Group Social Capital and Lending Outcomes in the Financial Credit Market:

An Empirical Study of Online Peer-to-Peer Lending

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Abstract: We studied the relationship between individuals' group social capital and their lending outcomes in the online peer-to-peer financial credit market, where individual lenders make direct unsecured microloans to other individual borrowers. Despite its ability to facilitate economic exchange, social capital as public goods may also cause free-rider problems, particularly in an online environment. Based on the analyses of transaction data collected from one of the largest online peer-to-peer lending platform in the U.S., we found that the borrower's general group social capital (i.e., group membership) and relational social capital (i.e., group credibility and verifiability, and group trust) yielded inconsistent effects, and the borrower's structural social capital (i.e., group inclusiveness) had a negative impact on, his/her funding and repayment performance. We discuss the implications of our findings for reconciling two major but conflicting theoretical views of social capital and for improving institutional mechanism design in a decentralized online financial credit market.

Key Words: peer-to-peer (P2P) lending; social capital; group social capital; institutional environment; funding performance; repayment performance

1. Introduction

As a new platform of Internet-based financial credit market, online peer-to-peer (P2P) lending presents an alternative source of credit for individual borrowers and a potential investment opportunity for individual lenders to earn higher returns than traditional saving vehicles or to seek charitable interests (Chaffee and Rapp, 2012). Such a platform has grown and evolved rapidly since inception (North American, 2014). Prosper.com, one of the largest online P2P lending markets in the U.S., had originated nearly \$5 billion in loans by September, 2015. However, the market is highly decentralized with no financial intermediaries (Lee and Lee, 2012), which leads to the problem of information asymmetries (Allen and Santomero, 1997). As a result, lenders and borrowers within the market face worse lending outcomes such as high default rates on loans (Chaffee and Rapp, 2012).

Social capital, given its informational and solidarity benefits, has the ability to ameliorate potential inefficiencies caused by information imperfection and to enhance market efficiency (Durlauf and Fafchamps, 2005; Cassar et al., 2007). A core proposition of social capital theory is that valuable resources are embedded within networks of relationship, providing collectively-owned capital for their members to use as credit (Bourdieu, 1986). Social capital can be constructed either as an individual attribute that captures the embedded resources within the individual's social relations to generate a personal economic benefit (Granovetter, 1973; Glaeser et al., 2002), or as a group attribute that enhances group members' transactional efficacy for economic gain (Coleman, 1990; Mizuchi, 1992; Putnam, 1995). Additionally, the group-level social capital in the online P2P lending market such as Prosper.com can be manifested in two types of social networks: group and friendship networks. A group network is formed from within the market *a posteriori*^{II}. In contrast, a friendship network is established outside the online market *a priori*^{III} (Lin et al., 2013).

Despite that the friendship networks of borrowers have been found to be positively associated with the likelihood of their loans getting funded, and negatively related to the interest rate and default risk on funded loans (Lin et al., 2013), there have been few published studies on group networks in the online P2P lending to date. Berger and Gleisner (2009) showed that group membership could help borrowers get access to capital; nevertheless, it overlooked the issue that the effect of group-level social capital might be weakened due to its inherent free-rider problem (Coleman, 1990). Greiner and Wang (2009) revealed that social capital does not provide equal benefits to all members in the P2P lending market. However, the study failed to differentiate group networks from friendship networks. In addition, the ineffectiveness of group networks accounts for many customer complaints (Jaworski, 2007) and anecdotal evidence suggests that group networks do not make a difference to the default risk (Renton, 2011). Thus, it remains unclear as to the effect of group-level social capital on the lending performance. Moreover, the previous studies have yet to examine the possible impact of institutional environment (e.g., formal rules) on social capital.

^{II} Any Prosper's member can create a group and become the group leader who sets up membership criteria; then other members can join the group if they meet the membership criteria. Each individual can be a member of only one group at a time and cannot leave the group or join any other group unless his/her loan has been repaid in full.

^{III} In Prosper.com, a member who has a valid user ID can invite offline friends to join the platform, which migrates offline friendship network to the online environment. Accordingly, members in a friendship network have the offline connections and nonpublic information about each other (Lin et al., 2013).

To fill the research gaps, this study aims to address the following interrelated research questions: *Does the social capital generated from group networks have an effect on lending outcomes in the online P2P lending? What factors contribute to the effect of group networks, if any? How can lending outcomes in the online P2P lending be improved through the institutional design for group networks?*

To answer the research questions, we developed hypotheses by drawing on social capital theories. The online P2P lending provides a suitable context for studying the relationship between social capital and its economic outcomes in an online environment. The hypotheses were tested with transaction data collected from Prosper.com. The results show that the group social capital generated from group networks improves funding performance but has no impact on repayment performance. These findings were further confirmed with two robustness tests.

This research makes multifold theoretical contributions. First, it provides a comprehensive understanding of the role of group-level social capital in an emerging online financial credit market by revealing its dual (i.e., positive and negative) effects and the environments in which either of them occurs. Second, viewing social capital as public goods (Coleman, 1990; Putnam, 1995), this research extends social capital theories by explaining the mixed effects of social capital through the introduction of a new factor – institutional environment. Third, the current study makes suggestions on how to mitigate the negative effects of group social capital via the design of appropriate institutional environments.

The rest of the paper is organized as follows. Section 2 provides the theoretical foundation. Section 3 introduces the research model and develops hypotheses. Section 4 describes data collection. Section 5 reports data analysis results. Section 6 tests the robustness of the main results. Finally, Section 7 discusses and concludes the paper.

2. Theoretical Foundation

2.1 Information Asymmetries in Online P2P lending

Compared with the traditional financial credit market, the online P2P lending market significantly differs in that it has no financial intermediaries (Lee and Lee, 2012), and accordingly its economic outcomes are expected to be worse (Akerlof, 1970). The financial intermediaries, owing to their incentives, expertise, and economies of

scale and scope (Fama, 1985), are commonly viewed as the repositories of "soft" information^{IV} about credit quality (Petersen and Rajan, 2002). Thus, the lack of financial intermediaries could engender information asymmetries (Allen and Santomero, 1997), and the latter contribute to adverse selection and moral hazard problems, which ultimately lead to economic losses (Petersen and Rajan, 2002). In addition, the inherent anonymity and the ubiquity of the Internet environment bring unique challenges to the online P2P lending platforms. First, the information supplied by borrowers often is not verified or accurate, leading to lenders' difficulty in determining the actual creditworthiness of borrowers (Lieber, 2011). Second, the return of the loan is unsecured, and the only dependable agencies to collect the default are the P2P lending platforms themselves, which are commonly known to be ineffective (Chaffee and Rapp, 2012). Therefore, according to the lemons market theory (Akerlof, 1970), information asymmetries that characterize financial markets become more pronounced in the online P2P lending market, which exacerbates the adverse selection and moral hazard problems.

2.2 Social capital

Social capital can play a role in alleviating information asymmetries. Conventionally social capital brings informational and solidarity benefits (Adler and Kwon, 2002). The benefits include improving the lending performance in small uncollateralized loans (Cassar et al., 2007), serving as addition credit information for specific borrowers to facilitate transactions and enhance the efficiency of the online financial market (Lin et al., 2013), increasing the participants' knowledge sharing behavior in a virtual community (Chang and Chuang, 2011), and enhancing venture performance by providing entrepreneurs with access to information (Birley, 1985). Therefore, we draw on social capital theories to examine P2P lending outcomes.

There is no common definition of social capital. Given the focus on the group-level social capital in this research, we adopted Putnam's (1995) definition: *"features of social organization such as network, norm, and social trust that facilitate coordination and cooperation for mutual benefit"*. The conceptualization highlights three direct sources of social capital: networks (Burt, 2009), norms and sanctions (Coleman, 1988), and trust (De Meo et al., 2015). In other words, social capital is developed from informal face-to-face interaction or

^{IV} The information about credit quality beyond credit scores and standard ratios, e.g., Fair Isaac Credit Organization [FICO] scores or debt-to-income ratios.

membership in civic associations, and norm of generalized reciprocity, and is maintained by mutual commitment and cooperation (Putnam et al., 1994; Adler and Kwon, 2002).

In view that the group-level social capital can be viewed by members within the same group and by others outside the group, we characterize the group-level social capital as both privileged (Bourdieu, 1984) and public goods (Coleman, 1990). From the outsider's perspective, group social capital is viewed as a process by which individuals in the dominating class, through the process of mutual recognition and acknowledgement, reinforce and reproduce a privileged group in which various kinds of capital (e.g., economic) are embedded (Bourdieu, 1986). In contrast, from the insider's perspective, social capital is treated as a collective asset that is available to all members regardless of whether members actually promote, sustain or contribute to such resources (Coleman, 1990). As public goods, the value and uses of the social capital are shared by all members. It relies on the good will of individual members who make contributions instead of take free ride, which would otherwise discount its benefits (Coleman, 1990). The above characterization of group-level social capital has important implications for gaining a comprehensive understanding of the role of social capital in online P2P lending.

2.3 Social networks in online P2P lending

To possess social capital a person must be connected to others, and it is a staple notation that the participation in social network has positive consequence for the individual and the community as a whole (Porte, 1998). As the business environment becomes more complex and uncertain, organizations are putting an increasing emphasis on the use of social networks (Mohrman et al., 1995). Despite previous studies on improving the resource availability for individuals or the entire network (e.g., (Oh et al., 2004)), they focused on the optimal network configuration but ignored the embedded context of a social network.

The embedded context likely affects the role of social capital (Leyden, 2003). There are two main types of social networks in an online P2P lending market (e.g., Prosper.com): friendship and group networks. Friendship networks, as strongly embedded relationships, are formed outside the target online economic context with potential real-life connection (Durlauf and Fafchamps, 2005; Lin et al., 2013). Such networks will better economic outcomes by the social stigma cost of default (Lin et al., 2013). In contrast, group networks are formed in a virtual online environment (e.g., online P2P lending market) where group members are anonymous and have little opportunity for face-to-face interaction. Despite that group-level social capital generated from the

social networks can be treated as public goods by the insiders (i.e., members within the networks), the group networks are distinctly different from friendship networks in that the former do not entail physical connections. Additionally, Putnam (1995) discounted social networks driven by financial motivation instead of community building. It is the monetary motivation rather than community building that can better characterize group networks, and the opposite is true for friendship networks in the online P2P lending market. Further, the advancement of network technology partly gives rise to the decline in social capital in the U.S. (Putnam, 1995). Although the Internet facilitates weak ties that may enhance the efficiency of information diffusion (Kavanaugh et al., 2005), these ties could also decrease members' commitment to the online community, and are less capable to foster complex friendships or provide intangible resources (e.g., emotional support) and tangible material aids (Wellman et al., 2001), when compared with offline ties. The lack of high interdependence, frequent interaction and closed structures in group networks may make it difficult to develop and maintain significant levels of social capital (Nahapiet and Ghoshal, 1998; Wasko and Faraj, 2005). As a result, the social sanctions (Besley and Coate, 1995) and peer monitoring (Stiglitz, 1990) in group networks may not be so strong as their offline counterparts to overcome the free-ride problems (Granovetter, 2005). This leads to the weakening effect of group social capital.

An appropriate institution can supply social capital in promoting obligation, norm and sanctions (Knowles, 2006). Institution is defined as "*the rules of the game in a society or, more formally, are the human devised constraints that shape human interaction*" (North, 1990). The institution of the P2P lending market is still fast evolving and is far from maturity (Chaffee and Rapp, 2012), so an emerging and important question is what constitutes an appropriate institution for online P2P lending.

In summary, the inherent limitations of weak ties, anonymity in virtual environment, and the imperfection of governance institutions may undermine the solidarity of group networks and exacerbate the phenomenon of free riders in the online financial market. These limitations could discount the benefits of group social capital, leading to negative lending outcomes.

3. The Research Model and Hypotheses

3.1 Market Background

This empirical study used the transaction data collected from one of the largest online peer-to-peer lending market, Prosper.com. Borrowers were allowed to acquire a maximum of two concurrent loans with the total amount of \$25,000 or less. All loans originated on Prosper amortize over a 36-month period.

Only those members who live in the U.S. with a minimum FICO credit scores better than 520 and who have provided a valid Social Security Number, a driver's license number, and some other personal information can enroll themselves as the borrower^V in Prosper.com. The prospective lenders are also subject to a verification process, and transferring the fund to their Prosper accounts before bidding^{VI}. Once a potential borrower has formally been accepted by Prosper.com as a borrower, he/she could start to make an online listing to seek funding. The listing contains several items reflecting personal credit status such as credit grade, debt-to-income ratio, and number of credit inquiries over the last six months, a free-formed text description of the purpose of the loan, and an image which is not verified by Prosper.com. The listing also includes auction characteristics which indicate the loan amount, the maximum interest rate, and the auction format chosen by the borrower. The actual bidding process follows a reverse auction mechanism, and a lender could bid partially on the loan amount and the minimum participant amount is \$50. The lender could provide his/her own interest rate less than or equal to the borrower's maximum interest rate. If the listing hasn't been fully funded, then the interest rate could be the borrower's asking rate even if the lender's rate is lower. If the loan amount has been fully funded, there would be one of the two results depending on the auction format. In case of closed format, the auction would be closed immediately and the interest rate would be the borrower's asking rate. In case of open format, the auction would stay open until the duration of the auction is ended. The ongoing rate decreases as the lender with the highest rate-bid is competed out, and thus the final rate could be lower than the borrower's asking rate. If the loan has not been fully funded at the end of the auction duration, the listing is deemed as failed.

Only after the listing has been fully funded and further reviewed and approved by Prosper.com is the borrower's listing considered a funding success, and the funds are transferred from the winning bidders' Prosper account to the borrower's bank account. The loan's monthly repayment performance will be recorded and if it is

^V Prosper had reopened after an SEC review in July 2009. After the relaunch, borrowers may reside in any of 47 states in the U.S. besides Iowa, Maine, and North Dakota (en.wikipedia.org/wiki/prosper_marketplace).

^{VI} Bidding on loans was restricted to residents of 29 U.S. states and the District of Columbia after July 2009 (en.wikipedia.org/wiki/prosper_marketplace).

late for two months or more, a collection agency would take charge of collecting the default. The borrower who defaults on his/her loan is not allowed to use Prosper.com anymore.

3.2 The Research Model

According to the lemons market theory (Akerlof, 1970), a rating system can help evaluate the borrower's default probability and collateral mechanism ensure the compensation of creditors' interest when the borrower defaults in financial markets. However, half of the world's population is unable to provide collateral or lacks of formal credit rating from the financial market in reality, which poses hindrance to their obtaining essential funds for fueling economic activities (Barboza and Trejos, 2009). The social capital of an individual may be understood as the certification of the individual's social credential, which substitutes the physical or financial collateral and facilitates the poor's access to the credit (Grootaert and Van Bastelaer, 2002).

In this research, we focus on the impact of group social capital on the funding and repayment performance in the online P2P lending market. Social capital can be described from both structural and relational aspects (Granovetter, 2005). Structural social capital is defined as "*impersonal configuration of linkages between people or unites*" (Nahapiet and Ghoshal, 1998), and relational social capital is defined as "*personal relationships people have developed with each other through a history of interactions*" (Nahapiet and Ghoshal, 1998). In other words, the structural social capital refers to the overall patterns of connections between actors (Bourdieu, 1986), and the relational one refers to the quality of the relationship among actors in the network (Portes, 1998). Both aspects of social capital could create value and impact economic outcomes (Granovetter, 2005).

The economic outcomes of P2P lending is commonly measured with funding performance such as funding success and interest rate, and repayment performance (or default probability) separately (e.g., (Greiner and Wang, 2009; Lin et al., 2013)). As the online P2P lending platform sustains and continues to grow, we are poised to evaluate its performance in terms of both funding and repayment. The research model is shown in Figure 1.

Figure 1. The Research Model

3.3 Hypothesis Development

3.3.1 Funding performance

When a lender makes a lending decision in Prosper.com, he would analyze both of the borrowers' traditional hard credit information and other soft information (e.g., friendship and group membership) (Freedom and Jin, 2014; Lin et al., 2013). The major borrowers in the market are those with low credit grade (Freedom and Jin, 2008). Prior to the SEC review in 2008, Prosper had not implemented stricter credit guidelines for borrowers. As a result, the lenders may have difficulty making their lending decision by solely based on the borrower's hard information. Thus, it is reasonable to expect that lenders rely on the borrower's soft information as a supplement, particularly their group membership, to make the final judgment. This is because only those prospect members who have met the membership criteria established by the group leader are allowed to join the group. Additionally, members within a specific group share some common attributes (e.g., the purpose of borrowing); and such common belief and experiences could create a strong sense of community that contributes to social capital (Portes, 1998).

The benefits of group social capital, as privilege goods, would only be available for the group members (Field, 2003). Thus, borrowers' group membership is expected to improve the funding performance (i.e., funding

success and interest rate) by alleviating the adverse selection problem in online P2P lending. Therefore, we propose the following hypotheses:

Hypothesis 1a: The borrower's group membership will improve his/her funding success.

Hypothesis 1b: The borrower's group membership will lower the interest rate on funded loans.

The above-mentioned borrowers' group membership rests on the assumption that all group-borrowers are homogeneous. However, members of a group can be heterogeneous with respect to their structural or relational social capital. Structural social capital could be measured by the size of social networks (Lin, 1999). Group *inclusiveness* (see Figure 2), which is operationalized as the effective size of a group, reflects the number of social ties that an individual can potentially have within the group (Ahuja, 2000). These ties could facilitate the exchange of resources and enhance the dispersion of novel information (Granovetter, 1973). Nevertheless, if the group size grows too big, individuals would not have enough time to maintain close social relationships and the group cohesion would suffer (Thomas and Fink, 1963). Additionally, since the pressure to repay microloans in the lending market can come from the desire to protect the social connection (Karlan, 2007), so the reduced group cohesion in larger groups would lessen the oversight and peer-pressure to repay. Therefore, according to the economic theories of signaling (Spence, 1973), and the view of social capital as prisms (Lin et al., 2013; Liu et al., 2015), we expect that the borrower from a large group send a negative signal to potential lenders.

Hypothesis 2a: The affiliated group size will lower the borrower's funding success.

Hypothesis 2b: The affiliated group size will increase the borrower's interest rate on funded loans.

From the relational aspect, the interpersonal trust and solidarity can reinforce norms, peer monitoring and peer pressure, enforce sanctions easily, and ultimately impacts the economic outcomes (Moran, 2005). The embedded group resources from which social capital is originated (Bourdieu, 1986) differ in terms of the amount of verifiable information that they can offer. Based on increasing verifiability and credibility of embedded resources, we classify group social capital in the online P2P lending market into a hierarchy using the following three group attributes. It is noted that we do not intend to provide formal definitions of these attributes, but merely provide their context-specific descriptions and rational (see Figure 2).

- *Group verifiability.* Verifiable members can be considered as a more reliable source of information than unverified members for risk assessment, because only the former was allowed to participate in the

transaction process.

- *Group selectivity*. Only a selective subset of the verified group members who were lenders were allowed to make lending decisions. These lender members represent a more credible source of social capital than the borrower-only role.
- *Group cohesion*. Cohesion refers to the interdependencies among group members. Compared with lenders who did not make a bid, the peer lender-members who took the bidding action convey a stronger signal for verification. Such a signal would be even more credible if the bid came from the borrower's group leader.

Figure 2. A Hierarchy of Group Social Capital

The stronger embedded relationships create more value (Granovetter, 1973); and the verified, credible information about the roles and identities of the borrower's friends can mitigate the skepticism about a borrower (Lin et al., 2013). Therefore, we expect that the funding performance show a striking gradation along the verifiability and credibility of a borrower's group social capital.

Hypothesis 3a: The verifiability and credibility of group social capital will show a gradation effect on improving the borrower's funding success.

Hypothesis 3b: The verifiability and credibility of group social capital will show a gradation effect on lowering the borrower's interest rate on funded loans.

The group leader sets up expectations and establishes shared norms (e.g., disclosure or reporting requirement) in the online P2P lending platform. Since the leader has more direct ties to fellow group members, he/she is more likely to comply with the norm and expectation of the group (Rogers and Kincaid, 1981). Accordingly, the group leader's endorsement reflects group *trust* (see Figure 2), or signals online trust (Mukherjee and Nath, 2003), which is an effective way to enhance personal reputation (Heider, 2013). Therefore, receiving the group

leader's endorsement on a borrowing request can be viewed as a positive signal of the borrower's credit quality to potential lenders either within or outside the group.

Hypothesis 4a: Group leader's endorsement will improve the borrower's funding success.

Hypothesis 4b: Group leader's endorsement will lower the borrower's interest rate on funded loans.

3.2.2 Repayment performance

Social capital in the form of strong personal relationships, peer monitoring, and social sanctions, could explain the high repayment performance in group loans (Cassar et al., 2007). However, in light of the online environment where the groups in the P2P lending market are formed, there is little opportunity for peer group members to have face-to-face contact. Additionally, due to its anonymity, the Internet enhances weak online ties and simultaneously decreases strong offline interactions (Kraut et al., 1998). Consequently, the online group may have less solidarity than its offline counterpart, and the personal relationships in the P2P lending market might be weakened. Thus, the borrower's group membership in the online P2P lending market may not help to reduce the loan's default probability.

In an online community where the member commitment is weakened (Wellman et al., 2001), members may not voluntarily contribute their time and effort to monitor other members' behavior, which weakens the effectiveness of peer monitoring. Although larger sized groups entail more peer-monitoring, they also hinder the ability of mutual monitoring when effort contributions are ambiguous and the social relationships are less cohesive, which in turn exacerbates the free-rider problems (Carpenter, 2007).

Group networks in the online P2P lending such as Prosper.com is open, where entry into or exit from a group is free, and a borrower is allowed to leave the current group or join another one once his/her loan is repaid in full. In such an open structure, violations of norms are more likely to go undetected and unpunished (Coleman, 1988); moreover, without strong sanction, moral hazard associated with loan repayment would not be eliminated easily (Stiglitz, 1990). Thus, in the open structure where personal ties are more easily formed and broken which weakens the stigma cost of default, the borrower's group social capital will not show a gradation effect on the loan's default probability. Accordingly, we propose the following hypotheses.

Hypothesis 1c: The borrower's group membership will have no impact on his/her default probability.

Hypothesis 2c: The affiliated group size will increase the borrower's default probability.

Hypothesis 3c: The verifiability and credibility of group social capital will not show a gradation effect on lowering the borrower's default probability.

Existing leadership theories have mainly focused on images of effective or ideal leaders, but given little attention to ineffective leadership (Fulmer and Conger, 2004). Nevertheless, the latter has been characterized as the inability to select good members and to take a long-term perspective (Stashevsky et al., 2006), low concern for tasks (Laissez-faire leadership) (Einarsen et al., 2007), and self-interest without considering the well-being of others (Gunn, 2006). In Prosper.com, a group leader must approve each funding request of his/her group member before it becomes live on the market; additionally, the group leader could receive group leader reward^{VII} (i.e., commission up to 2%), and/or referral reward (for a new borrower-member the leader invited from his pre-existing social networks), upon successful funding of the borrower's request. As a result, the prospective monetary enticement may exacerbate the group leaders' Laissez-fair, self-interests, and short-term perspective taking, which will negatively affect the repayment performance in the online P2P lending market. Thus, we propose the last hypothesis as the following.

Hypothesis 4c: The group leader's endorsement will increase the borrower's default probability.

4. Data Set

We collected the data from Prosper.com. All new listings were stopped in October 2008 due to an SEC review. In order to cover the entire loan lifecycle of 36 months, we selected the listings posted between June 2006 and July 2008^{VIII}. Each listing contains the information about borrower's group membership (if any) at the time. To confirm that the information of each group borrower's peer members was current at the time of a loan request, we matched the creation date of each listing to those of group-borrower's peer members. Each listing was described with three types of variables: 1) dependent variables; 2) independent variables (i.e., the borrower's group social capital); and 3) control variables (e.g., the borrower's financial characteristics, group characteristics, auction characteristics, and friendship network). Only the main variables of the first two categories and their

^{VII} The group leader reward policy had been terminated after October 2007.

^{VIII} Prosper.com ended their auction process and fixed interest rates started to take effect (Prosper 2.0) on Dec 16, 2010 (<http://www.lendacademy.com/prosper-com-ending-their-auction-process-dec-19th/>).

descriptions are listed in Table 1 for the sake of space (see Table 6 in the Appendix for a detailed list of control variables).

Table 1. Description of Key Variables

Variables*	Operationalization	Description
Funding Success	<i>listingStatus</i>	A dummy variable, 1 if the listing was fully funded and approved; 0 otherwise.
The Loan's interest rate	<i>interestRates</i>	The interest rate on listing that was fully funded.
Default Probability	<i>loanStatus</i>	A dummy variable, 1 if the loan defaulted; 0 if the loan was paid in full.
Group Membership	<i>ifGroup</i>	A dummy variable, 1 if the borrower belonged to a group; 0 otherwise.
Group Inclusiveness	<i>groupSize</i>	The total number of borrower's peer group members at the time of loan request.
Group Trust	<i>leaderEndorse</i>	A dummy variable, 1 if the group leader endorsed the borrower; 0 otherwise.
Group Verifiability	<i>ttlUnverifiedMems</i>	#borrower's group members whose identities were not verified.
	<i>ttlVerifiedMems</i>	#borrower's group members whose identities were verified by Prosper.com.
Group Selectivity	<i>ttlPureBorrowers</i>	#borrower's verified group members who were merely borrowers.
	<i>ttlLenders</i>	#borrower's verified group members who were lenders.
	<i>ttlLendersNoBid</i>	# borrower's lender-members who did not make a bid on the borrower's listing.
Group Cohesion	<i>ttlLendersBid</i>	#borrower's lender-members who made a bid on the specific borrower's listing.
	<i>leaderBids</i>	A dummy variable, 1 if the group leader made a bid on the listing; 0 otherwise.

* The first three are dependent variables and the rest are independent variables.

Borrower's group social capital: Given the focus on group networks in this study, we manually coded all the groups that have at least four members using a dummy variable *ifGroup*. Such group networks were selected as the base to measure the borrower's group social capital such as group membership and *groupSize*. In addition, we organized the relational social capital into a three-level hierarchy (see Figure 2). At level 1, group members were differentiated based on whether their identities had been verified (*ttlUnverifiedMems* vs. *ttlVerifiedMems*); the verified group members were further divided based on their role as lenders or merely borrowers at level 2 (*ttlPureBorrowers* vs. *ttlLenders*); lender-role members were in turn classified based on whether they had made a bid on the borrower's listing (*ttlLendersBid*, *leaderBids*, or *ttlLendersNoBid*). We also considered whether the borrower has acquired his/her group leader's endorsement (*leaderEndorse*).

Borrower's financial characteristics: The credit grade is a critical financial factor which reflects the borrower's comprehensive credit standing. The credit grade is categorized into seven levels based on the credit score obtained from FICO. Due to privacy concerns, the original FICO score was modified by Prosper.com using a proprietary model. We included a set of dummy variables, one for each letter grade. In addition, debt-to-income ratio, current delinquency rate, and frequency of inquiry over the last six months reflected a borrower's state of capital constraint; whether or not the borrower is a homeowner reflected the borrower's wealth status.

Group characteristics: We used three dummy variables *listingReview*, *isAcceptNewMem*, and *groupLeaderReward* to represent whether the group had a leader preview policy, whether the group was a close or an open one, and whether the group had a leader reward policy, respectively. We also included four variables

to indicate the different bases of group categories: geographical region, military affiliation, medical purposes, and small business.

Auction characteristics: We characterized each listing's auction by the requested loan amount, format, duration, and total number of biddings. Specifically, *fundingOption* was a dummy variable indicating either a closed or an open format. We also included the borrower's maximum interest rate and its square to test Stiglitz and Weiss's (1981) theoretical model^{IX}.

Other control variables: We took friendship networks into consideration by counting the total number of the borrower's friends in the entire online platform, or within the affiliated group if the borrower had group membership. We used a dummy variable *usuryLaw* to control the effect of interest rate cap in view that some states had usury laws^X in effect. Although the usury law protected the lender's interest, it could also negatively affect the likelihood of loans being funded (Rigbi, 2013). Additionally, we used a dummy variable *highSearchDay*^{XI} as a proxy for the media effect. Other control variables included bank prime rate, the TED spread^{XII} and national unemployment rate, which reflected the daily macroeconomic environment.

5. Analyses and Results

Our sample contains a total of 282,550 listings; among them, 23,935 (8.47%) listings had been successfully funded, and 15,003 (62.68%) of funded loans had been paid in full. The descriptive statistics of the dataset is reported in a hierarchical pie chart with the listings incrementally broken down from the inside out (see Figure 3). The statistics suggests that the borrowers who had group membership were easier to acquire funding but were less likely to repay their loans, compared with non-group borrowers.

Figure 3. Descriptive Statistics of the Listings

^{IX} The maximum interest rate one borrower is willing to pay could serve to attract the potential lenders while an inordinate high interest rate could be deemed with high default risk.

^X After April 15th, 2008, Prosper started collaboration with a bank in an effort to avoid the usury law.

^{XI} *highSearchDay* reflects the abnormal search volume on Google for "Prosper.com", which may be caused by the media and will be used as an IV for an exclusion restriction (Lin et al., 2013) in our empirical models, in view of the limitations (Puhani, 2000) of Heckman's two-stage method (Heckman, 1979).

^{XII} TED spread is defined as the differences between 3-month LIBOR and 3-month treasury bills.

We tested the hypotheses using regression models. *Hypotheses H1a-c* were tested on the whole listing by using *listingStatus*, *interestRates* and *loanStatus* as the dependent variables separately and *ifGroup* as the independent variable. Model 1 estimates the probability that a listing is funded successfully, using a Probit model (see eq. (1)). Model 2 estimates the effect on funded loans' interest rate, using Heckman's (1979) two-stage method (see eq. (2)). Model 3 estimates the probability that the funded loan will default, using Probit model with sample selection (Van de Ven and Van Praag, 1981) (see eq. (3)).

$$\text{Pr } \text{probability}(\text{ListingStatus} = 1 | x) = \alpha_0 + \alpha_1 \text{IfGroup} + \alpha_2 \text{Financial} + \alpha_3 \text{Auction} + \alpha_4 \text{OtherControls} + \varepsilon_i \quad (1)$$

$$E(\text{InterestRates} | x, \text{ListingStatus} = 1) = \beta_0 + \beta_1 \text{IfGroup} + \beta_2 \text{Financial} + \beta_3 \text{Auction} + \beta_4 \text{OtherControls} + \lambda(x, \hat{\alpha}) \quad (2)$$

$$\text{Probability}(\text{LoanStatus} = 1 | x, \text{ListingStatus} = 1) = \chi_0 + \chi_1 \text{IfGroup} + \chi_2 \text{Financial} + \chi_3 \text{Auction} + \chi_4 \text{OtherControls} + \varepsilon_i \quad (3)$$

where x represents the information set about the listing, ε_i the random term, and $\lambda(x, \hat{\alpha})$ the inverse Mill ratio.

These variables and their interpretations will be reused in the subsequent equations.

The results are reported in Table 2. As the table shows, borrowers' group membership positively influences their funding success ($p < 0.01$, $\beta = 0.556$), and negatively influences the interest rates of their funded loans ($p < 0.01$, $\beta = -0.007$); nevertheless, it yields no effect on the default probability of funded loans ($p > 0.1$). Thus, the results support *hypotheses H1a-c*.

Table 2. Results of Regression Analyses Estimating Lending Outcomes

	Model 1	Model 2	Model 3
<i>ifGroup</i>	0.556*** (0.000)	-0.007*** (0.000)	-0.019 (0.379)
<i>amountRequested</i>	-2.503*** (0.000)	0.044*** (0.000)	0.517*** (0.000)
<i>creditGradeAA (dummy)</i>	-0.047 (0.505)	0.0001 (0.880)	-0.267*** (0.000)
<i>creditGradeB (dummy)</i>	-0.096* (0.000)	0.004*** (0.000)	-0.033*** (0.000)

	(0.070)	(0.000)	(0.290)
<i>creditGradeD (dummy)</i>	-0.529***	0.010***	0.056*
	(0.000)	(0.000)	(0.064)
<i>creditGradeHR (dummy)</i>	-2.238***	0.037***	0.600***
	(0.000)	(0.000)	(0.000)
<i>borrowerMaximumRate</i>	13.066***	0.636***	11.021***
	(0.000)	(0.000)	(0.000)
<i>borrowerMaximumrate²</i>	-7.074***	0.131***	-18.011***
	(0.000)	(0.000)	(0.000)
<i>friendNum</i>	0.460***	-0.004***	-0.134***
	(0.000)	(0.000)	(0.000)
<i>(Remaining Controls)</i>		<i>(Included in Estimation)</i>	
<i>Inverse Mills Ratio</i>		-0.027***	
		(0.000)	
<i>Pseudo R²</i>	63.80%		
<i>Wald Chi2</i>	0.000***	0.000***	0.000***
<i>Log Likelihood</i>			-42124.35
<i>* highSearchDay</i>		-0.055***	-0.055***
		(0.000)	(0.000)
<i>Num of Obs</i>	282548	282548	282548

Notes: (1) Model 1 is the Probit model and we obtained similar results with a Logit model; (2) *highSearchDay* is used as an IV in the selection equation of Model 2 and Model 3 but was not included in the equation of interest and repayment performance due to the exclusion restriction; (3) White's heteroskedasticity-corrected statistics are shown in parentheses; (4) For brevity, some covariates are not shown. See Table 6 in the Appendix for detailed descriptions of the remaining control variables; (5) ":", ":", and ":", and ":", represent 0.1, 0.05, and 0.01 levels of significance, respectively.

The models in Table 2 assume that all group-borrowers are homogeneous, which may not hold, particularly in relation to their group social capital. In the following sections, we will examine the effects of group-borrowers' social capital on the lending outcomes in detail.

5.1 Funding Success

Hypotheses H2a-4a were tested using the listings of borrowers who belonged to a group. The Probit model for testing the funding success is defined in equation (4).

$$\text{Probability}(\text{ListingStatus} = 1 | x) = \mu_0 + \mu_1 \text{GroupSocialCapital} + \mu_2 \text{Financial} + \mu_3 \text{Auction} + \mu_4 \text{OtherControls} + \varepsilon_i, \quad (4)$$

where *groupSocialCapital* indicates the structural and relational factors of the borrower's group social capital, which will be reused in subsequent equations.

Table 3 reports the regression results of four models on funding success. Model 1 was refined into other models by gradually increasing the level of verifiability and credibility of the borrower's group social capital in the order of *group verifiability* (Model 2), *group selectivity* (Model 3) and *group cohesion* (Model 4). The results of testing Model 1 show that the number of the borrower's peer group members (*group inclusiveness*) has a negative effect on the funding success ($p < 0.01$, $\beta = -0.1$). The results of Model 2 show that the unverified group members have a negative effect on the funding success ($p < 0.01$, $\beta = -0.086$), and verified group members have no

impact on the funding success ($p>0.1$). The results of testing Model 3 show that peer lender-role group members have a positive effect ($p<0.01$, $\beta=0.182$), the peer borrowing-only members ($p<0.01$, $\beta=-0.157$) and the unverified members ($p<0.01$, $\beta=-0.091$) have a negative effect on the borrower's funding success. The results of Model 4 show that biddings from the borrower's group leader ($p<0.01$, $\beta=0.532$) and peer members ($p<0.01$, $\beta=0.468$) have a positive effect on the funding success, particularly both of the coefficients tripled relative to those for the total number of lender-role group members; even the borrower's peer lender-role group members who did make a bid still contributed to the funding success ($p<0.05$, $\beta=0.076$), with halved coefficient relative to that for the total number of lender-role group members. The effects of peer borrowing-only ($p<0.05$, $\beta=-0.075$) and unverified members ($p<0.01$, $\beta=-0.082$) on the funding success remain negative. In addition, group leader's endorsement yields a positive effect on the borrower's chance of getting funded ($p<0.01$, $\beta=0.5$). Therefore, *Hypotheses H2a, H3a, and H4a* are supported.

Table 3. Results of Regression Analyses Estimating Group-borrowers' Funding Success

	Model 1	Model 2	Model 3	Model 4
<i># groupSize</i>	-0.100*** (0.000)			
<i># ttlUnverifiedMems</i>		-0.086*** (0.000)	-0.091*** (0.000)	-0.082*** (0.000)
<i># ttlVerifiedMems</i>		-0.001 (0.959)		
<i># ttlPureBorrowers</i>			-0.157*** (0.000)	-0.075** (0.024)
<i># ttlLenders</i>			0.182*** (0.000)	
<i>leaderBids</i>				0.532*** (0.000)
<i># ttlLendersBid</i>				0.468*** (0.000)
<i># ttlLendersNoBid</i>				0.076** (0.020)
<i>leaderEndorse</i>	0.578*** (0.000)	0.561*** (0.000)	0.521*** (0.000)	0.304*** (0.000)
<i>(All Controls)</i>		<i>(Included in Estimation)</i>		
<i>Wald Chi2</i>	0.000***	0.000***	0.000***	0.000***
<i>Pseudo R²</i>	63.26%	63.27%	63.33%	63.69%
<i>Number of Obs</i>	73404	73404	73404	73404

Notes: (1) we obtained similar results with a Logit model; (2) White's heteroskedasticity-corrected statistics are shown in parentheses; (3) We only report the results of the independent variables for the sake of space constraint. See Table 6 in the Appendix for detailed descriptions of the control variables; (4) "**", "***", and "****" represent 0.1, 0.05, and 0.01 levels of significance respectively.

5.2 Interest Rate

The fixed interest rate could be acquired only after a listing has been successfully funded. In order to eliminate the selection bias, we adopted the Heckman's (1979) two-step method, with the first step focusing on the funding success and the second step on the funded loan's interest rate (see eq. (5)), to test the *hypotheses H2-4b*.

$$E(\text{InterestRates} | x, \text{Listingstatus} = 1) = \omega_0 + \omega_1 \text{GroupSocialCapital} + \omega_2 \text{Financial} + \omega_3 \text{Auction} + \omega_4 \text{OtherControls} + \lambda(x, \hat{\alpha}) \quad (5)$$

As shown from Table 4, the results on interest rates appear to be consistent with those for funding success (see Table 3). Specifically, in Model 1, one additional member in a borrower's group increases his/her interest rate by 10 basis points (or 0.1%). In Model 2, one additional unverified group member increases the borrower's interest rate by 10 basis points, whereas one additional verified group member has no impact on the interest rate. A breakdown of verified group members based on their roles reveals that one additional borrowing-only group member increases the borrower's interest rate by 10 basis points, but one additional lender-role group member reduces the interest rate by 20 basis points. Furthermore, a lender-role group member who did not make a bid on the borrower's listing contributed to a decrease in the interest rate by 8 basis points; nevertheless, the effect on the interest rate would be stronger if the borrower's peer lender-role group member had made a bid (a reduction of 20 basis points), and would be much stronger if the group leader had made a bid (a reduction of 60 basis points). In addition, the group leader's endorsement decreases the interest rate of borrower's funded loans by 30 basis points. Thus, *Hypotheses H2b, H3b, and H4b* are supported.

Table 4. Results of Regression Analyses Estimating Group-borrowers' Interest Rates

	Model 1	Model 2	Model 3	Model 4
<i># groupSize</i>	0.001*** (0.000)			
<i># ttlUnverifiedMems</i>		0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
<i># ttlVerifiedMems</i>		-0.0001 (0.621)		
<i># ttlPureBorrowers</i>			0.001*** (0.000)	0.0005 (0.160)
<i># ttlLenders</i>			-0.002*** (0.000)	
<i>leaderBids</i>				-0.006*** (0.000)
<i># ttlLendersBid</i>				-0.002*** (0.000)
<i># ttlLendersNoBid</i>				-0.0008* (0.051)
<i>leaderEndorse</i>	-0.004*** (0.000)	-0.004*** (0.000)	-0.003*** (0.000)	-0.001* (0.077)

<i>(All Controls)</i>		<i>(Included in Estimation)</i>			
<i>Inverse Mills Ratio</i>	-0.028*** (0.000)	-0.028*** (0.000)	-0.028*** (0.000)	-0.027*** (0.000)	
* <i>highSearchDay</i>	-0.051** (0.027)	-0.050** (0.029)	-0.054** (0.018)	-0.057** (0.014)	
<i>Number of Obs</i>	73404	73404	73404	73404	

Notes: (1) *highSearchDay* is used as an IV in the selection equations of all the four models but is not included in the equation of interest due to the exclusion restriction; (2) We only report the results of the independent variables for the sake of space constraint. See Table 6 in the Appendix for detailed descriptions of the control variables. The estimates of the first-stage Probit model are consistent with the estimates in Table 3; (3) "*", "**", and "***" represent 0.1, 0.05, and 0.01 levels of significance respectively.

5.3 Repayment Performance

Our data covers the full lifecycle of all the listings originated between June 2006 and July 2008, ending in either full repayments or default. Thus, we were in a position to build a Probit model with sample selection (Van de Ven and Van Praag, 1981) to test the loan's default probability, which can eliminate possible selection bias. The basic model is defined in equation (6).

$$\text{Probability}(\text{LoanStatus} = 1 | x, \text{ListingStatus} = 1) = \kappa_0 + \kappa_1 \text{GroupSocialCapital} + \kappa_2 \text{Financial} + \kappa_3 \text{Auction} + \kappa_4 \text{OtherControls} + \varepsilon_i \quad (6)$$

Table 5 reports the results of model testing. The testing results of Model 1 show that the number of the borrower's peer group members has a positive effect on the default probability ($p < 0.01$, $\beta = 0.034$). The results of testing Model 2 show that the number of unverified group members has a negative effect ($p < 0.01$, $\beta = -0.057$), and that of verified group members has a positive effect, on the default probability ($p < 0.01$, $\beta = 0.1$). The results of testing Model 3 show that the number of lender-role group members has no effect ($p > 0.1$), that of unverified group members has a negative effect ($p < 0.01$, $\beta = -0.058$), and that of group borrower-only members has a positive effect ($p < 0.01$, $\beta = 0.127$), on the borrower's default probability. The results of testing Model 4 reveal that the number of peer lender-role members who have made a bid on the borrower's listing has a negative effect ($p < 0.05$, $\beta = -0.074$), but neither the number of peer non-bidding lender-role group members nor the group leader's bidding has an effect, on the borrower's default probability ($p > 0.1$). In addition, the effects of the borrower's unverified group members and the borrowing-only group members remain unchanged from the results of Model 3. Further, the group leader's endorsement has a positive effect on the borrower's loan default probability ($p < 0.01$, $\beta = 0.11$). Thus, *Hypotheses H2c*, *H3c*, and *H4c* are supported. The results of hypotheses testing are summarized in Figure 4.

Table 5. Results of Regression Analyses Estimating Group-borrowers' Default Probability

	Model 1	Model 2	Model 3	Model 4
# groupSize	0.034*** (0.000)			
# ttlUnverifiedMems		-0.057*** (0.000)	-0.058*** (0.000)	-0.056*** (0.000)
# ttlVerifiedMems		0.100*** (0.000)		
# ttlPureBorrowers			0.127*** (0.000)	0.113*** (0.000)
# ttlLenders			-0.036 (0.108)	
leaderBids				0.006 (0.867)
# ttlLendersBid				-0.074** (0.016)
# ttlLendersNoBid				-0.015 (0.520)
leaderEndorse	0.125*** (0.001)	0.101*** (0.009)	0.112*** (0.004)	0.118*** (0.003)
(All Controls)		(Included in Estimation)		
* highSearchDay	-0.050** (0.031)	-0.049** (0.033)	-0.053** (0.020)	-0.055** (0.016)
Log Likelihood	-15285.83	-15276.38	-15253.94	-15152.87
Num of Obs	73404	73404	73404	73404

Notes: (1) The first stage is Probit regression model and the results are consistent with the estimates in Table 3; (2) highSearchDay is used as an IV in the selection equations of all the four models but is not included in the equation of default probability due to the exclusion restriction; (3) We only report the results of the independent variables for the sake of space constraint. See Table 6 in the Appendix for detailed descriptions of the control variables; (4) "*", "**", and "***" represent 0.1, 0.05, and 0.01 levels of significance respectively.

Figure 4. A Summary of Hypotheses Testing Results

We attempted to include an exhaustive list of control variables in the models following the practice of previous studies on the P2P lending (Greiner and Wang, 2009; Duarte et al., 2012; Lin et al., 2013). Among the key

controls, group-borrowers with better personal financial characteristics were found to be more likely to acquire funding with lower interest rates, and have lower default probability. Conversely, if borrowers had house property, they would be less inclined to repay their loans fully.

The auction characteristics influence the borrowers' funding and repayment performance. Specifically, the closed format encourages aggressive early bidding and helps the listing to become more successfully funded with higher interest rate. However, the two auction formats make no difference to loan defaults ($p>0.1$). In addition, the linear term in the borrower's maximum interest rates has a positive coefficient, and the square term has a negative coefficient with the funding success, which support Stiglitz and Weiss's (1981) model. The total number of bids for a listing have a positive effect ($p<0.01$) on its funding success, and a negative effect ($p<0.01$) on the interest rates of the funded loan and the default probability.

Consistent with Lin et al. (2013), the number of group-borrower's friends was found to have a positive effect on funding success ($p<0.01$) and a negative effect on funded loan's interest rate and default probability ($p<0.01$); and the high search volume on Google has a negative effect on funded loan's interest rate and default probability ($p<0.05$).

We also considered some unique characteristics of the group networks. The results show that compared with open groups, borrowers from closed groups have better funding success ($p<0.01$) and lower interest rates ($p<0.01$), but high default probability ($p<0.01$). In addition, the borrowers from groups with leader reward policies instituted have worse lending outcomes ($p<0.01$). The review by group leaders before publishing increases the borrowers' funding success ($p<0.01$), but makes no difference to their interest rate ($p>0.1$) and default probability ($p>0.1$). Further, the results show that the group category of borrowers has an impact on lending outcomes. Specifically, borrowers from the geography groups more easily attract funding ($p<0.01$), and have lower default probability ($p<0.05$). In contrast, borrowers from the business groups are less likely to attract funding ($p<0.01$); and even if they were funded, they tend to receive higher interest rates ($p<0.01$), and have higher default probability ($p<0.01$).

6. Robustness Test

To examine the robustness of our results, we considered two alternative methods to our main models. The detailed results of the robustness tests are not reported here for the sake of space, but are available from the authors.

6.1 Institutional Environment

When people decide how to behave, they take into account the social, economic and legal implications of their action (Sobel, 2002). Viewing from the perspective of public goods, the benefits of the social capital could be weakened by lacking of both individual's contribution to the resources and strong sanctions to constrict the free-riders (Coleman, 1990). In contrast, an appropriate institution maximizes voluntary contribution to the public goods (Kosfeld et al., 2009). Therefore, institution is likely to have an impact on the role of social capital generated from the group networks.

We classified the institutional environment of Prosper.com into three types based on two significant historical events with respect to its group institutional design. The first event was the introduction of group rating mechanism on Oct 25, 2006 (previously with group leader reward only), and the second was the removal of group leader reward on Sep 5, 2007. Accordingly, we investigated the impact of the institutional environment by segmenting and comparing our panel data when each of the following three types of institutional environment was in place: group leader reward policy only, both group leader reward and group rating, and group rating only.

As we discussed earlier, the group leader reward could exacerbate the leader's self-interest and Laissez-faire (Einarsen et al., 2007), which motivates them to endorse high-risk borrowers (free-riders) to enter the lending market. In contrast, group rating, as a surrogate of group's reputation (Collier and Hampshire, 2010), is a collective property (Tirole, 1996), which influences individual member's welfare and incentive. If any borrower from a group has a default, it will hurt the group rating and reduce other group members' future funding probability. In addition, the group leaders also cherish the group reputation since it is an important asset in his/her own right (Lord and Maher, 2002). Nevertheless, positive reputations are acquired gradually over time (Whitmeyer, 2000), and individuals' behavior exhibits significant time lag in the face of institutional change (Welter and Smallbone, 2011), so the group rating policy may not produce an immediate effect. Thus, we expected that the group leader reward would have a positive impact on the default probability, and the group

rating would gradually reduce group member's default probability by promoting members' conformity, peer monitoring, and peer-pressure.

The results show that, compared with borrowers who did not have group membership, the borrower who belonged to a group more likely to get funded on his/her listing and the funded loan's interest rate was more likely to be lower across the three types of institutions. In addition, the borrower's group membership yielded no effect with group leader reward policy only ($p>0.1$), a positive effect when both group leader reward and group rating were in place ($p<0.05$), and a negative effect ($p<0.05$) when there was only the group rating, on the default probability^{XIII}. Therefore, these results suggest that institution influences social capital and the appropriate institutions could cultivate social capital in promoting economic outcomes.

6.2 Images and Member Endorsement

We included three additional explanation variables into our main model: whether the borrower uploaded a personal image into his/her listing, the number of endorsements from the borrower's peer group members, and the number of endorsements from the borrower's group members who share geographical similarity (a cross-multiply item).

Although personal images are optional and unverifiable, which may naturally be viewed as "cheap talk" in an online lending market, people respond negatively to listings in Prosper that do not contain a picture (Pope and Sydnor, 2011). In addition, adding an image has shown to have a positive effect on the likelihood of getting a loan, and a negative effect on the interest rate (Ravina, 2012). On the other hand, although the more attractive people are treated better, perceived as more productive and are more confident, their actual productivity is the same as less attractive ones (Mobius and Rosenblat, 2006). Therefore, we expect that, providing an image will help the borrowers to attract funding with low interest rate but make no difference to the default probability.

Karlan (2007) found that a higher geographic proximity of the borrowers in a group reduces the default risk. This can be attributed to the fact that group monitoring is more active with greater geographic proximity (Hung, 2006). In addition, members from the groups founded on geographic proximity are likely to also have face-to-face contact and thus know each other better. The endorsement from geography group members could be treated

^{XIII} Using a Cox proportional hazards specification, Lin et al. (2013) showed that the baseline hazard reached a peak at about 10 months, and then slowly wore off.

as a positive signal to the outside lenders, which is expected to help the borrower to attract funding with low interest rates and to lower their default probability.

The results of model testing confirm our predictions and our main results remain unchanged. In addition, providing an image was found to significantly increase the funding success ($p < 0.01$), decrease the interest rate ($p < 0.01$) and have no effect on the default probability ($p > 0.1$). Besides, a member's endorsement has no impact on the lending outcomes ($p > 0.1$); however, the endorsement from group members with geographical similarity would increase a borrower's funding success ($p < 0.1$), lower his/her interest rates on funded loans ($p < 0.01$), and decrease the default probability ($p < 0.05$). Therefore, the two robustness tests demonstrate that our results are robust.

7. Discussion and Conclusion

We propose a research model for explaining the outcomes of online P2P lending via the lens of social capital originated from the online group networks. The first question we asked was: *Does the social capital generated from group networks have an effect on the lending outcomes in online P2P lending?* Based on the data analysis results, we answer 'yes' to the question by showing that the borrower's group affiliation leads to improved funding performance, but no improvement on repayment performance. To answer the second question of *what factors may contribute to the effect of group networks, if any*, we further examined the group social capital from its structural and relational dimensions. Our results show that both dimensions of group social capital influence lending outcomes, and specifically, the borrower's structural group social capital (i.e., group inclusiveness) has a negative effect on his/her lending outcomes; and the borrower's relational group social capital yields inconsistent effects on the *ex ante* and *ex post* outcomes. More specifically, the borrower's group credibility and verifiability has a gradation effect on his/her funding performance but no such an effect on repayment performance; and group trust (i.e., group leader endorsement) helps improve the borrower's funding performance but worsen the repayment performance. Considering the third question, *how can lending outcomes in the online P2P lending be improved through the institutional design for group networks*, we examined whether the effect of social capital is moderated by context factors such as institutional environment. Our results

reveal that the borrower's general group social capital (i.e., group membership) helps improve the repayment performance and alleviate default probability when only the group rating mechanism was in place.

Our findings make several important contributions to the social capital and online markets research. First, the model takes a useful and necessary step toward providing a complete understanding of the role of social capital by reconciling two major but conflicting theoretical views of social capital as privileged and public goods. This study demonstrates that social capital originated from the group networks would be discounted in imperfect institutions, which complements the findings that social capital generated from the friendship networks should facilitate economic exchanges. Moreover, the benefits of such social capital can manifest themselves with the gradual evolvement of institutional environments.

Second, the empirical validations of our research model add new evidence to the fact that the Internet matters, by revealing the "dark side" of social capital through examining the online P2P lending marketplace. The online marketplace is infused with imprecise information and uncertainty attributable to its anonymity and ubiquity. Despite the growing reliance on group social capital in reducing uncertainty and risks in the fast evolving internet-based platforms, this social capital may mislead potential lenders into making wrong lending decisions, worsening their economic outcomes.

Third, this study takes social capital research one step further by shedding light on how to realize the benefits of group social capital in online P2P lending. Our findings suggest that an appropriate institutional environment could serve to supply social capital in improving repayment performance in online P2P lending by enhancing solidarity of the community. Grounded on our empirical findings from the real-world data, our recommendations for institutional mechanism design for the online marketplace have ecological validity.

Indeed, this research fills a gap in the literature by providing explanations for the mixed viewpoints and findings on social capital. Although our research model is expected to be generalizable, the model was tested with one major online P2P lending platform in the U.S. The effects of group social capital could vary with the collectivism of members that emphasizes group goals above individual needs or stresses the importance of cohesion within social groups. Future research may validate the findings of the current study with the online P2P lending market from a distinct national culture. Additionally, despite that our regression models incorporated a large number of control variables, there are other factors that might be relevant but overlooked or inaccessible

due to the nature of the real-world data. Further, the different types of institutions were drawn from the evolving practice of Prosper.com as a convenience sample, which did not consider other alternative institutional mechanisms that might be effective for mitigating information asymmetry in the online environment (e.g., collateral or secured loans in RenRenDai). On a related note, the net effect of institutional environment on the impact of group social capital on economic outcomes of online P2P lending is worthy of future investigation.

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Appendix

Table 6. Description of Control Variables

	Variable	Description
Borrower's Financial Characteristics	<i>creditGradeAA</i>	A dummy variable, 1 if the borrower's credit grade was AA at time of listing; 0 otherwise.
	<i>creditGradeA</i>	A dummy variable, 1 if the borrower's credit grade was A at time of listing; 0 otherwise.
	<i>creditGradeB</i>	A dummy variable, 1 if the borrower's credit grade was B at time of listing; 0 otherwise.
	<i>creditGradeC</i>	A dummy variable, 1 if the borrower's credit grade was C at time of listing; 0 otherwise.
	<i>creditGradeD</i>	A dummy variable, 1 if the borrower's credit grade was D at time of listing; 0 otherwise.
	<i>creditGradeE</i>	A dummy variable, 1 if the borrower's credit grade was E at time of listing; 0 otherwise.
	<i>creditGradeHR</i>	A dummy variable, 1 if the borrower's credit grade was HR at time of listing; 0 otherwise.
	<i>debtToIncomeRatio</i>	The borrower's debt-to-income ratio at time of listing.
	<i>isBorrowerHomeOwner</i>	A dummy variable, 1 if the borrower had his/her own house property at time of listing; 0 otherwise.
Group Characteristics	<i>inquiriesLast6Month</i>	Number of credit inquiries on borrower's credit report within the six months period prior to listing.
	<i>currentDelinquencies</i>	Number of borrower's delinquencies before the current listing.
	<i>groupLeaderReward</i>	A dummy variable, 1 if the borrower's group leader was awarded for successful borrowing; 0 otherwise.
	<i>listingReview</i>	A dummy variable, 1 if the listing was reviewed by the group leader; 0 otherwise.
	<i>isAcceptNewMember</i>	A dummy variable, 1 if the borrower's group was accepting new members; 0 otherwise.
	<i>geography</i>	A dummy variable, 1 if the group was geography based; 0 otherwise.
	<i>military</i>	A dummy variable, 1 if the group was formed based on military affiliation; 0 otherwise.
	<i>medical</i>	A dummy variable, 1 if the group was formed based on medical needs; 0 otherwise.
	<i>business</i>	A dummy variable, 1 if the group was business development based; 0 otherwise.
Auction Characteristics	<i>fundingOption</i>	A dummy variable, 1 if the auction was not closed until reaching the end of the auction duration; 0 if the auction was closed immediately once the listing was fully funded.
	<i>borrowerMaximumRate</i>	The maximum interest rate specified in the borrower's listing.
	<i>borrowerMaximumrate²</i>	The quadratic term of the maximum interest rate specified by the borrower.
	<i>amountRequested</i>	The loan amount requested by the borrower.
	<i>duration</i>	The number of days in which the listing was valid for, incl. 3 days, 5 days, 7 days, and 10 days.
Other Control Variables	<i>ttlBid</i>	The total number of bids on each listing.
	<i>friendNum</i>	Number of the borrower's friends in Prosper.com.
	<i>usuryLaw</i>	A dummy variable, 1 if the borrower was constrained by usury laws; 0 otherwise.
	<i>unemployment</i>	The state's unemployment rate.
	<i>prime</i>	The state's prime interest rate.
	<i>liborTreasury</i>	The difference between 3-month LIBOR and 3-month treasury bills.
	<i>highSearchDay</i>	A dummy variable, 1 if the search volume on Google for "Prosper.com" was higher than the median; 0 otherwise.