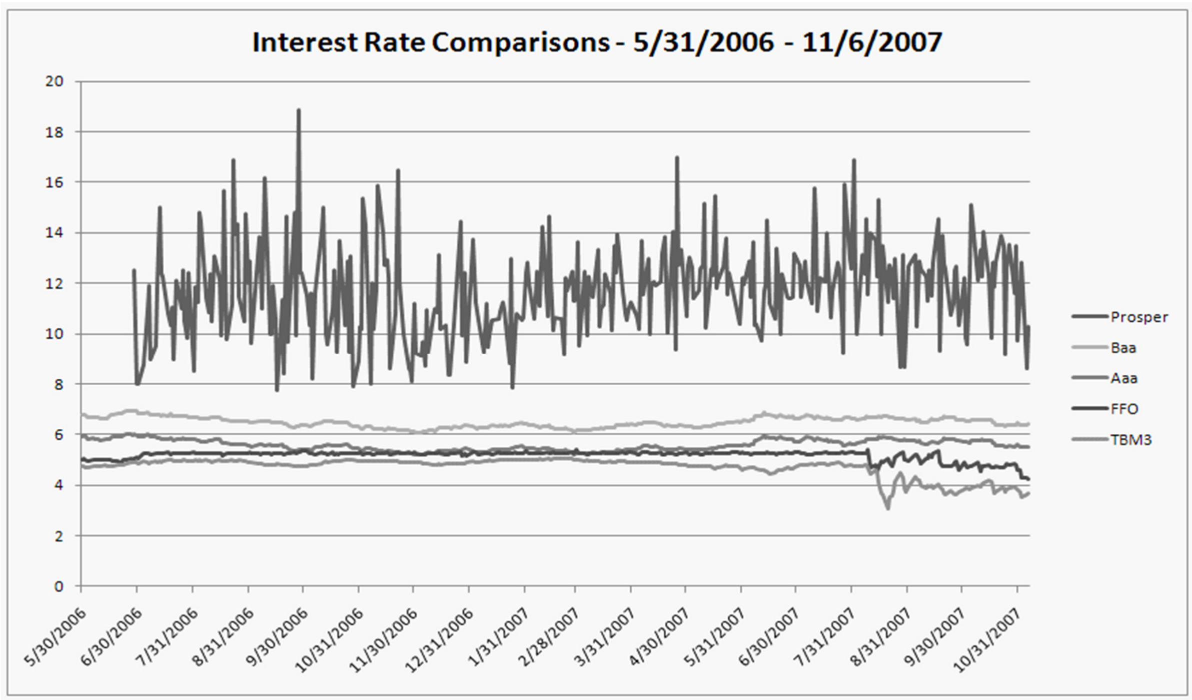
Table 1. The World of Online Social Lending

Lending Site	Inception	Description
Zopa.com (UK)	Mar 2005	Peer-to-Peer (P2P) lending in the UK
Kiva.org	Oct 2005	Non-profit. Allows individuals to make loans to entrepreneurs in developing countries.
Prosper.com	Feb 2006	P2P lending in the US. Allows borrowers to list their loan requirements and members can then bid as lenders. Prosper then services the loan for the 3-year term.
MyC4	Dec 2006	Denmark for-profit Microfinance Institution (MFI) in Africa
Boober.nl	Jan 2007	P2P lending in the Netherlands
Virginmoneyus.com	Feb 2007	Formally circelending.com, manages and services direct family and friend lending
Smava.de	Mar 2007	P2P lending in Germany
Fairrates.dk	Apr 2007	P2P lending in Denmark
LendingClub.com	May 2007	P2P lending in the US, originally limited to Facebook.com members
PPdai	Jun 2007	P2P lending in China
Microplace.com	Oct 2007	Ebay MFI investing in LDCs
IGrin.com.au	Oct 2007	P2P lending in Australia
Zopa.com (Italy)	Nov 2007	P2P lending in Italy
Boober.it (Italy)	Nov 2007	P2P lending in Italy
Loanland	Dec 2007	P2P lending in Sweden
Zopa.com (US)	Dec 2007	P2P lending in the US
IOUCentral.ca	Feb 2008	P2p lending in Canada
Zopa.com (Japan)	Mar 2008	P2P lending in Japan
CommunityLend.com	Apr 2008	P2P lending in Canada

Notes: This table lists the principal online social lending services that have appeared since 2005 but before May 2008. All listings are commercial for-profit enterprises unless otherwise indicated.

Figure I shows a comparison of interest rates for Prosper.com (borrowers with credit score of 720 and above), Baa rated corporate bonds, Aaa-rated corporate bonds, federal funds overnight rate, and the 3-month T-bill rate.

Figure I. Interest Rate Comparisons over Sample Period [2]



2.2. A Brief History of Social Lending

The advent of modern social lending is attributed to the English "friendly societies" of the 18th and 19th centuries that arose spontaneously during the industrial revolution as clubs that helped their members pool resources and risk. With the Friendly Societies Act of 1793, the British Parliament formally recognized and regulated the burgeoning industry. Although the records of the era are informal and incomplete, it is thought that by 1815 as many as 33% of the families in England were members of a friendly society (Gorsky, 1998). An even earlier implementation of a microfinance-style lending paradigm was instituted in Ireland in the early 18th century, when Jonathan Swift (author of Gulliver's Travels), with his own resources, instituted a fund for lending to poor tradesmen. To address the adverse selection problem, he required each borrower to obtain a personal guarantee from two neighbors. Any late payment would result in a notice being sent to the borrower and both guarantors (to help ensure future punctuality). There were apparently no defaults on the Swift loans (Hollis & Sweetman, 2001).

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[2] Sources of interest rate data are Prosper.com and federalreserve.gov

The concept of organized social lending was transplanted from England to the United States in 1831 with the Oxford Provident Building Association in Frankfort, PA (near Philadelphia). Individuals could purchase up to five shares for five hundred dollars per share. Whenever the association accumulated at least five hundred dollars, a loan would be made to the member offering the highest bid (Potter, 1954). This auction approach is remarkably similar to the structure of online social lending today.

2.3. Information Monopolies and the Hold-Up Problem

In an ideal lending world that is fully transparent and without information asymmetries, or transaction costs, borrowers and investors would deal directly with each other. There would be no need for financial intermediaries such as banks. In the presence of adverse selection and moral hazard problems, however, it is difficult for an individual investor to effectively determine the true risk characteristics of the borrower. Diamond (1984) proposed that delegated monitoring to a bank may be an efficient mitigation of moral hazard. His paper distinguished itself from previous literature in explicitly modeling the delegation and monitoring costs, thus exploring the risk-neutral financial intermediary's incentives to effectively monitor. Only when bankruptcy is costly will the debt contract be optimal, providing a sufficient net benefit to engagement in monitoring activities.

The potential downside to the monitored borrower is that during the course of the private banking relationship the bank will accumulate (and abuse) proprietary positive information about the borrower (Fama, 1985), particularly if the borrower is also a depositor at the bank (Black, 1975). This investment by the lender in private information acquisition creates a barrier to entry for other lenders, which makes it difficult for the borrower to switch banks. Sharpe (1990) formally models the informational hold-up problem in his theory of customer relationships in bank loan markets. In his model, banks are unable to directly observe a firm's quality, and thus only the bank that is currently the firm's lender can freely observe project success. Banks do not divulge this information since that would just assist competing banks in bidding away their clients. The natural consequence of these relationships is an information monopoly. Banks use the private information to hold up the borrower, which in turn may distort borrower behavior.

The borrower may attempt to mitigate the hold-up problem by developing multiple banking relationships, which is less efficient and thus increases total lending costs. Using data from the U.S. Small Business Administration, Petersen and Rajan (1994) empirically test how multiple relationships between lender and borrower impact interest rates and the availability of credit. They find that borrowing from more than one bank increases lending costs by reducing efficiency. They also test the effect of relationships on the availability of credit, as proxied by the firm's debt ratio, and find that having multiple banks is associated with reduced credit availability. In another empirical study of the hold-up problem, Farinha and Santos

(2002) find evidence that firms establish multiple banking relationships in order to hedge against future potential hold-up costs from their primary lender.

2.4. The Choice between Public and Private Debt

With online social lending, the only "insiders" that can be observed are the fellow group members of the borrower. Since group leaders on Prosper.com are permitted to impose additional disclosure and other reporting requirements upon potential members before joining, it follows that members of that same group may have private information that is unavailable to other investors. Therefore, the willingness of group members to lend money to fellow group members can be viewed as a signal that reveals the nature of their private information. Favorable private information should lower the interest rate, as long as lender competition is present to overcome the hold-up and credit rationing problems. When competition is present, banks cannot reasonably expect to share in the borrower's surplus, regardless of the length and strength of the relationship (Petersen and Rajan (1994, 1995); Berger and Udell, 1995; Boot, 2000; Boot and Thakor, 2000).

With private bank lending, the debt is more concentrated, which gives the lender greater incentive to actively monitor (Diamond, 1984). Less worthy borrowers thus have greater access to credit, since moral hazard associated with inferior borrowers can be mitigated via monitoring. Such borrowers cannot easily switch lenders, since they will be identified as lemons if they do so. Rajan (1992) proposes a theoretical model of the choice between private and public debt where the bank's monitoring activities impact the firm's investment decision, thereby changing the division of economic surplus between the bank and the firm. Thus, the firm's incentives are affected, introducing additional endogeneity into the choice between public and private debt.

Houston and James (1996), in their seminal paper, recognize the double-edged nature of the effects of the banking relationship on interest rates. Because of the bank's ability to mitigate adverse selection and moral hazard, and through the flexibility provided by recontracting, bank loans can actually be less expensive than bond issues. On the other hand, the private information collected over time by the bank (Fama, 1985) can create an information monopoly than may result in extraction of abnormal economic rents and thus higher interest rates (Rajan, 1992). Thus, the question of which effect dominates is an empirical issue. The authors do not attempt to measure the hold-up problem. Rather, they examine the effect of potential hold-up problems on the mix of private and public debt holdings of large publicly held firms. They hypothesize that the hold-up problem will be greater for firms with a single bank lender and significant growth opportunities (or intangible assets).

For firms using multiple banks, there is a significant positive relationship between the loan to debt ratio and the market-to-book ratio. This result is consistent with the idea that borrowing from more than one bank is associated with a less severe hold-up problem. For firms that only use one bank, however, there is a negative coefficient on growth opportunities. This result contradicts the common argument that growth opportunities are associated with increased reliance on bank loans. On the other hand, it is quite consistent with the idea that growing firms may avoid bank debt due to the hold-up problem.

Santos and Winton (2008) test the proposition that hold-up power increases with firm risk, as theorized by Rajan (1992). They start with the assumption that, on average, during economic recessions, risk levels increase for nearly all firms. This increase in risk makes it more difficult for borrows to switch lenders. Therefore, relationship banks should be able to extract higher rents during economic downturns. Using data from LPC Dealscan, SDC, and CRSP, they model interest rate spread (over LIBOR) as a function of public bond market access, state of the economy, firm risk characteristics and loan characteristics. They find that loan spreads do indeed rise during recessions (thirty-three basis points), but less so for firms with public debt access (only eleven basis points). Their interpretation of these results is that during recessions relationship banks extract additional rents from firms that cannot escape that lending relationship by issuing bonds. These results are consistent with the hold-up problem theorized by Rajan (1992).

So how large are these informational rents? Hale and Santos (2009) attempt to price the hold-up problem by comparing a firm's private loan spreads before gaining access to the public debt market (bond IPO) against its private loan spreads after the IPO and find that bank loans after the bond IPO have lower spreads (loan interest rate minus LIBOR). A high credit rating before the IPO is associated with a smaller spread (reduction of 35-50 basis points). A lower rating, however, is associated with less of a reduction. Among safe firms, not having a previous credit rating is associated with a larger decline in rates. This supports the hypothesis that the revelation of firm safety to the market increases outside investors' willingness to bid, thus driving down the spread.

Schenone (2010), like Hale and Santos (2009), seeks evidence of a hold-up problem by pricing private loans before and after a large public information event. She does this by examining loan pricing before and after the firm's equity IPO. The idea is that much private information becomes public at the IPO, thus reducing the relationship bank's information monopoly. The central hypothesis is that rent extraction by the bank will be concentrated before the IPO. The author develops an intensity measure which is the frequency of new loans with the same lender. Before IPO, the relationship between interest rate and intensity is U-shaped. After IPO, the rate consistently decreases with intensity. In general, she finds that interest rates are higher before firm IPO, as expected.

The studies cited above reflect alternative approaches to discerning the impact of private information monopolies on loan spread. The inherent limitation of these approaches is that they either require an assumption that the choice between private and public debt is exogenous, or must employ analytical techniques such as instrumental variables or propensity scoring to deal with the endogeneity. Peer-to-peer lending data, on the other hand, naturally exogenizes the private/public choice, since the borrower never actually makes the choice—the initiated loan is, in fact, simply a collection of smaller loans (both public and private). Loans for group members have bids from both group members (with private information) and bids from non-members (with only public information). This allows the study of information effects on loan spread while mitigating some of the endogeneity problems inherent in previous research.

3. Material And Methods

3.1 Adverse Selection

One of the purposes of financial intermediation is to mitigate adverse selection. Lenders are able to improve loan selection by collecting private information about their borrower customers over time (Fama, 1985). Using this private information to augment publicly available data, the lender is then able to select a portfolio of loan customers with a lower average default rate than would be possible using public data alone. Since loan defaults are costly to the lender, a lower average default rate for the portfolio reduces overall lending costs.

In the Prosper.com model of peer-to-peer lending, every group has a leader, typically the person who started the group. The group leader is the final arbiter of which borrowers will be allowed to join. The group leader has the option of requiring potential members to submit additional documentation above and beyond that which is required by Prosper.com. This ability to collect private information in order to improve selection is tightly analogous to the role played by traditional financial intermediation in mitigating adverse selection.

In peer-to-peer lending, however, groups are not monolithic. There are wide ranges of purposes, sizes and membership composition. Some group leaders may be more interested than others in expending the additional effort required to collect private data. For example, a group named "Quilters of Central Indiana" may be mostly interested in social networking, whereas a group named "Debt Consolidators" is more likely to take borrower screening more seriously. Therefore, in order to accurately capture the effects of group membership on outcomes in this lending market, it will be necessary to categorize groups in ways that reveal their propensity to engage in screening and monitoring efforts.

In the presence of competition between private relationship lenders (group members) and arm's-length lenders (public bidders), the arm's-length bidders are able to free-ride on the screening activities of the relationship lenders. Interest rates should fall due to the arm's-length lenders facing a reduced threat of adverse selection (Hauswald and Marquez, 2006). An online auction is, by its very nature, a highly competitive environment. Where competition is present, investors cannot reasonably expect to share in the borrower's surplus, regardless of the length and strength of the relationship (Rajan,1992; Petersen and Rajan (1994, 1995); Berger and Udell, 1995; Boot, 2000; Boot and Thakor, 2000). Therefore, we can reasonably expect that the lower cost of lending caused by the decreased default risk in a competitive environment will be passed along to the borrower in the form of a lower interest rate.

3.2 Moral Hazard

The other main purpose of financial intermediation is the mitigation of moral hazard. Once the loan is made, the borrower may act irresponsibly with the loan proceeds or take unnecessary risks. One way that a traditional financial intermediator addresses this issue is through monitoring of the borrower to ensure that contractually prohibited activities are not taking place. Similar to the Grameen Bank in Bangladesh, the online group lending model has no group-level enforcement teeth to strengthen the effects of monitoring. Instead, the Grameen lending model relies entirely upon shame and ostracism to pressure group members into compliance (Ghatak, 1999; Williams, 2004). Effective social punishment relies heavily upon the assumption that there are social relationships between group members outside of the lending transaction. Whether these relationships are established before or after the formation of the group should not matter as much as the level of ex-post importance of these relationships to the borrower. The financial impact of the relationships is influenced by the presence of competition (or the lack thereof). Relationships should decrease the cost of credit, since the presence of social connections has been shown to improve repayment rates (Woolcock, 2001).

Social sanctions are one of the enforcement mechanisms that can be imposed for borrower default. This, of course, only works if the group members actually care about the opinions of the others. The financial impact of social sanctions in a group lending environment is addressed by De Aghion and Morduch (2000) as part of a larger model of loan repayment incentives. In their model, a borrower will repay the loan only if the perceived cost of the shame (social sanctions) is greater than or equal to the value of the debt obligation (principal plus interest) minus the discounted project return. They interpret this to mean that with the additional social sanctions present, lenders are able to charge higher interest without increasing risk of default.

An alternative interpretation of the work of De Aghion and Morduch (2000) is that the presence of social sanctions should have a negative impact on interest rates, ceteris paribus. If default risk is exogenously reduced, then this should result in a decrease in the interest rate that the lender requires. However, default risk is itself endogenously affected by the interest rate. Stiglitz and Weiss (1981) demonstrate that when facing a given interest rate, if a risk-neutral borrower is indifferent between two projects and then the interest rate is increased, the borrower will prefer the riskier project. In a similar line of reasoning, Diamond (1991) shows that a higher interest rate leads to riskier project choice, but only for unmonitored borrowers, since the presence of monitoring impedes the borrower from selecting the riskier project in the higher interest rate environment.

3.3 Are Lending Cost Savings Passed Along to the Borrower?

The above discussion of adverse selection and moral hazard establish the basis for the first testable hypothesis of this paper:

> *Hypothesis 1: Membership in a group with private information or monitoring is associated with lower default rates.*

Before being able to answer the question of what lenders do with loan cost reductions, it is necessary to verify that membership in a group with enhanced selection or monitoring is truly associated with lower default rates. Toward that end, I identify proxies for enhanced private information and enhanced monitoring. During the time frame of this data set, group leaders have the option of establishing what are called "group leader rewards." This is an additional percentage (ranging from zero to one percent) that would be added to the borrower's interest rate and paid monthly to the group leader. Therefore, I identify the groups that have an observable profit motive as those that have their group leader rewards set at a rate greater than zero. For these groups I set the PrivateLender indicator to one (1). Lenders will collect private information over time (Fama, 1985) and make lending decisions based on that information. Unlike commercial banks, which make measurable investments over time in the acquisition of private information about their borrowers, the private lenders in this peer-to-peer data set appear to only invest their time (via collection of additional documentation) in private information acquisition.

In peer-to-peer lending, like any form of financing, it should be apparent that interest rate spread and risk are positively associated since investors expect to be compensated for risk. In an efficient lending market, competition should result in interest rates that are exactly equal to the lenders' marginal lending costs. Alternatively, it may be the case that the lending market is not perfectly efficient but subject to frictions such as the hold-up problem. If this is the case, then the cost savings from improved selection will not be passed along to the borrower, but will instead be extracted by the lender as surplus economic rents. If the hold-up problem exists, then spread should be positively associated with being a member of a group with an established propensity for rent extraction, since these lenders are more likely to seek monopoly rents. If there is no association, or if the relationship is negative, then that would be evidence against the existence of a hold-up problem.

> *Hypothesis 2: Group leaders that charge borrowers for their services are more likely to hold-up their borrowers and not pass along cost savings.*

Agarwal and Hauswald (2008) attempt to isolate the effects of private information when comparing online eloans (transactional) to local branch loans (relationship). They do this by orthogonalizing the internal and external (public) credit scores in order to extract the purely private component of the overall credit screen. For the local branch loans, the internal credit score will be impacted by proprietary information obtained by the bank over the course of their business relationship with the borrower. They captured the proprietary information in the residual (µi) in the following regression:

$$IntScore_i = \beta_0 + \beta_1 XSBI_i + 1_{eloan}(\gamma_0 + \gamma_1 XSBI_i) + \mu_i \quad (1)$$

The residuals (μ_i) are stored in a variable called the Private Information Residual (PIR) and used as an independent variable in subsequent regressions. XSBI is the firm's credit score.

I employ a similar approach to extract the purely private information available to online lending group members. The underlying assumption is that bidding behavior is based on all available information. Public information is available to all bidders, but additional private information is only available to insiders. Therefore, differences in insider vs. outsider bidding behavior must be driven by differences in information. As a proxy for the internal credit score, I use the de-meaned ratio of insider bids to total bids on each loan. This is a reasonable proxy since a credit score itself is simply a measure of the lender's positive opinion of the borrower. In the same sense, the ratio of insider bids to total bids measures the insider's relative positive opinion of the borrower as compared to outsider opinion. The intuition is that if the private information is adverse in nature, then the insiders will be less likely to bid (or bid a higher rate that could be crowded out by lower outsider bid rates) resulting in a lower ratio. If the private information is positive, then insiders will bid more aggressively, resulting in a higher ratio. Non-group loans, of course, have a ratio of zero. Thus, I calculated the residuals (PIR1) as follows:

$$\begin{aligned} RatioBidByGroup_i \\ &= \beta_0 + \beta_1 CreditScore_i + \beta_2 Ctrl\,Vars_i \\ &+ 1_{nongrouploan}(\gamma_0 + \gamma_1 CreditScore_i + \gamma_2 Ctrl\,Vars_i) + \mu_i \end{aligned} \quad (2)$$

The dependent variable RatioBidByGroup is noisy, since bidding behavior may be impacted by factors other than soft private information about credit worthiness. When the dependent variable is noisy, the residuals will be biased toward zero. Therefore, a significant result for PIR as an independent variable is all the more convincing. Of course, favorable proprietary info may lead to higher interest rates, due to information capture (Houston and James, 1987; Von Thadden, 2004). However, in the presence of competition between relationship lenders and arm's-length lenders, which is certainly the case here, interest rates should fall due to the arm's-length lenders facing a reduced threat of adverse selection (Hauswald and Marquez, 2006).

To measure the extent to which the credit marketplace incorporates these risk factors into their bids, I estimate the effect of these factors on the borrower interest rate by performing a Tobit analysis using interest rate spread as the dependent variable.

$$r_i = \alpha + \beta X_i + \gamma W_i + \delta Z_i + \varepsilon_i \quad (3)$$

In this model, X is a vector of independent variables representing borrower characteristics, W represents the loan characteristics and Z represents the group/investor characteristics.

The hold-up problem is about rent extraction by relationship lenders from borrowers that cannot easily escape said relationship. Therefore, if PrivateLender groups are excluded from the analysis, there should be no difference in spread for relationship versus non-relationship groups.

Monitoring will only affect borrower behavior if there is some negative consequence associated with bad behavior. Shame and ostracism only exist in the presence of relationships that are important to the borrower, which I proxy by combining the groups: friend, company, geographic, occupation, and alumni into a single dummy variable called SocialLender. Bertrand et al. (2004) findcontend that people that share a common educational background may have personal connections that influence financial outcomes. This is why I include alumni group membership among the proxies for personal relationships.

The univariate effects of monitoring on default and spread are measured using t-tests of differences in population means. The multivariate effects of monitoring on interest rate spreads are tested using OLS and Tobit analyses.

3.4 Data

The central data source for this thesis was obtained from Prosper.com, which represents the largest online social lending community in the United States. Prosper.com also has the unique feature of allowing borrowers to join "groups" that are designed to provide risk filtering as well as peer-pressure for borrowers to perform on the repayment of their loans.

The data include detail for 13,461 loans initiated between May 31, 2006 and November 6, 2007, borrower information including credit score (but excluding identity), lender information, loan performance information (through November 30, 2010), group information, and detail regarding every winning bid made for each loan listing. It is important to recognize that these loans were the result of successful loan listings. The majority of listings (more than 90%) never receive enough bids to become funded, and thus never become actual loans. Although the fact that I am only including funded loans may introduce some selection bias, there would have been significant problems with analysis of bidding behavior on the unsuccessful loan listings due to having far fewer bid observations with higher variability and more outliers. In successful loans, these outlier bids are self-censored as they are crowded out by competition. The loan principal amounts range from $1,000 to $25,000 (USD). Total funds borrowed during this period were $86 million (USD). Interest rate spreads were calculated using the three-month London Interbank Overnight Rate (LIBOR). Estimated 2007 population data for the geographic dispersion measure were obtained from the U.S. Census Bureau.

Table 2. Variable Definitions

Variable	Type	Description
DefaultInd	Dummy	Value of 1 if the loan is default, 0 otherwise. The soonest that a loan can transition from past due to default, even if the borrower never makes a payment, is six months.
MemberOfGroup	Dummy	Value of 1 if borrower is a member of any group, 0 otherwise.
SocialLender	Dummy	Value of 1 if borrower is a member of a group that has a higher likelihood of personal relationships (group categories: private, geographic, alumni, occupation, and company), value of 0 if member of group in the following categories: small business, hobby, ethnic, high-risk, low-risk, or other.
GLRewards	Continuous	Percentage of loan interest in a group that is paid to the group leader. This practice has been discontinued so newer loans all have a value of zero in this field.
ListRev	Dummy	Value of 1 indicates that group members in this group must have their loan listings reviewed by the group leader before being posted.
Ln(GroupLoans)	Continuous	Natural log of the total number of loans initiated in a particular group. This represents a proxy for the effective size and experience of the group.
RatioBidByGroup	Continuous	Numerator is total dollar value of bids made by fellow members of the borrower's group. Denominator is total dollar value of bids against the loan listing.
Ln(Amt)	Continuous	Natural log of the original loan principal amount.
BorrowerRate	Continuous	Interest rate to the borrower, expressed as a decimal.
QuickFunding	Dummy	Value of 1 if the borrower submitted loan listing with the QuickFunding option selected. This means that instead of waiting for the full bidding period to end (often resulting in the interest rate being bid down), the borrower wants the bidding to end and the loan to be originated as soon as the loan has received enough bids to be funded.

Table 2: continued

Variable	Type	Description
CreditScore	Discrete	ScoreXPlus Credit Score received from credit bureau (Experian). This is an integer between 520 and 800. Prosper does not provide this numeric score directly to lenders. Instead, lenders see a credit grade corresponding to the ranges listed: 1 HR 520-559 (high risk) 2 E 560-599 5 B 680-719 3 D 600-639 6 A 720-759 4 C 640-679 7 AA 760+
HomeownerInd	Dummy	Value of 1 if the borrower owns a home.
EndorsementsInd	Dummy	Value of 1 if the borrower has received personal endorsements from other members of the social lending site.
Ln(BorrowerAge)	Discrete	Calculated as the number of years since the initiation of the borrower's credit report file minus 18. The assumption is that most people first receive credit in their own name at around age 18.
Spread	Continuous	The difference between BorrowerRate and LIBOR.
Ln(DateBidCount)	Continuous	Natural log of the total number of bids placed on ALL loans on the website on the last day of bidding for the loan being analyzed. This is a proxy for total website traffic.
LIBOR	Continuous	This is the LIBOR rate on the last day of bidding for the loan.
Ln(Amt) * CreditScore	Continuous	Interaction term
PrivateLender * Ln(GrpLoans)	Continuous	Interaction term

There are more than 1,300 groups in the sample, which I categorized by reading each group's narrative self-description and then manually coding each group into the following categories: friend, small business, company, alumni, geographic, hobby, ethnic, occupation, religious, low-risk borrowers, high-risk borrowers, lending purpose, growth purpose, and other. Business groups (360 observations) specialize in making loans to small businesses or self-employed entrepreneurs. Occupation groups (513 observations) consist of people that share the same profession. Depending on the size of the profession, members may be impacted by their reputation within that profession and thus wish to avoid default if possible. Company groups (45 observations) consist of employees of the same company.

Geographic groups (99 observations) are based in a certain geographic area (the same city, in most cases). Alumni groups (219 observations) consist of alumni of a certain university, who generally must prove their status as an alumnus in order to join.

Since shame and ostracism (or any other social sanction) can only exist in the presence of relationships that are important to the borrower, I develop a proxy for personal connections by combining the groups: friend, company, occupation, geographic,[3] and alumni into a single dummy variable called SocialLender. These are the groups in which the borrower is most likely to have direct or indirect personal relationships. Private "friend" groups (167 observations) are the groups with descriptions such as "Family and friends of John Doe—by invitation only." Although ethnic groups have a rich history in social lending,[4] they were not included in the Social Lender group for this study. Historically, ethnic social lending occurred via building and loans or thrifts, which were largely neighborhood organizations with obvious appeal to the tight-knit ethnic communities of the late nineteenth century (Wright, 1894). Unfortunately, this data set only includes the geographic location of the borrower at the state level, which does not have the necessary granularity to establish neighborhood proximity. Therefore there is no basis for assuming that similar ethnic background implies personal relationships among the borrowers in the data set.

One of the important characteristics of this online social lending data set is that the loans have aspects of both relationship banking as well as capital market transactions. On the one hand, like auction-based capital markets, Prosper.com does not accept deposits—it just directly matches borrowers with investors. On the other hand, the group membership aspect with its information asymmetries induces behavior much like relationship banking. Each loan to a borrower who is a group member has the very useful property of having both relationship lenders (investors belonging to the same group), and arm's-length lenders (other investors who do not belong to that group). Because the data consists of loans that have both relationship and transactional lenders that can be distinguished from each other within the same loan, the effects of the relationships can be measured very cleanly with less noise and less potential for bias or endogeneity.

The idea that a hold-up problem might exist in this marketplace depends upon the condition that insiders and outsiders cannot observe each other's bidding

[3] Williams (2004) asserts that shame and ostracism can be a substitute for legal enforcement in the event of default, and these effects are enhanced by geographic proximity. Karlan (2007) also finds that geographic concentration in groups of borrowers leads to improved repayment rates, which is consistent with Agarwal and Hauswald (2008), who also find that geographic proximity is a good proxy for information quality.

[4] By the end of the nineteenth century, there were more than 550 ethnic thrifts in the United States. Most were in industrial cities and served European immigrant communities from places such as: Germany, Ireland, Scotland, Poland, Hungary, Serbia, Croatia, Yugoslavia, Italy, Lithuania, Estonia, Latvia, and Russia (Mason, 2004).

behavior. If outsiders could see the insiders' bids, then they would just assume that the insiders have an information advantage and mimic their bidding behavior. This problem is addressed by two characteristics of this data set: 1) The bidding data is quite unwieldy and although it is technically available to all investors, would be challenging for outsiders to use in a real-time bidding situation; and 2) the only bids available for view are losing bids, which means that outsiders cannot observe the behavior of the currently winning bidders.

4. Results And Discussion

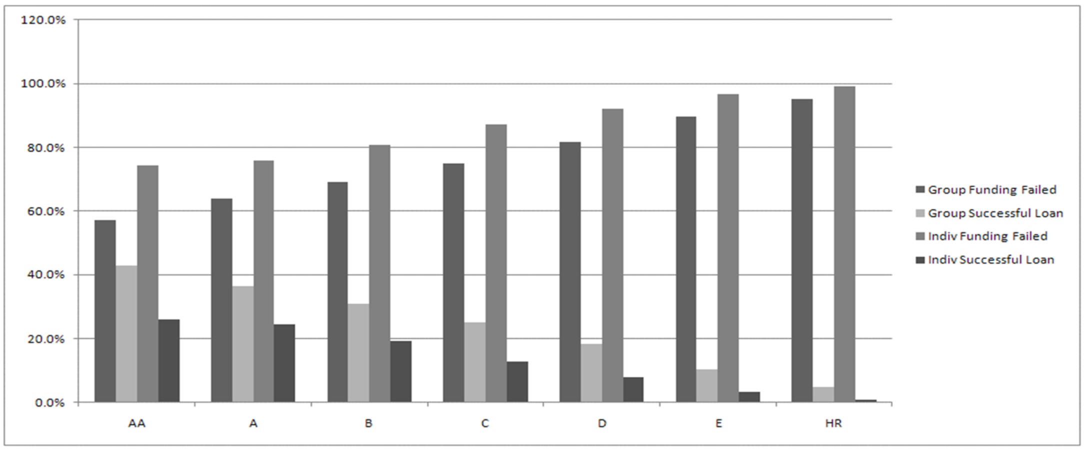
4.1 Univariate Results

Table 3, Table 4 and Table 5 contain descriptive statistics from the sample of 13,465 loans. Table 3 and Table 4 present summary data, divided into three groups of three columns. The first three columns represent data from all loans, regardless of group membership. The second set of three columns is restricted to only those loans to borrowers who are members of a group (any group). The third set of columns represents borrowers who are not members of any group. Table 3 reports interest rate spread means and Table 4 reports default rate means. The last column is the difference in mean between borrowers who are group members and those who are not. On average, members of groups pay higher rates than those who are not. However, it is also apparent that group members have higher default rates. These results are counterintuitive if the purpose of joining a group is to get a better deal. If, however, the purpose of joining a group is not to get a better deal, but instead is to increase the probability for substandard borrowers to have their loan request approved, then these results are consistent with the latter purpose.

The univariate results in Table 4 are not consistent with Hypothesis 1. Without controlling for other factors, being a member of a group is associated with higher default rates, and the difference in means is highly significant. This is consistent with the idea that borderline borrowers join groups in order to increase their odds of getting their loan approved. Of course, this is mitigated by the results reported in Table 3, where group members are shown to pay higher interest rates commensurate with their higher default risk. Table 5, on the other hand differentiates between groups that have the potential for private information and those that don't. The results are consistent with Hypothesis 1. The difference in default mean between relationship groups and non-relationship groups is negative and significant. Default is higher for loans in groups that do not have relationships. This is consistent with the idea that shame and ostracism are significant motivators to avoid loan default (Ghatak, 1999; Williams, 2004). Shame and ostracism would only be a factor where social relationships exist.

Recall that being a member of a group corresponds to the borrower choosing a mix of public and private funding for their debt, whereas not being a member of a group corresponds to the choice of purely public debt. Although it may seem counterintuitive at first that group members pay higher rates—it begs the question of why someone would join a group if the result is merely a more expensive loan. It is important to note that only 7.9% of loan listings during the sample period received enough bids to become funded. Figure II shows failed listings versus successful listings, broken out by credit score. Table 6 presents means of variable categories and the results of logit analyses of the probability of being a high-risk borrower.

Figure II. Listing Success by Credit Score Category



Many borrowers must make multiple attempts before successfully initiating a loan. Successful borrowers have an average of 2.7 unsuccessful listing attempts in their history. Joining a group may be viewed by borrowers as a way to increase the chances of funding, even if the interest rate is not as favorable. Figure III illustrates this concept by showing that group members are more than twice as likely to have their loan funded as non-group members. This explanation is consistent with Petersen and Rajan (1994), who find that deeper lending relationships do not necessarily lower the interest rate, but nevertheless have a positive impact on the availability of credit. The fact that the inclusion of private investors seems to result in higher rates is consistent with the hold-up problem.

The borrowers' decision whether or not to join a group—and then which group to join—is potentially a complex decision with determinants that may be difficult to measure. There is an obvious monetary cost of joining a group in this marketplace, which is the group leader reward (between zero and one percent added to the loan rate). But beyond this, there may be other intangible costs to group membership, such as revelation of private information to other group members, perceived loss of independence (if independence has private benefits), and the prohibition from joining a different group until all loans are repaid. This last cost makes the decision to join a particular group effectively a permanent decision, which may increase the difficulty of making that decision.

Table 3. Descriptive Statistics Concerning Loan Interest Rate Spreads Sorted by Whether They are Members of a Lending Group

	Total			**Member of Group**			**Not a Member**				
	Count	Mean	Median	Count	Mean	Median	Count	Mean	Median	Diff in	
	Obs	Spread	Spread	Obs	Spread	Spread	Obs	Spread	Spread	Mean	
Loan Amount											
1st quartile $0 - 2550	3444	0.13009	0.13163	2080	0.13763	0.14140	1364	0.11859	0.11140	0.0190	***
2nd quartile $2551 to 4600	3252	0.14143	0.14600	1927	0.14597	0.15140	1325	0.13484	0.12879	0.0111	***
3rd quartile $4601 to 8000	3379	0.11989	0.11478	1974	0.12337	0.11901	1405	0.11500	0.10640	0.0084	***
4th quartile $8001 +	3386	0.11294	0.10432	1999	0.11410	0.10640	1387	0.11127	0.09849	0.0028	
Total	13461	0.12496	0.12021	7980	0.13022	0.12640	5481	0.11974	0.10962	0.0105	***
Credit Score											
760+	1398	0.04148	0.03398	627	0.04047	0.03275	771	0.04230	0.03520	-0.0018	
720 - 759	1359	0.06233	0.05640	645	0.05969	0.05540	714	0.06472	0.05644	-0.0050	***
680 - 719	1752	0.08809	0.08253	901	0.08658	0.08083	851	0.08968	0.08440	-0.0031	*
640 - 679	2464	0.11690	0.10985	1399	0.11282	0.10494	1065	0.12227	0.11640	-0.0095	***
600 - 639	2521	0.14765	0.14560	1496	0.14051	0.13657	1025	0.15807	0.15691	-0.0176	***
560 - 599	1874	0.18742	0.19247	1259	0.18022	0.18390	615	0.20217	0.21647	-0.0220	***
520 - 559	2093	0.18489	0.19540	1653	0.18292	0.19126	440	0.19229	0.22660	-0.0094	***
Total	13461	0.12596	0.12021	7980	0.13022	0.12640	5481	0.11974	0.10962	0.0105	***

Table 3 : continued

	Total			Member of Group			Not a Member				
	Count Obs	Mean Spread	Median Spread	Count Obs	Mean Spread	Median Spread	Count Obs	Mean Spread	Median Spread	Diff in Mean	
Borrower Age											
1st quartile 0 - 27	2124	0.12997	0.12608	1235	0.13593	0.13629	889	0.12169	0.11295	0.0142	***
2nd quartile 28 - 31	3060	0.12738	0.12070	1860	0.13334	0.12972	1200	0.11814	0.10632	0.0152	***
3rd quartile 32 - 36	4163	0.12731	0.12374	2497	0.13172	0.12890	1666	0.12071	0.11113	0.0110	***
4th quartile 37 +	4078	0.12131	0.11590	2361	0.12306	0.11650	1717	0.11892	0.11028	0.0041	**
Total	13425	0.12593	0.12010	7953	0.13018	0.12635	5472	0.11974	0.10966	0.0105	***
Is Borrower Homeowner?											
Yes	5681	0.10877	0.09960	3152	0.11238	0.10529	2529	0.10428	0.09425	0.0081	***
No	7780	0.13850	0.13856	4828	0.14187	0.14245	2952	0.13299	0.12682	0.0089	***
Total	13461	0.12596	0.12021	7980	0.13022	0.12640	5481	0.11974	0.10962	0.0105	***
First Loan?											
Yes	13171	0.12653	0.12130	7828	0.13071	0.12650	5343	0.12041	0.11119	0.0103	***
No	290	0.09983	0.08685	152	0.10498	0.09381	138	0.09416	0.07675	0.0108	
Total	13461	0.12596	0.12021	7980	0.13022	0.12640	5481	0.11974	0.10962	0.0105	***

Notes: This table reports summary statistics for the interest rate spread for the sample of 13461 loans initiated between May 31, 2006 and November 6, 2007. Spread is borrower interest rate minus 3-month LIBOR minus group leader rewards. The sample also includes performance data for these same loans through November 30, 2010. Summary results are broken down into three groups: 1) all borrowers; 2) borrowers that are members of any lending group; and 3) borrowers that are not members of a group. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively for t-tests.

Table 4. Descriptive Statistics Concerning Default Rates Sorted by Whether the Borrower is in a Group or Not

	Total		**Group Members**		**Not Members**			
	Count	Mean	Count	Mean	Count	Mean	Diff in	
	Obs	Default	Obs	Default	Obs	Default	Mean	
Loan Amount								
1st quartile $0 - 2550	3444	0.35859	2080	0.41827	1364	0.26760	0.1507	***
2nd quartile $2551 to 4600	3252	0.40221	1927	0.44110	1325	0.34566	0.0954	***
3rd quartile $4601 to 8000	3379	0.34803	1974	0.37082	1405	0.31601	0.0548	***
4th quartile $8001 +	3386	0.41288	1999	0.42221	1387	0.39942	0.0228	
Total	13461	0.38014	7980	0.41303	5481	0.33224	0.0808	***
Credit Score								
760+	1398	0.10801	627	0.10367	771	0.11154	-0.0079	
720 - 759	1359	0.22222	645	0.22016	714	0.22409	-0.0039	
680 - 719	1752	0.29966	901	0.31410	851	0.28437	0.0297	
640 - 679	2464	0.37581	1399	0.39314	1065	0.35305	0.0401	**
600 - 639	2521	0.38754	1496	0.38436	1025	0.39220	-0.0078	
560 - 599	1874	0.50053	1259	0.49563	615	0.51057	-0.0149	
520 - 559	2093	0.62016	1653	0.63944	440	0.54773	0.0917	***
Total	13461	0.38014	7980	0.41303	5481	0.33224	0.0808	***

Table 4: continued

	Total		Group Members		Not Members			
	Count Obs	Mean Default	Count Obs	Mean Default	Count Obs	Mean Default	Diff in Mean	
Borrower Age								
1st quartile 0 - 27	2124	0.38983	1235	0.42186	889	0.34533	0.0765	***
2nd quartile 28 - 31	3060	0.37157	1860	0.42581	1200	0.28750	0.1383	***
3rd quartile 32 - 36	4163	0.38506	2497	0.41770	1666	0.33613	0.0816	***
4th quartile 37 +	4078	0.37567	2361	0.39178	1717	0.35352	0.0383	**
Total	13425	0.37989	7953	0.41255	5472	0.33224	0.0801	***
Is Borrower Homeowner?								
Yes	5681	0.37036	3152	0.39848	2529	0.33531	0.0632	***
No	7780	0.38728	4828	0.42254	2952	0.32961	0.0929	***
Total	13461	0.38014	7980	0.41303	5481	0.33224	0.0808	***
First Loan?								
Yes	13171	0.38251	7828	0.41505	5343	0.33483	0.0802	***
No	290	0.27241	152	0.30921	138	0.23188	0.0773	
Total	13461	0.38014	7980	0.41303	5481	0.33224	0.0808	***

Notes: This table reports summary statistics for loan default for the sample of 13461 loans initiated between May 31, 2006 and November 6, 2007. The sample also includes performance data for these same loans through November 30, 2010. Summary results are broken down into three groups: 1) all borrowers; 2) borrowers that are members of any lending group; and 3) borrowers that are not members of a group. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively for t-tests.

Table 5. Descriptive Statistics Concerning Default for Borrowers in a Lending Group Sorted by the Potential for Personal Relationships

	Total		Relationships Group		Non-Relationships Group			
	Count Obs	Mean Default	Count Obs	Mean Default	Count Obs	Mean Default	Diff in Mean	
Loan Amount								
1st quartile $0 - 2550	2080	0.41827	223	0.17489	1857	0.44750	-0.2726	***
2nd quartile $2551 to 4600	1927	0.44110	215	0.26047	1712	0.46379	-0.2033	***
3rd quartile $4601 to 8000	1974	0.37082	291	0.25086	1683	0.39156	-0.1407	***
4th quartile $8001 +	1999	0.42221	309	0.27184	1690	0.44970	-0.1779	***
Total	7980	0.41303	1038	0.24277	6942	0.43849	-0.1957	***
Credit Score								
760+	627	0.10367	166	0.03012	461	0.13015	-0.1000	***
720 - 759	645	0.22016	126	0.15079	519	0.23699	-0.0862	**
680 - 719	901	0.31410	158	0.16456	743	0.34590	-0.1813	***
640 - 679	1399	0.39314	176	0.30114	1223	0.40638	-0.1052	***
600 - 639	1496	0.38436	166	0.21084	1330	0.40602	-0.1952	***
560 - 599	1259	0.49563	146	0.40411	1113	0.50764	-0.1035	**
520 - 559	1653	0.63944	100	0.55000	1553	0.64520	-0.0952	*
Total	7980	0.41303	1038	0.24277	6942	0.43849	-0.1957	***

Table 5: continued

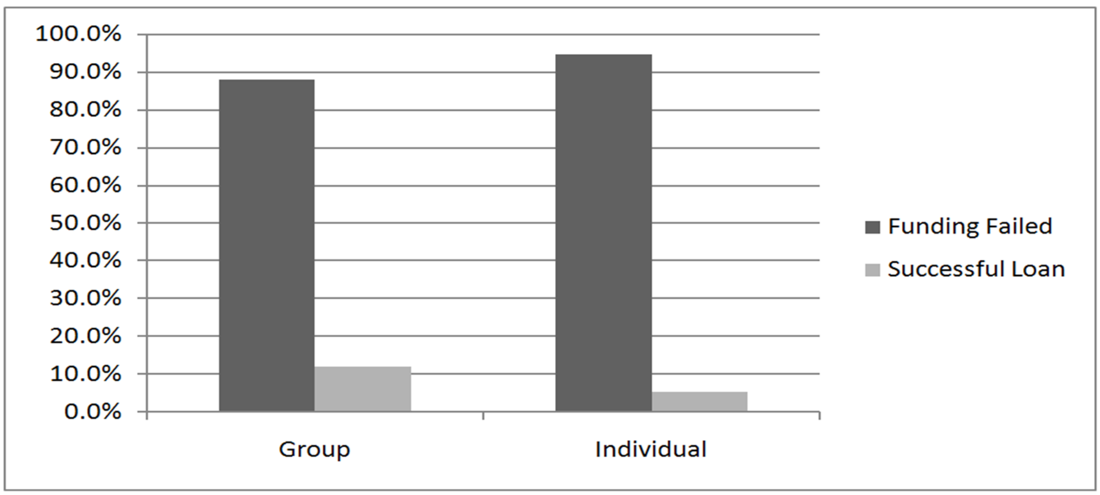
	Total		Relationships Group		Non-Relationships Group			
	Count Obs	Mean Default	Count Obs	Mean Default	Count Obs	Mean Default	Diff in Mean	
Borrower Age								
1st quartile 0 - 27	1235	0.42186	146	0.23288	1089	0.44720	-0.2143	***
2nd quartile 28 - 31	1860	0.42581	235	0.25106	1625	0.45108	-0.2000	***
3rd quartile 32 - 36	2497	0.41770	319	0.26646	2178	0.43985	-0.1734	***
4th quartile 37 +	2361	0.39178	337	0.21958	2024	0.42045	-0.2009	***
Total	7953	0.41255	1037	0.24301	6916	0.43797	-0.1950	***
Is Borrower Homeowner?								
Yes	3152	0.39848	495	0.24242	2657	0.42755	-0.1851	***
No	4828	0.42254	543	0.24309	4285	0.44527	-0.2022	***
Total	7980	0.41303	1038	0.24277	6942	0.43849	-0.1957	***
First Loan?								
Yes	7828	0.41505	1009	0.24579	6819	0.44009	-0.1943	***
No	152	0.30921	29	0.13793	123	0.34959	-0.2117	***
Total	7980	0.41303	1038	0.24277	6942	0.43849	-0.1957	***

Notes: This table reports summary statistics for loan default for the sample of 7980 loans to members of groups initiated between May 31, 2006 and November 6, 2007. The sample also includes performance data for these same loans through November 30, 2010. Summary results are broken down into three groups: 1) all borrowers who belong to a group; 2) borrowers that are members of a group where there is a potential for personal relationships; and 3) borrowers that belong to all other groups. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively for t-tests.

All of these costs are intuitively lower for the SocialLender groups, where the borrower ostensibly has pre-existing relationships that make group selection easier, and where group members may already have informal knowledge of personal information.

The main benefit of joining a group is increased access to credit (clearly represented in Figure II and Figure III). There is also the potential for lower interest rates if the group possesses private positive information about the borrower. For the SocialLender groups, there may exist an additional intangible benefit of increased social interaction.

Figure III. Listing Success by Group Membership



The higher overall default rates for group members in Table 4 suggest that group membership may not effectively mitigate the adverse selection and moral hazard problems associated with peer-to-peer lending. But examining Table 4 in more detail, when the default rates are broken out by credit risk, it is apparent that the higher overall default rates for group members are being driven by the extremely risky borrowers, who may be joining groups simply to gain greater access to credit (Rajan, 1992). If the highest risk borrowers are excluded, then there is generally no statistically significant difference in default mean between members of groups and non-members.

The results in Table 5 are similar to Table 4, in that the differences between the default rates of relationship versus non-relationship groups are negative and highly significant on average for the entire sample. However, when broken out by credit risk, the differences in mean are generally insignificant or of low significance, except for very high risk borrowers.

Since this data set is new and unfamiliar to most readers, Table 6 presents a concise view of the results of logistic estimations of the probability of being a high risk borrower.

Table 6. Risk Outcomes with Logit Estimations of Constraints

	Mean Proportion	Default (All)	Default Pre-Crisis	Default Post-Crisis	High Interest Rate
Loan Amount $0 - 2550	0.256	-0.258***	-0.127***	-0.098***	-0.505***
Loan Amount $2551 to 4600	0.242	-0.180***	-0.095***	-0.063***	-0.352***
Loan Amount $4601 to 8000	0.251	-0.146***	-0.076***	-0.053***	-0.244***
Loan Amount $8001 +	0.252	n/a	n/a	n/a	n/a
Credit Score 760+	0.104	-0.408***	-0.218***	-0.132***	-0.646***
Credit Score 720 - 759	0.101	-0.355***	-0.194***	-0.080***	-0.610***
Credit Score 680 - 719	0.130	-0.331***	-0.185***	-0.058***	-0.612***
Credit Score 640 - 679	0.183	-0.293***	-0.165***	-0.047***	-0.584***
Credit Score 600 - 639	0.187	-0.257***	-0.147***	-0.031***	-0.378***
Credit Score 560 - 599	0.139	-0.150***	-0.087***	-0.008	0.028
Credit Score 520 - 559	0.155	n/a	n/a	n/a	n/a
Borrower Age 0 - 27	0.158	-0.025*	0.006	-0.028***	-0.162***
Borrower Age 28 - 31	0.227	-0.045***	-0.002	-0.038***	-0.130***
Borrower Age 32 - 36	0.309	-0.019*	0.004	-0.020***	-0.046***
Borrower Age 37 +	0.303	n/a	n/a	n/a	n/a
Homeowner	0.442	0.075***	0.024***	0.040***	-0.007
First Loan	0.978	0.090***	0.061***	0.020	0.169***
Member of Group	0.593	0.027***	0.054***	-0.032***	-0.078***
Quickfunding Option	0.343	0.099***	0.075***	0.009	0.367***
Endorsements	0.361	-0.015	-0.054***	0.045***	-0.053***
Pseudo R-squared		0.112	0.132	0.033	0.502
Obs	13461	13461	13461	13461	13461

Notes: The first column presents the proportion of loan population in each variable category. The second column uses loan default as the dependent variable. The dependent variable in the third column is loan default occurring before November 1, 2008. The forth column represents defaults November 1, 2008 and after. The fifth column uses a dummy variable equal to one if the interest rate on the loan is above the mean, indicating that it is a high rate loan. Logit analyses use risk characteristic categories as constraints and report marginal effects. The sample represents bids made on loans between May 31, 2006 and November 6, 2007. The sample includes performance data for these same loans through November 30, 2010. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively for z-scores. Actual z-scores are not reported, in the interest of space.

The borrower categories presented in the previous tables are dummy control variables and the dependent variables are loan default and high interest, which are both ex-post indicators of high risk loans. Pseudo R2 values range from 0.033 to 0.502.

4.2 Multivariate Results

Table 7 reports a set of Probit tests performed in order to test the degree to which the explanatory risk characteristics discussed in the univariate section are actually associated with loan defaults. This is relevant since rational loan pricing should, in theory, depend upon the risk profile of the loan and the borrower. Two dependent variables are addressed in these analyses, default prior to November 1, 2008 (breakpoint for the beginning of the financial crisis that impaired the debt markets), and default anytime thereafter. The coefficients reported are marginal effects. The relevant group characteristics are PrivateLender, a dummy variable that indicates that the group leader has an explicit profit motive, and Ln(GroupLoans), a continuous variable that is a proxy for group activity level.

Table 7. Determinants of Loan Default

	(1)	(2)	(3)	(4)	(5)	(6)
MemberOfGroup	0.060***			-0.035***		
PrivateLender		-0.006			0.041***	
SocialLender			-0.007***			-0.056***
Ln(GroupLoans)		0.018***	0.013***		0.002	0.001
ListingReview		-0.013	-0.014		0.023	0.019
Ln(LoanAmount)	0.075***	0.080***	0.081***	0.066***	0.056***	0.058***
QuickFundingInd	0.082***	0.074***	0.073***	0.010	0.006	0.003
CreditScore	-0.082***	-0.095***	-0.094***	-0.032***	-0.028***	-0.028***
Ln(BorrowerAge)	-0.031*	-0.055*	-0.055*	0.087***	0.088***	0.088***
Endorsements	-0.059***	-0.048***	-0.055***	0.043***	0.035***	0.036***
HomeownerInd	0.030***	0.022**	0.023**	0.035***	0.042***	0.044***
UsuryRate	0.031	0.018	0.014	-0.074***	-0.080***	-0.080***
Pseudo R-squared	0.133	0.123	0.126	0.036	0.036	0.036
Obs	13425	7953	7953	13425	7953	7953

Notes: This table reports marginal effects from Probit analyses with loan default as the dependent variable. This table reports summary statistics for loan default for the sample of 13461 loans initiated between May 31, 2006 and November 6, 2007. The sample includes performance data for these same loans through November 30, 2010. Dependent variable for models 1-3 is default prior to November 1, 2008. Dependent variable for models 1-3 is default occurring November 1, 2008 and after. Standard errors are clustered by group id, except for models (1) and (4). *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively.

The results from Table 7 confirm that when a borrower is a member of a group that has personal relationships, loan default rate is significantly reduced. This result is consistent with Abbink, Irlenbusch and Renner (2006), who find a weakly significant result that private social contact (yet not professional contact) has a positive impact on the decision to repay. Cassar, Crowley and Wydick (2007), however, performed a series of experimental microlending games in South Africa and Armenia and found that mere social contact was not enough, but that reduction of default risk occurred only when those relationships included personal trust. Both of these results are consistent with the results of this paper.

Another interpretation of Table 7 comes from columns (3) and (6), which test Hypothesis 1 by adding the SocialLender dummy to the Probit specification. The coefficient is negative and significant at the 1% level, consistent with the idea that relationships reduce default risk due to increased monitoring (Diamond, 1991; De Aghion and Murdock, 2000; Williams, 2004).

Columns (2) and (5) of Table 7 tests the hypothesis that group leader rewards incentivize the group leader to monitor the loans more carefully, and thus should be associated with lower default rates. The coefficient on PrivateLender in Column (2) is indeed negative, consistent with the hypothesis, but statistically insignificant. The coefficient in column (5) is significant, yet positive. Both of the results are consistent with rejection of the idea that group leader rewards are simply efficient compensation for monitoring.

Table 8 reports the results of OLS regressions with interest rate spread as the dependent variable. Column 1 clearly shows that once control variables are introduced, being a member of a group (any type of group) is negatively associated with the interest rate spread. When differentiating between types of groups, PrivateLenders and SocialLenders display radically different trends. Being a member of a SocialLender group, which ostensibly implies personal relationships, is associated with lower default and that lower risk is reflected in lower interest spreads. PrivateLenders, on the other hand, have a documented profit motive and membership, although also associated with lower default rates, that is not passed along to the borrower in the form of lower interest rates. This is prima facie evidence of the hold-up problem, consistent with Hypothesis 2.

Table 8 reports OLS regressions with loan spread as the dependent variable and the same explanatory variables as Table 7. Since the relationship between risk and return is typically expected to be positive, it is reasonable to expect the coefficients in Table 7 and Table 8 to generally have the same direction and significance. Ln(BorrowerAge), for example remained significant but switched signs. Although older borrowers appear to be less risky, they actually receive higher rates when controlling for loan, group and borrower characteristics. This age effect appears to be inconsistent with extant literature on borrower risk characteristics. PrivateLender kept the same sign (+) but became highly significant (1% level) in Table 8.

If the hold-up problem exists and insider lenders are indeed extracting monopoly rents, then another empirical effect should be apparent. Rajan (1992) predicts that firms with a higher risk of default should be more susceptible to the hold-up problem. This is because for firms with a high probability of success (low risk), the relationship bank's information advantage is small. This prediction has been confirmed empirically by Hale and Santos (2009).

Table 8. Determinants of Loan Interest Rate Spread

	(1)	(2)	(3)	(4)	(5)
MemberOfGroup	-0.0064***				
PrivateLender		0.0053**	0.0053		
SocialLender				-0.0072***	-0.0072*
Private * Ln(GroupLoans)		-0.0012**	-0.0012		
Social * Ln(GroupLoans)				-0.0006	-0.0006
Ln(GroupLoans)		0.0015***	0.0015**	0.0003	0.0003
ListingReview		-0.0056***	-0.0056*	-0.0055***	-0.0055*
Ln(LoanAmount)	0.0197***	0.0212***	0.0212***	0.0212***	0.0212***
QuickFundingInd	0.0319***	0.0281***	0.0281***	0.0281***	0.0281***
Ln(BidCountLastDay)	-0.0025***	-0.0005	-0.0005	-0.0006	-0.0006
CreditScore	-0.0286***	-0.0285***	-0.0285***	-0.0283***	-0.0283***
Ln(BorrowerAge)	0.0224***	0.0186***	0.0186***	0.0187***	0.0187***
Endorsements	-0.0032***	-0.0025***	-0.0025***	-0.0035***	-0.0035***
HomeownerInd	-0.0020***	-0.0032***	-0.0032***	-0.0030***	-0.0030***
UsuryRate	0.0154***	0.0161***	0.0161***	0.0162***	0.0162***
RatioBidByGroup		-0.0824***	-0.0824***	-0.0806***	-0.0806***
Intercept	0.0005	-0.0240**	-0.0240	-0.0178*	-0.0178
R-squared	0.7020	0.6820	0.6820	0.6840	0.6840
Obs	13425	7953	7953	7953	7953

Notes: This table reports ordinary least squares analyses with SPREAD as the dependent variable, indicating the difference between the interest rate on the loan and the 3-month LIBOR rate for loans initiated between May 31, 2006 and November 6, 2007. The sample includes performance data for these same loans through November 30, 2010. SPREAD is net of group leader rewards. Standard errors are clustered by group in models (3) and (5). *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively.

Table 9. Impact of Loan and Borrower Risk Characteristics on the Difference Between Private and Public Bids

	(1)	(2)	(3)	(4)	(5)
PrivateLender		0.0048**	0.0048		
SocialLender				-0.0075***	-0.0075***
Ln(GroupLoans)	-0.0010***	-0.0003	-0.0003	-0.0013***	-0.0013***
Private * Ln(GroupLoans)		-0.0010*	-0.0010		
Social * Ln(GroupLoans)				0.0013**	0.0013**
ListingReview	0.0001	0.0001	0.0001	-0.0003	-0.0003
RatioBidByGroup	0.0051	0.0063	0.0063	0.0058	0.0058
Ln(LoanAmount)	0.0008*	0.0007	0.0007*	0.0008*	0.0008*
QuickFundingInd	-0.0010	-0.0014	-0.0014	-0.0012	-0.0012
Ln(BidCountLastDay)	-0.0000	0.0003	0.0003	-0.0000	-0.0000
CreditScore	-0.0002	-0.0001	-0.0001	-0.0002	-0.0002
Ln(BorrowerAge)	0.0020	0.0022	0.0022	0.0021	0.0021
Endorsements	-0.0002	-0.0003	-0.0003	-0.0003	-0.0003
HomeownerInd	-0.0001	-0.0001	-0.0001	-0.0000	-0.0000
UsuryRate	-0.0033	-0.0035	-0.0035	-0.0033	-0.0033
Intercept	-0.0057	-0.0112	-0.0112	-0.0042	-0.0042
R-squared	0.0160	0.0180	0.0180	0.0200	0.0200
Obs	2012	2012	2012	2012	2012

Notes: This table reports ordinary least squares analyses with DiffSpread as the dependent variable, indicating the difference between the weighted average of insider (private) bid interest rates and the weighted average of outsider (public) bid interest rates. The loans were initiated between May 31, 2006 and November 6, 2007. Standard errors are clustered by group in models (1), (3) and (5). *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively.

Table 10. Determinants of Bid Interest Rate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
MemberOfGroup	-0.0029***						
PrivateLender		0.0015***	0.0015***	0.0014***			
SocialLender					0.0010*	0.0010*	0.0009*
Ln(LoanAmount)	0.0164***	0.0156**	0.0156**	0.0163**	0.0156**	0.0156**	0.0163**
CreditScore	-0.0219***	-0.0213***	-0.0213***	-0.0218***	-0.0213***	-0.0213***	-0.0218***
QuickFundingInd	-0.0027***		-0.0029***	-0.0026***		-0.0029***	-0.0026***
HomeownerInd	0.0023***			0.0023***			0.0023***
Intercept	0.1185***	0.1221***	0.1222***	0.1176***	0.1221***	0.1222***	0.1176***
R^2	0.041	0.041	0.041	0.041	0.041	0.041	0.041
FE Overall R^2	0.626	0.611	0.611	0.625	0.611	0.611	0.625
Sigma u	0.045	0.048	0.048	0.045	0.048	0.048	0.045
Sigma e	0.018	0.019	0.019	0.018	0.019	0.019	0.018
Rho	0.855	0.868	0.867	0.855	0.868	0.867	0.855
Obs	1259532	1285214	1285214	1259532	1285214	1285214	1259532

Notes: This table reports the results of regressions with the bidder minimum acceptable rate as the dependent variable with borrower fixed effects. Controls are implemented for typical risk characteristics. The sample represents bids made on loans between May 31, 2006 and November 6, 2007. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively for t-tests.

Table 11. Effects of Insider Soft Information on Interest Rate Spread

PANEL A: Orthogonalization			
	PIR1	**PIR2**	**PIR3**
CreditScore	-0.002***	-0.000	-0.000
Income		0.000	0.001*
HomeownerInd		-0.002	-0.001
Endorsements		0.008***	0.008***
Ln(LoanAmount)		-0.004***	-0.004***
QuickFundingInd		-0.003**	-0.003**
Ln(BidCountLastDay)		0.000	0.002*
PrivateLender	-0.021***		-0.018***
SocialLender		0.009***	
ListingReview		0.001	-0.001
Ln(GroupLoans)		0.000	0.000
Private * CreditScore	0.001**		
Intercept	0.018***	0.029**	0.021*
R^2	0.025	0.017	0.039
Obs	7980	7980	7980

Table 11: continued

PANEL B: Effect of PIR on Spread								
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
CreditScore	-0.028***	-0.028***	-0.028***	-0.029***	-0.028***	-0.028***	-0.028***	-0.028***
Income			0.000***	0.000	0.001***	0.001***	0.001***	0.001***
BorrowerAge			0.001***	0.000***				
HomeownerInd					-0.002**	-0.002**	-0.002**	-0.002**
Endorsements					-0.005***	-0.005***	-0.004***	-0.004***
Ln(LoanAmount)	0.019***	0.021***	0.019***	0.021***	0.022***	0.022***	0.022***	0.022***
QuickFundingInd	0.035***	0.030***	0.034***	0.029***	0.029***	0.029***	0.029***	0.029***
Ln(BidCountLastDay)			-0.004***	-0.003***	-0.002***	-0.002***	-0.002***	-0.002***
ListingReview					-0.006***	-0.006***	-0.005***	-0.005***
Ln(GroupLoans)					0.000	0.000	0.001**	0.001**
PrivateLender							0.002**	0.002**
SocialLender					-0.010***	-0.010***		
PIR1		-0.106***		-0.104***				
PIR2						-0.098***		
PIR3								-0.102***
Intercept	0.053***	0.043***	0.070***	0.055***	0.058***	0.058***	0.057***	0.057***
Sigma Intercept	0.036***	0.036***	0.035***	0.036***	0.036***	0.035***	0.036***	0.036***
Pseudo R^2	-0.453	-0.419	-0.460	-0.424	-0.420	-0.426	-0.417	-0.424
Obs	13461	7980	13425	7953	7980	7980	7980	7980

Notes: This table reports Tobit regressions for 7,980 peer-to-peer group loans initiated between May 31, 2006 and November 6, 2007. Panel A represents the orthogonization utilized to produce the PIR residuals used in Panel B. In Panel A, the dependent variable is RatioBidByGroup, the ratio of internal bids to external bids for each loan. In Panel B, rate spread (the difference between borrower interest rate and LIBOR, net of group leader rewards) is the dependent variable, and it is censured at zero. The independent variable PIR represents the private information residual from the orthogonalization of public credit score against a proxy for internal credit score. *, **, and *** indicate significance at the 10%, 5%, and 1% levels respectively.

Control variables that should vary negatively with default risk (e.g. CreditScore, Endorsements) are indeed negative and significant, whereas QuickFunding (a proxy for borrower desperation), which is positively associated with default, has a positive and highly significant coefficient in all of the models in Table 8. These results are consistent with Hypothesis 2—the fundamental idea that risk and return are positively related.

Another principal finding from Table 8 is that the presence of relationship lenders vs. arm's-length lenders has a significant impact on the interest rate. In column (5), the coefficient on the variable RatioBidByGroup is negative, very large, and very significant. RatioBidByGroup represents the proportion of insider versus total bids on the loan. If insiders, who are members of the same group as the borrower, have positive soft information about the borrower, then it is reasonable to expect that they will bid on the loan in higher numbers and with more favorable rates than if they were less interested, which must necessarily drive down the ultimate rate charged to the borrower. The result in column (5) supports this conclusion. Table 8 also supports the presence of a hold-up problem by showing that after controlling for borrower characteristics, there is a positive relationship between PrivateLender and interest rate spread, even though group loans should have better selection and monitoring.

Table 9 reports results that address a key research question of this paper. DiffSpread is the dependent variable, which is the weighted average of insider (private) interest rate bids minus the weighted average of outsider (public) bids on each individual loan record. Since public and private data reside on the same loan record, all borrower, group, loan, and time characteristics are fixed, avoiding some of the endogeneity issues related to joint determination of interest rates. There is no need to exogenize the public/private debt choice by doing any econometric exercises such as instrumental variables, propensity score matching, or even fixed effects. In the presence of a hold-up problem, group characteristics should be positively related to DiffSpread. PrivateLender is positively associated with higher insider rates at the 1% level, consistent with a hold-up problem. Columns (4) and (5) test the idea that groups based on social relationships should not be positively associated with differences in spread. Consistent with this idea, the coefficient on SocialLender is negative, which is inconsistent with the presence of a hold-up problem for the social relationship groups.

Another approach to addressing endogeneity is to turn the analysis around by using the interest rate on each individual bid as the dependent variable and then see how group membership affects it. Causality, in this case, is much easier to establish since the bidder ultimately chooses the rate on his bid, based on the published risk characteristics on each loan/borrower. Table 10 presents the results of this analysis. We see that when the borrower and lender are members of the same PrivateLender group, the interest rate on the bid is significantly higher (at the 1% level) by fourteen basis points. Being members of a SocialLender group also appears to be positively associated with the interest rate, but by a smaller amount and at a barely statistically significant level.

Table 11 reports the results of the analyses testing the effects of the soft private group information on interest rates. PIR1 is the variable that represents the orthogonalized residuals of the regression of outside credit score onto the ratio of insider bids to total bids, which is the proxy for inside credit score. Due to the noisiness of the dependent variable, the residuals will be biased toward zero. Therefore a significant result when using PIR1 as an exogenous variable is particularly believable. It is clearly demonstrated in every analysis in Table 11 that private soft information, as captured by PIR1, is strongly significant and has a negative relationship with interest rates, consistent with Hauswald and Marquez (2006), and not consistent with Von Thadden's (2004) finding that favorable info will lead to higher rates.

It could be argued that the significant results for the PIR1 residual are due to omitted variables in the orthogonalization regression. To address this, I calculated two new residual variables called PIR2 and PIR3, which, in addition to credit score, also include all other variables that were previously shown to have significant effects on interest rate spreads (in Table 8). The only difference in the definitions of PIR2 and PIR3 is that PIR2 controls for the borrower being a member of a SocialLender group, whereas PIR3 controls for being in a PrivateLender group. The results of the inclusion of PIR2 and PIR3 as independent variables are shown in columns (6) and (8) of Panel B of Table 11, respectively. Private positive information continues to be associated with lower interest rates.

5. Conclusions

Relationship banking uses soft information gathered via proprietary means to overcome information asymmetries relating to borrower credit-worthiness. Loans granted by relationship lenders with accurate soft information have a lower risk of default and a lower cost. In the presence of open lender competition, these savings should be passed along to the borrower in the form of lower interest rates. But if lenders are able to maintain that soft information as proprietary, then they have the ability to extract monopoly rents from the borrower. This is the hold-up problem.

This paper uses peer-to-peer lending data to illustrate the effects of group composition on adverse selection and moral hazards problems in lending. This particular data set is effective for doing so because it uniquely contains both public and private investor bidding data on the same loan record. Thus, the typical econometric approaches for attempting to exogenize the public/private debt choice are rendered unnecessary. A major contribution of this paper is to show results consistent with the existence of a hold-up problem without the endogeneity problems of prior research in this area.

The paper finds that membership in a group with private information or enhanced monitoring is indeed associated with lower default rates in most scenarios.

In general, lower default rates imply lower lending costs, and these are generally associated with lower interest rate spreads in the data. The degree to which these cost reductions are passed down to the borrower in the form of lower interest rates depends entirely upon the nature of the group to which the borrower belongs. I find that the investors that have characteristics most similar to private banks do, in fact, “hold-up” their borrowers, extracting higher economic rents. I measure the hold-up problem as ranging between fourteen and thirty-eight basis points, which is lower than in previous studies. The hold-up problem appears to be more severe for borrowers with imperfect credit ratings, which is consistent with extant literature. Investors that have social relationships with borrowers, on the other hand, do not hold-up their borrowers but instead pass along the cost savings associated with better monitoring and private information.

Stated simply, the results in this paper are consistent with the existence of a hold-up problem in the peer-to-peer lending marketplace. This hold-up problem may or may not be the same hold-up problem that has been empirically observed in traditional financial intermediation research. Nevertheless, since both hold-up problems appear to be driven by similar information asymmetries, the results of this paper represents a contribution to the overall body of banking literature.

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