Social Networks in Online Peer-to-Peer Lending: The Case of Event-Type Ties as Pipes and Prisms

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Abstract

A considerable amount of academic research on crowdfunding has highlighted the importance of online social networks to crowdfunding success. Despite findings from these early studies, the focus of the extant literature has been on more persistent state-type ties such as friendship. In the current research, we examine how borrower-partner and borrower-team event-type ties affect lender behavior and loan success in online peer-to-peer (P2P) lending. Our empirical results using a multilevel mixed effects model reveal that borrower-team networks function as pipes that facilitate the flow of information and prospective lenders while borrower-partner ties function as prisms that signal borrowers' pressing financial need. Our results highlight the importance of establishing lending teams on crowdfunding platforms to enhance lender contribution.

1. Introduction

Over the last decade, crowdfunding has become a popular mechanism through which individuals and business can obtain donations for significant life changing events such as medical treatments and education, borrow money from other lenders, and bypass investors and the financial markets to obtain funds to support their start-up activities and continued growth. Among the different crowdfunding business models, online peer-to-peer (P2P) lending that allows individuals to lend and borrow money from each other has taken center stage. Research on P2P lending has examined how borrowers' project descriptions, category spanning and lenders' herding behavior affect fundraising success [1-3].

The extant crowdfunding literature highlights the importance of social capital and social networks to fundraising success across multiple crowdfunding business models [4-7]. Despite the significance of such social capital and social networks, there exists two gaps in research. First, current studies have focused on state-type social networks of more permanent relationships such as friendship [8]. Few have examined the impacts of event-type social networks that arise due to business transactions. To the best of our knowledge, the only exceptions are Colombo et al. [7] and Wang et al. [9] where they examine social capital and social networks emerged due to transactions on crowdfunding platforms. Second, no research except for Liu et al. [4] has examined the different mechanisms through which social networks affect lender behavior.

In the current study, we examine different types of social networks on Kiva.org, a leading P2P lending website, where organizations called field partners can review loan applications from borrowers and then post approved applications on Kiva. This process creates a tie between the borrower and the field partner that is specific to the particular loan transaction. In addition, lenders on Kiva can form lending teams based on shared interest, geography, or school and employer affiliation, and lenders from the same team can share information on the loans they have contributed to. Each loan's fundraising page also displays its lending teams. This creates a second event-based tie between the borrower(s) and a lending team. In the current study, we investigate how these two event-type social ties function differently as either signals of loan quality or channels through which prospective lenders learn about a loan. Results from our empirical research using a multilevel mixed effects model reveal that indeed these two types of social networks affect lender decision making and crowdfunding success differently. Specifically, ties between borrowers and their contributing teams function as pipes that raise awareness about a particular loan and facilitate the flow of prospective lenders to a loan's page. As a result, borrowers with more contributing teams receive more funding in the next period. In contrast, ties between borrowers and their field partners are prisms that convey information about the borrowers' financial need, and borrowers with a higher risk field partner are perceived more favorably by Kiva lenders and receive more contribution. Our results highlight the altruistic motivation behind Kiva lenders' decisions as they do not receive any interest rate

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on their loans to the borrowers and face the risk of not being able to obtain repayment on their loans. These results have implications to both P2P lending platforms and donation-based crowdfunding websites such as GoFundMe where crowdfunding participants donate to others in need for altruistic purposes.

2. Literature Review

2.1. Crowdfunding

Academic research on crowdfunding has examined factors that affect crowdfunding success at both the platform and the project levels. At the platform level, Jiang et al. [10] identified investors' herding behavior in their choice of crowdfunding platforms and revealed how such behaviors are moderated by the platform's market share, cumulative amount funded, and time in operation. The majority of the crowdfunding research focuses on the project level, where researchers have examined how characteristics of the borrowers and projects, similarity between the borrowers and lenders, group leader behavior and social networks affect project performance [2, 3, 5, 6, 11-14].

In P2P lending, because of the information asymmetry between the participants, borrowers and lenders often use signals to indicate and infer loan quality and make lending decisions. For example, project narratives that signal autonomy, competitive aggressiveness and risk-taking lead to more funding success while language that signals conscientiousness, courage, empathy and warmth are less favored by lenders [15]. In addition, lenders exhibit rational herding and infer signals of poor borrower quality as better creditworthiness while signals of high borrower quality are discounted [2]. However, lenders may also mistake group leaders' bids as signals of a high loan quality [3].

The extant crowdfunding literature also reveals the importance of social capital and social networks to crowdfunding success. Colombo et al. [7] showed that borrowers' internal social capital accumulated within a crowdfunding platform positively contributes to early project success and a higher likelihood of reaching the fundraising goal in rewards-based crowdfunding. Similarly, external social capital accumulated outside of the crowdfunding platform through online and offline friend networks leads to more funds received, a higher likelihood of reaching the funding goal, and lower interest rates in P2P lending [4, 5].

Despite the significance of social capital and social networks, two gaps in the literature exist. First, there is little research that explores the mechanisms through which different types of social networks affect lender behavior and loan success. To the best of our knowledge, the only exception is Liu et al. [4] that examined how the borrower's online and offline friends networks and the strength of the friendship ties differ in their impacts on lender decisions. Second, the focus of the crowdfunding literature has been on friendship networks of the borrowers or lenders. In the current study, we examine how the borrower-partner and borrower-team networks on Kiva, a P2P lending website, function differently in affecting loan success.

2.2. Social networks as pipes and prisms

Social networks represent the interactions and connections among individuals, entities and events [8]. Scholars across many disciplines including sociology, management and political science have used social network theory (SNT) to examine the formation of ties among individuals and entities, how the strength of these ties affect the flow of information and resources in a network, and how network positions affect individual, organizational and political performance and outcomes. Information Systems (IS) researchers have also applied SNT to the study of open source software development [16], information technology outsourcing [17], WOM and diffusion of innovation [18], social media user behavior [19-21], and crowdfunding [4, 5].

According to SNT, there are two types of ties in social networks. State-type ties such as kinship ties and friendship are more persistent, while event-type ties such as business transactions and committee membership are based on transactions and social interactions and are more discrete and transitory [8]. Irrespective of the type, social ties have long been recognized as valuable because they represent access to information, ideas and resources that flow in the network [8]. As a result, the strength of the ties especially the weak ties and the positions of the nodes such as structural holes are important determinants of how information and resources are shared or diffuse across a network [22, 23].

In a stark contrast to earlier social network research that views social ties of all types as roads or pipes through which news or resources flow, Podolny [24] distinguishes between two types of network ties: those as pipes and those as prisms. In the former case, network ties function as pipes through which information and resources flow, and traditional network theories such as the strength of weak ties and structural holes apply. In the latter case, social ties do not facilitate the flow of information or resources. Rather, they function as prisms that differentiate the nodes. Hence, being connected to a higher status alter indicates the social status of the ego and serves as a signal of trustworthiness and credibility. For example, in the organizational context, being associated with a high status organization indicates that a firm has obtained the approval of the more prominent other [25]. As a result, nodes occupying structural holes are not in an advantageous position.

We apply Podolny's notion of networks as pipes and prisms to examine how two crowdfunding event-type ties - those between a borrower and a field partner and those between a borrower and a lending team –function as pipes and prisms in affecting lender behavior and loan success.

3. Background and Hypotheses

3.1. P2P lending on Kiva

As a leading P2P lending platform, Kiva offers borrowers from around the world, especially those in developing countries, the opportunity to obtain loans from lenders. Most Kiva loans involve a field partner, very often a microfinance institution that has teamed up with Kiva to review borrower applications, pre-disburse loans to approved borrowers, post loans on Kiva, and collect repayments based on predetermined dates. While many field partners collect minimal interest on the loans to cover their operational expenses, the lenders do not receive interest on their loans. Hence, it is likely that lenders do not focus on the time value of money and lend for altruistic reasons under the risk of no repayment. A loan listing usually lasts up to 30 days or until the fundraising goal has been If the fundraising goal is not reached at the end of the listing period, the lenders get a refund of their contribution.

In addition to lending to borrowers on Kiva, lenders can also join one or more lending teams formed based on shared interests and beliefs, geographic proximity, or organizational or school affiliation. Each team can have one or more captains that manage team message boards and activities. As an example, Kiva Christians, one of the largest lending teams on Kiva, had three captains and over 21,000 members in May 2018 and has provided over $45 million in loans since its inception in 2008. On each team's webpage, team members' most recent loan activities are listed with hyperlinks to the loans. Members can also interact with other team members on the team's message board.

3.2. Hypotheses

The involvement of field partners and the presence of lending teams introduce two event-type networks on Kiva. First, there is a borrower-partner network when borrowers apply for Kiva loans through the field partners. This relationship is based on a particular loan application and is temporary. Hence, it is an event-type tie. Similarly, when one or more lenders in a team lend to the borrower(s) of a loan, a tie is created between the borrower(s) and the team based on the loan transaction. The team is listed under the "Contributing teams" section of the loan page, and members of the team can view the loan information through a hyperlink posted on the team's homepage. This creates a second event-type borrower-team tie based on the lending transactions. In the current research, we examine how these two event-type ties affect prospective lenders' decision-making and the amount of fund a loan is able to accumulate.

While both networks are event-type networks, the mechanisms through which they affect lending behavior are different. Field partners review borrowers' loan applications and post approved loans on Kiva. During this underwriting and approval process, a field partner can screen out risky borrowers. However, the process and criteria field partners use to approve loan applications are unknown to Kiva lenders. Prospective lenders can only rely on the information posted on the loan webpage to infer borrowers' quality. The field partner section on a loan's webpage lists information and statistics about the field partner including tenure on Kiva, number of borrowers helped, total amount of loans raised, overall risk rating, and more specific risk indicators such as delinquency rate, default rate, and loans at risk rate. Because prospective lenders do not have access to all information field partners have on the borrower(s) or the processes and criteria the field partner used to screen the borrower(s), field partner statistics become important prisms that convey borrower quality information. Hence, being associated with a more experienced field partner with a longer tenure, more loans secured for the borrowers, and lower risks may serve as status signals of the borrower(s)' credibility and trustworthiness. Prior research suggests that status signals very often reduce transaction costs, enhance access to financial capital, and improve organizational survival [26]. In crowdfunding, borrowers and lenders have frequently used signals to infer loan quality due to the uncertainty involved [5, 27]. For Kiva lenders, the borrower-partner tie may serve as a prism that signals the quality of the borrower(s) and the likelihood of getting repayment on their loan.

H1a: A loan with a field partner with longer tenure on Kiva is associated with a higher likelihood of fundraising success.

H1b: A loan with a field partner that has raised more loans is associated with a higher likelihood of fundraising success.

H1c: A loan with a lower-risk field partner is associated with a higher likelihood of fundraising success.

In contrast to the borrower-partner ties being prisms, the borrower-team ties are pipes that channel the flow of prospective lenders for three reasons. First, after one or more members of a lending team contribute to a loan, a hyperlink to the loan is added to the team activity section on the team's homepage on Kiva. This alerts other members of the team about the loan, and they can click on the loan's hyperlink to learn about it. Second, because lending teams are very often formed based on common lending interests, the likelihood of other team members contributing to a loan is higher than that of an average lender. Hence, once other members of the team become aware of the loan, their likelihood of lending to the borrowers is much higher than that of a random lender. Third, lenders can interact with others on the same team through the team's message board. This provides the members another opportunity to raise awareness about the loans they fund and introduce more prospective lenders to a listing. The online team forum also fosters an online community for team members with similar lending interests. Such an online community help its members develop a shared identity, enhance member commitment, and encourage altruistic behaviors [28]. As a result, borrowers with many contributing teams, with teams with more members, and with more active teams based on recent contributions are likely to receive more funding. Hence, we have:

H2a: A loan with more contributing teams is associated with a higher likelihood of fundraising success.

H2b: A loan with more members in its contributing teams is associated with a higher likelihood of fundraising success.

H2c: A loan with teams that have contributed more recently is associated with a higher likelihood of fundraising success.

4. Data and Methods

4.1. Data

We collected weekly loan data through the Kiva API from March to July 2017 using an automated data collection agent. Our sample consists of data on 34,771 loans with a total of 81,146 loan-week pairs. Each loan has up to four weekly observations since Kiva loans last up to 30 days. Table 1 summarizes the descriptive statistics on key loan variables at the end of each listing.

Table 1. Loan descriptive statistics (N=34,771)

Variable	Mean	Std. Dev.	Min	Max
# of borrowers	2.04	3.14	1	37
Amount raised in USD	312.05	909.37	0	44475
# lenders	9.12	22.84	0	1082
# teams	6.72	9.62	0	373

4.2. Econometric Models

While there is a screening process by the field partner prior to the loan being posted on Kiva, this process is exogenous in our research for three reasons. First, we focus on prospective lenders' decision-making based on loan, field partner and lending team information already posted on Kiva and how such information affects a loan's fundraising success. The underwriting process that occurs prior to the loan posting on Kiva is exogenous to our research. Second, Kiva is global and its goal is to reduce poverty. The lenders are from developed countries while the overwhelming majority of the borrowers are from developing countries. Hence, the chance of Kiva lenders having private information on the borrowers is very low. Third, Kiva lenders do not have access to the process or criteria field partners use in their underwriting process. Prospective lenders can only rely on the information posted on the loan webpage including field partner statistics and lending teams to make their lending decisions. Hence, we argue that, in presence of the unknown underwriting process and selection criteria used by the field partners, lenders view field partner statistics as prisms that convey important information about borrower(s) quality. As a result, we do not consider the field partner screening process as an endogeneity concern in our research.

Because we model loan success based on borrower(s), field partner and lending team data posted on a loan's webpage, we recognize that not all loans received funding and those that received funding did not all have lenders as members of lending teams. This introduces a selection bias in our data since we have to eliminate loans without lending teams, and there may be a systematic difference between loans with and without lending teams. To correct for this selection bias, we first estimate a Heckman [29] selection model on the likelihood of a loan having at least one lending team. We use the following model to predict the probability that a loan had at least one contributing team by time t:

$$\Pr(HadTeam_{it}=1|\boldsymbol{z_{it}})=\Phi(\boldsymbol{z_{it}\beta_1} + \mu_i + v_t + \varepsilon_{it}), \quad (1)$$

where $HadTeam_{it}$ is a dummy variable indicating if Loan i had at least one contributing team by time t, Φ denotes the standard cumulative normal distribution, and $\boldsymbol{z_{it}}$ is a vector of exogenous variables on loan characteristics at time t including the natural logarithm of the fundraising goal, the borrower count on the loan, the sector of the loan's intended use, the borrower(s)' country, whether the loan had a field partner, and the number of days left in the loan listing. These variables are exogenous to the probability of a loan having at least one lending team because they are either determined prior to the loan being posted on Kiva or they are based on time which is not determined by lender behavior. v_t represents the fixed effects of the week of the data collection. Because of the bias present in fixed effects nonlinear models, we estimate a random effects Probit model [30]. Loan i's random effect μ_i follows a $N(0,\sigma_\mu^2)$ distribution. We calculate the inverse Mills ratio based on Equation 1 and add it in our second-stage multilevel mixed effects model as an explanatory variable.

Our second stage model involves estimating the loan amount a listing received during week t. Because loans are nested under the field partners, we use a multilevel (a.k.a hierarchical) mixed-effects model with the loan being the first level and the field partner being the second level. The use of the multilevel model allows us to capture systematic variations in the impacts of loan and team characteristics among loans sponsored by the same field partner [31]. In the first level, we estimate the amount of loan a listing received during week t based on borrower, loan and team characteristics:

Level 1 ($Loan_{ij}$): $\Delta y_{ijt} = \beta_{0j} + \beta_{1j} y_{ijt-1} + \beta_{2j} DaysLeft_{ijt-1} + \beta_{3j} ln(NoTeams_{ijt-1}+1) + \beta_{4j} ln(TtlTeamMbrs_{ijt-1}+1) + \beta_{5j} ln(TtlTeamMoLoan_{ijt-1}+1) + \beta_6 \mathrm{IMR}_{ijt-1} + v_t + \varepsilon_{ijt}$, (2)

where Δy_{ijt} represents the natural logarithm of one plus the amount of loan listing i sponsored by field partner j received during week t ($ln(LoanAmtRcvd_{ijt}+1)$), y_{ijt-1} is the natural logarithm of the total amount of loan listing i with field partner j received up until week $t-1$ plus one ($ln(TtlAmtRcvd_{ijt-1}+1)$), IMR_{ijt-1} is the inverse Mills ratio for listing i at week t-1, and v_t is the fixed effects of the week of the data collection. ε_{ijt} is the error term in the prediction of the amount of loan a listing received and follows a $N(0,\sigma_\varepsilon^2)$ distribution. The other variables represent the impacts of loan and team characteristics on the amount of loan received. Because the number of lenders on a loan is highly correlated with the cumulative amount raised, we do not include the latter in our loan level model.

Next, we introduce field-partner characteristics in our Level 2 model to capture their impacts on loan listing success and how the impacts of lending teams may differ across loans with different field partners:

Level 2 ($Partner_j$): $\beta_{0j} = \gamma_{00} + \gamma_{01} ln(PtrTenure_{jt-1}) + \gamma_{02} ln(PtrTtlAmtRaised_{jt-1}) + \gamma_{03} PtrRating_{jt-1} + \xi_{0j}$,
$\beta_{1j} = \gamma_{10} + \xi_{1j}$, $\beta_{2j} = \gamma_{20} + \xi_{2j}$, $\beta_{3j} = \gamma_{30} + \xi_{3j}$, $\beta_{4j} = \gamma_{40} + \xi_{4j}$, and $\beta_{5j} = \gamma_{50} + \xi_{5j}$. (2)

Based on these specifications, the intercept β_{0j} in Equation 1 is a function of three field partner-related variables and a random effect ξ_{0j}. The slopes in Equation 1 are dependent on a fixed effect (γ) and a field partner-related random effect (ξ). These random effects are assumed to follow normal distributions with a mean of zero and their respective variances. By combining Equations 1 and 2, we have:

$\Delta y_{ijt} = \gamma_{00} + \gamma_{01} ln(PtrTenure_{jt-1}) + \gamma_{02} ln(PtrTtlAmtRaised_{jt-1}+1) + \gamma_{03} PtrRating_{jt-1} + \gamma_{10} y_{ijt-1} + \gamma_{20} DaysLeft_{ijt-1} + \gamma_{30} ln(NoTeams_{ijt-1}+1) + \gamma_{40} ln(TtlTeamMbrs_{ijt-1}+1) + \gamma_{50} ln(TtlTeamMoLoan_{ijt-1}+1) + \beta_6 \mathrm{IMR}_{ijt-1} + v_i + \varepsilon_{it} + \xi_{1j} y_{ijt-1} + \xi_{2j} DaysLeft_{ijt-1} + \xi_{3j} ln(NoTeams_{ijt-1}+1) + \xi_{4j} ln(TtlTeamMbrs_{ijt-1}+1) + \xi_{5j} ln(TtlTeamMoLoan_{ijt-1}+1) + \xi_{0j}$. (3)

In Equation 3, the γ's are the fixed effects and the ξ's are the random effects. Hence, we have a hierarchical mixed-effects model and estimate the coefficients for the fixed effects and the variances of the random effects. Table 2 summarizes our variable definitions.

Table 2. Variable definitions

Variable	Definition
$HadTeam_{it}$	1 if loan i had at least one contributing team by time t; 0 otherwise.
$ln(LoanAmtRcvd_{ijt}+1)$	The natural logarithm of one plus the contribution amount loan i received during time t.
$ln(TtlAmtRcvd_{ijt-1}+1)$	The natural logarithm of one plus the total contribution amount loan i received up until time t-1.
$ln(LoanGoal_i+1)$	The natural logarithm of one plus the fundraising goal of loan i.
$NoBorrowers_i$	The number of borrowers on loan i.
$DummyPtr_i$	Dummy variable with the value of 1 if loan i had a field partner; 0 otherwise.
$DaysLeft_{ijt-1}$	The number of fundraising days remaining at time t for loan i.
$ln(NoTeams_{ijt-1}+1)$	The natural logarithm of one plus the number of contributing teams for loan i posted by field partner j during time t-1.
$ln(TtlTeamMbrs_{ijt-1}+1)$	The natural logarithm of one plus the total number of members in loan i's contributing teams at time t-1.
$ln(TtlTeamMoLoan_{ijt-1}+1)$	The natural logarithm of one plus the total amount loan i's contributing teams had lent out on Kiva during the month immediately preceding time t-1.
$ln(PtrTenure_{jt-1})$	The natural logarithm of the number of days at time t-1 that field partner j had been posting loans on Kiva.
$ln(PtrTtlAmtRaised_{jt-1}+1)$	The natural logarithm of one plus the total amount field partner j had raised on Kiva up until time t-1.
$PtrRating_{jt-1}$	Field partner j's risk rating given by Kiva at time t-1; ranges from 0 to 5 with 5 being the least risky.
$IMR_{ijt\text{-}1}$	The inverse Mills ratio for loan i from partner j at time t-1.

5. Results

In this section, we first report our results of the first stage random effects Probit selection model, then we report the results of our second stage multilevel mixed-effects model.

5.1. Random effects Probit selection model results

Because we use one-week-lagged loan characteristic variables to predict the likelihood that a loan had at least one contributing team by time *t*, our sample size reduces to 42,286 loan-week pairs collected from 20,250 unique loans. Table 3 summarizes the results of our first stage random effects Probit selection model. Except for *DummyPtr*, all other independent variables are significant. The results indicate that having a higher fundraising goal and more borrowers on the loan increased the likelihood of the loan having at least one contributing team. In contrast, loans that were early in their fundraising process with more days remaining were less likely to have a contributing team. Based on the estimation model, we calculate the IMR and add it to our second stage multilevel mixed-effects model.

Table 3. Random effects Probit selection model results (N=42,286)

Variable	Coefficient (Std. Dev.)
$ln(LoanGoal_i+1)$	1.775*** (0.074)
$NoBorrowers_i$	0.179*** (0.014)
$DummyPtr_i$	5.968 (4.746)
$DaysLeft_{ijt-1}$	-0.458*** (0.005)
Sector Dummies	Included
Country Dummies	Included
Time Dummies	Included
Constant	-0.410 (4.825)
Wald χ^2	18061.89***

*p<0.1; ** p<0.05; ***p<0.01.

5.2. Multilevel mixed-effects model results

Table 4 summarizes our second-stage analysis results from multiple models. Model 2A is the baseline model without considering the nested field partner effect. Models 2B through 2E are multilevel mixed effects models that take into account the nested field partner effect on loan success. Model 2B includes the intercept only. Model 2C includes Level 1 loan fixed and random effects only. Model 2D includes Level 2 field partner and random effects only. Model 2E includes fixed and random effects for both the loan and field partner variables. Models 2B and 2D have much larger sample sizes because there is no selection bias of loans with contributing teams. In the other three models, we control for this selection bias by including the inverse Mills ratio for having a team. All models' variance inflation factors (VIFs) are under 5. As a result, multicollinearity is not an issue in our data analysis. We compare the model goodness of fit using the deviance [32, 33]. Because Models 2B and 2D have much larger sample sizes, their deviances are much larger. Overall, Model 2E with the fixed and random effects of both loan and partner level variables has the lowest deviance and the best model fit.

Overall, our fixed effects coefficient estimates are consistent across the five models. At the loan level, the coefficient estimate for $ln(TtlAmtRcvd_{ijt-1}+1)$ is negative and significant in Models 2A, 2C and 2E, while the coefficient for $DaysLeft_{ijt-1}$ is positive and significant in these three models. For lending team-related variables, the coefficient estimates for $ln(NoTeams_{ijt-1}+1)$ and $ln(TtlTeamMbrs_{ijt-1}+1)$ are positive and significant in Models 2A, 2C and 2E, indicating that having more contributing teams and having contributing teams with more members led to more funding received in the next week. Contrary to our expectation, the coefficient for $ln(TtlTeamMoLoan_{ijt-1}+1)$ is negative and significant across all three models. This shows that having contributing teams with more dollar amount lent in the previous month resulted in less funding received during the next week. The inverse Mills ratio for controlling the team selection bias is negative and significant in all three models.

At the field partner level, the coefficient estimate for $PtrRating_{jt-1}$ is negative and either significant or weakly significant in Models 2A, 2D and 2E. This contradicts H1c and indicates that loans with more risky field partners were able to obtain more funding during the next period. The coefficient estimate for $ln(PtrTenure_{jt-1})$ is positive and significant in Model 2A but not in Models 2D and 2E. The coefficient estimate for $ln(PtrTtlAmtRaised_{jt-1}+1)$ is negative across the three models but only significant or weakly significant in Models 2A and 2D.

By comparing the deviances and the significance of the random coefficients of the models, we can see that adding the field partner level into the data analysis provides additional explanatory power beyond that provided by the loan-level variables or the fixed effects. Based on the results from the unconditional Model 2B, we calculate the Intraclass Correlation Coefficient (ICC) as $\sigma^2_{\xi 0j} / (\sigma^2_{\xi 0j} + \sigma^2_{\varepsilon}) = 37\%$. This reveals that 37% of the total variation in $ln(LoanAmtRcvd_{ijt}+1)$ can be explained by the field partners. In Models 2C and 2E, the random coefficients for *ln(TtlAmtRcvd*$_{ijt-1}$+1), *DaysLeft*$_{ijt-1}$ and *ln(NoTeams*$_{ijt-1}$+1) are significant, while those for *ln(TtlTeamMoLoan*$_{ijt-1}$+1) are weakly significant. Hence, the impacts of these loan-level variables vary across field partners. Taken together, these results suggest the importance of incorporating the field partner as an additional level of analysis when examining loan contribution on Kiva.

Table 4. Results of baseline and multilevel mixed-effects models

	Model 2A (Baseline model)	Multilevel Mixed Effects Models			
		Model 2B (Intercepts only)	Model 2C (Level 1 only)	Model 2D (Level 2 only)	Model 2E (Both Level 1 and Level 2)
Fixed effects					
Intercept (γ_{00})	1.2247*** (0.2296)	4.8691*** (0.1404)	2.5098*** (0.0917)	8.8120*** (1.0667)	3.5449*** (0.6581)
ln(*PtrTenure*$_{jt-1}$) (γ_{01})	0.1778*** (0.0366)			0.2823 (0.2905)	-0.0956 (0.1337)
ln(*PtrTtlAmtRaised*$_{jt-1}$+1) (γ_{02})	-0.0178 (0.0200)			-0.3595** (0.1413)	0.0206 (0.0720)
PtrRating$_{jt-1}$ (γ_{03})	-0.1493*** (0.0170)			-0.3958*** (0.1327)	-0.1763*** (0.0630)
ln(TtlAmtRcvd$_{ijt-1}$+1) (γ_{10})	-0.3922*** (0.0092)		-0.3420*** (0.0130)		-0.3476*** (0.0135)
DaysLeft$_{ijt-1}$ (γ_{20})	0.0459*** (0.0023)		0.02309*** (0.0031)		0.0271*** (0.0033)
ln(NoTeams$_{ijt-1}$+1) (γ_{30})	2.2992*** (0.0296)		2.0342*** (0.0363)		2.0222*** (0.0388)
ln(TtlTeamMbrs$_{ijt-1}$+1) (γ_{40})	0.0385*** (0.0087)		0.0400*** (0.0091)		0.0384*** (0.0092)
ln(TtlTeamMoLoan$_{ijt-1}$+1) (γ_{50})	-0.0792*** (0.0112)		-0.0678*** (0.0117)		-0.0683*** (0.0117)
IMR $_{i,t-1}$ (β_6)	-0.1918*** (0.0071)		-0.0977*** (0.0114)		-0.0928*** (0.0116)
Time dummies	Included	Included	Included	Included	Included
Random effects					
Intercept ($\sigma^2_{\xi 0j}$)		2.4856*** (0.3293)		2.0397*** (0.2825)	0.0501* (0.0331)
ln(TtlAmtRcvd$_{ijt-1}$+1) ($\sigma^2_{\xi 1j}$)			0.0066*** (0.0015)		0.0070*** (0.0016)
DaysLeft$_{ijt-1}$ ($\sigma^2_{\xi 2j}$)			0.0003*** (0.0001)		0.0003*** (0.0001)
ln(NoTeams$_{ijt-1}$+1) ($\sigma^2_{\xi 3j}$)			0.0172** (0.0079)		0.0264*** (0.0108)
ln(TtlTeamMbrs$_{ijt-1}$+1) ($\sigma^2_{\xi 4j}$)			0.0003 (0.0002)		0.0003 (0.0003)
ln(TtlTeamMoLoan$_{ijt-1}$+1) ($\sigma^2_{\xi 5j}$)			0.0005* (0.0003)		0.0004* (0.0003)
Residual (σ^2_{ε})		4.2335*** (0.0281)	2.9727*** (0.0296)	4.2369*** (0.0282)	2.9693*** (0.0300)
N	20,596	45,434	20,779	45,211	20,596
Deviance	812,162.7	195,072.7	82,030.3	194,144.5	81,318.4

Notes: The standard errors are in parentheses. *p<0.1; ** p<0.05; ***p<0.01.

5.3. Robustness checks

We perform four robustness checks on our data analysis. First, because we are unable to include the number of lenders as an independent variable due to its high correlation with the cumulative amount raised, we test additional models by replacing the cumulative amount raised with the number of lenders. We obtain very similar results to those report in Table 4 in terms of coefficient estimates and significance levels.

Second, in addition to examining the impacts of the field partner and contributing teams on the amount of funding received, we also test additional models using the percentage of the loan received during a week as the dependent variable and the cumulative percentage of loan received up to the previous week as one of the independent variables. We also obtain results very similar to those reported in Table 4.

Third, we replaced the dummy variable indicating the presence of a field partner with three field partner statistics including tenure, amount of loan raised, and rating in the first-stage selection model to account for the impact of field partners on the likelihood of a loan having at least one lending team. Our results from the second-stage multilevel mixed-effects model have the same signs for the coefficient estimates with similar magnitudes and significance levels.

Fourth, because 98.5% of our sample loans involved a field partner, we are unable to run a Heckman selection model on the field partner due to the lack of enough variation. A closer examination of the data shows that the lack of a field partner is for U.S. borrowers only. We do not consider this to be a serious issue for two reasons. First, the U.S. is the only developed country where Kiva lenders lend to. Because Kiva lenders do not get any interest on their loans to the borrowers and they primarily lend to borrowers in developing countries for altruistic reasons, loans from U.S. lenders may perform systematically different from those with borrowers in developing countries as the underlying drivers may be different. Second, our second-stage multilevel analysis accounts for the fixed loan effect where the impacts of loan-invariant variables such as goal amount, country and sector are controlled.

6. Discussion

6.1. Theoretical contribution

We examine how two different types of transaction-based event-type social networks on P2P lending platform Kiva function differently as pipes and prisms to affect fundraising success. We have the following major results and contribution.

First, we extend the crowdfunding literature by examining the impacts of event-type social networks. The extant crowdfunding literature has recognized the importance of borrowers' and lenders' social networks on crowdfunding success. However, the focus has been on more permanent state-type social networks such as friendship networks [4, 5]. In the current research, we study more temporary event-type ties that develop based on business transactions between the borrowers and field partners and between the borrowers and their contributing teams and the impacts of such event-type ties on crowdfunding.

Second, our research contributes to the crowdfunding and social network literature by highlighting the different mechanisms through which social networks can influence crowdfunding success. While both borrower-partner and borrower-team networks are event-type networks, our theorizing and results show that the borrower-team networks function as pipes that facilitate the flow of information and prospective lenders from a lending team to the loan page, and borrower-partner ties serve as prisms that signal the pressing financial need of the borrowers.

Third, our results reveal the importance of contributing teams to the success of a Kiva loan. Specifically, having a larger number of contributing teams and more members in these teams result in more contribution received in the next period. The fact that not only the total number of contributing teams but also the total number of members in these teams affect fundraising success also confirms our hypothesis that the borrower-team ties serve as pipes that funnel more prospective lenders from the contributing teams' webpages to a loan's webpage, build up awareness, and result in more fundraising success. The team webpage serves as an online community for Kiva lenders with similar lending interests, shared identity or affiliation, or close geographic proximity. Empirical research shows that online communities foster members' identification with and commitment to the community and social media platform, thus resulting in more active member participation. On Kiva, members of a lending team can interact with each other through the team's discussion forum, review other team members' lending activities, and discover loans other team members have contributed to. This makes finding more information about a particular loan much easier given the large number of concurrent loans on Kiva. Contrary to our expectation, the total amount of contributing team loans in the last month is negatively correlated with a loan's fundraising success. There are two possible explanations, First, this can be indicative of the limited financial resources available to Kiva lenders. As the lenders contribute more to other loans in the immediate past, they have less financial resource to lend to the current borrowers. Second, when team members contributed more in the last months, more loans will show on the team's homepage, thus giving other team members more options to choose from. This intensified competition among loans may result in reduced loan contribution in the next period.

Fourth, our research highlights a different mechanism through which the borrower-partner ties affect fundraising success. Contrary to our expectation, field partner rating is negatively correlated with loan success. This suggests that, while lenders take the field partner's risk rating into consideration in their lending decisions, they do not interpret it as a signal of the borrower(s)' more desirable or trustworthy status. In contrast, a loan with a riskier field partner is perceived more favorably by lenders. We interpret this as another prism effect where altruistic lenders view more risky field partners as indicative of borrowers with more significant financial needs. Because Kiva lenders do not receive any interest on their loans and run the risk of not getting their loans back, they lend to borrowers from developing countries with the goal to help others rather than making a profit on their investment. As a result, the field partner's risk rating is not factored negatively into the lenders' decision making process.

Fifth, we confirm a substitution effect observed in prior crowdfunding research where prospective lenders favor loans with less contribution [11] and observe that Kiva loans receive more contribution early in their fundraising process.

Sixth, our multilevel mixed effects model results reveal the importance of considering the field partner as an additional level of analysis beyond the loan. Specifically, the field partner explains 37% of the total variation in the natural log of the loan contribution during a week. Moreover, there is significant variation in the impacts of loan-level variables such as the total contribution received, days left, the total number of contributing teams, and the amount of loan made by the contributing teams in the previous month among loans sponsored by different field partners.

6.2. Practical implications

Our research has the following implications for crowdfunding platforms in general and P2P lending providers in particular. First, our results highlight the importance of using lending teams to build communities of online lenders, encourage more active lender participation, and enhance fundraising success. Multiple studies have confirmed the significance of online communities in enhancing website stickiness. While many crowdfunding platforms allow users to post comments under a crowdfunding project, few supports online communities on their platforms. The project comment section only supports limited interaction among the users and requires them to first become aware of a particular fundraising project. In contrast, an online lending team on Kiva allows team members to post to the team's discussion forum, interact with each other, and discover other fundraising loans. The sense of community and the commitment to the team and to Kiva will lead to more team member lending behavior.

Second, our results suggest that, depending on the function and goal of a crowdfunding platform, the factors that affect lending behavior and crowdfunding success will be different. For example, contrary to our expectation, loans associated with more risky field partners are perceived more favorably by Kiva lenders. Hence, when designing crowdfunding platforms, the providers should consider the market they serve and the characteristics of their prospective lenders. For donation-based crowdfunding platform, the emphasis should be more on the emotional aspects of helping others and making a difference in their lives. In contrast, in profit-driven P2P lending or equity-based crowdfunding, the emphasis should be more on the return on investment and risks involved.

Third, due to the prevalence of the substitution effect observed in multiple crowdfunding studies including the current one, crowdfunding platforms should consider strategies to enhance contribution to late-stage fundraising projects to ensure fundraising success. This is especially important for platforms employing the all-or-nothing model where borrowers do not receive anything if they do not reach the fundraising goal by the end of the fundraising period. Strategies that can be employed include listing more active and close to fundraising goal projects on the platform's or each category/subcategory's front page and engaging in email marketing campaigns alerting members of such projects.

7. Conclusion

The current research examines how two types of transaction-based event-type ties on Kiva contribute differently to crowdfunding success. Our empirical research using a multilevel mixed effects model reveals that borrower-team ties function as pipes that facilitate the flow of information and prospective lenders to a loan's page, while borrower-partner ties serve as prisms that signal the urgency of the borrowers' financial need.

Our research has limitations. First, our results on two different types of event-type social networks are based on one P2P lending platform only. Future research can examine other event-type ties and how they affect crowdfunding success on other platforms. Second, while we observe the significance of the borrower-team and borrower-partner relationships to fundraising success on Kiva, we cannot infer causality as we do not test lenders' decision making directly. We plan to conduct additional analyses on how the number of current lenders on a loan from one team affect the number of new lenders from the same team. Future research can verify the impacts of such ties using laboratory experiments.

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