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From the wisdom of crowds to my own judgment in microfinance through online peer-to-peer lending platforms

Haewon Yum [a], Byungtae Lee [b,*], Myungsin Chae [c]

[a] Monitor Group, CCMM Buidling F9, Yeodo-dong 12, Yeongdongpo-gu, Seoul, Republic of Korea
[b] College of Business, KAIST, 85 Hoegiro, Dongdaemun-gu, Seoul, Republic of Korea
[c] Dept. of Business Administration, Seoul University Venture and Information, 405 Bongensa-ro Kangnam-gu #402, Seoul 135-090, Republic of Korea

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ABSTRACT

Information asymmetry is one of the fundamental problems that online peer-to-peer (P2P) lending platforms face. This problem becomes more acute when platforms are used for microfinance, where the targeted customers are mostly economically under-privileged people. Most of the prior empirical studies have been based on data from Prosper.com or similar sites that compete in traditional consumer loan markets. Our study examines P2P lending in microfinance for which borrowers are unbankable so that signals on creditworthiness of new borrowers are very limited. In addition, microfinance customers have more incentive to repeatedly seek loans from the market. Under this microfinance setting, we examine how lenders change their decisions as creditworthiness inference becomes increasingly possible through the accumulation of transaction history. Our findings confirm that lenders seek the *wisdom of crowds* when information on creditworthiness is extremely limited but switch to their own judgment when more signals are transmitted through the market. Different information sets are utilized according to the structures of decisions. Due to the possibility of a repeated game, it is also shown that borrowers try to maintain a good reputation, and direct communication with lenders may adjust incorrect inference from hard data when their creditworthiness is questioned.

1. Introduction

Peer-to-peer (P2P) *lending* is a new platform of financial transactions that bypasses conventional intermediaries by directly connecting borrowers and lenders. This new digital intermediary was created on the basis of microcredit principles (Magee 2011) and has rapidly grown in recent years.[1] As of March 2008, over US$500 million in loans originated from over twenty P2P lenders worldwide (Ashta and Assadi 2010a,b, Bruene 2008, Cain 2008, Magee 2011). This exponential growth seems to have continued in the United States (Pengo 2011, Renton 2011) and the United Kingdom (Bachmann et al. 2011). According to Gartner (2010), by 2013, the industry will soar to US$5 billion. Renton (2012) reported that the combined monthly loan volume of Lending Club (www.lendingclub.com) and Prosper.com (www.prosper.com) exceeded US$50 million in February 2012, representing a more than 100% annual growth rate. Some experts expected that P2P online exchange will become an alternative platform for traditional saving and investment (Slavin 2007). One prediction is that, within the next few years, such social banking platforms may have a market share of 10% of the worldwide market for retail lending and financial planning (Gartner 2008). The roots of the emergence of this crowd-sourced funding platform are both economic and philanthropic (Wang and Greiner 2011).

Due to the sudden popularity of this new kind of financial intermediation, P2P lending has garnered significant attention from the mainstream media and academia (Light 2012). P2P lending has quickly emerged as a popular research area in several disciplines (Wang and Greiner 2011, Bachmann et al. 2011). New digital intermediation and the reintermediation of earlier intermediaries offer new benefits as well as new challenges (Hawkins et al. 1999, Chircu and Kauffman 2000, Berger and Gleisner 2009). What has made the P2P lending platform so popular?

1.1. The benefits of P2P lending platforms

There are many benefits of P2P lending platforms compared to loan transactions made through traditional lending institutions. Perhaps the most widely advertised benefit of P2P lending is that borrowers can get loans at a lower rate without collateral, while

* Corresponding author. Tel.: +82 2 958 3604.
E-mail addresses: hyum@monitor.com (H. Yum), btlee@kaist.ac.kr (B. Lee), mlee31@naver.com (M. Chae).

[1] P2P-banking.com lists the largest P2P lending platforms at www.wiseclerk.com/group-news/countries/germany-state-of-selected-p2p-lending-companies.

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lenders can obtain a higher return on their investments (Magee 2011). Though the evidence for high returns on investment from microfinance has been questioned, P2P lending nevertheless has lured investors who have been discouraged by the stock market returns and lower interest rates offered by banks (Brennan 2009). The *Wall Street Journal* has reported that the leading P2P firms have provided investors with 10% or higher annual returns at a time of historically low interest rates. They also have attracted big institutional investors such as hedge funds and wealth-management firms (Light 2012).

The value proposition for P2P lending to borrowers is twofold. First, unbankable borrowers or ones with low credit scores will be attracted to P2P lending platforms, since technology now makes it possible to implement microfinance approaches that rely upon social collateral (Bruett 2007). According to Packer (2010), amid the recession triggered by the global financial crisis, the market for microfinance grew rapidly in 2009, building on the past success of traditional microfinance institutions. The second value proposition for borrowers is that they can acquire loans with lower rates of interest (Wang et al. 2009). Disintermediation of the expensive middlemen associated with traditional financial firms by a more cost-effective online platform has created lower operations costs for the online P2P firms (Klafft 2008a,b). In addition, the increased outreach they achieve through online media has created new economies of scale, and the lower financing costs have contributed to cost reductions for the micro-lending sites (Ashta and Assadi 2010a,b, Magee 2011). Sviokla (2009) reported that the best interest rate at the Lending Club was 7.3% while the bank rate for the same credit was over 13% on average in 2009.

1.2. The countervailing risks that P2P lending platforms experience

While risk may be managed by taking advantage of a portfolio that consists of a large number of microloans with diverse risk levels, there is an inherent risk of default on loans made via the online medium to strangers without collateral. In addition, evaluating a large number of small loans can be time-consuming (Slavin 2007). As online P2P lending platforms play a role in microfinance, the loans that are made have additional risk factors derived from borrower characteristics on top of those from the online environment. Most borrowers in traditional microfinance markets are poor and self-employed (Schreiner 2000). Earlier studies on P2P lending have shown that there is not much variance in borrower characteristics, especially in terms of financial strength and efforts to make a request (Herzenstein et al. 2008, Pope and Sydnor 2011). This is because microfinance serves predominantly disadvantaged customers. In the online P2P lending market, the traditional role of screening to determine whether borrowers are trustworthy is left to individual lenders rather than financial institutions. Thus, there is always the possibility of misrepresentation for borrowers in terms of their creditworthiness. The existence of information asymmetries in the financial market is well known (Sufi 2007), but the information asymmetry between a borrower and potential lenders in the P2P lending market is even more acute. As Cheung (1989) has argued, the sustainability of any economic institution is subject to transaction costs associated with the organization. In dealing with the risks that information asymmetry engenders, it seems that the creators of P2P lending platforms have aspired to the often-cited success story of the Grameen Bank, which reported a continuous and relatively low default rate on loans.

How to deal with the possibility of adverse selection in microfinance is a central theme of research in this area since the long-term success of this new platform depends on the lenders' willingness to place bids continuously when requests are made by risky borrowers in the online environment (Weiss et al. 2010). The prior studies focused mainly on how lenders screen the trustworthiness of borrowers and the effectiveness of different mechanism design features to mitigate the risk of information asymmetry. Many studies have addressed one distinguishing feature of the online P2P lending setting: the utilization of *soft information* by lenders. They show that unverifiable disclosures by borrowers, and the richness of the dialogues between lenders and borrowers tend to affect the loan outcomes, at least in terms of the likelihood of funding (Iyer et al. 2009, Larrimore et al. 2011, Sonenshein et al. 2011, Herzenstein et al. 2011b, Michaels 2012). These studies, as a whole, indicate that lenders combine objective and subjective information available on the market to assess the extent of their uncertainty with respect to the trustworthiness of potential borrowers.

Traditional microfinance institutions have relied upon social networks to overcome adverse selection in their lending practices. To replicate this in the online context, the new P2P lenders have attempted to foster artificial social relationships. The effectiveness of social features in online P2P lending platforms, including friendship, endorsement, and group affiliation – has been intensively studied also (Freedman and Jin 2008, Lin et al. 2011, Berger and Gleisner 2009, Collier and Hampshire 2010, Aghion and Morduch 2000). They claim that social networking built on the online platform has helped to overcome information asymmetries between lenders and borrowers (Herrero-Lopez 2009, Greiner and Wang 2007, Freedman and Jin 2008). Most studies on the social aspects of P2P lending have focused on the group lending feature of Prosper.com. *Group lending* is a mechanism that has been used by many traditional microfinance institutions as a way of monitoring borrower information to reduce information asymmetries and to enforce the rules for repayment (Everett 2010, Bruett 2007). The absence of group liability in the online platform makes it less effective in this market though (Michaels 2012). Wang and Greiner (2011) have claimed that Prosper discovered that the benefits of Grameen Bank's approach to lending, by involving offline groups, does not transfer very well to e-market settings.

There is clear evidence to suggest that an individual lender's capacity to infer from borrower information and group affiliation alone are not sufficient in dealing with the uncertainty associated with the trustworthiness of borrowers. This is partly due to the herding behavior that borrowers demonstrate (Puro et al. 2011, Shen et al. 2010, Zhang and Liu 2012, Herzenstein et al. 2011a). Through herding, lenders not only can interpret information provided by borrowers, but they also can try to infer the creditworthiness of borrowers from observing peer lending decisions. Plott (2000) has shown that markets perform tasks to gather information distributed across a system that describe beliefs, sentiments and opinions, and also aggregate and publish them. As a result, market participants can learn from the market. There is indirect evidence that learning takes place in online P2P lending markets also. Freedman and Jin (2008) have shown that there is a gap between group and individual borrower loan returns, but it is shrinking over time. This can be partially attributed to lender learning. The authors also revealed that the average funding rate on Prosper.com rose from 2005 to 2008, as the market matured. Puro et al. (2011) also have presented evidence about bidder learning. The time to when a loan is funded has become shorter and the dispersion of interest rates has increased. These developments indicate that bidders have improved confidence in evaluating potential borrowers. They also have observed different bidding strategies on the part of lenders over time. They did not elaborate on how lenders learn from different kinds of information though. This study aims to provide an explanation of the how lender learning occurs.

In the absence of effective social ties, it appears that the P2P platforms are continuing to experiment with various new mechanisms and features to internalize transaction costs by encouraging learning from peers and markets. The facilitation of peer learning is essentially an attempt to activate and leverage the *wisdom of crowds*. Ray (2006) has argued that *prediction markets* for financial variables produce surprisingly accurate information, revealing the wisdom of crowds. As a result, such e-markets are among the most efficient markets in history.

1.3. Exploring the wisdom of crowds for lending decisions at Popfunding.com

We will investigate one such experiment that explores how the wisdom of crowds works in our study context. Popfunding.com (www.popfunding.com), the largest P2P lending platform in South Korea, has added new functionality that gives prospective lenders the power to vote on the trustworthiness of borrowers who make loan requests. For each loan request for a few days afterit has been made, the lenders will participate in a voting process to provide their opinions ("yes" or "no") about whether a borrower can be expected to repay the loan successfully. Then, the platform will count the votes so that the collective wisdom is revealed. According to Mauboussin (2008), this wisdom of crowds approach works very well to solve probabilistic problems.

Surowiecki (2004) and Malone et al. (2009) also have pointed out that crowds make good guesses in situations where information resources reside in places that are not known in advance. Under certain conditions, collective intelligence will emerge even with naïve updating of individual beliefs in social networks (Golub and Jackson 2010). Given the relatively high uncertainty in borrower trustworthiness and the lack of lender expertise and information, estimating borrower trustworthiness is a probabilistic problem. So the online P2P lending environment appears to meet the conditions that prior theoretical studies have identified (Golub and Jackson 2010, Ray 2006). Thus, we expect the wisdom of crowds approach to work for the online P2P lending platform, and lenders may be able to take advantage of the voting results when they make credit decisions with respect to different borrowers.

On the other hand, focusing more on the P2P lending platform for the purposes of conducting microfinance activities, we expect that a small increase in information may significantly affect lenders' assessment due to the great initial uncertainty that is involved in this application area. A possible information sources is the past transaction history of the borrowers. In traditional microfinance, it has been shown that past late repayments are useful in predicting future late repayments. According to Schreiner (1999), for example, in Bolivia, borrowers with payments that are late more than fifteen days for a previous loan were 2.8% more likely to be late in repaying current loans by at least fifteen days. Actually, microfinance borrowers have an incentive to make loan requests more than once due to their limited access to funds from traditional financial institutions. Loan customers represented in the data set that we will discuss from Popfunding.com are like this. This is because the platform targets mainly subprime and unbankable customers.

Rational investors will adopt different strategies according to the structure of the decision-making problem they face in the P2P lending markets. As suggested by the prior literature, investors will take advantage of the collective intelligence of the marketplace in dealing with the uncertainties associated with unknown borrowers, but they will become more dependent on their own capacity to infer the trustworthiness of borrowers when more revealing information becomes available to them. In other words, with the accumulation of past loan history, predicting the creditworthiness of a borrower becomes more structured. We will assess Popfunding.com's experiment to exploit the wisdom of crowds.

1.4. Research questions

The idea that uncertainty may change for the lender as borrower transaction history accumulates in P2P lending prompts the following key questions for research. First, does collective intelligence gathered from Popfunding.com's voting mechanism have any impact on loan repayments? Do lenders change their investment strategies according to the structure of the uncertainty-related problems they face in P2P lending? Under what circumstance will lenders use collective intelligence versus their own inferences from more reliable information? We posit that the situations in which one works better than the other will be different depending on the degree of information revealed to the lenders. We expect that the wisdom of crowds will work well with the probabilistic problems that arise with novice borrowers. Past transaction history will work better as borrowers build their reputations through transaction histories. This will make the lenders' problems more structured. While learning and the wisdom of crowds have been hinted at in prior studies, to the best of our knowledge, structural changes in decision-making in P2P lending have not been studied to date.

We empirically tested whether the information set considered by lenders changes as borrowers build their transaction history. For borrowers with no history of receiving loaned funds, the voting results heavily affect the probability of loan success. For borrowers who have past transaction history though, especially for those who were successfully funded at least once before, the voting results were no longer very effective. Instead, the transaction history during the period of repayment turns out to be more important. Our findings thus indicate that the P2P lending market also works as an information gathering mechanism, as suggested by Plott (2000).

The rest of the paper is organized as follows. Section 2 discusses the available literature on P2P lending, microfinance and the wisdom of crowds, and discusses our data source. In Section 3, we present our hypotheses for this research. Section 4 describes the research methodology and the data used for our empirical tests. Section 5 presents the results, and Section 6 concludes.

2. Background and literature

2.1. P2P lending and microfinance

Since Zopa.com launched an online lending platform in 2005 in the United Kingdom, P2P lending sites have popped up everywhere (Ashta and Assadi 2010a,b). Online P2P lending platforms came into the spotlight as they began to provide an alternative to traditional microfinance institutions. *Microfinance*, an important theme in this special issue of *Electronic Commerce Research and Applications*, is often defined as financial services for poor and low-income clients who do not have access to other traditional financial institutions. The term is often used to indicate loans from providers that identify themselves as *microfinance institutions* (MFIs) (Kauffman and Riggins 2012).

This online platform plays a variety of roles in financial intermediation. The structure is well depicted in recent research (Ashta and Assadi 2010a,b, Bachmann et al. 2011, Kauffman and Riggins 2012). They include market-making, loan processing, enabling investment strategy, and community-building activities (Wang et al. 2009). Some of their intermediary roles are similar to traditional financial services firms but others are unique to these new online market-makers. One of the most notable features of P2P lending is that the lending decisions are left to individual lenders for unsecured loans to strangers (Meyer 2007).

There are three main sources of potential risk to lenders who want to invest through this platform: the targeted customers, the online environment, and the lending products. Today, there are many variations in how P2P platforms work (Bachmann et al. 2011), and many of them are for-profit commercial models that try to compete with other financial services. They are gaining popularity in lending to smaller-scale borrowers. Commercial platforms like Zopa.com target broader customer segments beyond those of traditional microfinance, but still have to deal with mostly unknown borrowers, who often lacking credit history or may actually be unbankable in terms of the risks they represent. The anonymous environment of the Internet also hinders the formation of trust among participants (Klafft 2008a,b). Transactions in e-credit marketplaces often involve fictitious user names, so that there is inherent risk of default through fraud in the online platform (Greiner and Wang 2007). As a result, like traditional microfinance, the fundamental problem with making unsecured loans to complete strangers over the Internet is getting any money back at all (Wang and Greiner 2011). In addition, lenders with less expertise in risk management than financial institutes bear significant risk of loan default.

All of these aspects point to the possibility of the borrowers exhibiting opportunistic behavior to exploit lenders by misrepresenting their trustworthiness. Lenders seem to be aware of such risks though. It has been reported that only a small fraction of the listings posted by borrowers at Prosper.com, for example, are ever successfully funded (Freedman and Jin 2008, Chen et al. 2011). In addition, the loan default rates on Prosper.com were reported to be higher than expected (Wang and Greiner 2011). The high level of defaulting borrowers has resulted in disappointingly low average annual returns (Magee 2011). It also has been reported that many lenders who invested funds through Prosper.com were not able to achieve acceptable returns due to the high rate of loan defaults, especially because of the repayment performance of poor borrowers (Klafft 2008a,b).

2.2. Group lending

The relevant theory in finance states that default risk may be lessened by either reducing the information gap between lenders and borrowers, or by strengthening the monitoring of the moral hazard that borrowers exhibit after they obtain a loan. Bruett (2007) shows that the former is the more important for financial institutions. Thus, a financial institution can control the extent of adverse selection by lowering the information asymmetry that occurs between lenders and borrowers. On the other hand, traditional microfinance institutions, including the Grameen Bank in Bangladesh, have implemented increased monitoring to curb the moral hazard that borrowers are likely to create. The Grameen Bank has utilized group lending and group liability as a mechanism to internalize default risk (Hartley 2010).

With the *group lending* mechanism, microfinance institutions provide capital to groups of borrowers rather than to just one borrower. Members within the group have *joint liability*, and thus also have an incentive to monitor each other to reduce the likelihood of default. Individual repayment performance is linked to the group's performance as a monitor (Hartley 2010). This process reduces moral hazard and the transaction costs associated with loan distribution and collection (Paxton 2000). This is exactly what Diamond (1984) found: he pointed out that intermediaries can help overcome asymmetric information by acting as *delegated monitors*. In this case, the intermediaries again delegate monitoring to group members, who serve to minimize the overall monitoring costs of the bank. They also are better, more effective monitors because they have good relationships with the borrowers (Everett 2010, Wydick 1999) and physical proximity to them (Agarwal and Hauswald 2008). Both support good information quality, which is widely known as a characteristic of community banking.

Encouraged by the success of microfinance, Prosper.com developed a mechanism that is analogous to the traditional group lending mechanism in microfinance, only in the online environment. In Prosper.com, both borrowers and lenders can join a group. By joining groups with good payment history, borrowers can enhance their reputations and lenders will be more likely to offer them better interest rates (Slavin 2007).

There have been several studies on the effect of this social feature of the online P2P platform. Everett (2010) hypothesized that group membership is negatively associated with the default rate. if there is a means of social punishment – such as shame or ostracism – that the borrower wishes to avoid. However, it turns out that group membership itself has a positive and significant effect on the default rate, which goes against Everett's hypothesis. His study showed that group membership results in a lower default rate only with groups that have personal relationships or at least the potential for actual face-to-face relationships. Thus, according to Everett (2010), even in a virtual world of limited physical relationships, group formation in the online P2P lending platform may not work very well as a way of risk mitigation. Lin et al. (2011) report that verifiable online friendship has positive impacts on both *ex ante* and *ex post* outcomes though. Friendship not only seems to increase the probability of successful funding but also lowers the loan default rates.

In other related research, Berger and Gleisner (2009) investigated the role of group leaders to whom the platform delegated the screening of potential borrowers and the monitoring of loan repayments. They found that group leaders reduce information asymmetry, especially in dealing with riskier borrowers. However, the results were not entirely consistent. Freedman and Jin (2008) reported that the estimated returns of group loans are significantly lower than those of non-group loans, while the effects of friendship-related endorsements are consistent with those found in other studies. They suspect there are inappropriate incentives for group leaders, who may fund lower quality loans in order to earn rewards. Wang and Greiner (2011) have reported that Prosper.com found that Grameen Bank's group lending practices to close-knit traditional social groups was difficult to transfer to an e-market. They further observed a gradual decline in the proportion of listings with group membership after Prosper.com eliminated rewards to leaders. Thereafter, endorsements from friends grew significantly. We conclude from the literature that traditional remedies successfully developed by the MFIs are not available in the online P2P lending, which presents a new and different set of challenges in financial risk management for the lenders.

2.3. Screening for borrower trustworthiness with unverifiable information disclosures

Since social networks and their related features have a limited impact on lenders' monitoring of borrower moral hazards, the remaining solution that lenders can explore is to alleviate information asymmetries by reducing the information gap between themselves and the borrower. If the market facilitates richer information transfer between these parties, market efficiency will improve. As a way of trying to reduce the information gap, P2P lending platforms have enabled their members to communicate and share knowledge, so that the lenders can utilize non-standard, soft information (Iyer et al. 2009). This kind of information includes such things as a person's identity, their picture, and even the vicissitudes of their life, family and so on. Given this information, lenders can act like private financial institutions (Sugar 2010), by performing value-added actions to screen the creditworthiness of a borrower.

There are many studies that discuss the kinds of information in the online P2P platform utilized by lenders to screen the trustworthiness of borrowers, and how effectively they can infer the creditworthiness of the borrower from this information. Lenders typically base most of their inferences on the borrower's creditworthiness from hard, factual information, but they also non-standard, subjective information (Iyer et al. 2009). This kind of soft information is utilized more in decision-making for the extension of lower credit approvals. As a result, unverifiable disclosures have the potential to affect lending decisions, just as objective, verifiable information does.

Soft information may increase loan funding but still adversely affect the overall quality of the decisions that are made (Michaels 2012, Herzenstein et al. 2011b). Prior research has shown that unverifiable information is associated with an increase in borrower defaults. Sonenshein et al. (2011) also have confirmed that borrower accounts may not provide sufficient information to predict loan performance very well, yet it nevertheless increases the likelihood of favorable lending decisions to borrowers. However, Larrimore et al.'s (2011) research has contradicted these findings. They claim that humanizing personal information does not have a positive association with the borrower's funding success. These findings may indicate that borrowers are misrepresenting themselves (Berger and Gleisner 2009), and this underscores the fact that lenders' ability to infer creditworthiness under uncertainty will be limited.

2.4. Social lending and the wisdom of crowds

The aforementioned findings strongly imply that lenders suffer from negative effects of imperfect information, and often seem to overestimate the quality of their credit decisioAom of crowds in *prediction markets* is much different from the feedback mechanism that is widely used in e-commerce sites such as Amazon (www.amazon.com), TripAdvisor (www.tripadvisor.com) and Yelp (www.yelp.com). Customers rate products and services after they have experienced them, although their sentiments are also the result of crowd-sourced opinions. For those web sites, online ranking systems suffer from a number of inherent biases (Moyer 2010): people who participate in the ranking systems offered by various online platforms have already made their purchases. Thus, they will have had a preference for the products and services they decided to buy, and so they will tend not to give reviews on the products and services with which they are not satisfied (Moyer 2010). In contrast in prediction markets, nobody knows the quality of the products or the services of interest. According to Surowiecki (2004), if the following three conditions are satisfied, then a crowd will be able to offer collectively useful input: (1) it must be diverse; (2) its members must be independent; and (3) it must have some degree of decentralization. Our view is that online P2P lending platforms seem to satisfy all of these conditions relative to crowd-sourced information.

Without financial expertise and lacking the ability to infer the creditworthiness of borrowers from imperfect information, individual investors will not be confident with their own loan decisions as P2P lenders, so they will try to learn from peers as much as possible. A related outcome is that, when people make decisions based on imperfect information in the financial markets, they tend to herd. Several studies have examined herding behavior in the P2P lending market (Lee and Lee 2012, Herzenstein et al. 2011a, Shen et al. 2010, Zhang and Liu 2012). Two aspects of online P2P lending seem to encourage herding. The online P2P microcredit market is a form of *social lending* in which multiple lenders come together to jointly fund a loan request. The online platform enables learning from peers due to transparent information. Zhang and Liu (2012) have shown that lenders accomplish observational learning from herd activity and also from the borrowers' characteristics. They claim, as a result, that herding in the microloan market is rational.

Market outcomes also indirectly suggest that learning is occurring on this platform. The average return for a lender increases as credit history information improves (Magee 2011). Freedman and Jin (2008) suggest that the return gap between group and non-group loans has been closing over time, and that this may be occurring in part due to lender learning. Puro et al. (2011) also have reported that people adjust their bidding strategies according to their learning experience.

With improvement in the market outcomes due to learning, and strong evidence of learning behavior involving herding, we expect that the P2P lending market will try to further leverage the wisdom of crowds to improve market efficiency. Golub and Jackson (2010) have suggested that the beliefs of all of the agents in large societies will converge to the truth if they naïvely update their beliefs by repeatedly taking the weighted average of their neighbors' opinions. On the other hand, Ray (2006) has commented that the comprehensive studies of financial prediction markets suggest that they are remarkably accurate. Popfunding.com, the data source for our study, similarly has been trying to take advantage of the wisdom of crowds by embedding a prediction market feature into its P2P lending platform.

2.5. Popfunding.com: an online P2P lending platform in Korea

This empirical study centers on Popfunding.com (www.popfunding.com), one of the biggest P2P lending platforms in Korea. It was launched in June 2007, and as of February 28, 2011, it had more than 55,000 members. Popfunding.com is an online P2P lending platform whose borrowers are mostly unbankable due to their low creditworthiness. The distribution of Popfunding.com's borrowers confirms that it has mostly been focusing on this segment of customers. Table 1 shows Popfunding.com's borrowers' distribution of credit grades, ranging from 0 to 10 representing the spectrum of the worst to the best risks, including those that are unbankable for most traditional financial institutions. We note that almost 80% of Popfunding.com's borrowers earn an income that is lower than the monthly average income in Korea of KRW2.03 million, as summarized in Table 2. Considering the distribution of borrower credit grades and monthly income levels, Popfunding.com is not a simple lending platform but more of a *microfinance marketplace.* In contrast, the three largest social lending sites – Prosper.com, Zopa.com, and Lending Club – report that approximately 20% of their loans actually are for small businesses (Farrell 2008).

Popfunding.com intentionally targets this segment of borrowers whose credit scores are below the threshold of traditional financial institutions for strategic reasons. The economic turmoil involving the foreign currency crisis in the late 1990s and the more recent global financial crisis has produced a large number of subprime or unbankable customers. Popfunding.com estimates that almost 30% of the workforce in Korea belong to this category, for example.

Table 1
Borrowers' Distribution of Credit Grades.

Credit grade	Number of requests	Credit grade	Number of requests
0	15	6	17
1	0	7	77
2	2	8	137
3	3	9	288
4	3	10	441
5	8		

Notes: This is the standard scoring system shared by all financial institutions in Korea, which is accessed by credit bureaus. Financial services share transaction records with the credit-scoring agencies for better assessment. There are two agencies in Korea for consumer credit scoring, but they use the same scoring system.

Table 2
Borrowers' distribution of monthly income.

Monthly income (KRW)	Number of requests	Monthly income (KRW)	Number of requests
0	420	2–3 M	117
~0.5 M	7	3–5 M	55
0.5–1 M	42	5 M~	6
1–2 M	344		

During the turbulent times of a financial crisis, financial institutions typically struggle with their own survival, and people with low credit scores are routinely denied loans by most retail banks (Pattern et al. 2001).

The financial industry in Korea is still under development and organizations that especially target subprime customers have yet to emerge. Hence, these customers sometimes have to rely on illegal loans by unlicensed loan sharks due to their limited access to mainstream banks. Such exploitation makes things worse for the underprivileged. According to what we learned in three interviews that we conducted between 2008 and 2010 with the founder and CEO of Popfunding.com, H.W. Shin, people with lower credit ratings represent the niche market that is targeted, since there will be no competition from incumbents in the financial industry, other than loan sharks. Shin has claimed: "I hear and see how desperately those unbankable customers want to restore their credit status. They feel that they belong to the lower class when they are denied by banks. It was [this] online community of such people that gave me the idea of this business opportunity. You can see that people with bad credit grades are desperately seeking advice and help to 'clean their names' and restore their dignity. We not only obviously provide lower interest rates but also try to give them the opportunity to restore their pride. These are our main value propositions."

To achieve this value proposition of restoring credit and avoiding the need for a lender's regulatory authority through a government license, the funding process that Popfunding.com uses for transactions is actually intermediated, although its P2P lending platform simulates the direct funding process for loans that traditional lenders use, based on what the borrower experiences. Each loan is disbursed from a savings bank, as a typical consumer loan would be. Popfunding.com provides the savings bank with the aggregate funding received from lenders for the specified loan in exchange for the assignment of the borrower's promissory note. Then, the financial intermediary provides the borrower with the loan proceeds in exchange for a corresponding promissory note from the borrower. Following the assignment from the savings bank, Popfunding.com collects the monthly payments from the borrower and distributes the proceeds to the lenders, based on each lender's pro rata investment in the loan according to the interest rates represented by their bids. This intermediation is very similar to that of Lending Club (Magee 2011). Popfunding.com claims that, by repaying loans to a savings bank, borrowers will be able to restore their credit ratings, which otherwise would remain in the range of unbankable credit.

Popfunding.com has a similar lending process and a reverse auction mechanism that is similar to other global players, such as Prosper.com and Zopa.com. The reverse auction mechanism requires sellers to bid on requests for quotations made by a potential buyer, a process that was popularized by e-commerce sites such as Priceline.com in the late 1990s and early 2000s (Ding et al. 2005). First, a borrower must create a loan request with a specified amount, duration, maximum interest rate, and personal profile, including age, gender and occupation. In addition, Popfunding.com solicits additional rich information based on volunteered disclosures by the borrower, who has an incentive to disclose such information to increase the likelihood of having the loan funded. As shown in Fig. 1, the personal profile includes certificates to verify their information such as certificates of identification, credit, phone number, address, job, income and tax. The platform posts the list of items verified through such certificates and other means. Submitted certificates to Popfunding.com are not shown to lenders publicly, but only the relevant individual financial status information. This included information such as credit grade, debt history and monthly income, and it will be not be revealed to unless a funded borrower delays making a payment so that it becomes

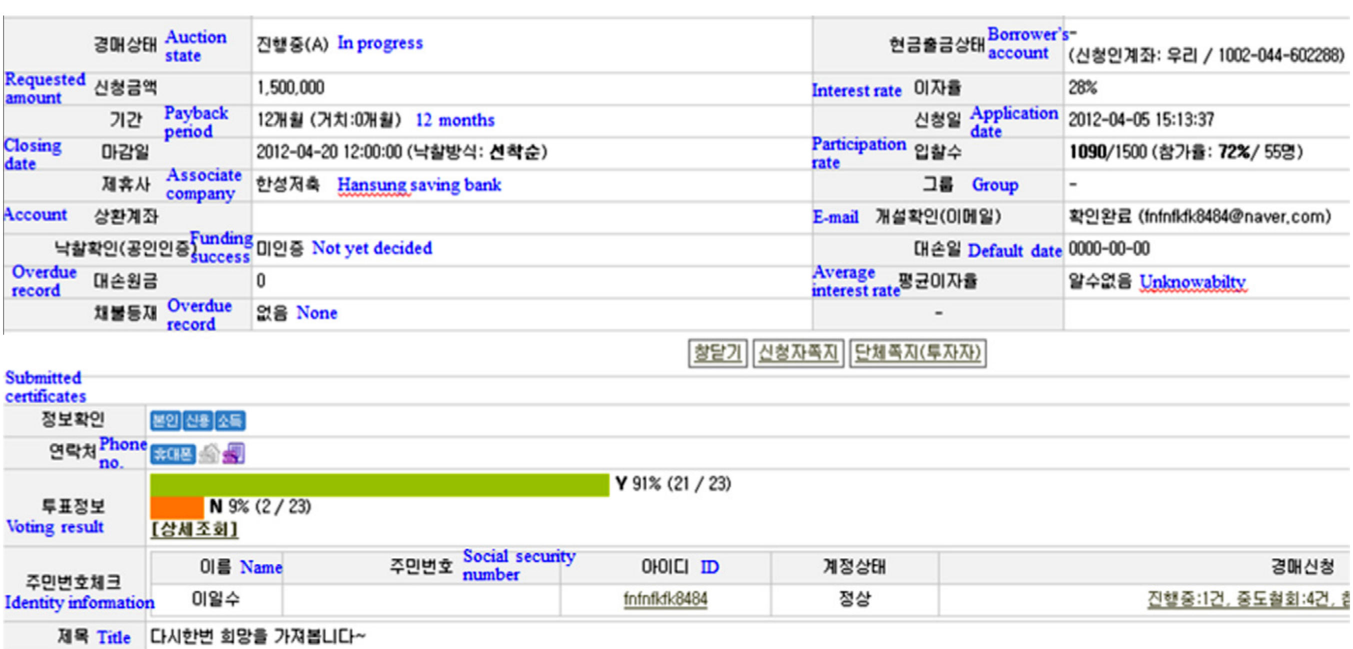

Fig. 1. Screenshot of a borrower's information based on the voting results.

ten days past due. Popfunding.com only reports the existence of the applicable certificates to lenders to help them in their decision-making, and so it acts like a process auditor.

Additionally, borrowers post detailed descriptions of the purpose of loans they would like to obtain and their plans for repayment (Ho 2010), and emotionally appeal to lenders by describing the urgency of their financial needs. Such personal vicissitudes occasionally seem to stimulate lenders' philanthropic motives: good story-telling has been reported to increases the likelihood that a borrower's loan will be funded (Herzenstein et al. 2011a). In addition, sometimes bids with the exceptionally low interest rates between zero and just a few percent can be found.

In the meantime, potential lenders place their bids on the listed loans with the properties described above. They go over basic information, and the loan request descriptions written by the borrowers. Like other online P2P lending platforms, Popfunding.com also provides access to a Q&A bulletin board for each loan request, so lenders can ask questions directly to a borrower in order to acquire additional information. Through the board, the lenders typically ask for more details about purpose of the request, and the borrower's ability to repay. Sometimes they post messages to indicate they are willing to support the borrower. There is also a free bulletin board, where any topic can be shared among every member. Borrowers especially use this space for the purpose of advertising their loans and building relationships with lenders in a friendly and more informal manner. According to Ho (2010), even without this group-lending support feature, social capital has significant effects on loan success. His research has offered empirical evidence to show that social interactions in Popfunding.com have positive effects on the probability of a borrower's success in getting a loan funded. His approach was to count the number of articles on a Q&A board related to the loan request, and use it as a proxy for the creation of social capital.

The next step of the process is for lenders to assess the risks and place a bid on a loan request. If the total bid amount reaches the borrower's requested amount, the loan will be initiated. In cases when the total bid amount exceeds the listed amount, lenders with the lowest interest rates will be granted a stake in the loan. If a loan fails to attract enough lenders, then the loan will be canceled automatically by the system.

What we are focusing on in this study is the simple voting feature that solicits prospective lenders' predictions of the likelihood of repayment by a borrower. The earlier Fig. 1 also shows the results of the potential lenders' voting process. For this borrower, there were 23 prospective lenders who expressed opinions, and 91% of them were positive. For each loan request, for the first few days after the request for funding is listed, lenders vote for screening whether a borrower is reliable enough to successfully repay.

According to previous research on the likelihood of funding success in online P2P lending platforms, each lender who participates in the kind of voting process we have described might consider various factors. They include the borrower's demographic and financial information, such as age, gender and job, and also the borrower's financial strength based on credit grade (Herzenstein et al. 2008), debt history and the number of credit inquiries, the existence of certificates, and past transaction history, if it exists. In addition, the lenders will be interested in the borrower's social activities, including whether any effort has been made to build relationships with them (Ho 2010), as well as the purpose of the loan request.

This feature has a similar function to prediction markets in enabling information to be surfaced that represents the financial wisdom of crowds (Ray 2006). While lenders' predictions are not directly linked to their betting as in normal prediction markets, anyone can check whether lenders who vote actually make a bid on a borrower's loan request. This feature bears a close resemblance to prediction markets. To the best of our knowledge though, Popfunding.com's approach seems unique in that it explicitly explores the possibility of collective intelligence in the P2P lending market. Ray (2006) reported that prediction markets are accurate in predicting many different types of events, and cited another comprehensive study by Credit Suisse First Boston on this topic. If this claim also holds for P2P lending, then this approach should have a beneficial impact to improve the efficiency of the market. This is even more interesting since we have shown that lender inference and other means of information exchange in social settings are still very limited in dealing with the inherent information problems of P2P lending markets.

As we mentioned early, there are three necessary conditions for the crowd to be good at prediction: diversity, independence and decentralization. Additionally, an aggregation mechanism is required that turns disaggregated information on private judgments into aggregated information for collective decision-making (Surowiecki 2004). In Popfunding.com, there is a innovative aggregation mechanism that serves in this capacity. The number of votes and the percentages of "yes" and "no" votes are shown as bar graphs with the number of participants included in Fig. 1 also.

There is no clear explanation about why some prospective lenders participate in the voting process. Motives for knowledge sharing in virtual communities have been intensively studied (Chiu et al. 2006). This voting seems like beneficial knowledge sharing, but there is another possible explanation. Popfunding.com has been experimenting with another way to lure hesitant investors by providing a means for automatically allocating funds according to the investment decisions of the designated successful investors. Popfunding.com publishes a list of *best investors* based on the average return of their loan investments, as well as the cumulative return on investment for those who volunteer to be financial intermediaries. If any novice investor designates one of them and realizes profit, a certain percentage of return will be rewarded to the designated investor. So a possible explanation is that some of these potential lenders may use the voting process as a means of advertising loan opportunities they are interesting in funding, but where others need to come in also.

3. Theory and hypothesis development

3.1. Lender strategies for making credit decisions for high-risk borrowers

Mauboussin (2008) identified the type of decision problems in which collective intelligence prevails. Problems that can be solved with a rule-based process should be left to experts, while collective intelligence from crowds is superior in handling probabilistic problems. Our conjectures on the wisdom of crowds in P2P lending markets are based on Mauboussin's problem classification. We are interested in under what conditions screening a borrower's creditworthiness can be resolved by seeking crowd-sourced opinions.

As we explained earlier, additional disclosures tend to lure more bidding, but are often associated with negative market outcomes. Freedman and Jin (2008) reported that about 30% of Prosper.com's loans that were originated in 2006 were in default by August 1, 2008. So it is obvious that lenders make mistakes in loan selection. Persistent herding behavior in P2P lending also is associated with the information asymmetry-fostered uncertainties in loan selection. An insecure online environment also will only add more uncertainty to the decision-making process.

There is anecdotal evidence that lenders are handling the problem of screening borrowers with different strategies, according to the uncertainty level associated with the borrower. Lenders seem to be much more confident with borrowers who have good credit histories, but they are still struggling with those with poor credit. Freedman and Jin (2008) have reported that the rate at which borrowers' loans are funded in Prosper.com are positively associated with credit grades. Funding rates for the different credit categories are as follows there: 2A: 32.08%; A: 25.45%; B: 21.88%; C: 15.76%; D: 10.35%; E: 5.56%; and HR: 2.39%. Klafft (2008a,b) also has confirmed that P2P lending primarily works well with debtors of good quality in the AA and A categories. Borrowers with weaker credit-ratings are unlikely to be able to borrow so easily via the P2P lending channel. On the other hand, lenders make their investment decisions based on hard information for borrowers of strong credit quality, and use non-standard information when it is likely to provide credible signals regarding borrower creditworthiness (Iyer et al. 2009). Klafft (2008a,b) maintains that the rules that apply in P2P lending are very similar to those of the traditional banking system. Lenders judge seemingly low-risk borrowers with hard, objective information, and use a somewhat different process for deciding about high-risk borrowers. In such cases, in a word, they tend to herd more.

Larrimore et al. (2011) offered evidence that humanizing the personal details for one's current financial situation was negatively associated with funding success. In other words, lenders do not make positive inferences based on the unverifiable disclosures from borrowers when hard information is not enough to do a proper evaluation. Therefore, there is a spectrum of uncertainty regarding the trustworthiness of a borrower in P2P lending that ranges from good enough to be judged by hard information to highly uncertain given a weak credit grade. The former involves a decision about which solutions may be sought with rule-based logic and the latter is a probabilistic one according to Mauboussin (2008).

3.2. The role of collective intelligence

Given the high degree of uncertainty in the P2P lending market, we conjecture that lenders will try to take advantage of collective intelligence in their loan decision-making process. Herding could be a strategic choice under uncertainty but the decision-maker may blindly follow others. However, the voting results explicitly represent the opinions of others with objective measures. If you can observe who participates, the richness of information would be improved further. For example, if lenders with good track records favor a borrower, others may weigh that information more favorably. Note though that there is not much variance in credit grades among Popfunding.com's borrowers because they are predominantly unbankable. There are several factors that may reduce uncertainty in the prediction of a borrower's creditworthiness.

Since Popfunding.com's business model is based on microfinance, participating lenders provide only microcredit, not large sums of money to borrowers. Hence, the borrowers may need to repeatedly borrow money from this platform. Our survey of borrowers reveals that the purposes of the loans they seek are mostly to cover basic living expenses. See Table 3. In addition, unbankable borrowers can improve their credit grades by successful repaying their loans through Popfunding.com, since they are actually offered as typical customer loans from a savings bank. The more they use the system, the more their creditworthiness scores will improve.

Thus, they will have a strong economic incentive to obtain loans repeatedly via Popfunding.com. This leads us to expect that borrowers will strategically try to maintain a good reputation for future loan funding success. Such strategic behavior and transaction history may change the structure of the loan decision problem to lenders though. In fact, good credit in the traditional lending markets is a result of the borrower having a good track record. Hence, collective intelligence from crowds remains more relevant to lender decisions when there is no such historical information on the borrower or her reputation. This is line with Mauboussin's reasoning (2008). Hence, the following hypothesis defines the conditions under which the wisdom of crowds or collective intelligence applies:

Hypothesis 1 (*Collective Intelligence*). Collective intelligence, represented by the aggregated voting results, has a positive effect on the funding success of borrowers who have never been funded previously

Table 3
The purpose of loan requests.

Purpose of loan requests	No. of requests	Purpose of loan requests	Number of requests
Marriage expenses	1	Leisure activities expenses	2
Funeral expenses	15	Medical expenses	142
Payment of a fine	3	Moving expenses	9
Tuition	30	Loan switching fees	112
Housing rent	75	Paying back a private loan	99
Debt guarantee	2	Purchasing or fixing a vehicle	7
Capital for business	53	Credit card payment	2
Cost of living	99	Settlement expenses	1

Table 4
Survey results for the borrowers.

Psychologically pressing factors arising during the repayment period	Number of recipients	Percentage
Relationships with lenders on Q&A or other b-boards	17	47%
Voting results	4	11%
Disclosed documents of certifications	1	3%
The possibility of the next loan request	11	31%
Other	3	8%
Total	36	100%

3.3. The role of transaction history

We already have illustrated why borrowers in this P2P lending platform may seek loans more than once to build good reputation. Our data confirm this. As of July 31, 2010, out of a total 5723 loan listings, there were 3402 requests that had at least one past request. In addition, borrowers who were funded before requested 452 loans. This observation implies that repeated loan demand is strong in this microloan market.

We also asked whether borrowers will try to maintain good reputations. To this end, we conducted a survey for two weeks between November 29 and December 13, 2010. It included participants who were successfully funded and who repaid their loans on Popfunding.com. We posted survey questions on Popfunding.com's webpage with help from the platform. There were 534 subjects out of 738 funded borrowers during the period our data covers. They were asked: What is the most pressing psychological factor that arises during the repayment period? Table 4 summarizes our results. It is clear that the social relationship with lenders and the possibility of a future loan request influence borrowers to keep up with their loan repayment schedules. Thus, it is reasonable that borrowers have an incentive to maintain a good reputation even after they have had a loan funded.

In traditional microfinance, first-time borrowers are known to be riskier to finance than second-time borrowers (Schreiner 1999). We observed very intensive information exchanges between a borrower and lenders when a loan request was listed. It appears that some borrowers learn from sharing information in the market, since their loan requests were funded after they experienced a few failed trials for funding. This implies that lenders also learn as more information is exchanged with a borrower and from the borrower's repeated loan requests.

The next hypothesis examines whether lenders are able to make inferences from the transaction history of borrowers and their effort to keep good reputations. The number of loan requests that a borrower makes after having a loan funded once should be more likely to be funded, since additional historical information on repayment is available to potential lenders. In other words, a transaction history is a substitute for a good credit rating. That changes the decision problem from a probabilistic to a logical one. As a result, lenders may seek collective intelligence somewhat less for loan requests that have an accompanying transaction history, especially for borrowers who have been funded before.

Hypothesis 2.1 (*Past Loan Activities*). The number of loan requests significantly affects the funding success of a borrower

Hypothesis 2.2 (*Past Loan Success*). The number of loan requests after a borrower has been funded has a positive effect on the borrower's funding success

3.4. The role of past investment history and loan amounts

Though online P2P lending adopted the reverse auction mechanism by which a borrower (acting as the seller) lists a loan request (as the product) and lenders (acting as buyers) place bids with certain amounts and interest rates, the boundary between the lenders and the borrower is not that clear. Because of the small amounts of funds that are permissible in a Popfunding.com transaction, some of the past borrowers also become lenders. As of July 30, 2010, among 3077 distinct borrowers who posted loan requests, 8% of them (276 people) had an investment history. However, this number only counts successful bidders among past borrowers. If all trials of bids by borrowers who made loan requests at least once were considered, the proportion would be expected to be higher. When it comes to successfully funded borrowers, this figure is strikingly high. Among 551 unique borrowers over 863 loan auctions, 276 borrowers had investment experiences (32%). Hence, past investment history seems to improve the likelihood of current funding.

In such a case, the borrowers' investment activities are expected to signal to other lenders that the borrowers will remain in the platform. Therefore, investment records, in terms of frequency and amount of investment, may be viewed as positive signals of a past borrower's commitment to the P2P lending community. Hence, we expect similar effects of this information on lenders' decisions, as follows:

Hypothesis 3.1 (*Past Investment Frequency*). For borrowers who were funded before, the greater the number of investments they have made, the higher the probability of current loan funding success

Hypothesis 3.2 (*Past Investment Amounts*). For borrowers who were funded before, the greater the investment amount was, the higher the probability of current loan funding success.

3.5. The role of past repayment records and creditworthiness

When lenders make a decision about placing a bid on a loan, if a previous delay of payments on the borrower's part is observable, this will diminish the uncertainty associated with decision-making, by providing risk-related information to lenders. According to Schreiner (1999) on microfinance borrowers in Bolivia, those with arrears of more than fifteen days in their previous loan were 2.8% more likely to delay payment for at least fifteen days in their current loan. According to Ba and Pavlou (2002), in the online auction market eBay, negative ratings are significant when expensive products are involved in the transactions. A product's faults are more seriously discussed, and negative feedback becomes more important. We anticipate that a history of past delays will have negative effects on a potential borrower's success to get a loan funded. In this research, we will consider both payment delay frequency and payment delay length. In contrast, a record that shows early payment behavior is expected to positively influence loan funding success. Thus, we propose:

Hypothesis 4.1 (*Overdue Payment Frequency*). For borrowers who were funded before, the number of overdue payments will have a negative effect on the probability of a borrower's loan funding success.

Hypothesis 4.2 (*Overdue Payment Time*). For borrowers who were funded before, the length of time that payments are overdue will have a negative effect on the probability of a borrower's loan funding success.

We further propose:

Hypothesis 5 (*Early Payment Frequency*). For borrowers who were funded before, early payments will have a positive effect on the probability of the borrower's loan funding success.

Although borrowers keep in mind the possibility of their next loan requests and their relationships with lenders, sometimes they are not able to meet their loan payment deadlines due to external factors. It is hard for lenders to distinguish inevitable delays from deliberate ones though. Borrowers can present information about their situations by posting articles on the bulletin boards, and signal lenders so that they can prevent failure the next time they list a loan request.

The use of extended narratives, accounts, and concrete descriptions is positively associated with the likelihood of funding (Herzenstein et al. 2011a, Larrimore et al. 2011, Sonenshein et al. 2011), Ho (2010) also has shown that the number of articles written by a borrower on a Q&A board can significantly affect a borrower's loan success. We are testing whether such qualitative information still has a positive impact on loan funding success when lenders are exposed to the negative information associated with a borrower's payment delay.

Hypothesis 6 (*Information Exchanges During Overdue Payment Period*). For borrowers who were funded before, in spite of having a repayment delay, the number of postings by a borrower on Q&A or free bulletin board still will have a positive effect on the probability of the borrower's funding success.

An overview of the hypotheses is presented in Table 5.

4. Research methodology and data

4.1. Methodology and variables

We will test the role of the voting results on the online P2P platform considered in Hypothesis 1, and the impact of transaction history on loan funding success when a borrower has experienced loan funding success before in Hypotheses 2–6. We analyze a binary logistic regression, using SPSS 18's backward LR method. Since the dependent variable, loan funding success, is binary, linear regression is inappropriate, and a limited dependent variable model will be more effective.

Table 5
Hypotheses in this study.

Number	Hypotheses
H1	**The Collective Intelligence Hypothesis.** The collective intelligence, represented by the voting results, has a positive effect on the funding success of borrowers who have never been funded.
H2.1	**The Past Loan Activities Hypothesis.** The number of loan requests borrowers make affects their current loan funding success.
H2.2	**The Past Loan Amount Hypothesis.** The number of loan requests borrowers makes after being funded has a positive effect on their current loan funding success.
H3.1	**The Past Investment Frequency Hypothesis.** For borrowers who had loans funded before, the greater the number of prior investments, the higher the probability of current loan funding success.
H3.2	**The Past Investment Amount Hypothesis.** For borrowers who had loans funded before, the greater their prior investment amount, the higher the probability of current loan funding success.
H4.1	**The Overdue Payment Hypothesis.** For borrowers who had loans funded before, the number of overdue loan payments has a negative effect on the probability of current loan funding success.
H4.2	**The Overdue Payment Time Hypothesis.** For borrowers who had loans funded before, longer payment delays have a negative effect on the probability of current loan funding success.
H5	**The Early Payment Hypothesis.** For borrowers who had loans funded before, early loan payment has a positive effect on the probability of current loan funding success.
H6	**The Information Exchanges During Overdue Payment Period Hypothesis.** For borrowers who had loans funded before, though they may have had a payment delay, the number of their postings on a Q&A bulletin board or a free bulletin board has a positive effect on the probability of current loan funding success.

This study is about factors affecting lenders' decision-making for placing a bid under different levels of uncertainty. Since observing each bid is too costly, we will use the auction as the unit of analysis. Since funding success reflects the collective opinion of every participating lender, to measure the effects of collective intelligence and social dynamics on P2P lending, use the auction as the unit of analysis is appropriate. The heterogeneous characteristics of each lender also are eliminated by using this unit of analysis.

The fundamental premise in this research is that, to lenders, the prior transaction records bear information value regarding the creditworthiness of the borrower. To test this, we split the borrowers into two sample groups: (1) those who did not have any prior funding history and (2) those whose loan requests were funded once. We tested these two samples using two regression models. Model 1 examines a sample of borrowers who received no prior loan funding. In contrast, Model 2 estimates a sample of borrowers who received prior funding. Table 6 shows the distribution of prior loan funding successes.

In both models, the dependent variable is loan funding success (with 0 for failure and 1 for success). The independent variables used in common across both models are presented in Table 7. The variables are observable regardless of the borrower's prior funding success. The variables documented borrower information based on verified certificates, the number of past loans, social activities represented by the number of articles on a Q&A bulletin board, loan investment activities, the voting results and the related loan characteristics. The latter includes the amount and duration of the loan. The number of articles written by a borrower before a loan is successfully funded and the total number of articles written by both a borrower and lenders are added to reflect the extent of social interaction between them. The specification of this variable is consistent with previous empirical studies (Herzenstein et al. 2011a, Larrimore et al. 2011, Sonenshein et al. 2011, Ho 2010).

Table 6
Distribution of the number of loans according to previous funding successes.

Number of previous successes before the current one	Number of loan requests	Sample group
0	4822	Sample 1
1	252	Sample 2
2	85	Sample 2
3	32	Sample 2
4	11	Sample 2
5 or more	9	Sample 2

Table 7
Independent variables for both regression models.

Variable	Description	Possible Value
Cert_id	Whether borrower ID certificate exists	0/1
Cert_addr	Whether borrower address certificate exists	0/1
Cert_cohab	Whether borrower is certified as living with others	0/1
Cert_marriage	Whether borrower marriage is certified	0/1
Cert_income	Whether borrower income is certified	0/1
Cert_credit	Whether borrower credit rating is certified	0/1
Cert_asset	Whether borrower assets are certified	0/1
Cert_num	Total number of existing certificates for borrower	[0, 1, ..., 7]
Past_req_num	# past loan requests by borrower	[0, 1, ...]
Bor_qa_bf_num	# Q&A board articles written by borrower	[0, 1, ...]
Tot_qa_bf_num	# Q&A board articles by borrower, lenders	[0, 1, ...]
Bor_ivt_num	# loan investments made by a borrower	[0, 1, ...]
Bor_ivt_amt	KRW loan investment amount by borrower	[0, 1, ...]
Voting_num	# votes cast for a loan auction	[0, 1, ...]
Y_ratio	Proportion of "yes" (*Y*) votes	Continuous between 0 and 1
Auc_amt	Requested loan amount by borrower	{0.5, 1, 1.5, 2, 2.5, 3, 4, 5, 10} million KRW
Auc_dur	Requested duration for borrower loan repayment	{3, 6, 9, 12, 15, 18, 21, 24} months

Model 1 uses a number of control variables. The lending decision variables include the borrower's requested loan amount and payback duration. We excluded the maximum interest rate the borrower was willing to pay for the loan, although most other studies that have this (Iyer et al. 2009, Pope and Sydnor 2011, Herzenstein et al. 2008, 2011a, Ravina 2008, Duarte et al. 2010). This is because most funded loans represented in our data have the same interest rate of 30%, which is the upper limit imposed on interest by law. As an alternative to Popfunding.com, unbankable borrowers in Korea have been subject to exploitation by loan sharks, who set interest rates above the legal limit. The legal maximum interest rate is much lower than the alternatives that borrowers face, so they are willing to pay an interest rate up to the maximum threshold due to their poor credit grades.

Model 2, which deals with borrowers whose loans were funded before, includes variables on repayment and the borrower's effort to communicate with the lenders, if there was any delay of repayment. See Table 8. We observe that some borrowers with overdue payments proactively communicate with the lenders to keep them informed about why the delay took place. This behavior may be viewed as an effort by the borrowers to manage their reputations.

Table 8
Additional independent variables in the second regression model.

Variable	Description
Past_req_af_num	# requests after first being funded
Past_delay_num	# delayed payments for the previous funded loan
Past_delay_days	# delay days for the previously funded loan
Past_early_num	# early repayments for the previously funded loans
D_qa_num	# articles on Q&A b-board borrower posted in payment delay period
D_board_num	# articles on free b-board borrower posted in payment delay period

Note: All variables are integer values of 0 or greater.

Table 9
Summary statistics for the independent variables for Model 1.

	N	Mean	Std. dev.
Cert_id	4703	0.44	0.496
Cert_addr	4751	0.21	0.411
Cert_cohab	4762	0.18	0.385
Cert_merriage	4769	0.18	0.380
Cert_income	4775	0.16	0.364
Cert_credit	4486	0.39	0.488
Cert_asset	4809	0.12	0.322
Cert_num	4822	1.62	2.081
Voting_num	4822	28.62	22.772
Y_ratio	3852	.4199	0.268
Past_req_num	4822	3.10	10.761
Bor_ivt_num	4822	0.46	3.723
Bor_ivt_amt	4822	3490	50,678
Bor_qa_bf_num	4822	2.03	4.799
Tot_qa_bf_num	4822	5.00	11.158
Auc_amt	4822	2156,159	784,616
Auc_dur	4822	14.07	5.622

Two variables proxy for such effort in our model. One is the number of articles written by a borrower on a Q&A bulletin board. The other is the number of articles posted on a free bulletin board during the period when the borrower's loan repayment was delayed.

4.2. Description of the data

Popfunding.com launched its service in 2007, but the voting feature was added on May 26, 2008. Hence, our data consist of loans listed on Popfunding.com from the date of the voting feature launching for a more than two-year period through July 31, 2010. Popfunding.com made all of the transaction data during this period available to us for this research. We then selected all of the loan requests that were relevant to our research. For each borrower-requested loan, we identified the borrower and then got the person's prior funding records from Popfunding.com's transaction database. The membership database stored the member's income, credit grade and other personal information so that the data listed in Tables 1 and 2 could be built easily. For each loan request, borrowers declared the purpose of their loans. This allowed us to derive the summary statistics presented in Table 4 as well.

During that period of the time, 2884 unique borrowers requested a total of 5211 loans. Among them, 738 loan requests were successfully funded (14%). Borrowers who had prior loan funding successes listed 389 loans. This gave them a history of repayment to lenders. Repeated transactions in Popfunding.com reflect the platform's microfinance aspect.

To test the Collective Intelligence Hypothesis (H1), we include the loans with borrowers who had never been successfully funded before in the analysis. This is because we expect that the lenders' use of the voting results will work better in probabilistic situations

Table 10
Summary statistics for the independent variables for Model 2.

	N	Mean	Std. dev.
Cert_id	243	.89	0.315
Cert_addr	246	.37	0.485
Cert_cohab	247	.31	0.464
Cert_marriage	247	.27	0.446
Cert_income	246	.46	0.500
Cert_credit	235	.87	0.339
Cert_asset	248	.20	0.402
Cert_num	249	3.29	1.892
Past_req_num	249	4.77	3.838
Past_req_af_lsuc	249	2.23	1.774
Past_delay_num	163	2.08	2.669
Past_delay_days	163	14.64	29.167
D_qa_num	131	.52	1.624
D_board_num	131	1.49	2.199
Past_early_num	249	2.81	2.965
Term_bf_sec	249	187.18	89.360
Bor_ivt_num	249	8.09	18.911
Bor_ivt_amt	249	56,855	207,818
Bor_qa_bf_num	249	6.65	7.063
Tot_qa_bf_num	249	17.02	20.368
Voting_num	249	44.67	21.115
Y_ratio	246	.6654	0.167
Auc_amt	249	2074.30	1052.79
Auc_dur	249	14.04	5.012

(Mauboussin 2008). Thus, weexcluded all of the repayment-related variables in our test of this hypothesis.

For the remaining hypotheses, we included all of the independent variables in Tables 7 and 8 in the analysis. In addition, we only considered requests by borrowers who were previously funded. The loans of borrowers who had more than one instance of loan funding success were excluded because each instance of prior funding may affect the outcome of the current loan differently. For instance, the last one may be the most influential among them all. As a result of this decision, the number of data points that we had available for analysis drastically decreased.

Summary statistics for the independent variables of Models 1 and 2 are presented below in Tables 9 and 10. In both regression models, we used the logarithm of the listed loan amounts.

5. Results

The results of Model 1's analysis of the impact of lenders' votes on the funding success are shown in Table 11. Analysis based on the backward LR method starts with all of the variables, but they are removed one by one if they do not contribute enough information to the regression equation. So not all of the independent variables in Table 7 are shown in the regression results.

5.1. Results for Model 1: a test of Hypothesis 1

5.1.1. Effects of hard information

Consistent with previous research, the variables representing economic ability and verified certificates were positively associated with loan funding success (Greiner and Wang 2007). Since the certificate-related variables have two possible values 0 or 1, we treated them as dummy variables, and the values for each variable are presented in parentheses. The variables for the existence of certificates for borrower identification, cohabitation, income and credit were significant, however, those for address, marriage, and assets were removed by the backward LR algorithm because they did not explain sufficient variance in the dependent variable.

5.1.2. Collective intelligence under a high level uncertainty

The effect of certificates on loan funding success was smaller compared to the proportion of "yes" votes by lenders. On the

Table 11
Results for Model 1: effects of the voting results on current loan funding success (*, **, and *** represent significant in 90%, 95%, and 99% confidence level respectively).

	β	Std. err.	Wals	p-Value	Exp(β)
Cert_id(0)	−4.981	1.152	18.696	0.000***	0.007
Cert_cohab(0)	−0.452	0.211	4.587	0.032**	0.637
Cert_income(0)	−1.651	0.211	61.150	0.000***	0.192
Cert_credit(0)	−1.632	0.432	14.292	0.000***	0.195
Voting_num	−0.030	0.006	22.073	0.000***	0.971
Y_ratio	6.787	0.686	97.839	0.000***	886.666
Bor_ivt_num	0.046	0.026	3.154	0.076*	1.047
Bor_qa_bf_num	−0.200	0.043	21.879	0.000***	0.818
Tot_qa_bf_num	0.211	0.022	94.802	0.000***	1.234
Log_amt	−11.075	0.682	263.538	0.000***	0.000
Constant	64.576	4.185	238.145	0.000***	1.11E + 28

online microfinance platform, since the borrowers' characteristics do not vary much, the initial information given to lenders on the borrowers' creditworthiness also did not vary much either across the borrowers. Hence, collective intelligence shows a much more significant impact on the likelihood of loan success. This result supports the Collective Intelligence Hypothesis (H1). Lenders will use the voting results representing collective intelligence more when the loan requests are by unknown borrowers. After adding the total number of votes (*Voting_num*) into the model to control for the number of total participants in the voting – essential the *degree of collectiveness* in the opinions offered, we found that it had a slightly negative effect on the funding success of a loan request. Thus, it seems that lenders do not link the quality of collective intelligence to the degree of participation in making a loan decision.

5.1.3. Borrower's prior participation as an investor

The number of investments by a borrower, and the number of bulletin board articles written by both borrowers and lenders have slightly positive effects on the success of a borrower to have a loan funded. This is consistent with previous research (Ho 2010).

5.2. Results for Model 2: tests of Hypotheses 2–6

For borrowers with a history of past funding, we added all of the independent variables in Tables 7 and 8 to the second regression. The results for Hypotheses 2–6 are shown in Table 12.

5.2.1. Collective intelligence with past transaction history

Interestingly, the variable for the proportion of "yes" vote responses (*Y_ratio*) does not show up. This represents empirical evidence in support of the idea that the weight given to collective intelligence represented by voting diminishes as lenders infer borrower trustworthiness from their past transaction history and other efforts by the borrower. As Mauboussin (2008)) suggested, lenders may make a decision based on rules involving more objective information.

5.2.2. Prior loan requests

It is interesting that the number of loan requests (*Past_req_num*) has a negative impact on loan funding success, while the number of requests after a borrower has had a loan funded once (*Past_req_af_lsuc*) has the opposite effect on the outcome. It appears that frequent requests may be interpreted as an indication of desperation on the borrower's part, and so they are less persuasive to the peer lenders. However, once a borrower has had a loan funded, the same actions by the borrower may be viewed as a confidence-builder, supporting the borrower's relationship with the lenders. It seems that lenders trust another form of collective intelligence: they react in a manner that is consistent with the judgment of their peers on the funding of a borrower's loan. This herding may be the

Table 12
Results for Model 2: effects of various variables on current loan funding success .(*, **, and *** represent significant in 90%, 95%, and 99% confidence level respectively).

	β	Std. err.	p-Value	Exp(β)
Cert_cohab(0)	−1.498	0.89	0.092*	0.224
Cert_income(0)	−1.416	0.872	0.104	0.243
Past_req_num	−0.741	0.301	0.014**	0.477
Past_req_af_lsuc	0.796	0.408	0.051*	2.217
D_qa_num	1.833	0.792	0.021**	6.252
Past_early_num	0.376	0.209	0.071*	1.457
Tot_qa_bf_num	0.14	0.041	0.001***	1.15
Auc_dur(24)			0.257	
Auc_dur(6)	28.319	22494.302	0.999	1.99E + 12
Auc_dur(9)	5.779	2.443	0.018**	323.354
Auc_dur(12)	4.312	1.945	0.027**	74.567
Auc_dur(15)	2.93	1.737	0.092*	18.721
Auc_dur(18)	5.604	2.291	0.014**	271.438
Auc_dur(21)	5.947	2.679	0.026**	382.47
Constant	−4.507	2.169	0.038**	0.011

collective approval of creditworthiness by peers. Hence, both the Past Loan Activities Hypothesis (H2.1) and the Past Loan Success Hypothesis (H2.2) are accepted.

5.2.3. Borrower's past investment record

The hypotheses about the impacts of borrowers' investment activities – the Past Investment Frequency Hypothesis (H3.1) and the Past Investment Amount Hypothesis (H3.2) – are rejected though. This is because the variables about the number and the amount of the borrower's peer investments in loans do not show up in the final step of the back LR method's output. We speculate that a borrower's past investments may signal the borrower's strong association with the platform community, and this develops more trust among members. However, both investment frequency and amount were not significant in explaining the variance of loan funding success. From these results, we conjecture that this kind of informational signaling may not be persuasive to the lenders when they make their loan funding decisions. Converting from an investor to a borrower could be understood as a drastically worsening financial situation for the borrower who lists a loan.

5.2.4. Repayment records

Contrary to expectations, the history of past delays in payment – in this study, the number of overdue payments and total overdue days – did not significantly affect the loan success. The two delay-related variables are not shown on the table, as a result. Thus, both the Overdue Payment Frequency Hypothesis (H4.1) and the Overdue Payment Time Hypothesis (H4.2) are rejected. According to previous research on traditional microfinance in Bolivia (Schreiner 1999), borrowers who have past payment delay history are more likely to delay payment of their current loans. It turns out, however, that past payment delay history does not directly affect current loan funding success in the online P2P lending platform. This may be because delays are not the same as final default. Given that the borrowers in Popfunding.com are predominantly unbankable anyway, lenders expect that their vulnerable financial situation may make them delay their payments to some extent anyway, but still hope that the borrowers will continue to repay when their situation improves. The result of Information Exchanges During Overdue Payment Period Hypothesis (H6) seems to support this interpretation.

At the same time, our results also suggest that information on the number of early payments (*Past_early_num*) had a significant and positive impact on current loan funding success. Therefore, the Early Payment Frequency Hypothesis (H5) is accepted. Lenders who deal with unbankable borrowers are likely to view a positive repayment history as being more useful than a negative repayment record because lender expectations are already low, given the nature of poor borrowers.

5.2.5. Social activities by borrowers to manage creditworthiness

Finally, we present one of our most interesting results. We found that even during a period when a borrower's loan payment was delayed, the number of postings (*D_qa_num*) by a borrower on a Q&A bulletin board had a positive effect on current loan funding success. The same effort on the free bulletin board had no effect though. Hence, the Information Exchanges During Overdue Payment Period Hypothesis (H6) is partly accepted. Communication through the Q&A bulletin board apparently involves direct and personal communication with lenders. They are customized responses to lenders' specific questions. Borrower postings on the free bulletin board, in contrast, are unilateral broadcasts to lenders. This result matches Sonenshein et al. (2011), who showed that a more structured narrative, involving *explanation-acknowledgment* and *explanation-denial*, increases the likelihood of favorable lending decisions. In other words, the narratives must be good (Herzenstein et al. 2011a).

6. Conclusion

6.1. Contributions

Our research is unique. (See Table 13 for a concluding overview of our main results.) First, we have shown that the experimental feature to encourage collective intelligence works in the realm that the theory suggests. That is, people seek the wisdom from peers when problems are probabilistic, and the P2P lending market – like any other market – appears to function as an information gathering mechanism, as Plott (2000) suggested. Golub and Jackson (2010) maintain that social networks are primary conduits for information, opinions and behavior. One of our research questions is whether the voting feature in Popfunding.com improved the P2P lending platform so that it is a more efficient information conduit. Although we could not test the repayment performance implications of collective intelligence since most of the loans have not matured, our study nevertheless shows that decision-makers seem to act in a more effective way when the structure of their decision problems matches those that can be solved by collective intelligence. Popfunding.com's voting feature is very simple and experimental, but it still shows that herds take account of the information generated by this feature. Hence, our findings suggest the possibility that one of the most fundamental problems of P2P lending markets can be alleviated, by taking advantage of collective intelligence engendered by an innovation application of information technology.

We also have presented evidence that the structure of loan decisions evolves as the market reveals more information. The upshot is that decision-makers will adjust their decision strategies and utilize a different set of information to support what they decide to do. Hence, when more verifiable information accumulates, lenders will tend to switch and rely upon their own reasoning and abandon the collective opinion of the marketplace. Indeed, there is much evidence of learning in P2P lending markets, but how participants actually learn has not explicitly been studied, so far we know. This study is an attempt to fill this knowledge void. P2P lending platforms still retain information and financial intermediary roles, but we have shown the new possibility of an improved information intermediation mechanism that can be accomplished by this platform.

Most of the prior empirical published works have studied Prosper.com, largely due to the availability of data. Prosper.com and Zopa.com compete with traditional financial services firm While online P2P lending platforms are utilized both for general personal loan markets and microfinance, empirical studies that study P2P lending platforms for microfinance have been very rare to date. The market we studied deals with relatively homogeneous borrowers who present high risk to lenders. The associated information problems are more clearly manifest as a result. Microloan borrowers also have strong incentives to borrow repeatedly. So far though, there has not been any research on online P2P lending which takes into account repeated transactions by borrowers. Moreover, when considering borrower characteristics, a small increase of information may significantly help lenders distinguish the reliable borrowers from the rest for an array of different loan requests. This makes their decision-making problems more structured, which will be beneficial.

We also confirm based on our empirical research that lenders put more weight on hard information generated from repeated transactions. This may induce borrowers to play a repeated game, which will assuage the moral hazard of the borrowers. Borrowers' strategic investments to maintain a good reputation seem to be effective to some extent, if they act appropriately. Also their direct communication with lenders prevents damage to their creditworthiness, if they can show that contract breaches are not due to moral hazard but to the vagaries of personal finances in a changing economy.

6.2. Limitations

Our data set is from only one company. Hence, the generalizability of our findings may be limited. In this research, we did not take into account the contents of the soft information revealed by borrowers, except for the number of articles they posted on the Q&A board. Unverifiable disclosures and the use of soft information have been examined in prior studies. Thus, our research may present the possibility of biased estimation due to omitted variables. Popfunding.com is still a young startup with a relatively small number of listings, which makes it very difficult for us to construct the variables that would be possible to work with in a more mature P2P lending platform. As transaction records grow, however, we may be about to capture a lot more information and new variable to support future research.

Finally, we did not consider loans requested by the borrowers who had two or more successful transactions in this study. The available data points for such loans were too few to make this additional analysis meaningful. This led us to test our hypotheses with only samples that involved one prior loan success versus loans that were not funded. Hence the extent of the impact of past transaction records must be re-examined to incorporate the possibility of repeated transactions over a longer time horizon.

Table 13
Summary of hypothesis test results.

Number	Hypothesis name	Results
H1	The Collective Intelligence Hypothesis	Accepted
H2.1	The Past Loan Activities Hypothesis	Accepted
H2.2	The Past Loan Amount Hypothesis	Accepted
H3.1	The Past Investment Frequency Hypothesis	Rejected
H3.2	The Past Investment Amount Hypothesis	Rejected
H4.1	The Overdue Payment Hypothesis	Accepted
H4.2	The Overdue Payment Time Hypothesis	Rejected
H5	The Early Payment Hypothesis	Accepted
H6	The Information Exchanges During Overdue Payment Period Hypothesis	Partly Accepted

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References

Agarwal, S., and Hauswald, R. The choice between arm's-length and relationship debt: Evidence from eloans. Working paper, Social Science Research Network, November 24, 2008. Available at papers.ssrn.com/sol3/papers.cfm?abstract_id=1306455.

Aghion, B. A., and Morduch, J. Microfinance beyond group lending. *Economics of Transition*, 8, 2, 2000, 401–420.

Ashta, A., and Assadi, D. An analysis of European online microlending websites. *Innovative Marketing*, 6, 2, 2010a, 7–17.

Ashta, A., and Assadi, D. Should online micro-lending be for profit or for philanthropy? Dhanax and Rang De. *Journal of Innovation Economics*, 2, 6, 2010b, 123–146.

Ba, S., and Pavlou, P. A. Evidence of the effect of trust building technology in electronic markets: price premiums and buyer behavior. *MIS Quarterly*, 26, 3, 2002, 243–268.

Bachmann, A., Becker, A., Buerckner, D., Hilker, M., Kock, F., Lehmann, M., and Tiburtius, P. Online peer-to-peer lending: a literature review. *Journal of Internet Banking and Commerce*, 16, 2, 2011, 2–18.

Berger, S. C., and Gleisner, F. Emergence of financial intermediaries on electronic markets: the case of online P2P lending. *Journal of Verband der Hochschullehrer für Betriebswirtschaft*, 2, 1, 2009, 39–65. Available from the German Academic Association for Business Research, representing Austria, Germany and Switzerland, at www.business-research.org/2009/1/finance/1940.

Brennan, P.J. Peer-to-peer lending lures investors with 12% return (update 2). *Bloomberg*, July 16, 2009.

Bruene, J. Peer-to-peer lending volumes worldwide. Netbanker.com, November 12, 2008.

Bruett, T. Cows, Kiva, and Prosper.com: how disintermediation and the Internet are changing microfinance. *Community Development Investment Review*, Federal Reserve Bank of San Francisco, 3, 2, 2007, 44–76.

Cain, R. Peer to peer lending, Report, VRLFinancialNews.com, March 2008. Available at www.vrl-financial-news.com/retail-banking/retail-banker-intl/reports/peer-to-peer-lending.aspx.

Chen, D., Chen, G., Ding, J., Jiang, S. and Sehn, J. Antecedents of initial trust in the online peer-to-peer lending marketplace. In *Proceedings of the 8th International Conference on Service Systems and Service Management*, Tianjing, China, June 25–27, 2011, IEEE Computer Society, Washington, DC, 2011.

Cheung, S. Economic organization and transaction costs. In J. Eatwell, M. Milgate, and P. Newman (eds.), *The New Palgrave: Allocation, Information and Market*, W.W. Norton & Company, New York, NY, 1989.

Chircu, A. M., and Kauffman, R. J. Reintermediation strategies in business-to-business electronic commerce. *International Journal of Electronic Commerce*, 4, 4, 2000, 7–42.

Chiu, C., Hsu, M., and Wang, E. Understanding knowledge sharing in virtual communities: an integration of social capital and social cognitive theories. *Decision Support Systems*, 42, 3, 2006, 1872–1888.

Collier, B., and Hampshire, R. Sending mixed signals: multilevel reputation effects in peer-to-peer lending markets. In *Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work*, Savannah, GA, February 6–10, 2010, ACM Press, New York, NY, 2010.

Diamond, D. W. Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 51, 3, 1984, 393–414.

Ding, M., Eliashberg, J., Huber, J., and Saini, R. Emotional bidders: an analytical and experimental examination of consumers' behavior in a Priceline-like reverse auctions. *Management Science*, 51, 3, 2005, 352–364.

Duarte, J., Siegel, S., and Young, L.A. Trust and credit. Paper presented at the 2010 American Finance Association Atlanta Meetings, Atlanta, GA, June 2, 2010. Available at papers.ssrn.com/sol3/papers.cfm?abstract_id=1343275.

Everett, C. R. Group membership, relationship banking and loan default risk: The case of online social lending. Working paper, Social Science Research Network, March 15, 2010. Available at papers.ssrn.com/sol3/papers.cfm?abstract_id=1114428.

Farrell, M. Banking 2.0: New capital connections for entrepreneurs. Forbes.com, February 11, 2008. Available at www.forbes.com/2008/02/11/lending-online-banking-ent-fin-cx_mf_0211capital.html.

Freedman, S., and Jin, G.Z. Do social networks solve information problems for peer-to-peer lending? Evidence from Prosper.com. Working paper, Social Science Research Network, November 14, 2008. Available at papers.ssrn.com/sol3/papers.cfm?abstract_id=1304138.

Gartner. Gartner says social banking platforms threaten traditional banks for control of financial relationships. Egham, UK, February, 8, 2008.

Gartner. Gartner says 50 per cent of banks will still lack an innovation programme and budget by 2013. Egham, UK, January 5, 2010.

Golub, B., and Jackson, M. O. Naïve learning in social networks: convergence, influence, and the wisdom of crowds. *American Economic Journal: Microeconomics*, 2, 1, 2010, 112–149.

Greiner, M. and Wang, H. Building consumer-to-consumer trust in e-finance marketplaces. In *Proceedings of the 13th Americas Conference on Information Systems*, Keystone, CO, August 9–12, 2007.

Hartley, S. E. Kiva.org: Crowd-sourced microfinance and cooperation in group lending. Working paper, Social Science Research Network, March 25, 2010. Available at papers.ssrn.com/sol3/papers.cfm?abstract_id=1572182.

Hawkins, R., Mansell, R., and Steinmueller, W. E. Toward digital intermediation in the information society. *Journal of Economic Issues*, 33, 2, 1999, 383–391.

Herrero-Lopez, S. Social interactions in P2P lending. In *Proceedings of the 3rd Workshop on Social Network Mining and Analysis*, Paris, France, June 28–July 1, 2009, ACM Press, New York, NY, 2009.

Herzenstein, M., Andrews, R. L., Dholakia, U. M., and Lyandres, E. The democratization of personal consumer loans? Determinants of success in online peer-to-peer lending communities. Working paper, University of Delaware, Wilmington, DE, June 2008.

Herzenstein, M., Dholakia, U. M., and Andrews, R. Strategic herding behavior in peer-to-peer loan auctions. *Journal of Interactive Marketing*, 25, 1, 2011a, 27–36.

Herzenstein, M., Sonenshein, S., and Dholakia, U. M. Tell me a good story and I may lend you my money: the role of narratives in peer-to-peer lending decisions. *Journal of Marketing Research*, 48, 2011b, S138–S149.

Ho, J. *An Empirical Study on the Effect of Creation and Utilization of Social Capital on Market Transactions in Online Peer-to-Peer Lending*. Unpublished thesis, Korea Advanced Institute of Science and Technology, Seoul, Korea, 2010.

Iyer, R., Khwaja, A. I., Luttmer, E. F.P., and Shue, K. Screening in new credit markets: Can individual lenders infer borrower creditworthiness in peer-to-peer lending? Working paper no. 15242, National Bureau of Economic Research, Cambridge, MA, 2009. Available at www.nber.org/papers/w15242.

Kauffman, R. J., and Riggins, F. R. Information and communication technologies and the sustainability of microfinance. *Electronic Commerce Research and Applications*, 10, 5, 2012.

Klafft, M. Online peer-to-peer lending: A lenders' perspective. In H. R. Arabnia and A. Bahrami (eds.), *Proceedings of the 2008 International Conference on E-Learning, E-Business, Enterprise Information Systems, and E-Government, Las Vegas, NV, July 14–17*, CSREA Press, Athens, GA, 2008a.

Klafft, M. Peer to peer lending: auctioning microcredits over the Internet. In A. Agarwal and R. Khurana (eds.), *Proceedings of the International Conference on Information Systems, Technology and Management*, IMT, Dubai, 2008b.

Larrimore, L., Jiang, L., Larrimore, J., Markowitz, D., and Gorski, S. Peer to peer lending: the relationship between language features, trustworthiness, and persuasion success. *Journal of Applied Communication Research*, 39, 1, 2011, 19–37.

Lee, E., and Lee, B. Herding behavior in online P2P lending: an empirical investigation. *Electronic Commerce Research and Applications*, 10, 5, 2012.

Light, J. Is 'Peer-to-peer' lending worth the risk? *Wall Street Journal*, April 13, 2012. Available at topics.wsj.com/subject/J/jordan/3065.

Lin, M., Prabhala, N.R., and Viswanathan, S. Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending, Working paper, Social Science Research Network, July 1, 2011. Available at papers.ssrn.com/sol3/papers.cfm?abstract_id=1355679.

Magee, J. Peer-to-peer lending in the United States: surviving after Dodd-Frank. *North Carolina Banking Institute Journal*, 15, 2011, 139–174.

Malone, T. W., Laubacher, R., and Dellarocas, C. Harnessing crowds: Mapping the genome of collective intelligence. Working paper no. 2009–001, Center for Collective Intelligence, MIT, Cambridge, MA, February 2009.

Mauboussin, M. J. *What Good Are Experts?* Harvard Business Review, 2008. 43–44.

Meyer, T. Power of people: online P2P lending nibbles at banks' loan business. E-Banking Snapshot, 22, Deutsche Bank Research, Frankfurt, Germany, July 2007.

Michaels, J. Do unverifiable disclosures matters? Evidence from peer-to-peer lending. *The Accounting Review*, 87, 4, 2012.

Moyer, M. Manipulation of the crowd. *Scientific American*, 303, 1, 2010, 26–28.

Packer, R. Session takeaway: the rise of P2P lending. Conference blog post, Microfinance USA Conference, May 21, 2010. Available at microfinanceusaconference.org/blog/2010/05/21/session-take-aways-the-rise-of-p2p-lending.

Pattern, R. H., Rosengard, J. K., and Johnston, D. E. Jr., Microfinance success amidst macroeconomic failure: the experience of Bank Rakyat Indonesia during the East Asian crisis. *World Development*, 29, 6, 2001, 1057–1069.

Paxton, J. Modeling group loan repayment behavior: new insights from Burkina Faso. *Economic Development and Cultural Change*, 48, 3, 2000, 639–655.

Pengoloans.com. P2P lending volume tops $700 million. Pengo Inc., December 16, 2011. Available at pengoloans.wordpress.com/2011/12/16/p2p-lending-volume-tops-700-million.

Plott, C. R. Markets as information gathering tools. *Southern Economic Journal*, 67, 1, 2000, 1–15.

Pope, D. G., and Sydnor, J. R. What's in a picture? Evidence of discrimination from Prosper.com. *Journal of Human Resources*, 46, 1, 2011, 53–92.

Puro, L., Teich, J. E., Wallenius, H., and Wallenius, J. Bidding strategies for real-life small loan auctions. *Decision Support Systems*, 51, 1, 2011, 31–41.

Ravina, E. Love and loans: The effect of beauty and personal characteristics in credit markets. Working paper, Columbia University, New York, NY, March 2008. Available at papers.ssrn.com/sol3/papers.cfm?abstract_id=1101647.

Ray, R. Prediction markets and the financial 'wisdom of crowds'. *The Journal of Behavioral Finance*, 7, 1, 2006, 2–4.

Renton, P. A huge month for U.S. peer to peer lenders. Social Lending Network, August 31, 2011. Available at www.sociallending.net/news/a-huge-month-for-u-s-peer-to-peer-lenders.

Renton, P. U.S. P2P lenders issue $50.8 million in loans. Social Lending Network, March 30, 2012. Available at www.sociallending.net/state-of-the-industry/u-s-p2p-lenders-issue-50-8-million-in-loans.

Schreiner, M. A scoring model of the risk of costly arrears at a microfinance lender in Bolivia. Working paper, Center for Social Development, Washington University, St. Louis, MO, 1999.
Schreiner, M. Credit scoring for microfinance: can it work? *Journal of Microfinance*, 2, 2, 2000, 105–118.
Shen, D., Krumme, C., and Lippman, A. Follow the profit or the herd? Exploring social effects in peer-to-peer lending. In *Proceedings of the 2010 IEEE Second International Conference on Social Computing, Minneapolis, MN, August 20–22*, IEEE Computer Society, Washington, DC, 2010, 137–144.
Slavin, B. Peer-to-peer lending: an industry insight. BradSlavin.com, 2007. Available at www.bradslavin.com/wp-content/uploads/2007/06/peer-to-peer-lending.pdf.
Sonenshein, S., Herzenstein, M., and Dholakia, U. M. How accounts shape lending decisions through fostering perceived trustworthiness. *Organizational Behavior and Human Decision Processes*, 115, 1, 2011, 69–84.
Sufi, A. Information asymmetry and financing arrangements: evidence from syndicated loans. *Journal of Finance*, 62, 2, 2007, 393–410.
Sugar, R. Crowdsourced loans to SMEs. Changemakers.com, Ashoka, Arlington, VA, June 27, 2010. Available at www.changemakers.com/SME-Finance/entries/crowdsourced-loans-smes.
Surowiecki, J. *The Wisdom of Crowds*. Doubleday, New York, NY, 2004.
Sviokla, J. Breakthrough ideas: forget Citibank – borrow from Bob. *Harvard Business Review*, 87, 2, 2009, 19–40.
Wang, H., and Greiner, M. E. Prosper: the eBay for money in lending 2.0. *Communications of the Association for Information Systems*, 29, 1, 13, 2011, 243–258.
Wang, H., Greiner, M. E., and Aronson, J. E. Peer-to-peer lending: the emerging e-commerce transformation of a financial market. In M. Nelson, M. Shaw, and T. Strader (eds.), *Value Creation in E-Business Management*, Springer, Heidelberg, Germany, 2009, 182–195.
Weiss, G.N., Pelger, K., and Horsch, A. Mitigating adverse selection in P2P lending: Empirical evidence from Prosper.com. Working paper, TU Dortmund, Germany, 2010. Available at papers.ssrn.com/sol3/papers.cfm?abstract_id=1650774.
Wydick, B. Can social cohesion be harnessed to repair market failures? Evidence from group lending in Guatemala. *The Economic Journal*, 109, 457, 1999, 463–475.
Zhang, J., and Liu, P. Rational herding in microloan markets. *Management Science*, 58, 5, 2012, 892–912.