Recommending teams promotes giving

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Charles Darwin conjectured that the main evolutionary force behind human cooperation is inter-tribal competition (*1*). However, while this conjecture has been borne out in the laboratory, its effectiveness in sustaining real-world cooperation remains an open question. In recent years, online communities, such as Wikipedia and Kiva, have been developed to bring together labor and resource contributions to help the public at large. One key challenge facing these communities, though, is how to sustain member engagement and contributions to public goods. In a large-scale field experiment on Kiva, we recommend teams to lenders and find that lenders who join a team contribute significantly more compared to those who do not. The magnitude of the effect is fifteen times that of the median Kiva lender's lifetime contributions. Our results suggest team recommendation can be an effective behavioral mechanism to increase giving.

With three billion people subsisting on the equivalence of $2.5 per day, alleviating poverty is one of the most urgent challenges facing the world today (*2*). One solution to this problem has been to encourage the growth of micro and small enterprises in developing countries (*3*). However, despite being the largest employers in developing countries, micro and small enterprises are often stifled by a lack of access to credit or other financial services. To address this issue, microfinance programs provide small loans and other financial services to these enterprises. Unfortunately, the 10 million households served by these microfinance programs represents only a small fraction of those in need.

To meet the need for entrepreneurial support, some organizations have turned to the Internet to increase the participation of ordinary people around the world in microlending. One such opportunity is provided by Kiva (`http://www.kiva.org`), the world's first peer-to-peer microfinance website. Specifically, Kiva partners with microfinance institutions to match individual lenders with low-income entrepreneurs in developing countries as well as selected cities within the United States. Through Kiva's platform, anyone can make a zero-interest loan of $25 or more to support an entrepreneur. Since its inception in 2005, Kiva has increased its membership significantly. However, while many lenders join Kiva for pro-social motives, they do not participate fully. Indeed, thirty-six percent of them have never made a single loan, and many others do not come back to Kiva after making their first loan (*4*). Kiva's challenge is not unique, as many online contribution communities struggle with the issue of how to sustain member engagement and increase contributions to public goods.

To increase member engagement, some online communities have created group structures. For example, in 2008, Kiva instituted a lending teams program, a system through which lenders can create teams or join existing teams. Once a team is created, it appears on Kiva's team leaderboard, which sorts teams by the total loan amounts designated to them by their team members. Since 2008, more than 38,957 Kiva teams have been created based on lender group

affiliations such as organization, geographic location, religious affiliation, or sports interests.

The use of groups to increase member contributions to public goods has intuitive appeal, but its success is difficult to measure with naturally-occurring field data because of sample selection bias. For example, lenders who join teams might simply be those who are more active in general (*5*). To establish the *causal* relationship between group membership and pro-social lending, we use a randomized field experiment which enables us to combine the control of a laboratory experiment with the external validity of a field study (*6*).

Our novel approach is inspired by the economic theory of social identity (*7, 8*) as well as the development of big data analytics in computer science. Research on social identity has consistently found that people derive their sense of identity from groups (*9, 10*). This group identity can be used to increase public goods provision and improve coordination among team members in the laboratory (*11–16*). Building on these findings, we conduct a large-scale randomized field experiment to evaluate the effectiveness of team recommendation and membership as a behavioral mechanism for increasing participation among Kiva members. Our approach enables us to synthesize the predictive accuracy of machine learning with the causal inference from economic theory and field experiments (*17*).

The likelihood of joining an online social group depends on an individual's demographic profile, social connections, and past behavior, and can be predicted by a machine learning algorithm that combines and weighs these factors (*18, 19*). The results of these predictions are used in our field experiment to recommend lending teams to Kiva lenders.

In our study, we use a lender's likelihood of joining a team to recommend teams based on both homophily and status. Homophily refers to the tendency to associate with similar others (*20–22*). As such, we recommend teams to lenders based on their similarity to the existing members of those teams. In our study, we use two different measures of homophily: location similarity and loan history similarity. The former is based on the number of lenders in a team

who share the same location as the target lender, whereas the latter is based on how often the lenders have lent to the same borrowers. In addition to homophily, we recommend teams based on status (*23*), using the top three teams on the Kiva leaderboard to identify high-status teams. Using a 3×2 factorial design (Table S1), we vary our recommendation algorithms along one factor based on lender-team location similarity, loan history similarity, or team status. Along the other factor, we vary whether our recommendation rationale is explained to the lender. Computer science literature suggests that providing an explanation can increase the acceptance of a recommendation (*24, 25*). By varying whether a lender receives an explanation, we can obtain a better understanding about whether a factor impacts the effectiveness of the recommender system. We also include a control condition where we do not contact lenders (no contact) and a placebo condition where we email lenders to make them aware that there are lending teams on Kiva without providing any specific recommendations (teams exist) to control for any contact effect. The text of the email is completely identical across treatments, except for the variables that change across treatments (see Supplemental Information).

To study the causal effects of team recommendations on the likelihood to join a team and to increase contributions, we use a group of 69,802 lenders who have made at least two loans in the past six months but have never joined a team. We then randomly assign each lender to one of eight experimental conditions with equal probability. Pairwise Kolmogorov-Smirnov tests based on observable characteristics verify that our randomization works (Table S2).

We send each lender in our treatment groups an email from Kiva. After excluding lenders whose emails bounced and those who switched their accounts to private, we have a total of 64,800 lenders whom we intend to treat (henceforth *All*). Of these lenders, we find that one-third ($n = 20,371$) open our email, constituting our treated sub-sample (henceforth *Opened*). We then track the team joining and lending behavior of each lender for the next two months. The Supplemental Information section includes a detailed description of our experimental procedure

and email scripts.

We first examine what types of recommendations are most effective in increasing team membership. Figure 1 presents the proportion of lenders who join a lending team in each treatment after our email intervention, for both all lenders (left panel) and those who open our emails (right panel). For both groups, lenders who receive a location similarity explanation are most likely to join a team, accounting for 3% of the group who open their emails. This participation rate is comparable to that in other charitable-giving field experiments using mailing campaigns (*26, 27*).

We next conduct a regression analysis (Table 1 and Figure 2) and find that every treatment leads to a significantly higher likelihood of joining a team, compared to the no-contact control condition, for both the all lenders (column 1) and opened-email (column 2) groups ($p < 0.01$). Of those who open their emails, lenders in the location similarity with explanations treatment are more likely to join a team compared to those in the teams-exist condition ($p < 0.01$). These results are robust to a multiple hypothesis testing correction (*28*).

We next explore the types of teams lenders are most likely to join by examining the characteristics of teams joined by our lenders. Table 2 displays the results of eight conditional logit specifications with odds ratios reported, with one specification per treatment. In our regressions, we use whether each lender joined each team as our dependent variable, and location similarity, loan history similarity, team status, team size, and experimenter recommendation as our independent variables.

The results for our control and teams-exist conditions (columns 1 and 2) show that lenders are more likely to join teams with higher location similarity and status. The odds of a lender joining a team whose location similarity is 1 percentile higher is 2% higher, while the odds of a lender joining a top ten team is 13 times higher than those of joining a non-top ten team. On the other hand, we find that neither lending history nor team size impacts lenders' choices. These

findings show that lenders value both homophily and status when deciding to join a team. It is also noteworthy that location and status information are easily found on the Kiva site while lending histories are more difficult to locate.

Interestingly, we find that the provision of a location similarity recommendation mitigates the influence of team status, leading lenders to join recommended teams or teams with higher history similarity (columns 3 and 4). By contrast, our recommendations based on loan history similarity (columns 5 and 6) do not substantially change how lenders choose their teams. Finally, recommendations based on team status (columns 7 and 8) seem to change lender behavior in a way similar to that of location-based recommendations, but only when we explain our recommendations.

Finally, we study whether joining a team increases pro-social lending. To address any potential endogeneity issues caused by self selection, we use the random treatment assignment in our experiment, namely whether the lender received an email, as an instrumental variable for joining a team. Figure 3 and Table 3 display the results of our two-stage least squares instrumental variable regression. In the first stage, we find that the "Email" variable, denoting whether a lender received an email, is not a weak instrument for joining a team, with an F-statistic of 23.55. Next, for this instrument to satisfy the exclusion restriction, it must be the case that an email does not directly affect lending except through increasing the likelihood that a lender joins a team. This might occur if contacting the lenders regarding Kiva reminds them of Kiva's existence, prompting them to lend. However, since our previous field experiment on Kiva has shown that simply contacting the lenders does not affect lending (*5*), we conclude that the instrument satisfies the exclusion restriction.

This regression employs a difference-in-differences approach. For three different window sizes, the dependent variable in each second-stage regression is the difference in total loan amounts t days before and after our treatment, where t is the window size. Thus, the coeffi-

cients on the "Join Team" variable indicate how much more lenders who join teams give than those who do not join teams after the treatment, controlling for the same difference before the treatment. The results of this regression show that joining a team significantly increases lending. However, this effect is insignificant beyond one week. One possible reason for the lack of an observed long term effect is that lenders may wait until initial loans are repaid before lending again, a process which may take 12-18 months. However, even the one-week effect ($392) is more than fifteen times the lifetime contribution of the median Kiva lender ($25), indicating that team membership is effective in increasing member contributions.

Online communities have become societally important platforms for information exchange, peer-to-peer lending, peer content production, education and social interaction. However, despite some successes, the majority of online communities fail to maintain member involvement or to meet their goals in the production of public goods. One reason for this high failure rate is a lack of evidence-based guidance for designing and managing contribution incentives in online communities. Our results suggest that recommending teams to members of an online lending community based on homophily or team status is an effective mechanism to engage community members and increase their contributions. Furthermore, our recommender algorithms, which have been proven effective on Kiva, can be modified and deployed in other communities to help them achieve their goals. By understanding the optimal design of team recommendation in online settings, we can improve the success of a wide variety of online communities and facilitate desirable outcomes whether it be alleviating poverty through crowd-sourced loans, improving the psychological well-being of cancer patients in health support groups, or enhancing the learning of students taking STEM courses.

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Table 1: **Treatment Effects on the Likelihood of Joining Teams.** Probit estimates. Reported results are marginal effects calculated at the mean level of the covariates. Robust standard errors corrected for clustering at the individual level are in parentheses. (a) The decision to join a team is regressed on the seven treatment dummies for all lenders in our sample ($n = 64,800$). (b) The second model uses the same specifications but is restricted to the lenders who opened their emails ($n = 29,055$). Significance levels: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. Applying a multiple hypothesis testing correction (*28*) yields the same significance levels as above, except for the "History-Explanation" variable in column (3) which becomes insignificant at the 10% level.

Dependent Variable: Joined a team			
	(1)	(2)	(3)
	All Users	Opened & No-Contact	Opened
Team-Exist	0.0045***	0.0155***	
	(0.002)	(0.003)	
Location-Explanation	0.0094***	0.0256***	0.0145***
	(0.002)	(0.002)	(0.004)
Location-NoExplanation	0.0062***	0.0189***	0.0050
	(0.002)	(0.002)	(0.004)
History-Explanation	0.0070***	0.0212***	0.0083**
	(0.002)	(0.002)	(0.004)
History-NoExplanation	0.0061***	0.0182***	0.0039
	(0.002)	(0.003)	(0.004)
Leaderboard-Explanation	0.0062***	0.0185***	0.0043
	(0.002)	(0.002)	(0.004)
Leaderboard-NoExplanation	0.0063***	0.0197***	0.0062
	(0.002)	(0.002)	(0.004)
Number of Subjects	64,800	29,055	20,371

Table 2: **Choice model: conditional logit regression.** Odds ratios reported. Whether the subjects join teams is regressed against the two similarity measures (coded as the percentile of the measure for each subject-team pair), whether the team is one of the top teams, the team size, and whether or not the team was recommended through the experiment. This regression is performed separately for each treatment. While team size never significantly affects the joining decision, and a recommendation always significantly increases the likelihood of joining a team, the effects of the other variables depend on the treatment. When the teams are recommended based on either lending history (columns 5 and 6) or the leaderboard (columns 7 and 8), both similarity measures and whether the team is a top ten team significantly increases the likelihood that the subject joins the team. A location recommendation (columns 3 and 4) causes subjects to ignore the top ten teams. Compared to the cases where no recommendation is made (columns 1 and 2), any type of recommendation increases the degree to which subjects pay attention to lending history. When no recommendation is made, lending history similarity decreases subjects' likelihood of joining a team.

	Dependent Variable: Joined a Team							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	No-Contact	Team-Exist	Loc.-Exp	Loc.-NoExp	Hist.-Exp	Hist.-NoExp	Lead.-Exp	Lead.-NoExp
Location Similarity (Percentile)	1.03***	1.02***	1.02***	1.05***	1.02***	1.01***	1.02***	1.02***
	(0.011)	(0.005)	(0.006)	(0.017)	(0.005)	(0.005)	(0.007)	(0.005)
History Similarity (Percentile)	1.00	1.00	1.02**	1.01	1.01	1.00	1.02**	1.00
	(0.007)	(0.007)	(0.008)	(0.009)	(0.011)	(0.008)	(0.010)	(0.010)
Top Ten Team	13.07***	13.60***	0.81	1.01	6.98***	13.85***	16.74***	6.22***
	(6.476)	(5.305)	(0.264)	(0.390)	(2.759)	(5.662)	(8.326)	(2.535)
Team Size (Percentile)	1.00	1.00	0.99	0.99	1.00	1.01*	0.98***	1.01
	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)	(0.008)	(0.008)	(0.012)
Recommended			82.39***	37.32***	119.52***	213.82***	7.78***	7.26***
			(27.780)	(14.638)	(36.696)	(71.360)	(2.473)	(2.504)
Number of Teams	491	491	491	491	491	491	491	491
Number of Subjects	35	61	105	74	80	72	72	74

Notes: 1) Standard errors (in parentheses), clustered at the subject level.
2) Significant at the: * 10%, ** 5%, and *** 1% levels.

Table 3: **Difference-in-Differences Regressions of Average Daily Lending Amount (2SLS).** Our instrumental variables diff-in-diff regression, using receiving an email as an instrument for joining a team, shows that up to a 7-day window, joining a team increases lending significantly.

	IV 1st Stage	IV 2nd Stage: Average Amount			OLS		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		1-Day	7-Day	30-Day	1-Day	7-Day	30-Day
Email	0.0053***						
	(0.001)						
Join Team		298.5579***	55.9145***	10.2310	5.2565***	0.5662*	0.5166***
		(72.283)	(21.058)	(7.318)	(0.755)	(0.337)	(0.134)
Constant	0.0045***	-2.6593***	-0.9359***	-0.2357***	0.0066	-0.4328***	-0.1474***
	(0.001)	(0.670)	(0.195)	(0.068)	(0.072)	(0.032)	(0.013)
Observations	64,800	64,800	64,800	64,800	64,800	64,800	64,800

Note: Standard errors in parentheses
Significant at the: * 10%, ** 5%, and *** 1% levels.
Uninstrumented OLS regressions are reported as comparisons.

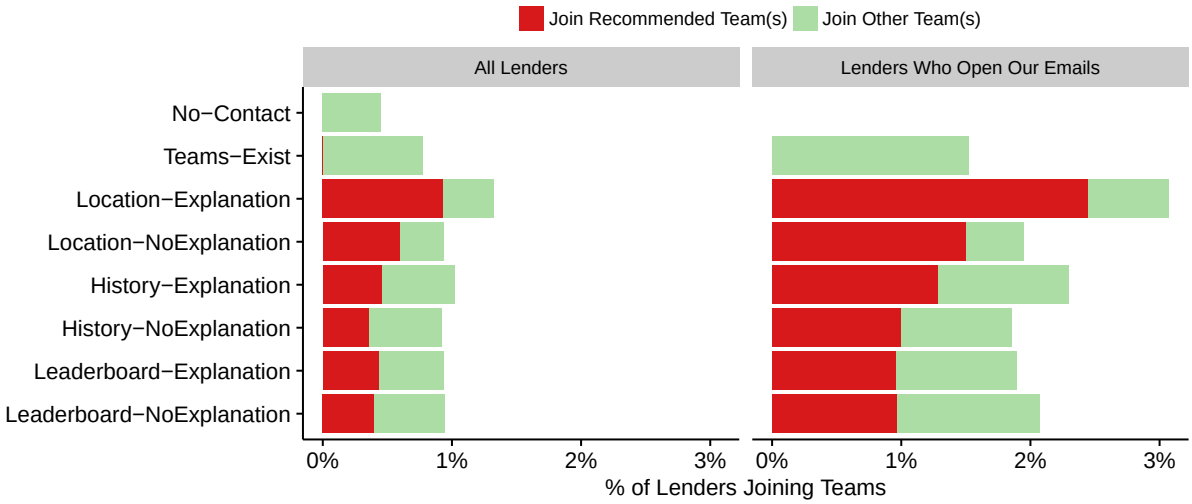


Figure 1: **Proportion of lenders joining teams in each experimental condition.** This figure presents the proportion of lenders who join a lending team in each experimental condition after our email intervention. Location-based recommendations exhibit a higher proportion of lenders joining recommended teams (67.96%), compared to lending history similarity (42.31%) or leaderboard (44.37%) based recommendations ($p < 0.01$, proportion of t-tests). Similar results are observed when we focus on lenders who open our email (right panel).

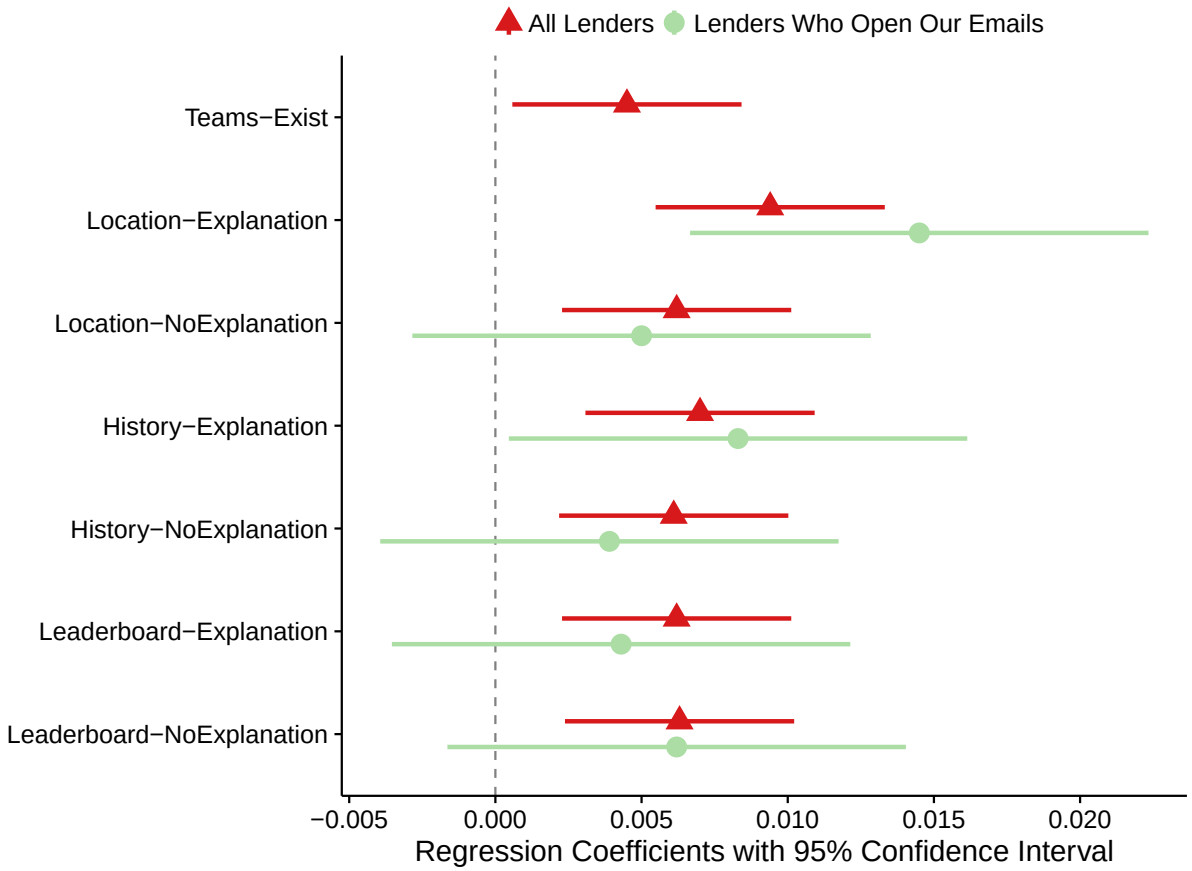


Figure 2: **Treatment effects on the likelihood of joining teams.** This figure presents the treatment effects on the likelihood that a lender joins a lending team (Table 1). When we focus on all lenders (lines with red triangle), we find that every treatment significantly increases the likelihood of joining a team compared to the control condition. When focusing on lenders who open our email (lines with green circle), we find that the homophily-based recommendations with an explanation also significantly increase the likelihood of joining a team, compared to the teams-exist condition. Explanations increase the likelihood of joining a team for only the location-based recommendations (All: $p = 0.02$; Lenders who open our email: $p = 0.01$; Wald tests).

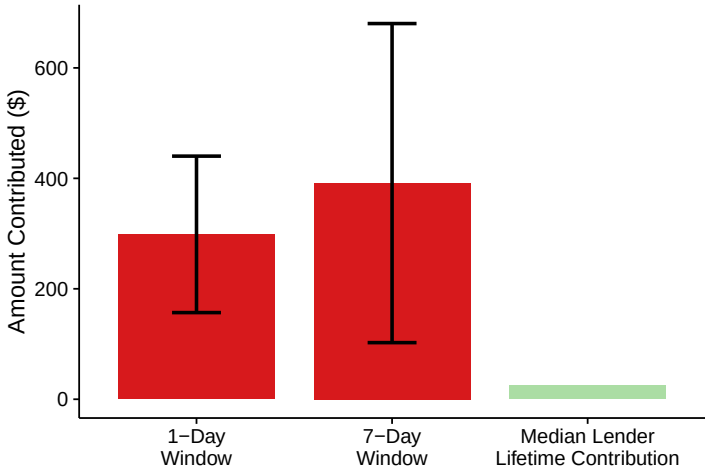


Figure 3: **Effects of team membership on pro-social lending.** This figure reports the results of our two-stage least squares instrumental variable regression coefficients (Table 3), indicating the effects of joining a lending team on contributions for the 1-day (left red bar) and 7-day (middle red bar) window. The median Kiva lender's lifetime contributions ($25) is plotted to provide a benchmark (green bar).

Supplementary Information

1 Methods

We first determine the experimental design and our subject pool. Then, in collaboration with Kiva, we implement our study by sending out mass emails with our recommendations.

1.1 Experimental Design

Our experiment consists of 6 treatments (3 types of recommendations, with and without explanation), a control condition (no contact) and a placebo condition (teams exist). Table S1 displays our experimental design.

While lenders in the control condition were not contacted during the experiment, for each treatment, we sent one of five email messages. Each email consists of three parts. Part 1 is common to all treatments and the placebo,

"*Hi [FirstName], Since you're such an awesome Kiva lender, we wanted to let you know about a fun feature of the Kiva experience: Kiva Lending Teams! Lending Teams are self-organized groups around shared interests location, alumni orgs, social causes, you name it. You can connect with other lenders, discover loans you might be interested in, and track your collective impact.*"

Likewise, each email ends with Part 3,

"*[Or] Check out the thousands of [other] lending teams to find the right one for you.*"

"*Thanks for being a part of the Kiva community and making a difference around the world.*"

While the text of emails sent to lenders in the placebo ("teams exist") condition consists of Parts 1 and 3, lenders in the six treatments also received one of the following in the second part of the email:

1. Leaderboard with explanation treatment (Leaderboard-Explanation):

"*Some of the most popular teams are: [TEAMS].*"

2. Location similarity with explanation treatment (Location-Explanation):

   "*Other lenders who live near you enjoy being a part of these teams: [TEAMS].*"

3. Loan history similarity with explanation treatment (History-Explanation):

   "*Based on your past lending, people who have made similar loans enjoy being a part of these teams: [TEAMS].*

4. Recommendations without explanations treatments (Leaderboard-NoExplanation, Location-NoExplanation, History-NoExplanation)

   "*Here are a few teams you may want to check out: [TEAMS].*"

A sample email from the Location-Explanation treatment is included in Extended Figure S1. We now explain our recommendation algorithms.

1.1.1 Recommendations based on team status

The simplest recommendation strategy is to recommend teams that are ranked highly on the team leaderboard. Kiva provides several leaderboards that rank teams based on either the total loan amount attributed to the team or the number of team members, in the most recent month or all time. For the experiment, we use the default leaderboard that lenders see when they visit the Kiva Team page, the all time total amount lent.

Note that every lender receives the same recommendations under this strategy. The three teams we recommend to the lenders are "Atheists, Agnostics, Skeptics,...", "Kiva Christians," and "Guys holding fish."

1.1.2 Recommendations based on location similarity

The goal of this algorithm is to recommend the most popular teams in a lender's local area. This is motivated by the fact that there are many location-based teams on Kiva and by the conclusion of our previous work that the maximum location similarity between a lender and all the teams is partially correlated with whether the lender has joined a team (*5*). This also reflects the results of an online data mining competition we ran with doctoral students at the University of Michigan using the Kiva API data. The following algorithm, written by the first author, is the one that performed best in that competition. We calculate the location similarity between two lenders i and j as $l_{ij} \in \{0, 1, 2\}$ (*5*). If the two lenders are from different countries, $l_{ij} = 0$. If two lenders are from the same city, $l_{ij} = 2$. The condition for $l_{ij} = 1$ includes the following two cases: 1) if the two lenders are not in the same city but in the same state in the United States or Australia, or the same province in Canada, or 2) if they are from the same country other than the United States, Australia or Canada. This is because there are significantly more lenders on Kiva from the United States, Australia or Canada than from any other country.

The location similarity of a team t in the neighborhood of a lender i is calculated as the sum of the location similarities between that lender and all lenders in that team. That is, $L_{it} = \sum_{j \in T} l_{ij}$. For every lender, we rank all teams by the location similarity of these teams and recommend the three highest-ranked teams. For these recommendations, we exclude the three teams highest on the leaderboard: "Atheists, Agnostics, Skeptics,...," "Kiva Christians," and "Guys holding fish," for two reasons. First, the Atheists and Christians are outliers in that they overwhelm all other teams in size. Consequently, they often appear as winners of location-similarity based recommendations. Second, to differentiate between status-based and homophily-based recommendations, we exclude all three teams.

1.1.3 Recommendations based on loan history similarity

We also construct a recommender system based on the loan history of a lender. This is motivated by the homophily conjecture that lenders who lend to similar borrowers share similar interests and are thus more likely to join the same teams.

Borrowers on Kiva are registered in 80 countries from 8 geographical regions (Oceania, Asia, etc). They loan to facilitate 149 types of activities which are further categorized into 15 sectors. Let $\mathcal{S}_u$ be a set of loans made by a user u and $\mathcal{S}_t$ be a set of loans that are attributed to a team t. The **relevance** of the team to the user is scored by the following function:

$$Relevance(u,t) = \sum_{i \in \mathcal{S}_u} \sum_{j \in \mathcal{S}_t} [f_g(i,j) + f_a(i,j)], \tag{1}$$

where $f_g(i,j)$ equals 2 if the two loans i and j are from the same country, 1 if they are from two different countries in the same region, and 0 if they are not from the same region; $f_a(i,j)$ equals 2 if the two loans i and j are for the same activities, 1 if they are for different activities in the same sector, and 0 if they are not for activities in the same sector.

Note that the relevance score as defined in Equation (1) favors large teams that have made many loans. We further normalize the score by taking into account the total number of loans made by each team. That is,

$$Normalized\_Relevance(u,t) = \frac{Relevance(u,t)}{|\mathcal{S}_t| + 50}. \tag{2}$$

Given a user who has not joined a team, we calculate the normalized relevance score for every team and recommend the three top-scoring teams to that user. For consistency with the recommendations based on location similarity, we also exclude the top three teams on the leaderboard, “Atheists, Agnostics, Skeptics,...,” “Kiva Christians,” and “Guys holding fish,” for these recommendations.

1.2 Subject Pool

Based on Kiva Privacy Policy and the information need of our recommendation algorithms, we select lenders for our experiment based on the following criteria:

- Their pages and loans are set to public in their account settings.
- They allow marketing emails in their communication settings.
- They have never joined a team.
- They provide location information in their profile.
- They have made at least two non-promotion loans in the past six months.

This gives us 69,845 users.

We then assign each user to one of the treatments, the placebo, or the control condition using stratified randomization. The stratified random assignment is based on the total loan amount by each lender before the experiment. We want to ensure that the most active Kiva lenders are not all concentrated into one treatment, so we rank the lenders based their total loan amounts, taking the top 8 lenders and randomly assigning them to different conditions. We then repeat this for each group of 8 lenders, proceeding down the ranked list. Between assigning lenders to conditions and running the experiment, 43 users joined a team and were dropped from our sample. This yields a final sample of 69,802 users. The size of the sample and population is summarized with a Venn Diagram in Extended Data Figure S2.

Before running the experiment, we run pair-wise Kolmogorov-Smirnov tests of the equality of distributions based on the user statistics to verify that our randomization produces balanced treatments across observable characteristics. The results of these tests show that the number of loans, average amount per loan, balance, average loan terms for fundraising or repayment, and

auto lending settings do not differ significantly at the 10% level between any treatments. Thus, the Kolmogorov-Smirnov tests do not reject the hypothesis that these values are drawn from the same distribution. We summarize the lending and location statistics of each treatment in Extended Data Table S2.

1.3 Experimental Procedure

The experiment was conducted when the first author undertook an internship at Kiva.org in May 2014.

We conduct the experiment on May 23, 2014, with Kiva sending out 61,077 emails to lenders in our sample (all except those in the no-contact control condition). After excluding lenders whose emails bounced and those who switched their pages to private and re-including the lenders from our no-contact control group, we have a total of 64,800 lenders whom we intend to treat (henceforth *All*). Of these lenders, 20,371 open our email, constituting our treated sub-sample (henceforth *Opened*). We follow the team joining and lending behavior of each participant for two months.

2 Extended Data Figures and Tables

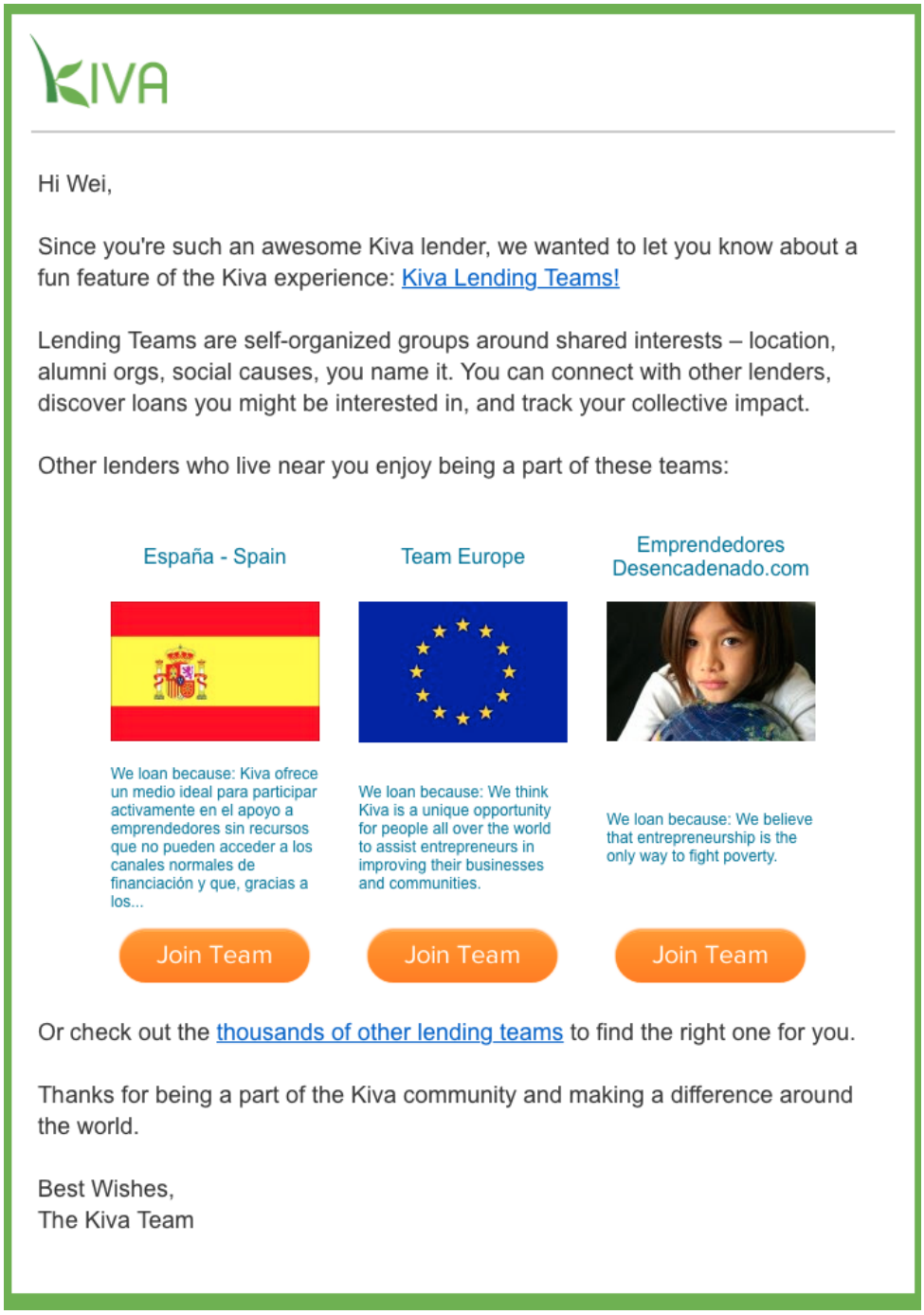
Table S1: **Summary of Experimental Treatments.**

		Explanation of Recommender Algorithm	
		Explanation	No Explanation
Recommendation Algorithm	Location	Location-Explanation	Location-NoExplanation
	Loan History	History-Explanation	History-NoExplanation
	Leaderboard	Leaderboard-Explanation	Leaderboard-NoExplanation
Control		No Contact	
Placebo		Teams Exist	

Table S2: **Lending and Location Statistics of Each Treatment.**

Experimental Condition	# of Users	Lending Statistics (average)			
		Amount Loaned	# Loans	Repayment Term	Account Balance
No-Contact	8725	1423.57	45.49	18.50	36.24
Teams-Exist	8725	1405.55	45.06	18.33	35.89
Location-Explanation	8726	1381.11	45.05	18.45	35.22
Location-NoExplanation	8726	1403.77	44.42	18.32	37.13
History-Explanation	8726	1417.29	44.69	18.29	37.89
History-NoExplanation	8725	1399.23	43.74	18.38	35.62
Leaderboard-Explanation	8723	1372.00	44.43	18.40	34.37
Leaderboard-NoExplanation	8726	1447.86	45.67	18.28	37.89

Note: Pairwise Kolmogorov-Smirnov tests comparing each experimental condition with the other yield $p > 0.10$ for each observable characteristic. Amount Loaned and Account Balance are in United States dollars, whereas Repayment Term is in months.



KIVA

Hi Wei,

Since you're such an awesome Kiva lender, we wanted to let you know about a fun feature of the Kiva experience: Kiva Lending Teams!

Lending Teams are self-organized groups around shared interests – location, alumni orgs, social causes, you name it. You can connect with other lenders, discover loans you might be interested in, and track your collective impact.

Other lenders who live near you enjoy being a part of these teams:

España - Spain

We loan because: Kiva ofrece un medio ideal para participar activamente en el apoyo a emprendedores sin recursos que no pueden acceder a los canales normales de financiación y que, gracias a los...

Join Team

Team Europe

We loan because: We think Kiva is a unique opportunity for people all over the world to assist entrepreneurs in improving their businesses and communities.

Join Team

Emprendedores Desencadenado.com

We loan because: We believe that entrepreneurship is the only way to fight poverty.

Join Team

Or check out the thousands of other lending teams to find the right one for you.

Thanks for being a part of the Kiva community and making a difference around the world.

Best Wishes,
The Kiva Team

Figure S1: **Email Screenshot.** This email is an example from the Location-Explanation treatment.

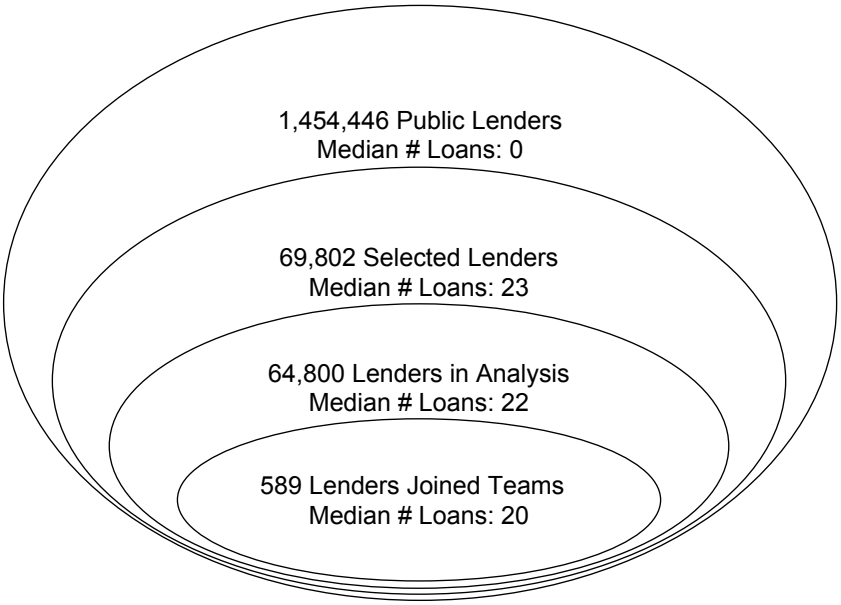


Figure S2: **Sample and Population Comparison.** The number of lenders and median number of loans of all public users, those who are selected as participants, those whose data is used in our analyses, and those who joined at least one team during our experiment.