# Understanding Lending Behaviors on Online Microlending Platforms: The Case for Kiva

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**Abstract**

Microfinance institutions focus on providing financial services for low-income citizens who typically lack access to traditional banking systems. In recent years there has been an significant growth in the number of online microlending sites that connect lenders to microfinance institutions and individuals that require funding. Although traditional (offline) microfinance has been widely studied, there exist many open questions regarding lending behaviors when the activity is carried online. In this paper, we present an in-depth analysis of the relationship between the information that lenders can explore in an online microlending platform and the lending activity it generates. Specifically, we carry out our analysis on the Kiva platform and focus on three important features: ratings of the microfinance institutions, loan characteristics and lending teams. Our results show, among others, that lenders appear to lend more to highly rated institutions, and with what appears to be better planned lending decisions; and that smaller, homogeneous teams seem to drive more lending activity and to achieve larger team lending agreements.

## Introduction

Microfinance services offer financial solutions for low-income citizens who lack access to traditional banking. There exist different types of microfinance providers including *informal services* like moneylenders or ROSCAs (Rotating Savings and Credit Associations); and *microfinance institutions (MFIs)* like the Grameen Bank in Bangladesh or the Banco do Nordeste in Brazil (Helms 2006). Informal services are mostly based on ad-hoc agreements between lenders and borrowers who typically live in the same neighborhoods and know each others' financial reality. On the other hand, MFIs are non-profit organizations that give small loans to low-income borrowers, typically at low interest rates. Their main aim is to contribute to the socioeconomic development of the regions where they operate while remaining financially sound. MFIs can vary in size from hundreds to millions of customers but they all require transparency and financial stability to become successful and trustworthy. The microlending responsibilities of an MFI cover the full lending cycle: from loan approval for an individual or a group to making sure that the borrowers reimburse their loans.

In recent years, there has been a significant growth in the number of online microlending sites that connect individuals to small businesses led by low-income citizens. This type of social lending platforms allow individuals from all over the world to explore large online databases of businesses that require small loans to succeed; and citizens without access to formal banking systems to borrow the money they need to carry out their projects. Despite having a similar objective, online platforms might differ widely in their implementation of microlending. For example, online platforms such as *Kiva* or *Global Giving* collaborate with local MFIs who take care of all the microlending cycle: from the selection of borrowers and small businesses to support, to the reimbursement process. As a result, the online microlending platforms are only responsible for the selection of the MFIs they collaborate with and for the payments platform that connects lenders to MFIs and borrowers. In this microlending approach, lenders only recover their investments but do not receive any interests which are typically processed by the local MFIs. On the other hand, online platforms like *Zidisha* offer a pure peer-to-peer network where lenders act as informal MFIs lending their money to borrowers at an agreed interest rate. In this type of platforms, both investment and interests are transferred directly to the lenders rather than to the intermediary MFI.

Understanding lending and borrowing activity is critical to improve the way microfinance services work. However, although there exists an important body of work regarding traditional (offline) microfinance, the research in the area of online microlending is much more limited. Previous work in traditional microlending has covered various research questions including the relationship between gender and loan reimbursement (Marrez and Schmit 2009); the impact that MFI ratings have on total investments and growth (Gutierrez and Serrano 2007; Sufi 2009); or the way lending teams influence lending behaviors (Eckel and Grossman 2005). Nevertheless, there only exist a few studies that focus on the analysis of *online* microlending platforms (Ly and Mason 2010; Desai and Kharas ). These works use econometric techniques on data snapshots provided by the microlending platforms to evaluate the role that various behavioral and business properties play on the lending process. However, many aspects that have been typically addressed in traditional microlending studies such as the role that MFI ratings or teams play in the lending process, have not been fully analyzed online.

In this paper, we propose an in-depth study of lending behaviors in Kiva using a mix of quantitative and large-scale data mining techniques. Our objective is to understand the relationship between lending activity and various features offered by the online platform. Specifically, we focus on three research questions: (i) the role that MFI ratings play in driving lending activity, (ii) the role that various loan features have in the lending behavior and (iii) the role that group lending plays as opposed to individual lending activity. The first question analyzes whether there exists a relationship between the MFI ratings – that lenders can explore online – and their lending volumes. The second research question attempts to understand if certain loan features – available online at Kiva– such as the type of small business, the gender of the borrower, or the loan's country information might affect the way lenders lend. Finally, since Kiva lenders can make donations individually or as members of an online team, the third question focuses on evaluating whether there exist specific team properties that make teams more or less successful in driving lending activity. We expect that this analysis will provide Kiva and other similar microlending platforms with findings and techniques to better cater to their lenders so as to facilitate and enhance lending activity.

## Related Work

There exists an important body of literature related to the three research questions we analyze.

**MFI Ratings**. An important body of work analyzes the relationship between MFI ratings and the lending volumes that microfinance institutions manage. Most of these studies use the information provided by the *MIXMARKET* platform which collects financial information from multiple existing MFIs worldwide (Lafourcade 2005). The platform also provides rating information typically computed by rating agencies such as *Rating Fund*, *Crisil* or *Planet Rating* that focus on evaluating the quality of microfinance institutions. Using a cross-country econometric approach, various researchers have found a positive and significant relationship between ratings and the profitability of an MFI (Gutierrez and Serrano 2007; Garmaise and Natividad 2010). However, others have not found such strong correlations after accounting for the endogeneity of ratings in their model (unobservable effects on the ratings) (Hartarska and Nadolnyak 2008). Similar studies have also been carried out in the for-profit sector with larger lending and borrower organizations. In general, results show that higher ratings are typically related to larger investments and growth as well as to larger borrowing power (Sufi 2009; Elsas and Krahnen 1998). These results for profit and non-profit organizations suggest that ratings might offer lenders a confidence that results in an increase in lending and investment activity. However, these studies focus on aggregate analyses across lending activity and MFIs. Our research provides a complementary perspective by analyzing the relationship between individual lending patterns and MFI ratings. Our aim is to reveal how different types of lending behaviors are related to MFI ratings.

**Loan Features**. Unlike professional lending agencies, microlending initiatives such as Kiva typically work thanks to contributions from non-professional lenders who lend for different reasons. To understand these motivations, Desai *et. al* analyzed similarities and differences between official donor agencies and private aid through microlending websites such as Kiva or GlobalGiving (Desai and Kharas ). Using data from official agencies as well as from the two peer-to-peer lending sites, the authors revealed that while official agencies appear to focus on macroeconomic indicators to allocate their aid, individuals lending through microlending websites focus more on the specifics of the loan or the borrower. Similarly, Li *et al.* analyzed the speed at which different types of Kiva projects get fully funded. The authors highlight various results including the fact that small loans and loans for women appear to get funded faster (Ly and Mason 2010). More general studies, analyze microlending from a broader perspective such as Marrez *et al.* who report that loss rates for microloans are higher for male clients than females (Marrez and Schmit 2009). Our research complements these findings by providing an in-depth analysis of the relationship between individual lending activity and loan features or the borrower country's macroeconomic indicators. Additionally, we also analyze the relationship wih the macroeconomic indicators from the lenders' countries.

**Teams**. There is a large body of literature in behavioral economics that analyzes the impact of groups on individual behaviors. Tajfel *et al.* found that individuals within a group might behave differently depending on whether their affiliation is interpersonal (family or friends) or intergroup (colleagues or clubs). The former appeared to show more collaboration strategies, whereas the latter mostly focused on winning the other groups (Tajfel and Turner 1979). Similar results were found by Kollock, Rabbie or Mummendey (Kollock 1998; Rabbie, Schot, and Visser 1989; Mummendey et al. 1992). Specifically focused on lending groups, researchers have shown that very well defined group identities tend to show larger lending activity (Eckel and Grossman 2005). However, there exist only a couple of references that touch upon teams and lending activity in Kiva. Hartley presented a taxonomy of the 120 top and bottom performing teams in Kiva using a combination of qualitative and quantitative analysis (Hartley ). On the other hand, Liu *et al.* used machine learning and econometric models to predict the lending activity of Kiva's lenders based on their motivations and their team membership (Liu et al. 2012). Our work extends the related literature providing an analysis of the influence that lending teams might have on individual lending activity combining both aggregated and individual lending behaviors.

## Inside Kiva

Kiva is a non-profit organization that offers an online platform to connect lenders with borrowers. Their site, *kiva.org*, allows citizens to microlend small amounts of money to entrepreneurs (borrowers) from different countries. The borrowers are always affiliated with a Field Partner (FP) which can be a microfinance institution (MFI) or other type of local organization that has partnered with Kiva. Field partners give loans to selected businesses based on their local knowledge regarding the country, the business sector including agriculture, health or manufacture among others, and the borrower. The microlending process starts with Field partners publishing their loans on Kiva's website including a description of the project and the amount of money needed. Once published, lenders can browse through Kiva's database and select one or multiple projects to lend to (lending amounts start at $25). When Kiva gathers all the amount for the loan, the money is disbursed to the FP who is responsible for the repayment to Kiva's. However, Field partners can grant loans to the borrowers either before (if they have available funds from other sources) or after the loan has been fully funded on Kiva's website. Finally, lenders are periodically informed when the repayments take place and reimbursed when the loan is fully repaid (no interests are collected by the lender). Typically, lenders decide to lend again their money once the repayments happen.

From a lender's perspective, Kiva's platform allows individuals to check existing loans and to lend money through their website although there also exist mobile applications by third-party developers that provide enhanced lending interfaces for iphones and androids. The Kiva platform offers lenders the possibility of exploring across a wide range of loans. Lenders can randomly select a loan from the Kiva pannel where pictures from different borrowers are displayed or alternatively explore all loans using a set of filters. Filters allow lenders to explore loans by country, size (individual or group), gender of the borrower(s) or sector. Lenders can lend once or several times to any given loan.

Additionally, Kiva also offers lenders the possibility of (1) inviting friends to become Kiva lenders and (2) creating a team or joining one or multiple existing teams. There exist over $25,000$ different lending teams, organized by categories, that lenders can browse through at Kiva's website. Categories include sports groups, religious congregations, schools or common interest among others. Kiva's website also displays a leaderboard showing the total amounts raised by each teams. Once a lender joins a team, she can choose whether any of her lending actions will be counted towards the team's total raised amount. If a lender is a member of multiple teams, she can choose to lend without associating the lending action to any team, or make it count towards one (and only one) of the teams she is a member of.

**Kiva Data**

Kiva offers two options to access data regarding online lending activity: (i) a loan-lender snapshot, which only provides information regarding lenders and the loans they are associated with (independently of the number of times a lender has lent to any given loan) (Kiva ); and (ii) an API to query, in real-time, for all information regarding lenders, their individual, timestamped, lending actions to specific loans and field partners, and their team memberships. We employ both sources of information to answer our research questions.

First, we use Kiva's API to retrieve the individual lending actions and their timestamps for each lender. We refer to lending action as a one-time donation made by a given lender to a specific loan. Each loan can receive one or multiple lending actions from the same lender. On the other hand, we refer to lending activity as the total number of individual lending actions and not the amount of money raised by those actions, since Kiva does not provide such information for privacy reasons. As a result, our research questions will focus on the analysis of lending activity as a measure of social interest on a given loan, rather than economic activity. We carry out our analysis with a dataset collected by Schaaf *et al.* from May 10th 2012 until September 4th 2012 (Schaaf and Sander ). The dataset was gathered querying Kiva's API for the last $50$ lending actions every minute and collecting, for each lending action, its lender id, the loan to which the lending action was associated and its timestamp, which represents the approximate time at which the lending action took place. The resulting four-month dataset contains over a million different lending actions ($1,217,627$), $47,790$ loans and $263,121$ unique lenders (approximately $25\%$ of all the lenders in Kiva at the time). We will refer to this dataset as Kiva API data as opposed to Kiva's snapshot dataset.

To answer our research questions, we also need information regarding the Field Partners (FP) as well as loan and team features. Querying Kiva's API we can retrieve the FP's ratings together with the number of loans that each field partner handles. The ratings are values between one and five (with $0.5$ increments) that Kiva computes using a combination of the FP's past borrowing history, the interest fees it charges to borrowers and its delinquency rate (late repayments), among others. Additionally, a rating with a value of zero means that the Field Partner has not been evaluated yet. We also gather information characterizing the membership of lenders to teams, which we retrieve using the API. Since team memberships can change over time, we retrieve for each lender the team affiliations together with the dates when these happened. Our dataset contains a total of $23,390$ teams that we characterize by its size and category. The size determines the number of lenders that are members of the team while the category is a feature that characterizes the type of team including businesses, events, family or colleges among others.

We also require information regarding loan features, which we can extract from Kiva's snapshot without querying the API. The snapshot has one entry per loan with a description of its main characteristics such as location, purpose of the loan, sector (*e.g.,* agriculture or retail), date at which the loan was posted, the status of the loan: whether it's fundraising, fully funded or in repayment, and the scheduled dates for repayment. Finally, we also extract features characterizing each lender such as her whereabouts (city, country), occupation, membership since, invitee count as well as an open field "I loan because" where lenders can express the reasons that made them microlend though Kiva.

As mentioned earlier, the four-month Kiva API dataset with lending actions that we use in our analysis, captures the activity of approximately $25\%$ of all lenders in Kiva. To understand the representativeness of this dataset with respect to the whole Kiva community, we compare the percentage of loans per country and the percentage of lenders per country

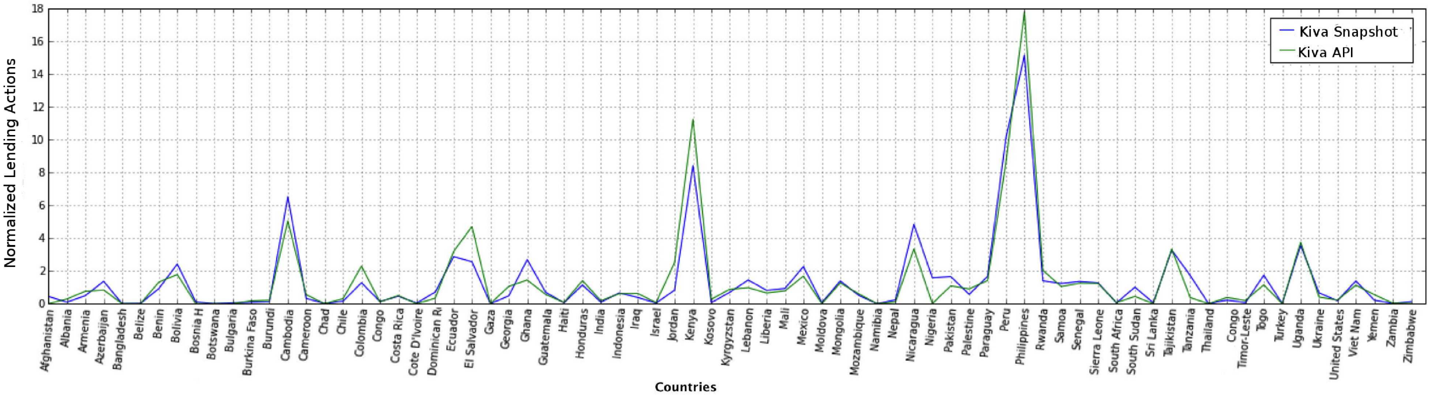


Figure 1: Percentage of loans per country.

in our four-month dataset (Kiva API) with the whole Kiva community (Kiva snapshot dataset). In Figure 1 we observe that the whole Kiva community has loans for $75$ countries while our dataset only contains loans for $60$ countries. For the countries captured in the four-month dataset, their percentage of loans only oscillates $\pm 2.3\%$ when compared to the whole Kiva community percentages. This means that for the $60$ countries, we capture a similar activity in terms of loan participation. As for the countries missing from our dataset, we observe that these are mostly countries with a very small percentage of loans in the Kiva community (an average of $0.2\%$). We posit that because the lending activity for these countries is much smaller (and infrequent) than for countries with more loans, we cannot capture their borrowing behavior in just four months of data collection.

On the other hand, an analysis of the percentage of lenders from each country in the whole Kiva community and in our dataset also reveals similar distributions. For example, lenders from the US represent around a $65\%$ of the whole Kiva community whereas in our four-month dataset they are $55\%$; while for Great Britain, which represents $6\%$ of lenders in the community, is present in our dataset as $5\%$ of the total lenders. These differences are probably due to more inactive lenders that lend with a low frequency (once or twice a year) and which we are not able to capture in our four-month dataset. In general, for the top $10$ lender countries, differences in percentages of lenders between our dataset and the whole community are, on average, $\approx 1.9\%$; whereas for the rest of the countries the differences are $< 0.2\%$. Since the variations in percentage of loans and percentage of lenders are small for the $60$ countries present in our dataset, it is fair to say that our conclusions will characterize Kiva's activity for those countries, which represent the majority, but not for the whole community.

## Understanding Lending Behavior

The objective of this paper is to understand the relationship between the lenders' lending activity and the loan features they can explore on Kiva's online platform. For that purpose, we use a mix of qualitative and large-scale data mining techniques. Specifically, we focus on three research questions:

**RQ1: Role of Field Partner Ratings.** When lenders browse through loans, they can check details about the FP associated to the loan. Information such as the total number of loans, the amount of money raised, or the delinquency rates (late payments from borrowers) are shown together with a rating value computed by Kiva, which associates a number of stars between one and five to the FP. This first research question explores whether ratings play a role in determining the way lenders lend *i.e.,* are higher ratings more prone to accumulate larger lending activity?

**RQ2: Role of Loan Features.** Kiva lenders can browse through a large set of loan features such as the sector of the loan (agriculture, manufacturing, retail, etc.), or the gender or country of the borrower. The second research question analyzes whether specific loan characteristics have an impact on the lending activity. For example, do borrowers from countries with lower socioeconomic levels receive more money than borrowers from countries that are better off?

**RQ3: Role of Teams.** Kiva lenders can create or join lending teams of different nature. In this research question we aim to understand whether there exist specific team features that are associated to higher lending activity *e.g.,* is the lending activity of a team related to its size or to the number of loans it covers? and, what does it tell us about team influence?

## Field Partner Ratings

The first research question focuses on understanding the relationship between Field Partner ratings and lending activity. For that purpose, we analyze the relationship between the number of lending actions to specific loans and the rating of the FPs associated to those loans. However, the lending actions of an individual to a given rating logically depend on the number of loans that are available to the lender on Kiva's website. In other words, the larger the number of loans from FP's with a given rating, the higher the probability that a lender will lend to that rating, independently of her/his will.

In fact, Kiva statistics reveal that the distribution of loans per rating is not homogeneous with a large number of loans associated to Field Partners with ratings three ($> 140K$) and zero ($> 80K$), while other FP ratings have considerably smaller number of loans ($\approx 50K$, on average). Similarly, a large number of Field Partners (90) have ratings between $2.5$ and $3.5$ while higher and lower ratings are associated to

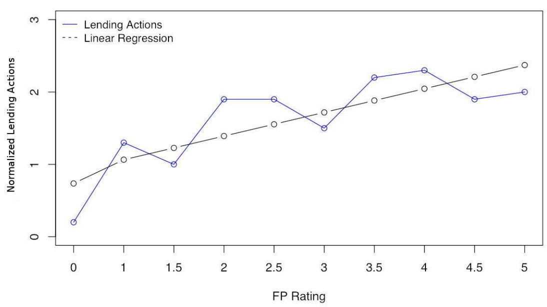


Figure 2: Normalized lending actions per FP rating.

fewer FPs. For example, there exist only 24 FPs with ratings between 1 and 2 or 31 between 4 and 5. As a result, an individual might have fewer lending actions for a given rating simply because the selection of loans for that rating in Kiva is smaller. In order to account for these differences and to be able to compare and correlate lending actions across ratings, we define *normalized lending actions* as the total number of lending actions to a given rating divided by the number of loans associated to FPs with that rating: $l.a_r = \frac{l.a_r}{loans_r}$ where $l.a_r$ represents the total number of individual lending actions to FPs with rating $r$ and $loans_r$ the total number of loans offered by FPs with rating $r$. Therefore, if certain ratings have more loans, the number of lending actions is scaled down to account for that bias.

To test the relationship between lending activity and ratings, we compute the correlation coefficients between the sum of all individual lending actions per rating ($l.a_r$) and the ratings themselves. Figure 2 shows the normalized activity for each rating value. Since Kiva expresses the ratings as zero or a number between one and five in increments of $0.5$, the sample size for the correlation analysis is only ten. Given that small size, we cannot guarantee normality or linearity. For that reason we compute correlations for both parametric (Pearson's) and non-parametric (Spearman's rank) tests. Our analysis shows a strong positive correlation between the two with a correlation coefficient of $r(8) = 0.78$ and p-value of $p = 0.006$. Similarly, Spearman's rank produced a correlation coefficient of $\rho(8) = 0.74$ (with $p = 0.01$). Additionally, we also performed a linear regression on the ratings to see how predictive these are of the lending activity. We obtained an $F(1, 8) = 10.24$ with $p = 0.01$ and an adjusted $R^2 = 0.61$. Thus, the tests determine that the trend in Figure 2 approximately follows a monotonic linear trend. This means that the higher the rating of a Field Partner, the larger the number of lending actions we observe. Thus, consciously or unconsciously, ratings seem to play a role on individual lending actions. In fact, lenders appear to be more prone to lend to loans managed by Field Partners with higher ratings. Furthermore, the figure also shows that lenders seem to favor loans that have a rating (high or low) over loans without a rating (rating of value zero). Similar results have been reported in one-to-one lending systems (Sufi 2009).

To better characterize the relationship between lending activity and ratings, we are also interested in understanding what type of lenders are more prone to lend to highly rated Field Partners. Specifically, we seek lending patterns that exclusively characterize lenders whose lending activity is mostly focused on high FP ratings. For that purpose, we will first model each individual lender in our dataset with six different lending features: (1) number of loans that the lender has lent money to, (2) invitee count, (3) number of days since she has been a member at Kiva, (4) average team size of the teams the lender is a member of, (5) number of distinct FP's the lender has lent to and (6) entropy of the lender's lending behavior.

Variables one to five are computed straightforward from the four-month dataset. As for the lending entropy, we compute it as the Kolmogorov Complexity of the four-month lending actions' time series for each individual (Li 1997). Specifically, for each lender $l$, we represent her lending actions as a time series $\{l_{t_1}, ..., l_{t_n}\}$ where each $l_{t_i}$ is a lending action at time $t_i$. We compute the complexity of the time series representing the time (in days) elapsed between each pair of consecutive lending actions *i.e.,* the complexity of $l' = \{t_2 - t_1, ..., t_n - t_{n-1}\}$. Higher complexity values are associated to burstier behaviors where lending patterns are harder to model as opposed to low complexity values which we associate to more stable, planned lending behaviors *e.g.,* lenders that lend approximately once every two weeks will have lower complexity values than those who lend more unpredictably. Finally, we require that lenders have at least three lending actions in the four months of activity so as to be able to model entropy.

To carry out this analysis, we characterize each individual in our dataset with the six lending features. For each feature and rating, we compute their median values and compare them. For simplicity purposes, we consider five different ratings: zero, one ([1,2)), two ([2,3)), three ([3,4)) and four ([4,5]). Our results reveal differences for two features: (1) loan count and (6) complexity. Figure 3 and Figure 4 show the mean loan count and the mean lending complexity for lenders with a majority of lending actions on one of the five ratings, respectively. We observe that lenders whose lending activity mostly focuses on FP's with ratings four or higher, appear to lend to a larger number of loans while showing lower lending complexity than lenders that focus their activity on lower ratings. In fact, it appears that lenders that concentrate on higher ratings might have more stable lending behaviors probably implying regularly planned lending decisions. On the other hand, lenders whose majority lending actions are mostly focused on FPs with lower ratings, appear to lend to fewer loans and their behaviors are far more complex, which might reveal burstier, more impulsive behavior. Without claiming causality, these results might suggest that offering more highly ranked Field Partners on Kiva's website could also potentially increase lending activity. Additionally, given that planned lending decisions appear to be related to higher lending volumes, Kiva could offer planning tools to lenders such as lending calendars or lending reminders, which might also help to increase the lending activity of their users.

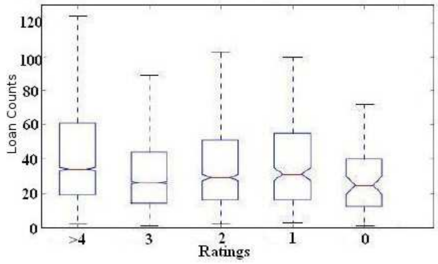


Figure 3: Box plot for median individual loan counts versus ratings. Boxes represent the 1st and 3rd quartiles and values outside the box are values within 1.5 the interquartile distance (1.5*Q3-Q1).

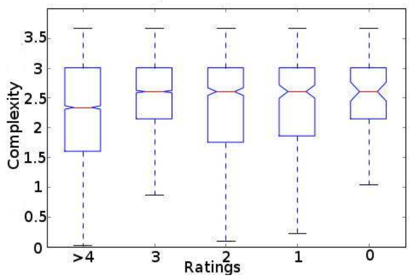


Figure 4: Box plots for median individual complexity values that characterize lending patterns.

## Loan Features

Our second research question seeks to understand the relationship between lending activity and features that characterize the loan including: (1) country of the loan, (2) sector: agriculture, retail or health among others, (3) size of the loan: individual or group-based and (4) gender of the borrowers in the loan. Our focus is to evaluate, at large-scale, the role that specific loan features play when deciding what loans to support.

As discussed in the previous section, to study the relationship between lending activity and loan features we first need to *normalize* the number of lending actions. In fact, a lender might lend more to a given country, not by personal preference, but rather because Kiva offers a larger choice of loans for that country. Thus, to eliminate the bias and to be able to fairly compare lending activity with loan's features, we normalize the number of lending actions to a loan feature (country, sector, gender or size) dividing the total number of lending actions by the number loans associated to that feature. The computation is done as $l.a_f = \frac{l.a_f}{loans_f}\ with\ f \in \{c, s, g, z\}$ where $f$ represents one of the loan features: the country $c$, the sector $s$, the gender $g$ or the size $z$ of the loan; $l.a_f$ the number of lending actions to loans with feature $f$ and $loans_f$ the total number of loans with that feature.

Once normalized, we proceed to analyze the relationship between lending activity and loans' features. To evaluate how lending actions and the country of the loan relate to each other, we first characterize each borrower country by a set of over $1000$ socioeconomic indicators extracted from the World's Bank Open Data website including GDP or number of mobile cellular subscriptions, among others. Next, we compute Pearson's correlations between the total number of lending actions ($l.a_c$) to each borrower country $c$ and the values for each socioeconomic variable. Our objective is to explore what country indicators have the largest correlations with the volumes of lending actions. This will allow us to understand whether lenders might be lending more to countries with specific socioeconomic characteristics. Since not all indicators are present for all the countries in our dataset, we only report correlations that have indicators for at least $45$ countries out of the $60$ in our dataset. Additionally, given the large number of correlations performed (over $1000$), we need to adjust the p-values *i.e.,* control for the Type I error (False Positives). Bonferroni correction is one of the most common approaches to adjust for multiple testing. However, given the large set of correlations that we perform, Bonferroni's p-values would be too stringent *e.g.,* for a Type I error rate of 0.01, it would require a $p > 0.00001$. For that reason, we apply instead the False Discovery Rate (FDR) which controls the fraction of positive detections that are wrong. Specifically, we use the Benjamini-Yekutieli's FDR adjustment and report the correlation results together with their p-values and their q-values *i.e.,* percentage of false discoveries accepted for that test, also known as adjusted p-values (Benjamini and Hochberg 1995).

Table 1 shows some of the most relevant findings (the majority with $q \leq 0.05$). We observe a significant positive correlation between a country's urban population and the lending activity it receives (recall that lending activity is normalized by the number of loans in the country). It appears that countries with a larger urban population have a higher probability of benefiting from lending than countries that are more rural. To promote more heterogeneous lending activity, Kiva could explore putting online *lending recommendations* to drive lending activity towards countries that benefit the least at each moment in time. Interestingly, we also observe a negative correlation between lending activity towards a country and its agricultural added value. This shows that Kiva lenders are lending more to countries whose agricultural production is poor and in need (the smaller the production, the larger the lending activity). This might suggest that Kiva is doing a good job at selecting Field Partners in countries with low agriculture-related indicators and shows that by targeting specific needs through Field Partners, Kiva might manage to have a larger impact on the development of the country (at a macro level).

Other correlations indicate that larger lending activity is associated to countries with less manufacturing which is indirectly related to job creation. In fact, the lack of manufacturing industries can negatively impact the creation of jobs. As a result, Kiva appears to be successfully driving lending activity towards countries where job creation is harder to achieve. On the other hand, lending activity is negatively correlated to the strength of legal rights in the country, which might reveal a lending activity focused on supporting development and indirectly the improvement of freedom and rights in borrower countries. We also observe negative correlations between lending activity and the domestic credit provided by the banking sector, which might show a lending trend that favors countries where getting money from the

| Name | Code | CC | p-value | q-value |
|---|---|---|---|---|
| Urban population (in largest city) | EN.URB.LCTY.UR.ZS | $r(55) = 0.332$ | 0.01 | 0.019 |
| Agriculture (added value) | NV.AGR.TOTL.KD | $r(51) = -0.23$ | 0.07 | 0.08 |
| Strength of legal rights index (0=weak to 10=strong) | IC.LGL.CRED.XQ | $r(54) = -0.27$ | 0.03 | 0.045 |
| Manufacturing, value added (% of GDP) | NV.IND.MANF.ZS | $r(46) = -0.22$ | 0.01 | 0.019 |
| Domestic credit provided by banking sector (% of GDP) | FS.AST.DOMS.GD.ZS | $r(52) = -0.2$ | 0.01 | 0.020 |
| Incidence of tuberculosis (per 100,000 people) | SH.TBS.INCD | $r(56) = -0.23$ | 0.07 | 0.08 |

Table 1: Pearson's correlations with FDR adjustments between normalized lending actions and WB indicators.

formal banking sector is more difficult. Interestingly, similar results using other country indicators are reported in (Desai and Kharas ; Riddel 2007). Finally, we observe a negative correlation between lending activity and the incidence of tuberculosis: the more cases, the fewer lending actions. Exploring the countries involved in this correlation, we observe that some of them have Kiva loans in the health sector whereas others do not. For countries who have health-related loans, this finding could suggest that the Field Parters that collaborate with Kiva do not focus their activity specifically on tuberculosis. However, it could also mean that the loans are not having the desired impact on the country at a macro level i.e., these projects are not affecting the overall WB indicators. As a suggestion, Kiva could develop a more targeted selection of Field Partners clustered around the country's critical issues so as to address these types of imbalances.

To understand better lending actions, it is important to realize that lenders can also be influenced by the socioeconomic conditions of their own countries: a lender might have more lending activity towards countries with certain socioeconomic characteristics either for personal reasons or for reasons that can be explained by the socioeconomic conditions of her own country (*e.g.,* rich countries might lend more to poorer countries). Thus, in an attempt to disentangle which factors play a role, we also analyze the relationship between borrower countries and the lending activity of lender countries characterized by their socioeconomic indicators. For that purpose, we compute the total number of lending actions per lender country to each borrower country in our dataset. Next, we characterize each lender country with its socioeconomic indicators extracted from the World's Bank Open Data website. For each indicator, we create three groups of lender countries depending on whether the country has a low, medium or high value for that indicator, and compute their total lending activity to each borrower country. This will allow us to refer to the lending activity of, for example, *lender countries that have a low GDP* or *lender countries with high mobile cellular subscriptions*. Next, for each lender indicator (GDP, inflation,...) and group (low, medium or high), we compute Pearson's correlations (adjusted with FDR) between their lending activities to each borrower country and the values for each socioeconomic indicator from the borrower countries. These tests might reveal important relationships between groups of lender countries and borrower countries being able to draw statements such as *the lower the GDP of the borrower country, the larger lending activity they attract from countries with high GDP*.

Table 2 shows some of the most relevant correlations between the indicators of the borrower countries previously discussed and the lending activity they receive from countries with certain low, medium or high socioeconomic values. We observe a positive correlation between lender countries that have low average interests on external debt and borrower countries with large urban populations ($EN.URB.LCTY.UR.ZS$). As discussed earlier, borrower countries with large urban populations seem to receive more lending activity which they appear to be getting from lender countries that are not strangled by their external debt payments. We also observe that lender countries where most citizens finish primary education have a lending activity that is positively correlated to the borrower's agricultural production ($NV.AGR.TOTL.KD$). This implies that the little lending activity that borrower countries with large agricultural production manage to bring in (as shown in Table 1) is mostly from lender countries with high education levels.

In terms of mobile penetration ($IT.CEL.SETS$), Table 1 showed a tendency to lend more to countries with low penetration rates, and Table 2 shows that it is mostly countries with high youth literacy rates, the ones who generate that lending activity. We also observe that countries with high military expenditure ($MS.MIL.XPND.GD.ZS$) focus their lending activity on borrower countries with low manufacturing rates ($NV.IND.MANF.ZS$). Additionally, lending actions to countries with high incidence of tuberculosis appear to be mostly driven by countries with low prevalence of overweight children ($SH.STA.OWGH.ZS$). We posit that countries that are aware of the importance of health related issues might be focusing on lending to countries who could improve their health status. To summarize, it is fair to say that the general trend is for countries with higher rates of educated citizens and larger economic activity to be more prone to lend, which is a feature that has also been found in official development assistance (Desai and Kharas ).

Finally, to analyze the relationship between lending activity and the sector of the loan, the size of the loan and the gender, we take a different approach to account for the discrete nature of the variables. We compute the median number of normalized lending actions and its standard deviations for: each type of loan sector (health, agriculture, retail, etc.); each group size range(1, [2-10], [10-20] and [20-48]) and for each gender (female, female or both for loans that go to a group of borrowers rather than an individual). Our final objective is to understand whether certain sectors, size ranges or gender appear to be favored – in terms of larger median lending activity– by the lenders.

In terms of sectors, we observe a larger median number of normalized lending actions in the retail sector with (M=3.2,IQR=6.2), followed by the agricul-

| Borrower Country | Lender Country | CC | p-value | q-value |
|---|---|---|---|---|
| EN.URB.LCTY.UR.ZS | Low Average Interests on External Debt ($DT.INR.OFFT$) | $r(51) = 0.38$ | 0.004 | 0.01 |
| NV.AGR.TOTL.KD | High Persistence to Last Grade Primary Education ($SE.PRM.PRSL.ZS$) | $r(49) = 0.44$ | 0.002 | 0.008 |
| IT.CEL.SETS | High Youth Literacy Rates ($SE.ADT.1524.LT.ZS$) | $r(53) = -0.35$ | 0.001 | 0.006 |
| NV.IND.MANF.ZS | High Military Expenditure ($MS.MIL.XPND.GD.ZS$) | $r(49) = -0.45$ | 0.001 | 0.006 |
| SH.TBS.INCD | Low Prevalence of overweight children ($SH.STA.OWGH.ZS$) | $r(46) = 0.38$ | 0.003 | 0.008 |

Table 2: Pearson's correlations with FDR adjustments between lending activity of lender countries characterized by low, medium or high socioeconomic indicators and borrower countries socioeconomic values'.

tural (M=3.1,IQR=6.2) and food (M=2.9,IQR=6.1) sectors, where $M$ represents the median and $IQR$ the interquartile range. The other sectors showed considerably lower values, although these differences were not statistically significant. This shows that lenders appear to favor the retail sector which is probably far more present in urban than rural settings. We hypothesize that, in general, lenders feel that they can contribute the most by donating to sectors that inherently move the economy as opposed to sectors with a less clear or with longer-term economic impact such as the arts or entertainment. In terms of group size, we observe that individuals appear to focus their lending activity on loans which are borrowed by one person (M=2.3,IQR=3) or group loans of up to ten individuals (M=4.1,IQR=6). Larger loans are not as favored which is also coherent with the findings reported in (Ghatak and Guinnane 1999; Owusu and Tetteh 1982). Finally, gender presents a slight minimal advantage for female loans (M=2.4,IQR=3) versus male (M=2.1,IQR=3), but nothing conclusive, although similar results have been reported in (Ly and Mason 2010; Pitt and Khandker 1997; Mayoux 2001). These lending patterns might be a result of individual preferences or rather a consequence of the way Kiva presents the information on their website. If the latter, Kiva could attempt to personalize loan suggestions to lenders so that sectors or groups that are not as favored (education, health or manufacturing or larger loan sizes), gain more attention.

## Teams

The third research question focuses on understanding the relationship between different types of teams and their lending power. Specifically, we define the *lending power* of a team as the number of individual lending actions that manages to drive from its members, independently of the amount of money raised. Our assumption is that the power and influence of a team lies in managing to convince as many members as possible to lend whatever amount they can afford through that team. Recall that Kiva lenders can be members of more than one team, and that lenders can choose whether they want their lending activity to count towards one of the teams they are members of or to leave it as an individual donation. Thus, we compute the lending power ($l.p.$) of a team $T$ as: $l.p_T = \frac{\sum_{i=1}^{size(T)} l.a_{i,T}}{size(T)}$, where $i$ is an individual member of team $T$, $l.a_{i,T}$ represents the total number of lending actions that individual $i$ has made through team $T$, and $size(T)$ is the size of the team.

It is important to clarify a limitation regarding Kiva's datasets. The Kiva snapshot provides a list of the teams and team members that participate in each loan. However, the information provided by Kiva's API does not reveal whether a lender has lent to a loan through one of the teams she is a member of or as an individual. Thus, to compute lending power, we approximate the number of individual lending actions to a team ($l.a_{i,T}$) by distributing the lending actions of a lender to each loan equally across all the teams that participate in the loan and for which she is a member. This results in the final computation of $l.a_{i,T}$ as $l.a_{i,T} = \sum_{l=1}^{L} \frac{l.a_{i,l}}{teams(i,l)+1}$, where $i$ is an individual, $T$ is a team she is a member of, $l.a_{i,l}$ is the total number of lending actions from that individual to a loan $l$, $L$ is the total number of loans to which $i$ lends and $teams(i,l)$ is the total number of teams that participate in the loan and for which the individual is a member (the $+1$ models the case in which the lending action is individual rather than assigned to a team). Although in reality some lenders might lend more to specific teams, we assume that they are equally active across all of them and distribute their activity homogeneously. Such assumption might imply the loss of certain relationships between lending power and team features, however the findings that our analyses reveal will be real, yet maybe incomplete. We expect to better address this assumption in future work when Kiva releases specific lender-loan-team information.

To understand the relationship between lending power and teams, we also need to characterize the different types of existing teams in Kiva. For that purpose, we compute three team variables using both Kiva's snapshot and API datasets: (1) *team agreement* or average percentage of team members that agree to participate on a loan; (2) *loan coverage* or average percentage of a loan that team members cover with their participation and (3) *team size* or number of individuals that have joined that team. The first variable, team agreement, is defined to understand whether teams that typically have a high percentage of their members participate on the same loans have more or less lending power than teams with lower agreements, whose lending activity might be more widespread across loans. We compute this variable as: $t.a_T = \frac{\sum_{l=1}^{L} \frac{members(l)}{size(T)}}{L}$, where $L$ represents the total number of loans a team participates in, $members(l)$ is the number of lenders that are members of $T$ and lend to a loan $l$ in $L$, and $size(T)$ is the size of the team. As such, team agreement exclusively measures whether individual actions of team members are homogeneous (focus on the same loans) or heterogeneous (distributed across different loans), independently of whether the team is a major or minor contributor to the loan.

The second variable, loan coverage, is defined to analyze whether teams that focus their lending activity on largely covering one or more loans have more or less lending power than teams whose lending activity represents a minor contribution to the loans they participate in. Teams with high loan coverages will refer to those whose lending activity constitutes a large percentage of all the lending actions associated to any given loan. As opposed to team agreement, this variable allows us to understand whether a team has a major impact on the loans they contribute to, independently of their agreement. In fact, it can be the whole team or small clusters of team members that manage to lead the coverage of large portions of loans, depending on both team and loan size. As a result, we compute loan coverage as: $l.c_T = \frac{\sum_{l=1}^{L} \frac{l.a_{T,l}}{l.a_l}}{L}$, where $l.a_{T,l}$ represents the number of lending actions from team $T$ members to loan $l$, $l.a_l$ is the total number of lending actions to loan $l$ and $L$ is the total number of loans team $T$ participates in. High values for $l.c_T$ represent teams that are major contributors to the loans the participate in. We use the third team variable, team size $size(T)$, to understand whether larger teams can drive more or less lending power from their members than smaller teams.

To carry out this analysis, we first compute the lending power for each team in our dataset and correlate these values against their team agreements, team sizes and loan coverages using Pearson's and Spearman's rank correlations. Our results show a positive correlation between lending power and team agreement using Spearman's rank correlation ($r_S(7998) = 0.406$ with $p < 0.01$). Since Pearson's correlation coefficient was close to zero, we can determine that the relationship between the two distributions is monotonic, but not linear. Thus, to analyze better the consistency between the two tests, we computed Pearson's correlation with the team variable values modified after applying a log transform. The new test confirmed a positive correlation with $r_P(7998) = 0.431$ and $p < 0.01$. This finding highlights that teams that have higher lending power appear to be reaching much larger team agreements thus concentrating their lending activity on a limited set of loans. We hypothesize that groups that lend more manage to better coordinate their lending decisions either because they are more similar in terms of interests or because they manage to communicate better. In fact, qualitative research carried out by Hartley showed that high performing teams use message boards to communicate and set up coordinated lending goals (Hartley ). On the other hand, it could be that teams that lend less might be composed of more diverse members in terms of backgrounds and motivations. As a result, they might find it harder to agree on their lending decisions thus lowering their team agreement.

To better understand these hypotheses, Figure 5 shows the percentage of teams per category for (1) the top $1\%$ teams with larger team agreements and (2) all teams in our dataset. For clarity purposes, only the top categories are shown. Comparing the two, we observe that an important percentage of teams with large agreements are categorized as *families* and *friends* whereas when looking at all teams in our dataset, the top category is *common interest*, followed by *business*. This reveals that team agreement is probably easily achieved among members that have a certain type of

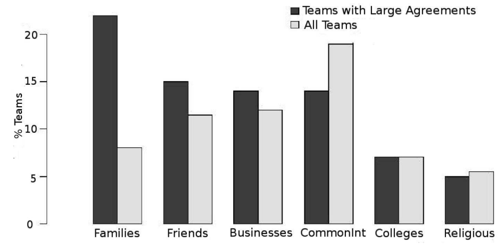

Figure 5: Percentage of teams per category for the top $1\%$ teams with larger agreements and for all teams.

personal relationship (online or offline) like friends or family members. Such personal closeness, probably allows them to coordinate better thus driving more lending activity. On the other hand, more heterogeneous groups like *common interest* might find it much harder to coordinate and agree which could negatively impact the lending power of the team. To address this issue, Kiva could offer online communication tools that might allow teams to improve their relationships and agreements while potentially increasing their lending power.

Moving to the second variable, team size, we observe a negative Spearman's rank correlation with the lending power $r_S(7998) = -0.403$ and $p < 0.01$. A similar outcome was observed with Pearson's applied to log-transformed values showing $r_P(7998) = -0.416$ and $p < 0.01$. Such result reveals that lenders that are members of smaller teams appear to have more lending activity than those who are members of larger groups. We hypothesize that this could be related to team agreement. In fact, smaller teams probably manage to coordinate better their lending actions and have higher team agreements than larger teams. As a result, smaller teams might be creating an environment that encourages team members to lend more. To test that hypothesis, we computed the correlation between team agreement and team size and found indeed a strong negative correlation ($r = -0.98, p < 0.01$), implying that smaller teams typically reach larger team agreements. We posit that smaller teams might be able to have offline (in person) meetings that are harder to happen in larger teams whose members are probably geographically located across various locations. Although some large teams set up Facebook groups to communicate online, our results could reveal that offline communications might be more efficient in encouraging lending activity. Additionally, these results are inline with research showing that more cohesive, smaller groups tend to coordinate better (Kandel and Lazear 1992; Kollock 1998).

With respect to loan coverage, we did not find any statistically significant correlation with the lending power *i.e.,* teams that are the major participants in a loan, are not necessarily associated to higher lending activity. Additionally, we did not find any correlations between loan coverage and team size or team agreement. This reveals that the ability to cover large parts of loans is not specific to any team size or to teams that manage to agree and coordinate their lending activity better. A deeper inspection into the categories of the top $1\%$ teams with the largest loan coverages shows mostly *common interest* and *business* groups with average loan coverages of $60\%$ of the loans they participate in. In an attempt to better understand the behavioral differences between team members from high and low coverage teams, we compute the average lending entropy for the members of the top $1\%$ high coverage teams and bottom $1\%$ low coverage teams. Recall that lower entropy values are associated to individuals that plan more their lending activities *i.e.,* have more structure in their lending patterns. Our results show that teams with high loan coverages have lower median entropies ($1.5$ vs. $2.1$). This finding could reveal that large coverages might be achieved with lenders whose lending activities are carefully planned and more structured to, for example, individually observe that there are existing loans that are not fully covered and lend to them, rather than lending randomly.

## Conclusions

We have presented a large-scale analysis of the role that various features might play on online microlending environments. Specifically, we have used a combined quantitative and data mining approach to analyze over a million individual lending actions from the online microfinance platform Kiva. Our results show that lenders appear to favor highly rated Field Partners that manage to drive more lending activity. Additionally, we have observed that lenders seem to lend to loans in sectors that are often times aligned with official aid donors. Finally, teams that drive more lending activity from their members seem to share large lending decision agreements. We believe that our work provides a better understanding of online microlending behaviors as well as a set of suggestions to improve the service that Kiva, or other similar online microfinance platforms, currently offer to their lenders and borrowers.

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