PACIS 2016 Proceedings

Pacific Asia Conference on Information Systems (PACIS)

Summer 6-27-2016

THE IMPACT OF TEAM RANKING ON TEAM LENDING PERFORMANCE: AN EMPIRICAL STUDY ON KIVA

Xuechen Luo
City University of Hong Kong, xuecheluo2-c@my.cityu.edu.hk

Ling Ge
City University of Hong Kong, lingge@cityu.edu.hk

Chong (Alex) Wang
City University of Hong Kong, alex.wang@cityu.edu.hk

THE IMPACT OF TEAM RANKING ON TEAM LENDING PERFORMANCE: AN EMPIRICAL STUDY ON KIVA

Xuechen Luo, Department of Information Systems, City University of Hong Kong, Hong Kong, xuecheluo2-c@my.cityu.edu.hk

Ling Ge, Department of Information Systems, City University of Hong Kong, Hong Kong, lingge@cityu.edu.hk

Chong (Alex) Wang, Department of Information Systems, City University of Hong Kong, Hong Kong, alex.wang@cityu.edu.hk

Abstract

Prosocial crowdfunding, such as Kiva, puzzles researchers regarding what motivates online peers to lend for free, and how voluntary online participation could be organized to create great social goods. A common practice of prosocial lending websites is to enable self-organizing teams. In this paper, we are interested in the impact of team ranking, and thus team reputation on its lending performance. Contradicting predictions could be derived depending on the theoretical lenses. While social identity theory suggests that better ranking strengthens individual identification and promotes lending participation; economic theory on public goods indicates that good ranking may trigger a crowd-out effect. To empirically explore the relationship between team ranking and team performance, we collected data from Kiva, the largest prosocial crowdfunding platform. Kiva enables lenders to form teams, and teams are ranked monthly on both lending performance and member recruitment. Our data analysis suggests that appearance on the top ranking list leads to a reduction in future team lending indicating that good team-rank triggers the crowd-out effect. Meanwhile, salience on the member recruitment list does not show any significant impact on lending performance. Our finding suggests that team reputation may not promote identification in this context.

Keywords: Prosocial Lending, Crowdfunding, Lending Team, Team Ranking, Reputation, Group Identity, Public Goods

1 INTRODUCTION

Crowdfunding has emerged as a new way of financing. According to the Crowdfunding Industry Report, the market achieved an annual growth rate of 167% in 2014.[1] A variety of crowdfunding platforms raise funds for different purposes such as personal financial needs, business ventures, creative projects, or charity. While some of these platforms provide profitable investment opportunities, such as P2P lending platforms and equity-based crowdfunding, others are dedicated to funding creative, culture, or philanthropic projects in the form of donations (Belleflamme and Lambert 2014; Burtch et al. 2014; Lin and Viswanathan 2015). Funders on donation-based crowdfunding platforms require no explicit financial rewards (Burtch et al. 2013).

Kiva (www.kiva.org) is one of the earliest and the most successful crowdfunding platform. Launched in 2005, it now serves low-income entrepreneurs in 83 countries to alleviate poverty with prosocial, interest-free loans from lenders all over the world. Kiva lenders do not collect interest and have little protection for loan defaults. They are motivated by prosocial and altruistic incentives rather than reciprocity (Burtch et al. 2013).

To enhance social interaction between lenders and strengthen philanthropic behavior, Kiva enables lenders to form self-organized teams. Teams may be created on different bases, such as common interests, shared beliefs, and similar social affiliations. Lenders can join multiple teams, and they can attribute their loans to their teams, which will be counted as the team's lending performance. Kiva ranks teams regarding the funding performance and new member recruitment. Top-ranked teams are shown on the team Team Leaderboards with Leader Tags attached to the teams' profile pages (Figure 1). Team ranking creates a team-based reputation system. Given the voluntary nature of lending participation and the loans are without credit assurance and bears no interest, team and team reputation is a critical mechanism to organize and motivate prosocial lending on Kiva. However, it is not clear whether and how self-organized teams were able to leverage its reputation to maintain and enhance member participation. Specifically, when people observe their teams on the Team Leaderboards, would they feel more motivated and thus lend more? In this paper, we empirically investigate the impact of team ranking (reputation) on team lending performance using data collected from Kiva.

Reputation has been recognized and studied as an important motivation for prosocial behavior in the economic literature in public goods provision (e.g., Harbaugh 1998; Bénabou and Tirole 2006; Ariely et al. 2009). In the information systems literature, the effect of online reputation has been studied in different contexts where voluntary participation presents (Resnick et al. 2000; Lerner and Tirole 2002; Pavlou and Gefen 2004; Roberts et al. 2006; Shen et al. 2015). For instance, Lerner and Tirole (2002) illustrated that reputation is an important motive for developers to make contributions to open source software projects in the absence of monetary incentives. It was shown that contribution-based reputation positively related to the success of open source projects (Daniel et al. 2013). In online communities, Pavlon and Gefen (2004) suggested that positive reputation motivates people to maintain continuous contributions. In the context of user-generated online reviews, Shen et al. (2015) showed that users react to reputation systems and make contributions strategically to build and maintain a good reputation. Specifically, comparing with users on review websites without ranking systems, reviewers on websites with such systems are more likely to avoid reviewing crowed items.

There, however, has been little discussion on the team-based reputation system and team performance. Team-based organization introduces additional layers to individual motivation. It has repeatedly been demonstrated that people behave differently when acting in a team (Heap and Zizzo 2009; Tan and Bolle 2007). For example, Charness et al. (2007) showed that salient group membership significantly affects the perception of the environment. In the economic literature, Akerlof and Kranton (2000)

[1] 2015CF Crowdfunding industry report. http://reports.crowdsourcing.org/index.php?route=product/product&product_id=54

proposed that group identity should be considered as a component of the utility function. They show that group identity leads to distinctive model predictions in the situations as gender discrimination in the workplace and household labor division.

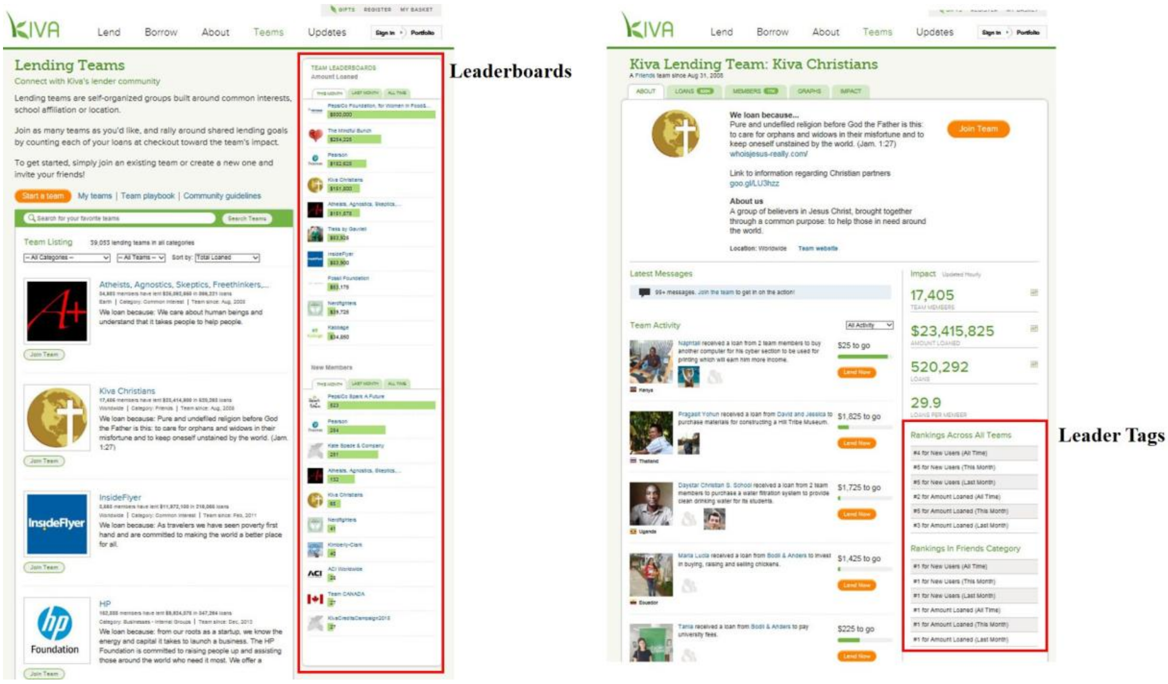

Figure 1. The Team Page, LeaderBoards, and LeaderTags on Kiva

Theoretically, team-based organization and reputation mechanism introduce additional factors that call on different theoretical lenses. First, belonging to a team creates virtual social identities. Social identity theory suggests that when individuals identify with the team, they consider themselves as a part of a team, and behave consistently with the identity (Shih et al. 1999; Benjamin et al. 2007). Being part of a reputable team strengthen identification and motivate members to participate and enhance team lending performance. Second, team reputation and team performance are collective outcomes. While each member may value good team reputation, the production of good team performance depends on others' lending participation. From the perspective of public goods economics, good team reputation may serve as an indication that other members of the team are making significant efforts, which gives the incentive for individual members to reduce contribution and free-ride. In other words, team reputation may trigger a "crowd-out" effect. From this perspective, ranking high may lead to worse team performance.

Given the contradictory theoretical predictions and the research gap in our understanding of team organization and reputation systems in the context of prosocial crowdfunding, we empirically study the impact of team ranking on team lending performance with data collected from Kiva. Our preliminary results suggest that appearance on the Team Leaderboards (and the presence of Leader Tags) regarding lending performance leads to a reduction in subsequent team lending, which demonstrates a significant crowd-out effect of team reputation in the focal context. Meanwhile, we fail to find any significant impact of the appearance of the Team Leaderboards regarding member recruitment, suggesting an insignificant identity effect.

This research makes several contributions to the IS literature on crowdfunding. First, to the best of our knowledge, this research is among the first to examine the impact of team level reputation mechanism on prosocial lending behavior while the previous discussion on reputation mechanism focuses on the individual level. Second, this research adds to growing literature on crowdfunding participation.

Researchers have identified various factors that affect individuals' funding decisions (Agrawal et al. 2015; Lin et al. 2013; Zhang and Liu 2012; Gerber and Hui 2013; Bretschneider et al. 2014). Specifically, a few recent studies investigated what motivate prosocial lending behavior. For example, Burtch et al. (2014) documented the impact of geographic distance and cultural differences and showed that lenders prefer to lend to borrowers who have similar culture and proximate geographical location. Galsk et al. (2011) shown that lenders on Kiva showed a preference for individual borrowers over groups of borrowers, which is consistent with the identified victim effect. Heller and Badding (2012) demonstrate that lenders are selective on borrowers' demographic characteristics and the proposed uses of funds. Adding to this line of research, the current study demonstrates the impact of team reputation. Third, this research broadly contributes to the literature on group-based incentive in online voluntary participation by generating interesting empirical observations in a new context (e.g., Zhang and Zhu 2011).

The rest of the paper is organized as follows. Section 2 introduce our research context and discusses the team reputation mechanism. A brief theoretical discussion is carried out in Section 3. Section 4 reports on our empirical study and results. Section 5 concludes and introduce the plan for follow-up studies.

2 RESEARCH CONTEXT

Kiva is an online crowdfunding platform created for the purpose of poverty alleviation. It serves as a platform for people to help others (poor people) to gain access to funds to start their small or micro projects to improve living standards. Since its inception, the idea of an online platform for poverty alleviation through crowdfunding has been echoed by individuals and organizations. Through collaboration with local partners (typically microfinance institutions), Kiva gradually expanded its reach globally. To date, More than two million users have joined to support projective on Kiva, and over 800 million loans have been made on the platform.

Lending on Kiva, while being in the form of loans, is of prosocial nature. Lenders receive no interest on their loans, and they lose the principal when borrowers default. Kiva charges no fees for its services, and promises that money from lenders will all be transferred to borrowers. Although loans are made on a project base and repayment is expected, lenders usually continue to support more projects with returned principals.

2.1 Kiva Teams and Ranking

Kiva lenders build self-organized teams around their common interest, belief, affiliation or location. The platform classifies teams into 17 different categories (e.g., alumni, business, common interest, and schools). The team founders may invite other lenders to join a team. Lenders may join one or more teams that are by their interests, beliefs or identities. A lender may attribute her loans to any of her teams. All attributed loans from the members of a team count as the team's lending performance (total amount loaned).

Kiva has a team-based reputation system. It ranks the teams periodically (monthly) based on two performance indicators: total amount loaned (lending performance) and the number of new members (member recruitment). For each indicator, three top-ten lists are published, namely, all-time, last month, and this month. The top-ten lists across all the teams and within each category are shown on the team front page. On each team's homepage, the ranking position of the focal team is presented saliently as leader tags once the team made the top-ten list (Figure 1). For example, if a team ranked number two (in the top ten) within its category regarding the lending performance last month, a tag "#2 for Amount Loaned (Last Month)" is shown on the team's profile page. Only teams with top-ten performance in either lending performance or member recruitment will be shown on the team front page and awarded with leader tags. With team and reputation features, Kiva is an ideal setting for studying the impact of team reputation on team lending performance.[2]

3 THEORETICAL DISCUSSION

Research on prosocial behavior has shown that reputation and thus reputation system has a significant impact on individual behavior (e.g., Resnick et al. 2000; Lerner and Tirole 2002; Pavlou and Gefen 2004; Roberts et al. 2006; Shen et al. 2015). Team-based organization adds layers to individual motivation systems. We discuss the impact of team reputation on team performance from two theoretical perspectives, social identity theory and economics theory on public goods provision.

Social identity refers to a person's self-perception derived from being a member of a social group (Tajfel 1974). Social identity theory points out that self-perception as a group member is an important source of self-esteem and pride. As a result, individuals will try to strengthen the status of the group or discriminate other groups to increase group identity and image (Tajfel and Turner 1979). When people consider themselves as one of a group, the self-esteem derives from the membership of the group makes them behave more consistent with the group identity to maintain the group status and image (Shih et al. 1999; Benjamin et al. 2007). By voluntarily joining a team, Kiva lenders associate themselves with a team and take upon the team identity. They would behave by the teams' identity and aim. When the team has a good reputation in lending or recruiting (appearing on the top-ten lists), the members would feel stronger identification with the team, behave more consistently with the team's objective and contribution more enthusiastically to the team. It is thus expected that members of reputable teams tend to show intensified lending behavior, which in turn strengthen the subsequent team performance. In other words, team-based reputation enables a positive feedback loop by creating enhanced team identification and good team reputation (high ranking) has a positive impact on lending performance.

Discussion on the economics of public goods provision focuses on how rational individual act when making contributions to public goods. An important insight in this research stream is that individual tends to free-ride on others' contribution, which leads to a crowd-out effect. In other words, when others increase their contributions, the supply of public goods increases and lead to the decrease of individual's marginal benefit from making a contribution. As a result, each will choose to decrease his or her contribution to the public goods (e.g., Andreoni 1990). Although it has been proposed that warm glow motivation may alleviate the extent of crowd-out effect in private provision of public goods, partial crowd-out may nevertheless result (Andreoni 1989; Andreoni 1990). In our context, while each member of the team cares about team reputation, the creation of good reputation depends on all team members' contribution. Team reputation, different from individual reputation, could be viewed as a public good. When the team makes to the top-ten list, members are signaled that other team members are making significant contributions. Realizing the superior of reputation has been achieved, the marginal utility that lenders gain from making an additional contribution to the team is decreased. From this perspective, good team ranking may lead to decrease in member contribution.

The above discussion leads to distinct predictions on the impact of team reputation on team lending performance. In the following, we report an empirical study using data collected from Kiva, offering evidence regarding which theoretical mechanism has a more salient impact.

[2] In our empirical analysis, we use category-level ranking in the last month as team reputation factor as we believe category individual users will take category level heterogeneity into consideration when evaluate ranking as reputation.

4 EMPIRICAL ANALYSIS

4.1 Data

Our study is based on observational data collected from Kiva.org. The dataset includes both a full site snapshot data set collected on the September 18th, 2015 and a weekly panel data set covering eight weeks from October 21st to December 9th, 2015.

The full site data set contains all the loans and teams since the launch of Kiva in 2005. There are in total 844,073 loans and 37,975 teams. We also collected weekly data from October 21st to December 9th, 2015 (8 weeks) to track real-time changes in ranking and team performance. Once a week, we obtained data on all loans listed during this period, each week's ranking lists (category level rankings) and team performance (total amount loaned and the number of new members). The 8-week data recorded 6,031 active teams (defined as at least one member contributed to one loan during the data collection period). Among them, 673 teams made to at least one of the top-ten lists in same category teams during the eight week period. As team reputation is reflected in these top-ten ranking lists in our context, we focused on these 673 teams in the preliminary analysis. For each team, we collect weekly data of their ranking positions, total amount loaned as well as team features such as starting date. For each loan, our data include the listing date and the size of the loan. With the weekly data, we can build panel data by team and week and track the dynamic performance of the teams.

4.2 Empirical Model and Results

The study aims to investigate the impact of team reputation on team performance of prosocial lending. For the dependent variable, team performance, we use amount loaned by the team every week. The weekly amount loaned is calculated as the difference between the amount loaned of two adjacent weeks. The independent variable of interest, team reputation is measured with a dummy variable: whether the team is on the top-ten list or not (within same category teams). It can be referred from the ranking position information on each team's homepage. To ensure the temporal sequence in a causal relationship, we use team reputation achieved in the last month to explain team lending performance in weeks in the following month. Control variables include both team and site-level factors. For each team, we control the tenure of the team on Kiva, calculated based on the starting date of the team. As projects available for funding may change from week to week and thus affect amount loaned, we control for the number and average size of projects listed on Kiva every week.

Our empirical model is as follows:

$$Performance_{it} = Reputation_{it} + Age_{it} + NumListed_{it} + AvgSize_{it} + u_i + \varepsilon_{it}$$

where *i* represents the teams and *t* indicates the time periods. u_i represents team fixed effect to control for unobserved team-level heterogeneity, such as team category, team size. $Performance_{it}$ is the log of the amount loaned by team *i* in week *t*. $Reputation_{it}$ is the reputation indicator, whether team *i* is on Last Month top-ten list of the same category teams at the beginning of week *t*, one for yes and zero otherwise. The list can be either for amount loaned or the number of new members. Age_{it} measures the number of weeks of team *i*'s existence on Kiva from the starting date until the beginning of week t. $NumListed_t$ and $AvgSize_t$ refer to the number and averages size of projects listed in week *t*. We also controlled for week-of-month fixed effect.

Table 1 reports the descriptive statistics of the variables. The average weekly amount loaned is $4,128 with relatively large standard deviation, indicating the distribution is skewed. We thus take the log of this variable in our estimation. In our sample, the average team age is 251 weeks, almost five years. There are on average 2,202 projects listed on Kiva per week, and the average size of projects listed is 910 USD.

Variable	N	Mean	Std. Dev.	Min	Max
Amount Loaned	4,711	4,128	25,344	0	684,250
Last Month Ranking (New Member)	4,711	0.156	0.363	0	1
Last Month Ranking (Amount)	4,711	0.222	0.416	0	1
Team Age (Weeks)	4,711	251	126	0	381
Number of Project Listed on Kiva	4,711	2,202	310	1,938	2,851
Average Size of Listed projects	4,711	910	68	799	992

Table1. Descriptive statistic of variables

Table 2 reports estimation results. We estimated three models. In the first model, we consider reputation indicator represented by the appearance on the top-ten list of the amount loaned. In the second model, we consider reputation indicator represented by the appearance on the top-ten list of new members. In the third model, we include both reputation indicators in the first and second model. The team fixed effect and week-of-month effect were controlled in all three models. As shown in the table, the reputation indicator, represented by the appearance on the top-ten list of the amount loaned has a significant negative impact on (at 1% significant level in Model 1 and 3). However, the reputation factor represented by the appearance on the top-ten list of new members are not significant (Model 2 and 3). The results also suggest that, on average, older teams have weaker leanding performance. Average loan amount reduces when there are more projects listed on Kiva.

Dependent Variable	Amount Loaned		
	Model 1	Model 2	Model 3
Dummy (On Top-ten List, Amount Loaned)	-0.984***		-0.994***
	(0.192)		(0.192)
Dummy (On Top-ten List, New Member)		-0.260	-0.292
		(0.189)	(0.188)
Age	-0.081***	-0.089***	-0.079***
	(0.023)	(0.023)	(0.023)
Number of Projects Listed on Kiva	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)
Average Size of Listed projects on Kiva	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Constant	27.38***	29.13***	26.70***
	(5.245)	(5.259)	(5.263)
Week-of-month effect	Yes	Yes	Yes
Team effect	Yes	Yes	Yes
Observations	4,711	4,711	4,711
R2	0.062	0.057	0.063
Note: Standard errors in parentheses, * p<0.05 ** p<0.01 *** p<0.001			

Table2. Investigating the relationship between last month ranking list and performance of teams

4.3 Discussion

The empirical results show that comparing to teams that do not appear on the top list, top-ranked teams, regarding amount loaned, have less team lending in subsequent periods. This surprising finding supports the prediction derived from economic theory on public goods provision. It indicates that team members treat team ranking (reputation) as a signal of other members' contributions. Good reputation thus leads to stronger crowd-out effect. Meanwhile, appearance on the top member recruitment list shows no significant impact on team lending afterward, which indicates that there is no significant enhancement in identification resulting from good team reputation in our context. Together, these findings suggest team based reputation mechanism appears to be not effective in enhance team identity and promote prosocial lending. On the contrary, users seem to treat reputation as a public good and exhibit crowd-out effect in team contributions.

Our finding has some interesting implications. First, it suggests team reputation takes effect in a different way from individual reputation on prosocial behavior. While reputation is often identified as an important motivation for people to do good things at the individual level (Lerner and Tirole 2002; Pavlon and Gefen 2004), team reputation may work through more complicated motivational mechanisms and could be treated as a public good. Second, team reputation mechanism could be designed differently to alleviate crowd-out effect. While we did not find a significant positive performance gain from the appearance on top recruitment list, it does not show a significant crowd-out effect. Other ways of award team with good reputations may be proved to enhance identification while avoid triggering the crowd-out effect.

5 CONCLUSION AND EXTENSION

In this paper, we empirically investigated the effect of team ranking on team performance in the context of prosocial crowdfunding. We find that reputation (as the appearance on top-ten lists) has a negative impact on subsequent team lending performance. While reputation has been a central focus in studies on online voluntary participation, most of the previous studies only focused on the individual level reputation. Our study suggests that team-based reputation mechanism functions differently and warrants further investigation.

The current study has some limitations. First, there could be alternative explanations for the negative impacts of previous rankings. For example, a member may face budget constraint or have depleted her social capital to work for the previous ranking. Thus, it is difficult for her to maintain a high level of contribution in the following month. However, it is not likely that all team members may have depleted their resources simultaneously. We plan to examine in further details of individual-level participation and attribution behavior under the influence of team reputation. We hope to identify whether the underlying mechanism for the diminishing effect of team reputation is crowd-out effect or other alternative explanations. Second, our results suggest that team reputation does not significantly improve identification with the team. It would be interesting to examine the moderating role of team characteristics and identify the causes of ineffective identification. Third, the current paper only looks at lending performance; one can further investigate other team level performance indicators as well as team-based interactions, aiming at a better understanding of team-based mechanisms in prosocial crowdfunding.

Acknowledgements

The work described in this paper was fully supported by a grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. 11504815).

References

Andreoni, J. (1989). Giving with impure altruism: Applications to charity and Ricardian equivalence. The Journal of Political Economy, 1447-1458.

Andreoni, J. (1990). Impure altruism and donations to public goods: A theory of warm-glow giving. The Economic Journal, 100(401), 464-477.

Akerlof, G. A., & Kranton, R. E. (2000). Economics and identity. Quarterly Journal of Economics, 715-753.

Ariely, D., Bracha, A., & Meier, S. (2009). Doing good or doing well? Image motivation and monetary incentives in behaving prosocially. The American Economic Review, 99 (1), 544-555.

Agrawal A, Catalini C, Goldfarb A (2015) Crowdfunding: Geography, social networks and the timing of investment decisions. Journal of Economics & Management Strategy. Forthcoming.

Belleflamme, P., & Lambert, T. (2014). Crowdfunding: Some empirical findings and microeconomic underpinnings. Available at SSRN 2437786.

Bénabou, R., & Tirole, J. (2006). Incentives and prosocial behaviour. The American Economic Review, 96 (5), 1653-1678.

Benjamin, D. J., Choi, J. J., & Strickland, A. J. (2007). Social identity and preferences. National Bureau of Economic Research.

Bretschneider, U., Knaub, K., & Wieck, E. (2014). Motivations for crowdfunding: What drives the crowd to invest in start-ups?. Paper presented at the 22nd European Conference on Information Systems, Tel Aviv, Israel

Burtch, Gordon, Anindya Ghose, and Sunil Wattal. "Burtch, G., Ghose, A., & Wattal, S. (2013). An empirical examination of the antecedents and consequences of contribution patterns in crowd-funded markets. Information Systems Research, 24 (3), 499-519.

Burtch, G., Ghose, A., & Wattal, S. (2014). Cultural differences and geography as determinants of onli ne prosocial lending. MIS Quarterly, 38 (3), 773-794.

Charness, G., Rigotti, L., & Rustichini, A. (2007). Individual behavior and group membership. The American Economic Review, 97 (4), 1340-52.

Daniel, S., Agarwal, R., & Stewart, K. J. (2013). The effects of diversity in global, distributed collectives: A study of open source project success. Information Systems Research, 24 (2), 312-333.

Galak, J., Small, D., & Stephen, A.T. (2011). Microfinance decision making: A field study of prosocial lending. Journal of Marketing Research, 48 (SPL), S130–S137.

Gerber, E. M., & Hui, J. (2013). Crowdfunding: Motivations and deterrents for participation. ACM Transactions on Computer-Human Interaction, 20 (6), 34.

Harbaugh, W. T. (1998). What do donations buy? : A model of philanthropy based on prestige and warm glow. Journal of Public Economics, 67 (2), 269-284.

Heap, S. P. H., & Zizzo, D. J. (2009). The value of groups. The American Economic Review, 99 (1), 295-323.

Heller, L. R., & Badding, K. D. (2012). For compassion or money? The factors influencing the funding of microloans. The Journal of Socio-Economics, 41 (6), 831-835.

Lerner, J., & Tirole, J. (2002). Some simple economics of open source. The Journal of Industrial Economics, 50 (2), 197-234.

Lin, M., & Viswanathan, S. (2015). Home bias in online investments: An empirical study of an online crowdfunding market. Management Science, forthcoming.

Lin, M., Prabhala, N. R., & Viswanathan, S. (2013). Judging borrowers by the company they keep: Friendship networks and information asymmetry in online peer-to-peer lending. Management Science, 59 (1), 17-35.

Pavlou, P. A., & Gefen, D. (2004). Building effective online marketplaces with institution-based trust. Information Systems Research, 15 (1), 37-59.

Resnick, P., Kuwabara, K., Zeckhauser, R., & Friedman, E. (2000). Reputation systems. Communications of the ACM, 43 (12), 45-48.

Roberts, J. A., Hann, I. H., & Slaughter, S. A. (2006). Understanding the motivations, participation, and performance of open source software developers: A longitudinal study of the Apache projects. Management science, 52 (7), 984-999.

Shen, W., Hu, Y. J., & Rees, J. (2015). Competing for attention: An empirical study of online reviewers' strategic behaviors. MIS Quarterly, 39 (3), 683-696.

Shih, M., Pittinsky, T. L., & Ambady, N. (1999). Stereotype susceptibility: Identity salience and shifts in quantitative performance. Psychological Science, 10 (1), 80-83.

Tajfel, H. (1974). Social identity and intergroup behaviour. Social Science Information, 13 (2) 65-93.

Tajfel, H., & Turner, J. C. (1979). An integrative theory of intergroup conflict. The Social Psychology of Intergroup Relations, 33 (47), 74.

Tan, J. H., & Bolle, F. (2007). Team competition and the public goods game. Economics Letters, 96 (1), 133-139.

Zhang, J., & Liu, P. (2012). Rational herding in microloan markets. Management Science, 58 (5), 892-912.

Zhang, X. M., & Zhu, F. (2011). Group size and incentives to contribute: A natural experiment at Chinese Wikipedia. The American Economic Review, 101 (4), 1601-1615.