Does Team Competition Increase Pro-Social Lending? Evidence from Online Microfinance

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Abstract

We investigate the effects of team competition on pro-social lending activity on Kiva.org, the first microlending website to match lenders with entrepreneurs in developing countries. Using naturally occurring field data, we find that lenders who join teams contribute 1.2 more loans ($30-$42) per month than those who do not. To further explore factors that differentiate successful teams from dormant ones, we run a large-scale randomized field experiment ($n = 22,233$) by posting forum messages. Compared to the control, we find that lenders make significantly more loans when exposed to a goal-setting and coordination message, whereas goal-setting alone significantly increases lending activities of previously inactive teams. Our findings suggest that goal-setting and coordination are effective mechanisms to increase pro-social behavior in teams.

JEL Classification: C1, C93, D64, H41

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1. Introduction

Understanding strategies to increase pro-social behavior is of major interest across the social sciences. The sizeable mechanism design literature has identified innovative tax-subsidy rules to reduce free-riding in the presence of public goods when a central authority can enforce the rules. Under the VCG mechanism, it is a dominant strategy for individuals to reveal their true values for the public good when preferences are quasi-linear, although the allocation is not fully Pareto efficient (Vickrey, 1961; Clarke, 1971; Groves, 1973). Preserving Pareto optimality at the cost of non-manipulability,

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Groves and Ledyard (1977) propose an allocation mechanism where the Nash equilibrium is Pareto efficient. Subsequent literature achieves similar goals using Nash or refinements of Nash equilibrium (Groves and Ledyard, 1987). In the incomplete information setting, Ledyard and Palfrey (1994) characterize interim efficient mechanisms for public good production and cost allocation.

In comparison to the mechanism design approach, we investigate a real-world mechanism designed to increase pro-social behavior in a public good environment without a central authority, namely, team competition. Our research question is whether team competition increases pro-social behavior in the field. A large body of experimental research in economics and social psychology has demonstrated that the existence of identity-based teams can increase public goods provision (Eckel and Grossman, 2005) and improve coordination (Bornstein et al., 2002; Croson et al., 2008; Chen and Chen, 2011).[3] However, one limitation of this research is that it has been conducted in a laboratory setting. Thus, it is an open question whether team competition increases pro-social behavior in a natural field setting, and if so, why.

Our research is conducted at Kiva.org, the world's first and largest peer-to-peer microfinance website. Kiva was created to help micro and small enterprises in developing countries, which comprise the largest group of employers in many developing countries. However, their growth is often stifled by a lack of access to credit and other financial services (Flannery, 2007). To meet this large ongoing need for entrepreneurial support, Kiva provides a unique opportunity to increase the participation of ordinary people around the world through the process of online microlending. Founded in 2005, Kiva partners with microfinance institutions and matches individual lenders from developed countries with low-income entrepreneurs in developing countries as well as in selected cities in the United States. Through Kiva's platform, anyone can make a zero-interest loan of $25 or more to support an entrepreneur. As of January 2015, more than 2 million lenders across 208 countries have contributed $666 million in loans, reaching over 1.5 million borrowers in more than 73 countries.[4] Through its online lending model, Kiva has transformed the entrepreneur lending landscape, creating a new form of capital market enabled by information technology.

Despite its success, Kiva faces a challenge in terms of lender engagement. Although the membership of Kiva, along with the number of loans made through Kiva, has increased greatly, only a few lenders give many loans, while most members give only a few or no loans (Liu et al., 2012). Indeed, Premal Shah, the president of Kiva, indicates that many Kiva lenders lend once, but then never come back to the site, despite the fact that their loans have been repaid and thus they could make another loan at no additional cost.[5]

To increase lender engagement, in August 2008, Kiva instituted a lending teams program, a system through which lenders can create teams or join existing teams. The lending team concept works as follows. First, any lender is allowed to create or join

[3] Goette et al. (2012) also demonstrate the dark side of intergroup competition in that group members might hurt outgroup memebers. In our field setting, this negative aspect does not apply.

[4] Source: `http://www.kiva.org/about/stats`, retrieved on January 30, 2015.

[5] Source: `http://www.youtube.com/watch?v=aEC3OwKWgfc`, retrieved on January 30, 2015.

any number of teams. When that lender next makes a loan, a prompt asks whether to assign that loan to any of the teams the lender has joined. For a given loan, a lender may choose to assign it to either one team or no team. Once a team is created, it appears on Kiva's team leaderboard (`http://www.kiva.org/teams`). This leaderboard sorts teams by the total loan amounts designated to them by their team members. Since 2008, more than 37,200 Kiva teams have been created, many of which are organized based on lender group affiliations such as school, organization, geographic location, religious affiliation, or sports. Of note, many of the highly ranked teams are identity-based, such as the "Atheists" and the "Kiva Christians."

To investigate the effect of team membership on pro-social lending behavior, we first conduct empirical analysis using naturally occurring field data. To further explore factors that differentiate successful teams from dormant ones, we run a randomized field experiment by posting forum messages designed to motivate lending activity. These messages relate to two possible underlying mechanisms that might affect team performance. One mechanism is team competition through goal setting. The second mechanism is team coordination to reduce transaction costs.

Our results provide both academic and practical insights. First, our study contributes to social identity research by demonstrating that group membership can be leveraged as a design tool to promote pro-social behavior in the real world. This approach takes social identity research from theory (Akerlof and Kranton, 2000; Tajfel and Turner, 1979) and the laboratory (Charness et al., 2007; Chen and Li, 2009) to the realm of market design and intervention. It also contributes to econometrics by incorporating data mining techniques from computer science to analyze both numerical and text data. Finally, our study is directly relevant for Kiva and other online public goods sites looking to increase participant engagement.

2. Literature Review

Our paper relates to two streams of economic research - the role of group identity in public goods provision and the effectiveness of online microfinance in motivating lender behavior. In economics, there is a large body of research examining why people give to charities (Andreoni, 2006b; Vesterlund, 2006). There is also a more recent literature that uncovers the positive effects of group identity and team competition on public goods provision and coordination. However, these studies are largely based on results obtained in a laboratory setting. These laboratory results show that participants with a salient group identity contribute more to public goods under the voluntary contribution mechanism (Eckel and Grossman, 2005), and coordinate to a more efficient Nash equilibrium in the context of the minimum-effort game (Bornstein et al., 2002; Chen and Chen, 2011), the provision point mechanism (Croson et al., 2008) and the Battle of the Sexes (Charness et al., 2007).

However, one challenge in interpreting these findings is the question of whether they can apply to naturally occurring settings. One study provides a positive answer in a field experiment of fruit harvesting in an orange grove (Erev et al., 1993). In this setting, the authors find that team competition increases productivity, but they do not explore mechanisms which might cause such a team effect. By contrast, our study takes advantage of the Kiva online forum, which enables communication among team members, to explore mechanisms which lead to successful team lending in a field setting. We then use our findings from the team forums to design a randomized field experiment to explore the relative effectiveness of these underlying mechanisms in increasing lender activity.

A second stream of literature on the economics of microfinance largely focuses on the borrower side (Armendáriz and Morduch, 2010). More recently, a few studies on online microfinance examine lender motivations (Liu et al., 2012), biases (Jenq et al., 2012) and sensitivity to transaction costs (Meer and Rigbi, 2013). Focusing on Kiva, these studies find that lenders appear to favor more attractive, lighter-skinned and less obese borrowers. They are also more likely to fund loan requests from borrowers they perceive to be needy, honest and creditworthy (Jenq et al., 2012). In one field experiment on Kiva which varies the language of the loan requests, Meer and Rigbi (2013) find that untranslated requests take substantially longer to obtain full funding than translated ones, indicating that transaction costs arising from translation significantly deter funding speed. The authors also find that social distance plays a role in funding decisions. Closer to our study, Hartley (2010) reports observations of 120 lending teams on Kiva over a two-month period. Specifically, the author compares team size and openness on group lending activities. However, the small sample size precludes an econometric analysis of the observations.[6] Lastly, using the Kiva application programming interface (API) data from a shorter time horizon (May – September 2012) than ours (February 2006 - February 2012) and a different statistical model (linear mixed model), Schaaf (2013) independently studies the effects of team membership on lending behavior in his masters thesis, and concludes that team membership significantly increases loan amount but not loan frequency. His analysis on loan amount uses the same approximation as we do in Table 3, both following the approximation method in our earlier work (Liu et al., 2012), and reaches similar conclusions as we do, whereas his coefficient on loan frequency is positive but insignificant, which might be due to a smaller number of observations. While Schaaf (2013) focuses on empirical analysis using naturally occurring data, our study also contains a randomized field experiment designed to explore mechanisms underlying the team effects.

Our study thus advances the existing literature in several dimensions. First, we investigate the effects of lending teams on pro-social lending with a large-scale empirical study. Second, the team forum data enable us to uncover the mechanisms behind the positive effects of team membership, and to verify the efficacy of these mechanisms using a randomized field experiment. Finally, the existing social identity literature in economics and social psychology is largely based on theory (Akerlof and Kranton, 2000; Tajfel and Turner, 1979) or laboratory experiments (Charness et al., 2007; Chen and Li, 2009). In comparison, our study examines the effects of identity-based team competition in a real-world setting.

[6]While Kiva loans are interest free, other microfinance websites, such as Prosper.com, allow users to make loans for profit. As we are interested in pro-social lending, we do not review the literature which investigates for-profit microfinance sites (Lin et al., 2012).

3. Field Setting: Kiva

Founded in 2005, Kiva enables citizen lenders from developed countries to make loans of at least $25 to borrowers in developing countries through its online platform. Kiva partners with 238 microfinance institutions across 68 countries to select borrowers and administer its loans (Flannery, 2007). These individual loans are then combined into a single loan to the borrower.

Table 1 displays the summary statistics for Kiva as of February 2012. These statistics show that, while 64% of those who have joined the site have made at least one loan, the remaining 36% have never made a loan. This is consistent with previous research that finds that only a few lenders give many loans, while many lenders give few to no loans (Liu et al., 2012). This uneven distribution of loans results in a small group of core lenders and a large group of peripheral lenders.

Table 1: Summary Statistics of Kiva.org (As of February 2012)

Number of Lenders	884,692
Lenders who have made:	
No loans	315,543
At least 1 loan	569,149
Avg. number of loans	13.41
At least 5 loans	246,673
Avg. number of loans	28.26
Lenders with:	
Location information	500,131
Motivation statements	129,731
Occupation information	436,986
Lenders who are:	
Male	175,219
Female	318,172
Companies	1,132
Families	3,558
Couples	3,171
Lenders who are members of:	
At least 1 team	159,833
Median number of teams	1
Number of teams	22,322
Avg. number of lenders per team	11.92
Avg. number of loans per team	120.55

To address this disparity in lending activity, in August 2008, Kiva instituted a lending teams program. This program allows any lender to create or join any number of teams. Once a team is created, it is displayed on Kiva's team leaderboard (`http://www.kiva.org/teams`). A lender who has joined a team is subsequently asked if she wants to assign any loan she makes to one of her teams. For a given loan, a lender may choose to assign it to either one team or no teams.

Kiva teams share a name and a motivation statement,[7] which form a basis for the group's identity. Furthermore, Kiva teams consist of open and closed teams, each designated by the team captain. While anyone can join an open team, one must have the permission of the team captain to join a closed team. Of the 22,322 teams in the 2012 data set, 17,194 (77%) are open, and 5,128 (23%) are closed. In addition, each Kiva lending team has a restricted forum accessible only to team members. The team forum enables communications between team members, which can foster both team identity and team bonds (Ren et al., 2007).

Premal Shah suggests that the lending teams program was designed to increase lender engagement on Kiva and to make Kiva "as fun and compelling as possible." To this end, the lending teams program provides a venue for team competition. Competition is implemented on Kiva through a team leaderboard. The team leaderboard sorts teams by the total loan amounts that their team members have assigned to them "this month," or "last month" or "all time."[8] As of January 2015, the top five lending teams displayed on the total-loan-amount leaderboard are "Atheists, Agnostics, Skeptics, Freethinkers, Secular Humanists and the Non-Religious," "Kiva Christians," "milepoint," "Guys Holding Fish," and "HP."[9] While the top lending teams are characterized by their vibrant forums and lending activity, many teams become dormant shortly after their creation. Among all open teams, 36.5% have not made a loan in the past year and 89.9% have not made a forum post in the past year.

Since Kiva teams were designed to increase lender engagement, these findings suggest they may benefit from a clearer understanding of how team membership motivates member behavior. To investigate this question, we draw on naturally occurring data on Kiva and a randomized field experiment. We obtain our data from two sources. First, we download data from Kiva's public application programming interface (API). This provides us with a snapshot of the information that Kiva collects about its lenders, teams and loans from February 2006 through February 2012. Our second data source comes from a Kiva data dump in April 2013, which contains encrypted loan team assignment information and a time stamp for each loan, as well as anonymized team forum messages for public users in open teams.

Of the 242,587 lenders who have joined at least one team as of April 2013, 202,018 (83%) have joined only one team, whereas the remaining have joined at least two teams. Among those who have joined one team, 134,297 (66%) have assigned at least 1 loan to the team. While 29% of the 134,297 lenders have not made a subsequent loan, the remaining 95,374 lenders have assigned 99% of their subsequent loans to their team. This indicates that most of the frequent lenders who belong to only one team are

[7]The team motivation statement can be found on each team's home page. When a team is formed, they can fill out a field called "We loan because: . . .." For example, the motivation statement for Team Canada says, "We loan because: So little means so much. And because we are so fortunate to be able to lend with the luxury of not worrying about whether we ever see that money again, while the clients borrow with the hope and determination that they will be able to repay, and improve their lives along the way."

[8]Alternative team leaderboards sort teams by new members "this month," "last month" and "all time." However, the new member leaderboards are less prominently displayed on the site.

[9]Source: `http://www.kiva.org/teams`, retrieved on January 30, 2015.

committed to their team.

It is important to note that Kiva does not report the amount that an individual lender lends, due to privacy concerns. While we know the number of loans each lender gives, we do not know how much money is lent for each of these loans, except that the minimum loan amount is \$25. Therefore, we will use the number of loans per lender as our main outcome variable. In our empirical analysis, in addition to the number of loans, we use a proxy variable for the amount loaned. Detailed descriptions of the list of variables and our (free-text) data coding methodology are contained in Appendix A.

4. Theoretical Framework

In this section, we outline our theoretical framework for pro-social lending on Kiva, which serves as a benchmark for our empirical analysis and experimental design. While our theoretical framework is closely related to the literature on sequential contributions to public goods (Varian, 1994; Vesterlund, 2003; Andreoni, 2006a) and charitable giving in the field (Shang and Croson, 2009; List, 2011; Kessler, 2013), we also incorporate features of online microfinance into our model to better represent the Kiva context.

One feature of our model is search cost. Kiva lenders make charitable loans for different reasons (Liu et al., 2012). Some want to help women entrepreneurs in Africa, whereas others want to help borrowers who share their religious beliefs. At any given time, thousands of borrowers with outstanding requests are displayed on the Kiva page.[10] Therefore, we assume that Kiva lender i incurs a search cost, k_i, to find a borrower whose profile is a good match for her lending criteria. Search cost can be thought of as the opportunity cost of time. In our model, we assume that lender i's search cost, k_i, is an i.i.d. draw from a continuous distribution, $F(\cdot)$, with support $[\underline{k}, \bar{k}]$. Let $\theta_i \in [0, \bar{\theta}]$ index the match quality of making a loan request, and $c_i > 0$ be lender i's opportunity cost of making a zero-interest loan.

We further let ω_i be i's initial endowment of private good, x_i be her composite private good, and g_i be her loan amount. If J represents the set of lenders who have made a loan to borrower j, then $G_j = \sum_{i \in J} g_i$ is the total loan amount to borrower j. From the lender's perspective, we assume only one borrower is her best match. Therefore, we omit the subscript j in subsequent notations.

Finally, we assume that individual lenders belong to preference classes, comprised of identical preferences. Define utility as $U_i = U(x_i, G; \theta_i)$. For simplicity, we assume the utility function is quasilinear,

$$U_i(x_i, G; \theta_i) = \theta_i v(G) + x_i = \theta_i v(G) + \omega_i - c_i g_i - k_i I(k_i \leq k_i^0), \tag{1}$$

where $v(\cdot)$ is lender i's value function for the public good; k_i^0 is the threshold of lender i's search cost if she does not belong to any team; and $I(k_i \leq k_i^0)$ is an indicator function which equals one if lender i decides to search and zero otherwise. We assume that $v(\cdot)$ is concave. We first consider the case of a lender who does not belong to any

[10] For example, a lender can choose among 2,552 loan requests on January 31, 2014.

team. This lender first decides whether to incur cost k_i to search among the thousands of borrowers. If she chooses to search, we assume that she will find a borrower who matches her criteria and will subsequently make a loan.

By contrast, if a lender belongs to a team, we assume that members within a team have identical preferences with regard to the public goods. In other words, team members agree on which loan is the best fit for the team, $\theta_i = \theta_j \equiv \theta_t$, for $i, j \in T$. This assumption is based on our similarity analysis which is explained in detail in Section 5. Using the Kiva API data, we explore two types of similarity: location and motivation. For each type of similarity, we first calculate the lender-lender similarity between each pair of lenders. Then, for each lender, we find the average of these lender-lender similarities for each existing team, giving us a lender-team similarity between each lender and each team. Finally, we break the teams into those that the lender has and has not joined and take the average of these lender-team similarities in each subset, treating each team as a unit. Doing so gives us both an ingroup and an outgroup lender-team similarity measure for each lender. The results of this analysis show that lenders are more locationally and motivationally similar to their team members than to non-team members.[11]

After establishing lender-team similarity, we next explore the effect of lending team competition and coordination on lender behavior. If a lender belongs to a team, in addition to her utility from private and public goods consumption, we assume that she cares about her team ranking. The extent to which she cares is represented by the parameter, $\gamma_i \in [0, 1]$. Using the Kiva API data, we estimate the equation, $\ln(\text{Rank}) = a - b\ln(\text{total team loan})$, and obtain the parameters $a = 10.208$ and $b = 0.504$. Based on this estimation, we make the assumption that the team ranking function, $R(G^t)$, is increasing and concave in the total amount of team T's loan, G^t.[12] We then modify the utility function (1) to the following:

$$U(x_i, G^t; \theta_t) = \theta_t v(G^t) + \omega_i - c_t g_t - k_i I(k_i \leq k_i^t) + \gamma_t R(G^t). \tag{2}$$

Going through the same exercise, we can derive conditions under which $G^t \geq G^0$. A lender will search if $k_i \leq k_i^t$. It can be shown that $k_i^t \geq k_i^0$ if γ_t is sufficiently high. Therefore, we obtain our first proposition.

Proposition 1 (Team Competition)**.** *When team ranking is sufficiently important to a lender, a lender who belongs to a lending team will be more likely to search and to make more loans than a lender who does not belong to any team.*

Proof: See Appendix B.

[11] For the motivation similarity measure, the average ingroup lender-team similarity is 0.014 and the average outgroup lender-team similarity is 0.009. A signed-rank test indicates that this difference is significant at the 1% level ($p < 0.0001$, two-sided test). For the location similarity measure, the average ingroup lender-team similarity is 0.417 and the average outgroup lender-team similarity is 0.099. A signed-rank test indicates that this difference is also significant at the 1% level ($p < 0.0001$, two-sided test). See Section 5 for the details of our similarity analysis.

[12] Alternatively, if lenders are motivated by warm glow instead of team ranking, using the specification in Andreoni (1990), we can obtain similar results.

Alternatively, rather than emphasizing team competition and ranking, team members might coordinate by recommending loans to each other, thus reducing search cost. If the lender with the lowest search cost conducts the search, the likelihood that a lender who belongs to a team will conduct a search is $[1 - F(k_i)]^{n-1} \leq 1$. Therefore, the lender's expected utility function in the lending stage becomes

$$U(x_i, G; \theta_t) = \theta_t v(G^t) + \omega_i - c_t g_t - k_i[1 - F(k_i)]^{n-1}. \tag{3}$$

This leads to our second proposition.

Proposition 2 (Team Coordination)**.** *A lender who belongs to a lending team where members recommend loans to each other will be more likely to make loans than a lender who does not belong to any team.*

Proof: See Appendix B.

It follows that if a team successfully emphasizes competition and coordination, the combined effects separately identified in the two propositions will be stronger.

5. Empirical Analysis

In this section, we present the findings from our analysis of the naturally occurring field data obtained from Kiva, examining whether joining a team increases lending activity. We also explore the factors that might differentiate active teams from dormant ones.

5.1. Team membership and lending behavior

We first examine whether joining a team increases individual lending. Based on Propositions 1 and 2, we expect that joining a Kiva team will increase individual lending when team members have a strong sense of team identity and coordinate to reduce search cost. Thus, in the Kiva setting, we expect the following hypothesis to hold:

Hypothesis 1 (Effect of Team Membership on Lending)**.** *Joining a team increases a lender's lending activity level.*

Figure 1 presents the average number of loans per person per month for those who have joined at least one team (black dots) compared to those who do not belong to any team (white triangles). The vertical line through August 2008 denotes the time when teams were introduced as an option on the Kiva site. While lenders who join teams lend more than those who do not join teams, given the behavior of these lenders before the team system was implemented, this difference may reflect a self-selection bias. That is, it is possible that lenders who join teams are simply more active on Kiva in general.

Without further analysis, it is unclear whether Kiva's team design has any effect on overall lending or whether it simply shifts the most active Kiva users into teams. To control for any potential selection bias, we employ an instrumental variables analysis. We begin with the following econometric model:

$$\textit{average loans}_i \quad = \quad \beta_0 * \textit{constant} + \beta_1 * \textit{joined team}_i + \mathbf{B} \cdot \textit{Demographics}_i + \varepsilon_i$$

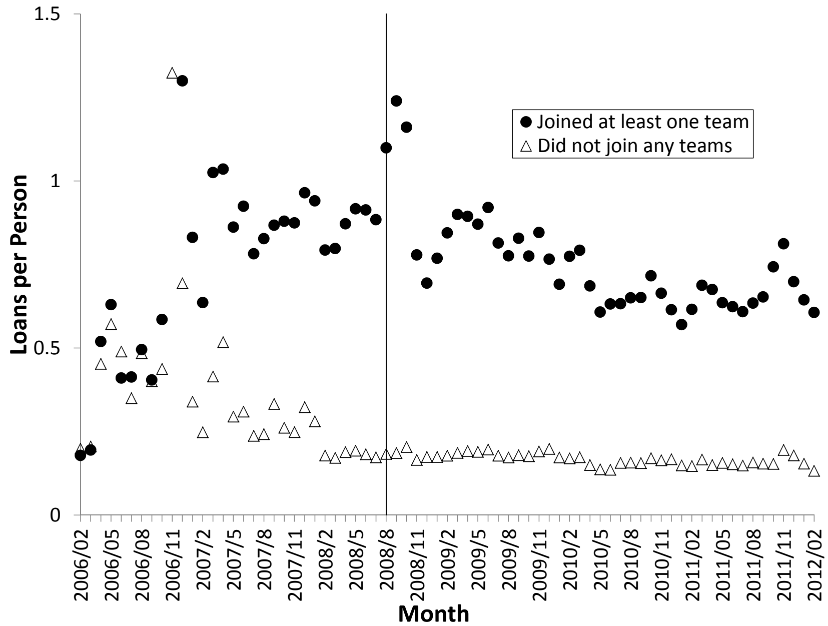

Figure 1: Average lending activity (number of loans per person per month), separated by whether lenders have joined at least one team on Kiva. The black dots denote lenders who joined at least one team between August 2008 and February 2012, while the white triangles denote lenders who did not belong to any team (as of February 2012).

where *average loans*$_i$ is the average number of loans (loans/day) given by lender i, *joined team*$_i$ is a dummy variable for whether lender i has joined a team, and *Demographics*$_i$ represents demographic variables including location, gender/type, and occupation. We find the variable *joined team*$_i$ to be correlated to the error term ε_i, verified by a Hausman test ($p < 0.0001$). Therefore, we instrument for *joined team*$_i$ using a version of the lender-team location similarity measure.

This measure is inspired by the empirical network science literature which tries to explain why users join certain communities. It is often observed that people tend to associate with others whom they perceive as similar to themselves in some way, a phenomenon known as *homophily* in the sociology literature (McPherson et al., 2001). To understand how homophily might play a role in the Kiva lending community, we first define a *location similarity* measure using a hierarchical network model (Watts et al., 2002) as displayed in Figure 2.

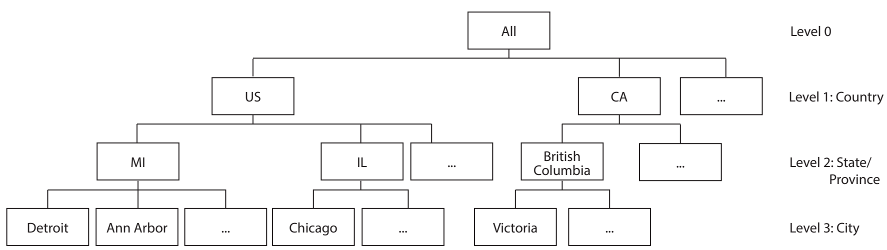

Figure 2: Location similarity hierarchy

The location similarity between two lenders i and j is denoted $l_{ij} \in \{0, 1, 2, 3\}$, defined as the level of their closest common parent node. For example, if two lenders are in two different countries, the similarity score will be 0. If Lender 1 is from Ann Arbor, Michigan and Lender 2 is from Chicago, Illinois, their closest common parent node is the United States, giving these two lenders a location similarity of 1. However, if Lender 1 is from Ann Arbor, Michigan and Lender 2 is from Detroit, Michigan, their closest common parent node will be Michigan, giving them a location similarity of 2. Therefore, a higher location similarity between two users indicates closer jurisdictional proximity between two users. For this measure, we assign a location similarity of 0 to all pairwise comparisons where at least one lender does not provide location information to Kiva.[13] The location similarity between lender i and team T is defined by $l_{iT} = \sum_{j \in T} l_{ij}/|T|$.

The instrument is calculated by taking the *maximum* of the similarity measures between the lender and the teams, $\bar{l}_i = \max_T l_{iT}$, i.e. the similarity between lender i and her most similar team, *regardless* of her membership in that team. We expect this

[13]This measure can also be seen as the worst case scenario, where we assume that each lender who does not provide location information lives in a different country.

measure to affect lending activity only through its correlation with whether the lender joins a team. In what follows, we discuss the two requirements for the validity of the instrument.

First, regarding the requirement that there exists partial correlation between the instrument and "joined team," we expect this correlation to exist due to the large number of location-based teams. Using teams' self categorization, we find that 69.99% of the 22,605 teams are location-based.[14] Furthermore, in our two-stage least squares IV regressions displayed in Table 2, the F-statistic on the maximum location similarity instrument is greater than 100 in all cases, eliminating potential weak-instrument problems. Thus, our first stage is strong.

Second, regarding the exclusion restriction requirement, i.e., the instrument influences the lending activities only through its correlation with whether the lender joins a team, we argue that the maximum location similarity does not enter the second stage, as the correlation between the instrument and lending activities is only 0.037. Furthermore, it is exogenous, as the maximum location similarity is the similarity between a lender and her most similar team *regardless* of whether she belongs to the team. Indeed, only 0.49% of the lenders belong to the team which has the maximum location similarity. Lastly, one might argue that lenders who live in large cities, and therefore more likely to have teams with which they are more similar according to our instrument, might tend to lend more. However, we find that this is not the case. Using a 1673-person random subsample of our lenders who provide their city information, we find that the correlation coefficient between the average number of loans and the population of their cities of residence is -0.0028.

The results of the two-stage least squares instrumental variables regression are displayed in Table 2. This table shows the results of two specifications of the regression. Columns (1) and (2) show the results of the first-stage regressions while columns (3) and (4) show the results of the second-stage regressions. In both specifications, we include only lenders that have made at least one loan, ignoring those who have signed up for Kiva but not done anything on the site. Columns (1) and (3) present the results of a regression with no demographic variables included. We find that increasing the maximum location similarity measure by 1 increases the probability of joining a team by 4.49%, and joining a team increases the number of loans given per day by 0.04. This represents an increase of about 1.2 loans per month, or at least $30 per month, since Kiva's minimum loan amount is $25.

Columns (2) and (4) include the demographic variables gender and occupation. Both of these variables are derived from human coders and trained classifiers. The occupation categories are treated as dummy variables. For this specification, we restrict the lenders included in the regression to individuals that provide occupation information and are coded as either male or female. This specification does not provide substantially different results from the first specification. Any differences are due to either the restriction to a more engaged set of lenders or the inclusion of these two demographic controls. When we run the original regression (no demographic controls) but for the subset of lenders included in the second regression (with demographic controls)

[14] See Appendix A.4 for the average member similarity in teams for each category.

Table 2: Effect of Team Membership on Number of Loans: 2SLS Instrumental Variables Regressions

	IV 1st Stage: Joined Team		IV 2nd Stage: Average #		OLS: Average #	
	(1)	(2)	(3)	(4)	(5)	(6)
Joined Team			0.0397***	0.0500***	0.0180***	0.0179***
			(0.005)	(0.003)	(0.001)	(0.000)
Max Location Similarity	0.0449***	0.0448***				
	(0.001)	(0.001)				
Constant	0.1407***	0.1873***	0.0095***	0.0052***	0.0141***	0.0139***
	(0.001)	(0.003)	(0.001)	(0.001)	(0.000)	(0.000)
Female		-0.0587***		-0.0049***		-0.0068***
		(0.002)		(0.000)		(0.000)
Occupation Controls	No	Yes	No	Yes	No	Yes
Observations	569,149	179,412	569,149	179,412	569,149	179,412

Note: Significant at the * 10%, ** 5%, and *** 1% levels.

in Table 11 in Appendix C, we find that lenders in this subset are 4.72% more likely to join a team if their location similarity measure increases by 1, and joining a team increases their lending by 0.057 loans per day (1.7 loans per month, or at least $42 more per month). Including the demographic controls reduces this to about 0.05 loans per day or at least $38 per month.

Finally, in columns (5) and (6), we repeat the regressions from columns (1) to (4), but using ordinary least squares rather than an instrumental variables regression. We find that the IV estimate of "joined team" is 0.0397, while the OLS estimate is 0.018. Thus, the IV estimate is more than twice as as large as the OLS estimate, indicating that the OLS estimators might suffer from the attenuation bias as a result of the correlation between "joined team" and the error term.

In Table 3, we repeat the exercise in Table 2, but use a proxy lending amount, rather than the number of loans, as the dependent variable. Since Kiva does not release the amount loaned, for each loan request in which a lender participates, we divide the total amount requested by the number of lenders who participate, and use this as a proxy for the amount that this lender loans. The results are robust. We find that lenders who join teams on average make $42 more in loans per month compared to those who do not belong to any team.

Overall, the results indicate support for Hypothesis 1, and show that joining a team significantly increases lending activity. We next explore the mechanisms which might explain this finding.

5.2. *Underlying mechanisms for team effects*

Based on our theoretical analysis, we expect that both team competition (Proposition 1) and coordination (Proposition 2) will increase the lending activities of team members. To examine the mechanisms by which this might occur, we analyze the characteristics of team forum discussions on Kiva. We do so to obtain insight into the underlying mechanisms that motivate members of successful teams. For example, we

Table 3: Effect of Team Membership on Proxy Loan Amounts: 2SLS Instrumental Variables Regressions

	IV 1st Stage: Joined Team		IV 2nd Stage: Average Amount		OLS: Average Amount	
	(1)	(2)	(3)	(4)	(5)	(6)
Joined Team			1.4071***	1.7781***	0.6157***	0.6108***
			(0.166)	(0.117)	(0.019)	(0.012)
Max Location Similarity	0.0449***	0.0448***				
	(0.001)	(0.001)				
Constant	0.1407***	0.1873***	0.3263***	0.1761***	0.4931***	0.4924***
	(0.001)	(0.003)	(0.036)	(0.034)	(0.009)	(0.011)
Female		-0.0587***		-0.1702***		-0.2416***
		(0.002)		(0.013)		(0.010)
Occupation Controls	No	Yes	No	Yes	No	Yes
Observations	569,149	179,412	569,149	179,412	569,149	179,412

Note: Significant at the * 10%, ** 5%, and *** 1% levels.

observe that members of high ranking teams often refer loan requests to other team members, as seen in this post from a member of a highly ranked team:

> I just loaned to Diarra's Group in Senegal. The featured borrower is a mother of 4 who sells vegetables. With the earnings she takes care of her children, mainly by buying food for them. Please kindly consider supporting this loan. Thanks! `www.kiva.org/lend/664224`

In this case, by pointing to the url link of a specific borrower (or borrower group), the lender saves the search costs of fellow team members. To identify team-prompted motivations, we examine two aspects of these team forums: the number of links to specific loans each month, and the number of members who have posted to the forums for the first time in that month. The number of links to specific loans measures the extent to which the forums facilitate coordination towards specific loans, while the number of members who post for the first time measures the level of activity and engagement of the team.

In addition to team coordination, we examine forum postings for messages that reinforce team competition. For example, a lender from an active team posted the following forum message:

> Except for July, when the Mormons surged to pass the $1,000,000 mark, we've steadily been increasing our lead on them. We've been slowly gaining on India. However, Trolltech is gaining on us, and Nerdfighters, with huge membership and lending numbers are rapidly outpacing all sorts of teams. They will soon be outdoing us in doing good.

This type of message appeals to members' competitive motivations. In particular, when a lender joins a team, particularly a highly-ranked team, the team leader board provides a level of prestige that the lender may wish to maintain or surpass. If competition motivates engagement, then we would expect that teams close to overtaking another team or being overtaken in terms of number of loans will attract more loans from their members. To explore this possibility, we first calculate each team's monthly percentile in terms of number of loans, as well as the loan differences between teams just above and below them in the rankings. Loan percentile is calculated as the number of teams with strictly fewer cumulative loans divided by the total number of teams (multiplied by 100). For the percentile and loan difference variables, we expect the month-to-month change to be more relevant to lending than the absolute values, so we calculate their first differences and then lag them by one period. Since we also wish to examine an interaction term between a team's percentile and their loan differences with other teams, we center the rank and loan difference variables before calculating these interaction terms. These possibilities yield the following econometric model, where we also include the lagged lending to account for persistence:

$$\begin{aligned} \mathit{loans}_{i,t} &= \beta_0 * \mathit{constant} + \beta_1 * \mathit{links}_{i,t} + \beta_2 * \mathit{percentilechange}_{i,t-1} \\ &\quad + \beta_3 * \mathit{newposters}_{i,t} + \beta_4 * \mathit{diffabovechange}_{i,t-1} \\ &\quad + \beta_5 * \mathit{diffbelowchange}_{i,t-1} + \beta_6 * \mathit{loans}_{i,t-1} + \epsilon_{i,t} \end{aligned}$$

Table 4: Team Loan Analysis: Fixed Effects

Dependent Variable: Number of Loans each Month [month t]			
	(1) All Teams	(2) $N \geq 5$	(3) Top 500 Teams
Number of Links	0.1587***	0.1525***	0.1568***
[month t]	(0.003)	(0.005)	(0.011)
Percentile Change	-0.1607***	-0.1687***	-0.3578***
[(month $t-1$) - (month $t-2$)]	(0.007)	(0.015)	(0.059)
Members who Posted for the First Time	0.8461***	0.8472***	0.8788***
[month t]	(0.002)	(0.003)	(0.006)
Loan Difference Change (Above)	0.0170***	0.0170***	0.0169***
[(month $t-1$) - (month $t-2$)]	(0.000)	(0.001)	(0.001)
Loan Difference Change (Below)	0.0496***	0.0457***	0.0492***
[(month $t-1$) - (month $t-2$)]	(0.001)	(0.001)	(0.003)
Number of Loans (Lagged)	0.7149***	0.7252***	0.7153***
[month $t-1$]	(0.001)	(0.001)	(0.002)
Constant	6.4248***	8.3690***	20.1708***
	(0.034)	(0.081)	(0.411)
Observations	651,491	270,340	56,821
Number of Teams	19,175	6,845	1,103
R^2	0.698	0.712	0.704

Note: Significant at the * 10%, ** 5%, and *** 1% levels.

We run the above model as a fixed-effects regression with i denoting teams and t denoting months. Table 4 displays three specifications of this regression.[15] In column (1), we run this regression on all teams. Note that all of the included regressors are significant at the 1% level. These results show that both the number of url links posted to a team's forum and that team's movement on the leaderboard significantly affect lending behavior. A team with one more link in the forum gives 0.16 more loans per month, or about one more loan per month for every six links. Also, a team with a 1 percentile decrease in rank gives 0.16 more loans in the next month.

Our results further show that there is a large amount of persistence in the number of loans a team gives in a month, as evidenced by the large coefficient on the lagged number of loans. In addition, when a member posts for the first time, lending increases by 0.85 for the month. This could be due to the poster's loan as well as loans by other members. We also see smaller effects when a team's loan difference to the team above it or below it increases. In these cases, a team lends more, indicating a desire to maintain their current rank against other teams. Note that the coefficient on the "below" variable is about twice as large as the coefficient on the "above" variable, showing that teams care more about maintaining vs. improving their rank.

In column (2), we restrict our attention to teams that have at least five members; this yields a subsample of about a third of the teams. This group is of interest because it is the sample for our field experiment. In column (3), we restrict our attention to teams ranked in the top 500 teams at some point in their history, with the expectation that team ranking might be more important for those ranked higher on the leaderboard. This ranking is based on the total number of loans in the teams' histories. The results of these regressions show very similar results. One difference is that when we restrict our attention to highly-ranked teams, the coefficient on percentile change doubles from the case where we include all teams. This indicates that highly-ranked teams care more about changes in rankings, and will respond more strongly than lower-ranked teams when these changes occur.

Together, these analyses indicate that coordination and competition messages on team forums are each correlated with increased lending activities. However, effective teams often use both types of messages. To separately evaluate the effects of coordination and competition, we run a field experiment that targets teams' forums, using both url links to specific loans and goal setting to determine the separate effects of competition and coordination on lender behavior.

6. Experimental Design

In this section, we describe the design of our randomized field experiment. This experimental design allows us to separately investigate the effects of coordination through a reduction of transaction costs and competition through goal setting on increasing lending behavior on the Kiva site.

[15]These specifications do not control for team size, as it is highly correlated with lagged loans. An alternative specification that does control for team size is included in Appendix C (the results are not greatly affected).

Our randomized field experiment takes advantage of the design of Kiva's team system. When a team is formed on Kiva, it receives a dedicated forum accessible to only that team's members. Our initial analysis of forum messages shows that highly-ranked teams often set goals and coordinate their lending around specific borrowers. Our experimental design draws on the team forum component in two ways. First, we utilize the forum as a means of posting messages to teams. Second, we use the nature of the forum messages to study both coordination through a reduction of search costs and competition through goal setting.

Specifically, we implement a 2×2 between-teams factorial design in which we vary the content of our posted messages between our treatment groups. Along one dimension of the experimental design, we vary whether the message includes a link to a specific borrower. Along the other dimension, we vary whether the message includes a team-competition related statement. Since Kiva sends a daily email summary of all messages on a team's forum to all team members, we know our experimental message is pushed to each team member's inbox.

Table 5: Features of Experimental Treatments

		Coordination	
		No Link	Link
Competition	No Goal	1. NoGoal-NoLink (109 teams) New team member intro.	2. NoGoal-Link (107 teams) Intro. + Link to a loan
	Goal	3. Goal-NoLink (106 teams) Intro. + Goal	4. Goal-Link (105 teams) Intro. + Link to a loan + Goal
	Control	0. No forum message (109 teams)	

Our control condition, in which a lender makes a $25 loan and credits it to her team without posting a forum message, controls for both new member and new loan effects. By contrast, in our NoGoal-NoLink treatment, a lender credits a $25 loan to her team and introduces herself by posting a message on the team forum, such as:

"*Hi, I am [ ], and I am new to the team. I just credited my first loan to the team.*"

In our next condition, the NoGoal-Link treatment, in addition to the introduction message, the lender's message links to a specific loan with a description of the borrower from the Kiva Web page:

"*Hi, I am [ ], and I am new to the team. I just credited my first loan to the team. I loaned to [Umurzok from Tajikistan]. [Umurzok raises cattle and he is requesting a loan of $1,900 to buy bulls and cows.] Here is the url to his request:* `http://www.kiva.org/lend/[476601]`."

In comparison, in the Goal-NoLink treatment, in addition to the introduction message, the lender sets a goal for the team to improve their ranking on the leaderboard:

"*Hi, I am [ ], and I am new to the team. I just credited my first loan to the team. If each of us make a $25 loan in the next month, we will improve our rank.*"

Lastly, in the Goal-Link treatment, in addition to the introduction message, the lender both provides a link to a specific loan, and sets a specific goal for the team:

"*Hi, I am [ ], and I am new to the team. I just credited my first loan to the team. I loaned to [Hranush from Armenia]. [She requested a loan of $3,000 to help her purchase wheat to feed the livestock.] Here is the url to her request:* `http://www.kiva.org/lend/[470174]`. *If each of us make a $25 loan in the next month, we will improve our rank.*"

Given this experimental design, we randomly select 2,000 open teams out of the pool of 17,194 open teams on the Kiva site. Recall that open teams are those any Kiva lender can join. From this initial pool, we exclude those with fewer than five current members, as such teams may consist of members with additional relations across them, such as family or friends. After eliminating these teams, we arrive at a sample of 550 teams. We then assign each team to the control or one of the treatment groups, using stratified random assignment.

This stratified random assignment is based on the level of team activity. While some teams have generated many loans, most teams have generated four or fewer loans.[16] To ensure that our treatments are balanced, we classify teams into three levels based on the number of loans they have given in their entire history: 100 or fewer loans, 101 to 1,000 loans, and more than 1,000 loans. We then randomly distribute the teams into the treatments evenly within these subsets.

Note that between assigning teams to treatments and running the experiment, 14 teams changed status and were thus dropped from our sample. Specifically, 8 teams switched from open (any Kiva user could join) to closed (joining required approval by the team captain) and 6 were disbanded. These 14 teams were distributed amongst the treatments as listed in Table 5. This yields a final sample of 536 teams, with a total sample size of 22,233 lenders across all teams.

Before running the experiment, we run pair-wise Kolmogorov-Smirnov tests of equality of distributions based on observable team characteristics to verify that our randomization works well in most dimensions. The results of tests show that the number of forum messages, words in the forum messages, team members who post forum messages, URLs posted per lender, plural pronouns (such as we, our, etc.), singular pronouns (such as I, me, etc.), loans and lenders do not differ significantly between any two treatments. Thus, the Kolmogorov-Smirnov tests do not reject the hypothesis that these values are drawn from the same distribution. However, for the number of days each team has existed, the Kolmogorov-Smirnov test finds differences significant at the 5% level between the Goal-NoLink treatment and the other three treatments where we post a forum message (NoGoal-NoLink, NoGoal-Link, and Goal-Link).[17] In addition, for the number of loans per member per number of days each team has existed, this test finds a difference, significant at the 10% level, between the Goal-NoLink treatment and the control, and between the Goal-NoLink treatment and the NoGoal-NoLink treatment.[18]

[16]The median number of loans of all teams in the data dump is 4. As our sample is comprised of teams with more than five members, the median number of loans given is 50.

[17]The mean number of days that a team has existed in each treatment is as follows: NoGoal-NoLink - 879.35 days; NoGoal-Link - 890.61 days; Goal-NoLink - 783.94 days; and Goal-Link - 897.04 days.

[18]The average number of loans for the control and treatments is as follows: Control - 0.0120; NoGoal-NoLink - 0.0102; and Goal-NoLink - 0.0098.

To implement our experiment, with Kiva's permission, we create 50 experimental lender identities. We choose lender names from among the top 25 most popular male and female first names and the top 50 most popular last names based on the 1990 US census. We choose lender locations as the capital city of each of the fifty states. We then randomly match names with locations. We allow each created identity to join eleven teams from our sample. The protocol of creating experimental online identities for the purpose of implementing an experimental design has been used in previous online field experiments (Resnick et al., 2006). Note that in our experimental forum messages, our experimental lenders do in fact make a loan of $25 (to the named borrower) and credit it to the team. This fact can be verified by any team member by clicking on the lender name or borrower URL. The only part which is not true is the first name of our experimental lender, which constitutes a minor form of deception. The use of experimental lenders follows the tradition of resume audit studies examining how employers respond to the characteristics of job seekers, such as race (Bertrand and Mullainathan, 2004) or postsecondary credentials (Deming et al., 2014).

To select the borrowers that would receive loans for our experiment, we use four criteria:

1. To ensure that the loans we select are not fulfilled immediately, we select loans where the requested amount is at least $1,000.
2. For the same reason, we select loans where the amount yet to be fulfilled in the request is above 50% of the original request.
3. To ensure sufficient timing, we choose loans that will not expire within the next 5 days.
4. To provide a consistent borrower profile across treatment groups, we choose only loans requested by individual borrowers.

Our experiment takes place in a three-week span between October 8 and 25, 2012. In each week, we make loans and post forum messages on Monday, Tuesday, Wednesday and Thursday (except for Thursday, October 11). The experimental process for each day is as follows:

1. Among the active loans available that day, we randomly select 50 loans, each of which satisfies all four criteria listed above. It was our intention to not repeat any loans for any team. However, 1 loan was repeated (separated by six days).
2. We then make 50 $25 loans through our experimental lenders, each attributed to a different team. The teams are evenly distributed among our five experimental conditions. The order that these teams are treated is randomized.
3. We then post 40 forum messages through our experimental lenders, one on each of the corresponding teams' forums. As 10 of our teams are in the control group, we do not post any messages to those teams' forums.

We then monitor the forum messages and lending activities for each team in the subsequent month. Here is one example of how team members responded to our forum message in the Goal-Link treatment:

Our message (October 18): I am Paul, and I am new to the team. I just credited my first loan to the team. I loaned to Sandra from Colombia. Sandra is asking for a loan of $1,400 in order to buy decorative items and aromatherapy products. Here is the url to her request: `www.kiva.org/lend/483106`. If each of us make a $25 loan in the next month, we will improve our rank.

Lender 1 (October 19): Welcome Paul. I added $25 more to Sandra as well. Happy [team name] to you!

Lender 2 (October 19): Good call Paul. Thanks for sending out the message. I'm in.

Lender 3 (October 19): Another thanks for sending out the message. I'm in!

Lender 4 (October 22): My 10-year old daughter and I just added some loans to the [team name] pool. Let's keep going!

Lender 5 (October 23): I'm in for $25.

Lender 6 (November 1): $100.

In this example, everything that Paul said in his message was true and verifiable through clicking on his profile and Sandra's loan request page, except that our research assistant's name was not Paul. In the three-week period, our experimental lenders make a total of $13,725 in loans, with each loan credited to one of their assigned teams. We then observe the subsequent lending behavior of members of the teams in our sample for a month to analyze the effects of our forum messages.

7. Experimental Results

Using the Kiva data dump on April 27, 2013, we run our analysis of lending behavior at the individual lender level. With this data, we are able to observe the behavior of lenders both before and after our treatment, allowing us to perform a difference-in-differences analysis. Along with analysis that includes all lenders, we also separately analyze lenders who join *active* vs. those who join *inactive* teams. To define team activity, we examine the recent history of the teams' forums. We consider a team to be *active* as long as at least one member of the team has posted at least one forum message within the year before we begin our experiment.[19] Using this definition, we find that approximately one quarter of the teams in our sample are active.[20] We also note that members of active teams make significantly more loans than those in inactive teams in the year before the start of our experiment (19.09 versus 6.67 loans per person, $p < 0.001$, two-sided rank-sum test).

We then further define lenders who join active teams as being *exposed* to forum messages, and those who do not to be *unexposed* to forum messages. The breakdown by treatment of these various categories is displayed in Table 6.[21]

[19]The first day of the experiment is October 8, 2012, so a team is considered active if someone has posted a forum message from October 7, 2011 to October 7, 2012.

[20]This percentage of inactive teams applies generally to teams with at least five members.

[21]Since our randomization is at the team level, and lenders can join multiple teams, 3% of the lenders in our experiment are treated multiple times (26 out of 4,189 unexposed and 715 out of 18,044 exposed

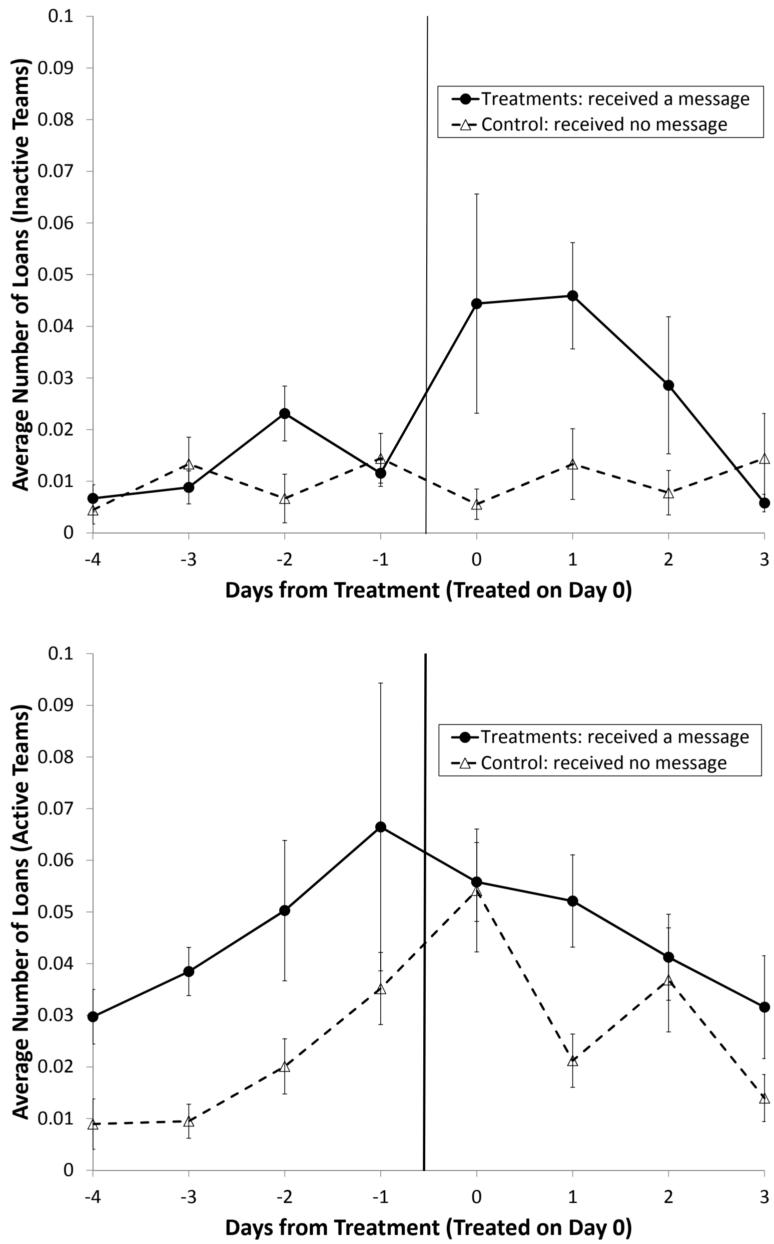

Figure 3: Average number of loans before and after treatment for lenders in inactive teams (Top) and for lenders in active teams (Bottom). Standard errors are indicated with error bars.

Table 6: Number of Teams and Lenders of Each Treatment in Various Categories

Treatment	Total Teams	Inactive Teams	Active Teams	Total Lenders	Unexposed Lenders	Exposed Lenders
Control	109	81	28	2691	900	1791
NoGoal-NoLink	109	85	24	2819	934	1885
NoGoal-Link	107	71	36	2403	634	1769
Goal-NoLink	106	79	27	11693	1164	10529
Goal-Link	105	78	27	3529	583	2946
Total	536	394	142	22233	4189	18044

Our experiment provides several results. First, Figure 3 indicates that treatment messages increase lending activity for lenders from previously inactive teams when we include the 4 days before and after the treatment (top panel).[22] In comparison, we find that the treatment effect is less pronounced for lenders from active teams (bottom panel).[23] This is verified by difference-in-differences regressions of the number of daily loans a lender makes on whether the lender has received a forum message, as represented below:

$$numloans_{i,t} = \beta_0 + \beta_1 * message_{i,t} + u_i + v_t + \varepsilon_{i,t},$$

where *numloans* is the number of loans contributed by lender i on day t. In the above specification, the treatment dummy, *message*, has a value of one if lender i has been treated with a forum message on or before day t and zero otherwise. Furthermore, the term, u_i, represents a full set of lender effects while the term, v_t, represents a full set of time effects. The message coefficient thus provides a difference-in-differences estimate of our pooled treatment effect.

Table 7 displays the results of this difference-in-differences regression. The columns indicate different window sizes (e.g., the "7-Day" specification includes data from 7 days before and 7 days after the treatment). We also run the regressions separately for the subset of active vs. inactive teams, clustering standard errors at the individual level. Doing so yields the following result:

Result 1 (Effect of Forum Message on Lending Activity)**.** *Lenders on inactive teams who are treated with a forum message make 0.007 more loans per lender per day, or*

lenders). The number of lenders in each treatment row includes those treated multiple times, while the number of lenders in the Total row does not. Subsequent regressions include all lenders who are treated multiple times. Removing this set of lenders does not change the results appreciably.

[22]The day that a team in the control was treated is defined as the day that team would have been treated had they been assigned to a treatment. All control teams are randomly assigned to days in the same way as the other teams are.

[23]One puzzling trend observed in the data is the pre-treatment increase in lending among active teams. This trend affects both the control and treatment, as both exhibit parallel increases in lending. This trend partially informs our decision to use difference-in-differences rather than OLS in our analysis.

Table 7: Difference-in-Differences Regressions of Number of Loans

	Lenders from Inactive Teams			
	1-Day	7-Day	14-Day	30-Day
Treated	0.0512	0.0127	0.0110**	0.0066**
	(0.043)	(0.010)	(0.006)	(0.003)
Constant	-0.0356	0.0174*	0.0041	0.0188
	(0.047)	(0.009)	(0.006)	(0.012)
Observations	8,378	58,646	117,292	251,340
R^2	0.501	0.091	0.051	0.040
	Lenders from Active Teams			
	1-Day	7-Day	14-Day	30-Day
Treated	-0.0663	-0.0058	-0.0029	-0.0038
	(0.088)	(0.010)	(0.005)	(0.004)
Constant	-0.0191	0.0066	-0.0007	-0.0109
	(0.069)	(0.062)	(0.050)	(0.063)
Observations	36,088	252,616	505,232	1,082,640
R^2	0.686	0.320	0.193	0.159

Notes: 1) Standard errors clustered at the individual level.
2) Significant at the: * 10%, ** 5%, and *** 1% levels.
3) Full set of day and lender dummies included.

0.2 more loans (at least $5) per month, compared to those in the control condition, in the month before and after treatment. There is no significant treatment effect for lenders on active teams.

We interpret this finding as an indication that forum messages have a significant effect on lenders unused to seeing such messages. To better understand how these messages impact their recipients, we conduct a difference-in-differences regression without pooling the treatments. The specification for this regression is as follows:

$$\begin{aligned} numloans_{i,t} &= \beta_0 + \beta_1 * nogoal\_nolink_{i,t} + \beta_2 * nogoal\_link_{i,t} + \\ &\quad \beta_3 * goal\_nolink_{i,t} + \beta_4 * goal\_link_{i,t} + u_i + v_t + \varepsilon_{i,t}, \end{aligned}$$

where the treatment dummy variables, *nogoal_nolink*, *nogoal_link*, *goal_nolink* and *goal_link* each have values of one if lender i has been treated in the respective treatment on or before day t and zero otherwise.

The results of this regression for all teams, inactive, and active teams are displayed in Tables 8, 9 and 13 (Appendix C), respectively. Standard errors are clustered at the individual level for each specification. We summarize the results below.

Result 2 (Goal Setting and Coordination: All Teams)**.** *In the 14-day window, lenders in the Goal-Link treatment make 0.018 more loans per lender per day (0.25 more loans, at least $6.25, in two weeks) than those in the control condition.*

Table 8: Difference-in-Differences Regressions of Number of Loans on Treatments

	1-Day	7-Day	14-Day	30-Day
NoGoal-NoLink	0.0240	-0.0004	0.0043	-0.0047
	(0.066)	(0.010)	(0.006)	(0.005)
NoGoal-Link	0.0083	-0.0166	0.0007	-0.0019
	(0.040)	(0.016)	(0.009)	(0.006)
Goal-NoLink	-0.0285	-0.0024	0.0102*	-0.0003
	(0.102)	(0.009)	(0.006)	(0.004)
Goal-Link	-0.0074	0.0069	0.0181**	-0.0027
	(0.046)	(0.011)	(0.009)	(0.005)
Constant	0.0385	0.0125	0.0112	0.0126
	(0.056)	(0.034)	(0.026)	(0.033)
Observations	44,466	311,262	622,524	1,333,980
R^2	0.682	0.316	0.190	0.157

Notes: 1) Standard errors clustered at the individual level.
2) Significant at the * 10%, ** 5%, and *** 1% levels.
3) Full set of day and lender dummies included.

In comparison, the results in Tables 9 and 13 show a differential effect based on whether the lenders have been exposed to forum messages in the past year. For lenders who do not normally receive forum messages, our Goal-NoLink messages, compared to the control, increase lending at both the 14- and 30-day windows. Within the 14-day window, individuals who receive a goal message gives 0.0118 more loans per day on average than their control counterparts. Over a month, this increase is smaller, but still significant, at 0.0080 more loans per day, or 0.24 more loans over a month, for the Goal-NoLink messages. Using the average team size of 46.7 members in our sample, this translates into 11 more loans per month.

Result 3 (Goal Setting: Inactive Teams)**.** *In the 14-day (30-day) window, lenders of inactive teams in the Goal-NoLink treatment make 0.012 (0.008) more loans per lender per day, 0.168 more loans in two weeks (0.24 more loans, at least $6, per month) than those in the control condition.*

Result 3 indicates that, in our experiment, competition through goal setting significantly increases lending for inactive teams compared to the control group. Inactive teams are precisely the set of teams that the designer would like to re-activate. The positive effect of goal setting has been demonstrated in a field experiment on individual productivity (Goerg and Kube, 2012). In comparison, our result shows that it is effective in public goods provision. Results 2 and 3 are both consistent with findings in behavioral economics that simple situational details, known as "channel factors," such as a concrete goal and a link to a borrower, can have great impact on participation (Bertrand et al., 2004).

It is also interesting to note that our competition message is fairly neutral, yet still has an impact on lending behavior. In comparison, the naturally-occurring competition

Table 9: Difference-in-Differences Regressions of Number of Loans on Treatments (Lenders Not Exposed to Forum Messages in Past Year)

	1-Day	7-Day	14-Day	30-Day
NoGoal-NoLink	0.0767	0.0103	0.0112	0.0048
	(0.102)	(0.016)	(0.009)	(0.003)
NoGoal-Link	0.0226	0.0059	0.0090	0.0051
	(0.024)	(0.009)	(0.007)	(0.004)
Goal-NoLink	0.0533*	0.0161*	0.0118**	0.0080**
	(0.030)	(0.010)	(0.005)	(0.003)
Goal-Link	0.0303	0.0167	0.0126	0.0091*
	(0.022)	(0.014)	(0.008)	(0.005)
Constant	0.0192	0.0173*	0.0042	0.0190
	(0.020)	(0.009)	(0.005)	(0.012)
Observations	8,378	58,646	117,292	251,340
R^2	0.502	0.091	0.051	0.040

Notes: 1) Standard errors clustered at the individual level.
2) Significant at the * 10%, ** 5%, and *** 1% levels.
3) Full set of day and lender dummies included.

messages posted to teams' forums are often emotionally charged and very specific to the team. For example, a member from an active team expresses the following goal-oriented sentiment:

> Guuuuuyys! We've beat both the Trolltech Foundation AND the Church of the Flying Spaghetti Monster in the past weeks! We're now number 17 on the most lended list! Next up, India!

Finally, we note that our link treatment messages are not as detailed as many actual messages in the forums. In our experiment, we compose our link messages as a restatement of the borrower's reason for borrowing. By contrast, many lenders in active teams provide borrower biographies along with the links. For instance, a member of an active team posts the following,

> Thought you might be interested:
>
> Dembe Development Association Group Business: Sale of used shoes, with loan: new shoes MFI: UGAFODE, secular www.kiva.org/partners/222
>
> Featured borrower is Julius, 34, his wife died during labor. Their three children go to school, one of them suffers from tuberculosis. Julius mainly sells used shoes in the Nakulabye market.
>
> He has insufficient capital because his profits go to the medical expenses. With the loan he will stock new shoes to sell to students who are going back to school.
>
> www.kiva.org/lend/523980

This distinction between our message lengths and naturally-occurring message lengths may explain the lack of effect obtained among the active groups in our treatment. In the active teams, lenders see messages much more detailed and sometimes more emotionally charged than the ones we post, perhaps on a regular basis. Thus, our shorter and neutral messages could have gone unnoticed. In the inactive teams, people rarely post messages (and none in the past a year), so our treatment stands out. The effects of our short and neutral messages should be taken as a lower bound for forum interventions.

In sum, we find that our goal-setting and coordination messages significantly increases lending for all team members in the 14-day window, whereas our goal-setting message alone increases lending for members of inactive teams in both the 14-day and 30-day window, compared to the control condition.

8. Conclusion

In this paper, we investigate whether team competition increases pro-social behavior in the field. We present the results of an empirical and experimental investigation of the effect of team membership on individual lending behavior on the microfinance site Kiva. Our study yields a number of interesting results. First, our results show that joining a team increases lending activity. By employing an instrumental variables analysis, we are able to show that teams do not simply gather the most active lenders. Rather, lenders who join teams make 1.2 more loans ($30-$42) per month than their counterparts who do not join teams. In addition, we find substantial heterogeneity in team participation levels. Indeed, of the 26,000 teams on the Kiva site, more than half have not made a loan for the past year. This heterogeneity leads us to design an experiment that explores lending motivations across active vs. inactive teams.

Our experiment makes use of the Kiva forum mechanism that allows team members to post messages to each other. An initial examination of team message boards shows that some forum messages promote competition in the form of encouraging members to help the team maintain or boost its ranking on Kiva's team leaderboard. We also find that teams whose forum users post more links to specific loans are more active lenders overall. This result indicates that the Kiva forums might be useful as a coordination device where the lenders of a team can share the information of borrowers they have found on Kiva and thus reduce transaction costs for other team members.

To separately estimate the effects of competition and coordination, we implement a field experiment by posting messages emphasizing competition through goal-setting or coordination through a reduction in transaction costs. Interestingly, we find that our goal-setting and coordination messages significantly increase lending for all team members in the 14-day window, compared to the control. By contrast, merely providing a link to a borrower does not increase participation, suggesting that online communities looking to increase engagement need to provide a concrete action goal for participants.

In addition, we find that our goal-setting messages have the strongest effect on inactive teams. This may be due to the fact that our messages remind inactive users of their team affiliation. If so, then our protocol provides Kiva with useful information on how to increase the participation of currently inactive members.

Lastly, we note that our experimental results were obtained even though our messages were relatively short and neutral compared to actual member postings. This suggests that the effects of real competition or coordination messages on lender activity may be even greater than those observed in our study.

Our study advances social identity research by using a field setting to examine team competition in a large-scale empirical study of an online microfinance community, and by evaluating team identity as a design tool to increase pro-social lending. Our results also provide direct value to Kiva and similar organizations. Specifically, we provide insight into how the team structure can be used to enhance participation. Kiva has already begun implementing changes based on these findings. Now, when a team member posts a link to a specific loan, Kiva automatically displays the borrowers information and picture along with the link.

Overall, our results may help guide Kiva's further development of its system as well as provide helpful guidance to other online communities just beginning to create their systems. As online lending sites evolve, further research will be needed to understand how best to utilize site features and mechanisms to enhance participation. Our research suggests that group identity and team competition will be important considerations in promoting pro-social behavior.

Encouraged by the research reported in this paper, Kiva partnered with us to implement a large-scale field experiment using our recommender algorithms to recommend lending teams to Kiva lenders who did not belong to any team as of May 2014, with promising results reported in a follow-up paper (Ai et al., 2015). Our results further suggest that Kiva should train team captains to post goal-setting messages on their team forums, the effects of which can again be evaluated using a randomized field experiment. Other organizations which rely on voluntary contributions to provide public goods, such as the Wikimedia Foundation, can draw lessons from our study and implement a team structure to encourage sustained contributions from new Wikipedia editors.

Finally, John Ledyard's seminal work on incentive-compatible mechanisms to encourage efficient public goods provision (Groves and Ledyard, 1977; Ledyard and Palfrey, 1994) has inspired not only the subsequent theoretical development (Groves and Ledyard, 1987) and laboratory testing of these mechanisms (see Chen and Ledyard (2008) for a survey), but also the behavioral mechanism design approach leveraging insights from both social psychology and economics, such as the work reported in this paper.

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Appendix A. Data Sources and Descriptions

In this appendix, we introduce our data sources (A.1), variable list (A.2), coding task categories for free-text data (A.3), and location similarity in teams (A.4).

A.1. Data Sources

Our data come from two sources. First, we download data from Kiva's application programming interface (API), located at `http://build.kiva.org/api`. This provides us with a snapshot of the information that Kiva collects about its lenders, teams and loans from February 2006 through February 2012. Two important pieces of data that we collect from Kiva's API are the number of loans each lender has made and a list of teams that each lender has joined. A full listing of the variables from the Kiva API is presented in Section A.2.

Some of these variables, such as location information, are provided in free text form, which we must process before using them in our analysis. Thus, we recruit subjects to code information which cannot be extracted from the API in a usable form. We obtain three variables from this process: lender gender/group type, occupation, and motivation for lending. For the occupation and motivation variables, lenders provide free text describing their jobs and why they are making loans on Kiva.[24]

We first have the coders code a subset of lenders. We then train automatic classifiers based on these examples to code the rest. For gender/group type, we ask the coders to look at each lender's username and profile picture to determine whether the lender is male, female, a couple, a company, a family, or another type of group. For occupation and motivation, we have our coders code the lenders' free-text descriptions into occupation and motivation categories. For a complete list of the categories we employ, see Section A.3. Prior to this coding task, the researchers code a subset of these profiles and randomly place them among the lender profiles that the coders see. The coders are paid based on how many of these pre-coded profiles they match to ensure consistency and reliability.

Our second data source comes from a Kiva data dump on April 27, 2013. The data dump contains encrypted loan-to-team assignment information and a time stamp for each loan, as well as anonymized team forum messages for public users in open teams.

It is important to note that Kiva does not report the amount that a lender lends, due to privacy concerns. While we know the number of loans each lender gives, we do not know how much money is lent for each of these loans, except that the minimum loan amount is $25. Therefore, throughout the paper, we use the number of loans per lender as our main outcome variable, except in one instance where we use a proxy for the amount lent.

A.2. Variable List

This section contains a list of the variables that we collect from Kiva. We break this data into those that concern lenders, teams, and loans.

[24]The prompts on Kiva are "Occupation" and "How would you describe your work?" for lender occupation, and "I loan because:" for lender motivation. See Liu et al. (2012) for a more detailed analysis of Kiva lender motivations.

1. Lenders
    (a) Kiva API
        i. name
        ii. profile picture
        iii. country code: lender's country
        iv. whereabouts: lender's detailed location information in free text form (i.e. state/province, and city information)
        v. member since: when the lender joined Kiva
        vi. occupation: lender's occupation information in free text form
        vii. I loan because: lender's motivation statement
        viii. number of loans: number of loans given by lender
        ix. teams: list of teams that the lender has joined
    (b) Incentivized coding
        i. gender or group type: lender's gender or group type. These are either hand coded or predicted using a name dictionary from the US Census. Possible values include: Male, Female, Couple, Family, Company, Other Group.
        ii. motivation category: 5250 randomly-selected motivation statements hand coded; the rest are classified using a trained machine learning classifier.
        iii. occupation category: 5250 randomly-selected occupation descriptions hand coded
2. Teams
    (a) name
    (b) category
    (c) whereabouts
    (d) We loan because
    (e) team since: when the team was founded
    (f) membership type: open or closed to all Kiva lenders
    (g) member count: number of members
    (h) loan count: number of loans belonging to the team
    (i) loaned amount: total amount of lending attributed to the team
3. Loans
    (a) id
    (b) posted date
    (c) loan amount
4. Lenders, Loans
    (a) the list of loans made by each lender
5. Teams, Loans
    (a) the list of loans belonging to the team
6. Teams, Lenders
    (a) the list of public lenders belonging to the team
    (b) team join date: when a team member joined the team

A.3. Coding Task Categories

This section contains a list of the categories for motivation statements and occupations that we use in the incentivized coding. Our coders take each motivation statement and occupation and place them into one or more of the following categories. Each statement is coded by three independent coders. All coders are recruited from a database of University of Michigan students willing to participate in behavioral economics experiments and trained in the School of Information Laboratory.[25] Afterwards, we take these examples and train machine-learning classifiers to classify the rest of the data.

Motivation categories:

1. **General altruism** (Gnl. Altruism): e.g., "I believe in a global community."
2. **Group-specific altruism** (Grp. Altruism): e.g., "I want to help women succeed in business and in life."
3. **Empathy**: e.g., "I am disabled and I know what it's like to feel helpless."
4. **Reciprocity**: e.g., "I am very fortunate to have several people in my life to lend me a hand when I needed help. I hope that I can do the same for someone."
5. **Equality and social safety net** (Equity): e.g., "I want to help others who are less fortunate. Everyone deserves a fair chance."
6. **Social responsibility and social norms** (Norms): e.g., "I have the ability and I'm lucky enough to be able to."
7. **Effective development tool** (Tool): e.g., "I believe in change through bottom-up initiatives and sustainable business models."
8. **Personal satisfaction** (Satisfaction): e.g., "It makes my heart smile."
9. **Religious duty** (Religious): e.g., "I believe that sometimes God works thru people to answer prayers. What a privilege!"
10. **External reasons** (External): e.g., "It's for a community service project at my university."

Occupation categories:

1. **Art, Media and Entertainment** (Entertainment): Artist, Musicians, Directors, Designers, Writers, Journalists, Producers, Editors
2. **Entrepreneurship** (Entrepreneur): Business Owners, Entrepreneurs, Venture Capitalists, Angel Investors, Business Incubator Managers
3. **Business and Finance** (Business): Financial Managers, CEOs, Management Consultants, Accountants, Bankers, CPAs, Bookkeepers, Loan Officers, Auditors, Business Analysts
4. **Information Technology** (IT): Computer Programmers, Software Developers, Systems Administrators, Web Developers, Technical Support Specialists
5. **Higher Education** (Higher Ed.): Professors, College/University Students, Researchers

[25] See (Liu et al., 2012) for details of our training protocol.

Table 10: Location similarity in each team category

Using Provided Location Information		Worst Case Scenario	
1.225	Religious Congregations	0.664	Local Area
1.213	Schools	0.599	Religious Congregations
1.194	Local Area	0.581	Families
1.149	Colleges/Universities	0.537	Clubs
1.090	Clubs	0.507	Colleges/Universities
1.012	Events	0.482	Schools
0.996	Businesses - Internal Groups	0.468	Friends
0.975	Families	0.461	Alumni Groups
0.952	Friends	0.460	Sports Groups
0.950	Businesses	0.458	Businesses - Internal Groups
0.914	Youth Groups	0.458	Events
0.908	Memorials	0.420	Businesses
0.880	Alumni Groups	0.419	Other
0.807	Sports Groups	0.411	Memorials
0.798	Other	0.406	Youth Groups
0.757	Common Interest	0.370	Common Interest
0.580	Field Partner Fans	0.293	Field Partner Fans

6. **Primary, Secondary, and other Education** (Education): Teachers, Educators, Non-College Students, School Administrators
7. **Engineering**: Mechanical Engineers, Electrical Engineers, Chemical Engineers, Civil Engineers, Environmental Engineers, Systems Engineers, Computer Engineers
8. **Health Care**: Doctors, Dentists, Nurses, Medical Assistants, Medical Students, Emergency Medical Personnel
9. **Household Management** (Home): Homemakers, Stay-at-Home Parents, Child Care Providers, Housekeepers
10. **Retail**: Salespeople, Retail Buyers, Cashiers, Clerks, Store Managers, Sales Managers
11. **Law and Government** (Government): Lawyers, Judges, Court Personnel, Elected Officials, Civil Servants, Military Personnel, Firefighters, Police Officers, Social Workers
12. **Non-profit**: Any work with non-profit organizations
13. **Retired**: Any lenders who say they are retired

A.4. Location Similarity in Teams

Each Kiva team can self categorize into one of 17 categories. We compute each team's average location similarities between all pairs of team members, then take the average of team similarity in each category, and present them in Table 10.

The left two columns only use location information provided by team members, whereas the right two columns compute the worst case scenario where we treat users with no location information as living in a different country. Based on this calculation, we label teams in the following categories as location-based teams: Religious Congregations, Schools, Local Area, Colleges/Universities, Clubs, Events, Businesses - Internal Groups, Families, (Friends), Businesses, Youth Groups, Memorials, Alumni Groups.

Appendix B. Proofs

In the proofs and examples in this appendix, we will omit the subscript i when we compare within a preference class where lenders have identical preferences, but different endowments and search costs.

Proof of Proposition 1: We first derive the equilibrium search decision and loan amount for a lender who does not belong to any team. Using backward induction, we first examine lender i's loan amount, g^0, after she searches and finds the best-match borrower:

$$\max_{g^0} U(x_i, G^0; \theta) = \theta v(G^0) + \omega_i - cg^0 - k_i. \tag{4}$$

The first-order condition is therefore $v'(G^0) = \frac{c}{\theta|J|}$. Thus, the total amount of loans made to borrower j and lender i's loan amount are, respectively:

$$G^0 = v'^{-1}\left(\frac{c}{\theta|J|}\right), \text{ and } g^0 = \frac{G^0}{|J|},$$

where J is the set of lenders who loan to borrower j. The latter comes from the assumption that lenders within each preference class have identical preferences. Let $G^0_{-i} = G^0 - g^0$.

In the search stage, lender i will search for the best-match borrower if doing so makes her at least as well off as not searching (and subsequently not making a loan):

$$\theta v(G^0) + \omega - cg^0 - k_i \geq \theta v(G^0_{-i}) + \omega, \text{ or}$$

$$k_i \leq \theta[v(G^0) - v(G^0_{-i})] - cg^0 \equiv k^0_i.$$

In comparison, if the same lender belongs to a team, in addition to her utility from private and public goods consumption, she also cares about her team's total loan amount, G^t, which affects her team ranking, $R(G^t)$. In the second stage, her loan amount is the solution to the following optimization problem:

$$\max_{g^t} U(x_i, G^t; \theta) = \theta v(G^t) + \omega_i - cg^t - k_i + \gamma R(G^t). \tag{5}$$

The corresponding first-order condition is therefore $\theta v'(G^t) + \gamma R'(G^t) = c$, which implicitly defines the equilibrium loan amount G^t. We characterize the total amount of loans made to borrower j as:

$$G^t = v'^{-1}\left[\frac{c}{\theta|J|} - \frac{\gamma}{\theta|J|}R'(G^t)\right].$$

By concavity of $v(\cdot)$ and monotonicity of $R(\cdot)$, we have $G^t \geq G^0$. It follows that lender i's loan amount is $g^t = \frac{G^t}{|J|} \geq g^0$, where J is the set of lenders who loan to borrower j.

Again, using backward induction, in the search stage, lender i will search for the best-match borrower if doing so makes her at least as well off as not searching:

$$\theta v(G^t) + \omega - cg^t - k_i + \gamma R(G^t) \geq \theta v(G^t_{-i}) + \omega + \gamma R(G^t_{-i}), \text{ or}$$

$$k_i \leq \theta[v(G^t) - v(G^t_{-i})] + \gamma[R(G^t) - R(G^t_{-i})] - cg^t \equiv k^t_i.$$

Comparing the search decisions, we obtain $k^t_i \geq k^0_i$ if the following inequality is satisfied:

$$\theta[v(G^t) - v(G^t_{-i})] + \gamma[R(G^t) - R(G^t_{-i})] - cg^t \geq \theta[v(G^0) - v(G^0_{-i}] - cg^0. \quad (6)$$

Let $\Delta v(G^t) \equiv v(G^t) - v(G^t_{-i})$, $\Delta v(G^0) \equiv v(G^0) - v(G^0_{-i})$, and $\Delta R(G^t) \equiv R(G^t) - R(G^t_{-i})$. Then (6) is reduced to the following:

$$\gamma \geq \frac{\theta[\Delta v(G^0) - \Delta v(G^t)] + c(g^t - g^0)}{\Delta R(G^t)}. \quad (7)$$

Note the right hand side is always non-negative. Therefore, when γ is sufficiently high, a lender who belongs to a team is more likely to search and make a loan compared to when she does not belong to a team. Furthermore, her loan amount is at least as large as when she does not belong to a team. ∎

Proof of Proposition 2: To prove that a lender who belongs to a lending team where members recommend loans to each other will be more likely to make a loan than a lender who does not belong to any team, we compare the team coordination outcomes with that of a stand-alone lender.

Using backward induction, we first characterize the total and individual loan amount, G^c and g^c_i, respectively. If team members do not care about team ranking, i.e., $\gamma_i = 0$ for all $i \in T$, the total loan amount is the same as if all lenders are stand-alone, i.e., $G^c = G^0$.

Next, we investigate the search stage. We model this stage as a simultaneous-move game. If team members coordinate by sharing search results, the most efficient outcome is for the lender with the lowest search cost, $k_i < k_j, \forall i, j \in T$, to search for and announce the best-match borrower. Other team members then make the optimal loan amount g^c to this borrower. For this stage to be interesting, we assume that there exists at least one lender who would rather incur the search cost than see the borrower not funded, i.e., $k_i \leq \theta v(G^c) - cg^c_i \equiv k^c_i$. Under this assumption, the search stage contains multiple asymmetric pure strategy Nash equilibria, each characterized by only one lender conducting the search. In each equilibrium, the payoff function for the searcher is $U(x_i, G^c; \theta) = \theta v(G^c) + \omega_i - cg^c - k_i$, whereas that for the non-searchers becomes $U(x_i, G^c; \theta) = \theta v(G^c) + \omega_i - cg^c$. We skip the equilibrium selection discussions as it is beyond the scope of this paper.

Among all Nash equilibria of the search stage, we discuss the efficient equilibrium, where the lender with the lowest search cost conducts the search and announces the results. *Ex ante*, the likelihood that a lender who belongs to a team will conduct a search is $(1 - F(k_i))^{n-1} \leq 1$. Therefore, lender i's expected utility becomes:

$$U(x_i, G; \theta) = \theta v(G^t) + \omega_i - cg - k_i(1 - F(k_i))^{n-1}. \quad (8)$$

Taking both stages into consideration, this equilibrium yields the highest efficiency. Regardless of which equilibrium is selected in the search stage, because of the reduction in total search cost, the overall efficiency is improved compared to the stand-alone case. Furthermore, as the entire team participates, it has a higher participation rate. ∎

Appendix C. Additional Tables

Table 11 reports the results of the two-stage least squares instrumental variables regression, with three specifications. Columns (1) through (3) show the results of the first-stage regressions while columns (4) through (6) show the results of the second-stage regressions. In both specifications, we include only lenders that have made at least one loan, ignoring those who have signed up for Kiva but not done anything on the site. Columns (1) and (4) present the results of a regression with no demographic variables included. We find that increasing the location similarity measure by 1, which is equivalent to changing the parent location node of a pair of lenders from a country to a state or from a state to a city, increases the probability of joining a team by 4.49%, and joining a team increases the number of loans given per day by 0.04. This represents an increase of about 1.2 loans per month, or at least $30 per month, since Kiva's minimum loan amount is $25.

Table 11: Effect of Team Membership on Lending: Instrumental Variables Regressions

	First Stage: Joined Team			Second Stage: Average Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
Joined Team				0.0397***	0.0566***	0.0500***
				(0.005)	(0.003)	(0.003)
Max Location Similarity	0.0449***	0.0472***	0.0448***			
	(0.001)	(0.001)	(0.001)			
Constant	0.1407***	0.1478***	0.1873***	0.0095***	0.0007	0.0052***
	(0.001)	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)
Female			-0.0587***			-0.0049***
			(0.002)			(0.000)
Occupation Controls	No	No	Yes	No	No	Yes
Observations	569,149	179,412	179,412	569,149	179,412	179,412

Notes: 1) Significant at the * 10%, ** 5%, and *** 1% levels.
2) Controls included for days since joining Kiva.

Our third specification includes the demographic variables gender and occupation. Both of these variables are derived from human coders and trained classifiers. The occupation categories are treated as dummy variables. For this specification (columns (3) and (6)), we restrict the lenders included in the regression to individuals that provide occupation information and are coded as either male or female. This specification does not provide substantially different results from the first specification. Any differences are due to either the restriction to a more engaged set of lenders or the inclusion of these two demographic controls. To separate these two possibilities, the second specification (columns (2) and (5)) shows the same regression as the first specification (no demographic controls) but for the subset of lenders included in the third specification. The results from this specification show that lenders in this subset are 4.72% more likely to join a team if their location similarity measure increases by 1, and joining a team increases their lending by 0.057 loans per day (1.7 loans per month, or at least $42 more per month). Including the demographic controls reduces this to about 0.05 loans per day or at least $38 per month.

Table 12 is a version of Table 4 (in the main text) that, in each specification of the fixed effects regression, controls for team size. This version is excluded from the main text due to a high degree of correlation between the number of members in a team and the number of lagged loans ($\rho = 0.85$). The results with these specifications are largely similar to those in Table 4, with no coefficients changing sign or becoming insignificant at the 1% level. An increase of one member in a team increases the number of loans that team makes each month by an average of about 0.055, meaning an increase of about 18 members in a group will increase monthly lending in that group by 1 loan. This is true whether we restrict our attention to teams with at least five members or to the top 500 teams.

Table 12: Team Loan Analysis: Fixed Effects

Dependent Variable: Number of Loans each Month [month t]			
	(1) All Teams	(2) $N \geq 5$	(3) Top 500 Teams
Number of Links	0.1491***	0.1455***	0.1480***
[month t]	(0.003)	(0.005)	(0.011)
Percentile Change	-0.1298***	-0.1356***	-0.2879***
[(month $t-1$) - (month $t-2$)]	(0.007)	(0.015)	(0.058)
Members who Posted for first time	0.7536***	0.7619***	0.7872***
[month t]	(0.002)	(0.003)	(0.007)
Loan Difference Change (Above)	0.0181***	0.0182***	0.0180***
[(month $t-1$) - (month $t-2$)]	(0.000)	(0.001)	(0.001)
Loan Difference Change (Below)	0.0462***	0.0433***	0.0460***
[(month $t-1$) - (month $t-2$)]	(0.001)	(0.001)	(0.003)
Number of Members	0.0573***	0.0530***	0.0547***
[month t]	(0.000)	(0.001)	(0.001)
Number of Loans (Lagged)	0.5934***	0.6096***	0.5992***
[month $t-1$]	(0.001)	(0.002)	(0.004)
Constant	5.5413***	7.5198***	20.1768***
	(0.034)	(0.080)	(0.404)
Observations	651,491	270,340	56,821
Number of Teams	19,175	6,845	1,103
R^2	0.709	0.721	0.714

Note: Significant at the * 10%, ** 5%, and *** 1% levels.

Table 13 displays the results of the differences-in-differences regression on the active teams. While our "Goal" treatments increase lending activity for the inactive teams, they do not for the active teams. None of our experimental treatments significantly increase lending in the active teams.

Table 13: Difference-in-Differences Regressions of Number of Loans on Treatments (Lenders Exposed to Forum Messages in Past Year)

	1-Day	7-Day	14-Day	30-Day
NoGoal-NoLink	-0.0243	-0.0043	0.0017	-0.0099
	(0.089)	(0.012)	(0.008)	(0.007)
NoGoal-Link	0.0014	-0.0240	-0.0014	-0.0050
	(0.059)	(0.023)	(0.012)	(0.008)
Goal-NoLink	-0.0762	-0.0056	0.0084	-0.0031
	(0.167)	(0.011)	(0.007)	(0.005)
Goal-Link	-0.0290	0.0010	0.0163	-0.0061
	(0.074)	(0.014)	(0.011)	(0.006)
Constant	0.0392	0.0005	-0.0002	-0.0123
	(0.100)	(0.067)	(0.051)	(0.064)
Observations	36,088	252,616	505,232	1,082,640
R^2	0.686	0.320	0.193	0.159

Notes: 1) Standard errors clustered at the individual level.
2) Significant at the * 10%, ** 5%, and *** 1% levels.
3) Full set of day and lender dummies included.