Aaron Perlmutter
ECON 497
Honors Thesis

Why Charity? Signaling and the Effects of Social Context on Individual Lending Behavior in Kiva.org Online Communities

Abstract

The website Kiva.org is a middle-man between microfinance institutions and zero-interest rate lenders who essentially practice charity by giving up the interest on their loans. This provides a good model for studying "Why Charity?" especially given the social/community nature of the website. The results support the theory that signaling can explain much charitable behavior. There is a non-normal distribution of risky loans. There is a high frequency of risky loans in groups where loans are easily observable and almost zero frequency of risky loans in groups where loans are hard to observe. This supports the signaling theory of charity because it appears that lenders are maximizing their risk, or their appearance of wealth, when others are watching and minimizing their risk when they are not watched.

Introduction

In my thesis I will attempt to uncover the determinants of lending behavior within "kiva.org" online lending communities and specifically investigate whether there is a signaling component to lending behavior. Kiva.org is a website that connects people interested in contributing to specific microfinance loans with microfinance institutions that will make those loans for them. On the website you browse through "entrepreneurs" who are trying to start businesses but cannot obtain loans from mainstream banks and so are working with microfinance institutions. The microfinance institutions create a profile for each entrepreneur with a description of the business they are trying to start, their personal history, the amount they are looking to borrow, how much has been raised so far and a photograph of them. The repayment term and schedule for the loan is listed in the profile as well as information on the profitability and interest rate of the microfinance institution and the historical delinquency rate of borrowers working through the microfinance institution.

Taking all of this into account, the Kiva.org user can decide that some amount of their money (in $25 increments) is better allocated to the microfinance institution, which will then lend it to the entrepreneur. The Kiva user gives their money to the microfinance institution with zero-interest and the microfinance institution will then take this money and loan it to entrepreneurs at typical for-profit interest rates (12%-90%). The Kiva user takes the risk inherent in lending - if the entrepreneur defaults they receive none of their money back. Further, the Kiva user receives none of the monetary reward from lending - they get their money back at zero-interest while the microfinance institution receives all of the interest and often has economic profits.

This behavior is clearly not providing utility to Kiva users in the monetary form, at least in a direct way. Users could put the money lent on Kiva into a CD earning 1% interest and not bear the risk of an entrepreneur defaulting and losing their entire loan. Because of this, the Kiva users are fundamentally practicing charity. They are donating the interest they could earn passively from a financial instrument plus the expected loss on the loan due to default risk. Naturally, the utility representing the money lost must be more than re-paid in non-monetary forms since individuals maximize their utility. This non-monetary source of utility is what I am trying to discover by looking at Kiva lending “communities” which I will now describe. The general question of my thesis could be stated as "Why charity?"

Kiva.org has been around since 2005 and approximately $210 million (up from $160 million since I began my thesis five months ago in December) has been loaned through the website. In 2008 Kiva introduced a lending team feature where users can join as many teams as they want (say "Team Norway" or "Team GLBT Kivans and Friends") and attribute a loan they make to *one* of those teams. (Hartley, 6) About $80 million has been loaned through the lending teams, providing a large amount of data. On the "community" section of Kiva there is data on the "top" lending teams – organized by total loaned by the team since its start and creating a sense of competition. If you join a team on Kiva you have an experience similar to being on Facebook where your team members are analogous to your Facebook friends (except you may have never met them). You create a "profile" of yourself with a picture, description and a messaging link at which you can be contacted by e-mail. Of course, your Kiva profile also includes history of all the loans you have made on Kiva, but it does *not* list the size of the loans you have made. My hypothesis is that this personal profile combined with the loans that users make is being used to signal wealth to other users on Kiva.

Literature Review

"Online community" as a place for signaling is what I am going to investigate as a determinant of individual lending behavior. Very little has been written on Kiva.org and community lending behavior. The paper that sparked my interest in Kiva was "Kiva.org: Crowd-Sourced Microfinance & Cooperation in Group Lending" written by Scott Hartley, a

Columbia M.B.A. student. In this paper he looks mainly at how team size (the number of people in a Kiva team) correlates with per capita lending (total amount loaned by the team divided by number of loans). The correlation he finds is that lower per capita lending is associated with larger team sizes. (Hartley, 38) This is only a correlation so no conclusions can be drawn but it might indicate that there is a social component (governed by group size) to the utility function of online lending. This paper provided interest in Kiva but my theoretical interest in signaling, the real point of my thesis, came from "A Signaling Explanation for Charity" by Glazer and Konrad.

I will answer the question of group size effect on lending behavior more clearly by going beyond correlation and looking at behavior within the team as it grows. I will also look for a signaling explanation for why this correlation exists relating to the quality of a signal decreasing with the more people/lending activity within a team. Hartley's paper was provocative, but is not economically rigorous and doesn't even present a theory to explain the correlation that was found. For instance, Hartley did not account for the fact that there might be something about people that join small lending teams that makes them more inclined to give larger loans and vice versa for those that join larger teams. I will create a PHP script that monitors how teams grow by collecting team data (# of loans, total amount loaned, etc) on a daily basis. If there is significant decrease in per capita lending as the team grows then this will support Hartley's correlation as a causation but there may be something more complex underlying online lending behavior. Also, I will be look at cross-sections of teams isolating different team variables (like team size, amount loaned, loan frequency) in order to discover determinants. Most importantly, I will propose signaling as the explanation for many of the trends seen in lending behavior.

Since lending on Kiva is essentially charity, it is worth considering the three major theories of charity. One theory of charity is that $u = u(x, G)$ where x is personal consumption and G is consumption of public goods. Within this theory, individuals will begin to allocate their money to the public good when they will receive more marginal utility than by putting that money toward private consumption. Theoretical analysis has shown that only the extremely wealthy would ever practice charity given this utility function. (Glazer, 1) Given the empirical finding that nine out of ten individuals on average practice charity, the public good theory of charity is generally not accepted. (Glazer, 1)

The second theory of charity is known most widely as the "warm-glow" theory where $u = u(x, g, G)$ where g is now the amount given to charity. Within this theory, there is something intrinsically pleasing about giving, regardless of how effective the gift is at creating public good. While it may be true that people do experience intrinsic pleasure from giving, it would not make sense evolutionarily that they would feel this pleasure if it didn't entail some tangible benefit. For example, food is intrinsically pleasurable because we need it to stay alive. So, if charity is pleasurable there is likely a reason – whether or not individuals are conscious of why it feels good to give. Of course I am not trying to get entangled with evolutionary psychology, but the reality of pleasure being tied to practicality leads to a signaling theory for charity where people give in order to demonstrate wealth. (Glazer, 1)

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Glazer et al. developed a signaling theory for charity where $u = u\ (x, y - g)$ where x is personal consumption, y is signaled wealth (not actual wealth), and g is the donation. This makes "y-g" the perceived amount of wealth possessed by an individual after they give to charity. The meaning behind this is that people derive utility out of how much wealth others perceive them as having, *not* how much wealth they actually have. Further, the amount of wealth people perceive others as having is a function of g, where the more someone gives the more likely they are wealthy. There are a few empirical examples supporting this signaling theory of charity. One major study supporting the signaling theory is on lawyers giving behavior to their alma mater. (Harbaugh, 1) Harbaugh et al. noted that there are brackets in alumni donation ("founders" donate $500-999, "trustees" donate $1000-1999, etc.) where you would expect a normal distribution of amounts, given the normal distribution of salary, but you find clumping of donations near the minimum to reach the next highest bracket. (3) So, almost one hundred percent of "founders" will donate $500, and "trustees" $1000. Since the bracket you donate in is published for all to see, this finding clearly supports the signaling theory of charity – the lawyers are maximizing $y{:}g$ or equivalently they are paying the lowest price possible for a perceived level of wealth. My findings further support the signaling theory of charity.

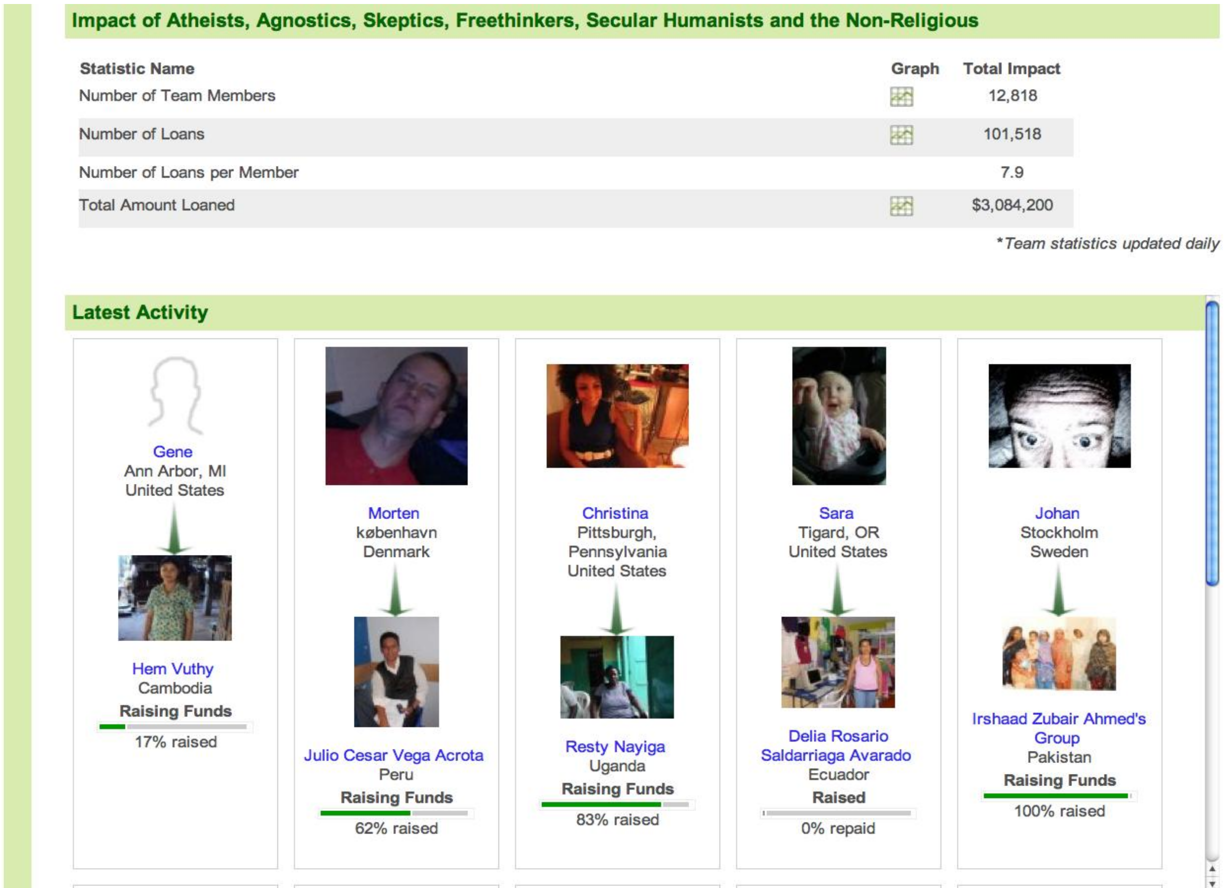

Fig. 1: Screenshot of team page.

Empirical Strategy

Does signaling play a role in lending behavior? To answer this I will first determine all observable information transmitted on kiva.org. Observable information is any information about individuals and groups that is observable by all other Kiva users. Upon determining the flows of information, we can understand the context in which signaling would occur, and then see how this relates to individual lending.

The observable information relating to individual and group lending is the most relevant in our analysis so I will describe what and where information is displayed when an individual makes a loan. First, upon making a loan, a Kiva user can attribute their loan to only one of the lending teams they belong to. This is the most important choice the user has to make – which team should they attribute their loan to? Above, Figure 1, is a snapshot of the information they are given on a particular team. The team name is listed at the top (in this case it is the "Impact of Atheists, Agnostics, Skeptics, Freethinkers, Secular Humanists and the Non-Religious"), with statistics listed directly below on number of team members, number of loans and total amount of money loaned. Below this is a photo gallery of the 10 members who have made the most recent loans that is updated instantly (strangely Kiva says they update daily but all of my tests indicate they update this information instantly) – with the most recent loan on the left and sequentially less recent loans as you move right. The amount of the loan is not listed with the photo and, regardless of the size of the loan a user made, their picture/profile information will be at the top of the list if they have the most recent loan. This means a Kiva user could make a $1000 loan or a $25 loan and get the same "latest activity" advertising. It is worth clarifying and emphasizing that other Kiva users can click on your profile when you are on the recent loans list and then observe more of your personal information (including other teams you are in) and e-mail you if they choose. On your profile you will have a history of all the loans you have made but again the amount of the loans will not be listed. It is *not* possible to explicitly list your loan amount.

Given this information, the user decides which team to attribute their loan to. If signaling provides the utility they derive from making a loan then they will consider these observable variables. Given the signaling utility function for charity $u = u\ (x, y - g)$ we can make some assumptions about lending behavior. For a given y (perceived wealth) lenders will try to minimize g (the amount they loan or, in terms of charity, the opportunity cost and risk of default of their loan) because by doing this they will have more money to spend on x (private consumption) and therefore maximize their utility. Likewise, for a given g, they will try to maximize their y. Of course, due to the marginal utility of goods, the greater the value is of g then the greater the perceived wealth of the lender (y). If signaling is occurring on Kiva, we should observe a lending strategy that is reminiscent of this maximization. It is easy to think of lenders as setting aside a certain amount of money (say $200) that will be their g, and then maximizing y given this amount. So, how would a lender obtain the best signal for their money?

The most relevant observable information that I have extracted relates to the "latest activity" section of the team home page (see Fig.1). Remember, the latest activity is the ten most recent loans attributed to a team. In a way this section is prime advertising space, separating the ten most recent loans from teams that can be very large (up to 15,000 members) into a manageable amount of information. The ten most recent loans are right in front of you when you open the team page – just like the front page of the newspaper. This decreases the transaction cost of finding these individuals because to find other team members it is many more clicks of the mouse and scrolling through extensive lists. Also, there are many inactive lenders within a team. If someone who views the team page was looking for active lenders, and was to look through an entire team, they would waste most of their time finding inactive members. The ten most recent loans section instantly selects for active lenders, and again decreases the transaction cost for observers looking for individuals that make loans.

Once a lender is found in the "latest activity" section you can click on their picture, which will bring you to a profile for the lender. The profile will list all of the loans they have made in the past but, again, will not list the dollar amount of those loans. Since the loans could be of any amount (in $25 increments), you can only figure out a range of what that lenders g is. Minimum g = $25 * # of loans and maximum g = $5000 * #of loans ($5000 is the maximum you could loan at once since microfinance loans on Kiva are never greater than this amount).

Being risk-averse, why would any lender ever loan more than $25? Given this range for what a lenders g could be, how could they make themselves appear to not be at the minimum? It turns out that after all there is a way for the exact amount of an individuals loan to be inferred but, this is not an easy task and the ability to infer goes away with time. The amount can be inferred if a Kiva user is keeping track of the "number of loans" and "total amount loaned" data that is on the front team page (Fig.1). Say that a Kiva user checks the team page on 3/17/2011 at 21:00 and notes that there have been 10 loans and a total amount loaned of $250. If this same user returns to the team page an hour later at 22:00 and sees that there are now 11 loans, a total amount of $1000 and that a person named "George" is listed in the "latest activity" section, then they can infer that "George" made a loan for $750. This user can then click to George's page and see all of the other loans that he has made, but now they will not be able to observe the amounts of these loans. But, there is one exception to this inability to see the amount - the other teams that George is a member of is also listed on his page. If the user clicks on these teams and finds that George is the *only* member of one of these teams then the user can easily infer the amounts of his other loans by dividing the total amount by number of loans. This goes for all single member teams, the average amount per loan the individual is making is always observable by this simple division.

Excluding the exceptions where George is a member of a one-man team, how will the Kiva user estimate the dollar amount of George's other loans on his page? An intuitive approach to estimating the value of George's other loans would be to look at the sample of George's loan values they are sure of, take an average of these, and apply this average as an expected value to the loan values they are unable to infer. In this case, the Kiva user would estimate George's g = $100 + 9EV = $1000, since expected value = $100. This is much greater than Georges actual g = $100 + (9 * $25) = $325. Even if the Kiva user has a highly skeptical estimation system where any loan that is not inferable is assumed to be the minimum ($25), it can still be argued using modern portfolio theory that George is signaling greater wealth making his one $100 loan rather than four $25 loans. In other words, even though the g = 1 * $100 = 4 * $25 = $100, y will differ between the two allocations. Also, the expected utility from one $100 loan will increase as the ability to infer the $100 loan is more likely (maximum likelihood in one member team) – I will delve deeper into ability to infer later and will now show how one $100 loan is a preferable signal to four $25 loans.

Modern portfolio theory predicts that a rational investor should not choose a portfolio if another portfolio exists that has an equal expected return but lower standard deviation on return. This prediction relies on the assumption that investors are risk-averse – something that I will also assume about Kiva lenders. Return on the portfolio is analogous to Kiva loans for the probability of default on the loan. Investors want to maximize return and lenders minimize probability of default. Altogether Kiva loans have about a 95% repayment rate and many microfinance institutions have a perfect record with a zero percent default history. There is always at least 1,000 different microfinance loans available to lend to on the website at one time so it is very easy to diversify – a lender could always find at least 50 different loans practically identical in their risk and return, all with historical default rates of zero percent. As well, it is easy to assume that these different loans are uncorrelated (a necessity in modern portfolio theory that correlation is not equal to absolute value of 1) given that the loans can be with different microfinance institutions, in different countries (one in Brazil, another in India), and for different purposes (one loan for laying bricks, another opening a hot dog stand). Given this ease in diversifying, if signaling does not play a role in Kiva lending, it would seem to be irrational for a lender to choose to make one $50 loan over two $25 loans. Here is the proof behind modern portfolio theory as applied to Kiva lending:

- Rp = return on portfolio, Ri = return on asset i, Wi = weighting of component asset i.
- So, expected return on portfolio is E (Rp) = SUM(i) Wi E (Ri)
- Say that Ri = 0.95 for all loans on Kiva. Choosing one $50 loan leads to Rp = W1 * R1 = (1) * (0.95) = 0.95. Choosing two $25 loans lead to Rp = (W1 * R1) + (W2 * R2) = (0.5 * 0.95) + (0.5 * 0.95) = 0.95. With this, E (Rp) two loans $25 = E (Rp) one loan $50.
- Say that the standard deviation of all loans is the same at 0.05, so that STDEVi = .05 where i is any loan. Standard deviation of a portfolio is calculated by STDEVp = (((W1)^2(STDEV1)^2) + ((W2)^2(STDEV2)^2) + 2(W1)(W2)(STDEV1)(STDEV2)(r)))^.5

where r=correlation. We have assumed that abs(r) < 1 which is all that is required for the variation of two loans to be less than the variation of a single loan given that all loans have the same variation (same variation is a reasonable assumption given the plethora of loans to choose from on Kiva, making it easy to find two nearly identical loans). If r = 0 then STDEV on one $50 loan equals 0.05 and STDEV on two $25 loans equals ((0.5)^2(0.05)^2 + (0.5)^2(0.05)^2)^.5 = 0.0354.

Variation of two $25 loans is less than variation of one $50 loan and they have equal expected returns therefore rational lenders on Kiva should never make loans above the minimum – unless there is a rational reason for demonstrating ability to tolerate risk. Ability to tolerate risk increases with wealth due to decreasing marginal utility. Making a single $50 loan rather than two $25 loans is choosing a larger g, and therefore increasing perceived wealth (y) if the $50 loan is observable. Also, given that many observers may use the inferred $100 loan as an expected value for non-observable loans, it makes even more sense to make loan greater than $25 if the lender is playing a signaling game.

An optimizing lender would ideally only lend greater than $25 if it were clear that the amount could be inferred – otherwise they are overpaying for their signal. As well, if the observed loans were used as an expected value for non-observable loans, an optimizing lender would make $25 loans for other reasons regardless of how hard it is to infer. When is it hard versus easy to infer the amount of the loan? Remember, the only time you can be sure of who made the loan and for what amount is when there has only been one loan since you last checked your team page. “Hard” to infer is better defined as less likely and “easy” as more likely you will be able to infer the loan amount. If there has been more than one loan since you last checked your team page, then you will not be able to infer who made loans for what amounts. This means that for any given amount of time between checking your team page (say you check it once a day), you will be less likely to infer the amount any individual has loaned if loaning frequency is higher for that team. So, if a team usually has one loan per day, and you check your team once a day, then on average you will be able to see who made a loan and for what amount by comparing the current “total amount loaned” and “number of loans” to the values from the day before. But, if there are 100 loans a day for a team you will not be able to figure out who loaned what.

This design means that if someone is making a loan greater than $25 then they should do it in a team with a low lending frequency so that the lenders signal lasts as long as possible. Seeing how a lender wants as many people as possible to see their signal, there very well may be a trade-off between longevity of signal and number of people that view the signal. This would be the case if frequency of lending on the team page is correlated with number of viewers of the team page. For now, we will assume that they are not correlated. Even if they are correlated a lender could get around the problem by making many $25 loans in teams with high frequency, baiting people to click on their profile, and then having links to single member teams where their greater than $25 loans are observable.

Data

Hartley used a similar data collection method to the one that I used. I obtained more detailed data in that it shows the change in groups over time and also records all loans greater than $25 and what time they occur at. I created an API parsing script in PHP that communicates with kiva.org (go here for more info: http://build.kiva.org/docs/data). This script pulls whatever data I want and however frequently I want it from kiva.org.

With this, I was able to infer almost all data imaginable. For instance, I was able to determine the size of each loan made by each individual – something that is not listed on the website. I did this by recording the change in total loaned by the team every time an additional loan was made (total money loaned by team after new loan is made minus total loaned by team before the loan was made). This gave me a measure of the time in between loans and with this the time that comes with making a loan where the person that made the last loan is listed first on the “latest activity” section of the team page. This time fact is essentially the longevity of the signal. Looking at longevity gave me an idea of how much advertising a signal gets depend on which team it is in – so it would get less advertising time in a team with more frequent lending.

I have made the assumption that an insignificant number of Kiva users have created scripts to track the loans of other members – if all users knew the amount that others were lending the entire information flow would change and so would my model. If a significant number of people were able to create scripts that tracked the identity of other Kiva users and connected them to the values of loans they were making then my theory of observable/inferable loans be ideal for signaling would break down. It would take an experienced computer programmer about an entire workweek to do this so I will confidently assume that this is not a problem.

One problem with my data is that I will not be able to determine whether people know each other in real life. This could have confounding effects on my study. For instance, it might be more likely that people in smaller groups know each other in real life. This could be a problem in comparing lending behavior to other groups. I can obtain lots of information to control for problems like this (for instance I could collect data on geographic proximity of individuals within a group – i.e. everyone in this group lives in Austin, TX). I planned on solving this problem by looking at a team as it grew from small to large. This would have controlled for everything other than team size and would have been ideal. But, unfortunately 27 days of data collection was not enough despite the fact that I was monitoring over 6,000 teams. While there is no shortage of information on Kiva, it is impossible to control for everything.

My number of observations was immense – looking at over 6,000 teams I found over 2,000 instances of loans greater than $25. On large teams you can see new loans occur by the minute so my data was extremely high resolution. One problem could have arisen looking at very small teams. I created a team myself and Kiva automatically gave me a team member named anonymous. I think that whenever a team is created, Kiva creates a dummy anonymous member in order to make the team seem larger than it is. Since this person does not exist they will not make loans and this could have definitely confounded my analysis by making it seem that teams of two have low participation because one of the members doesn't exist – but this did not appear to happen.

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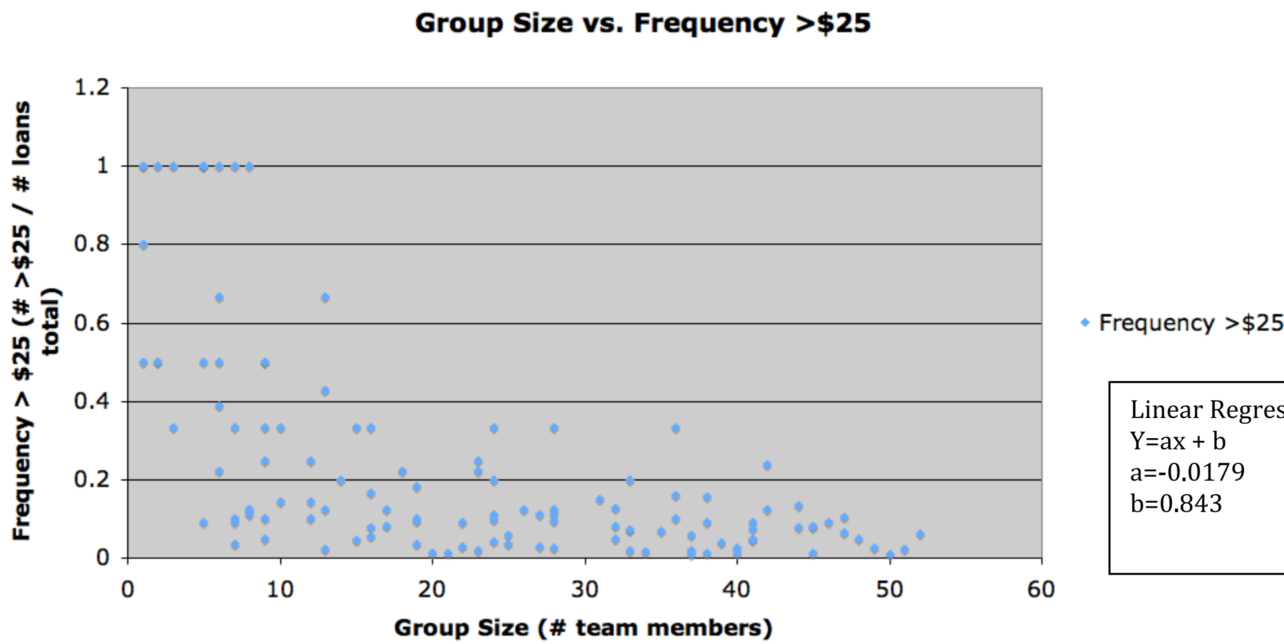
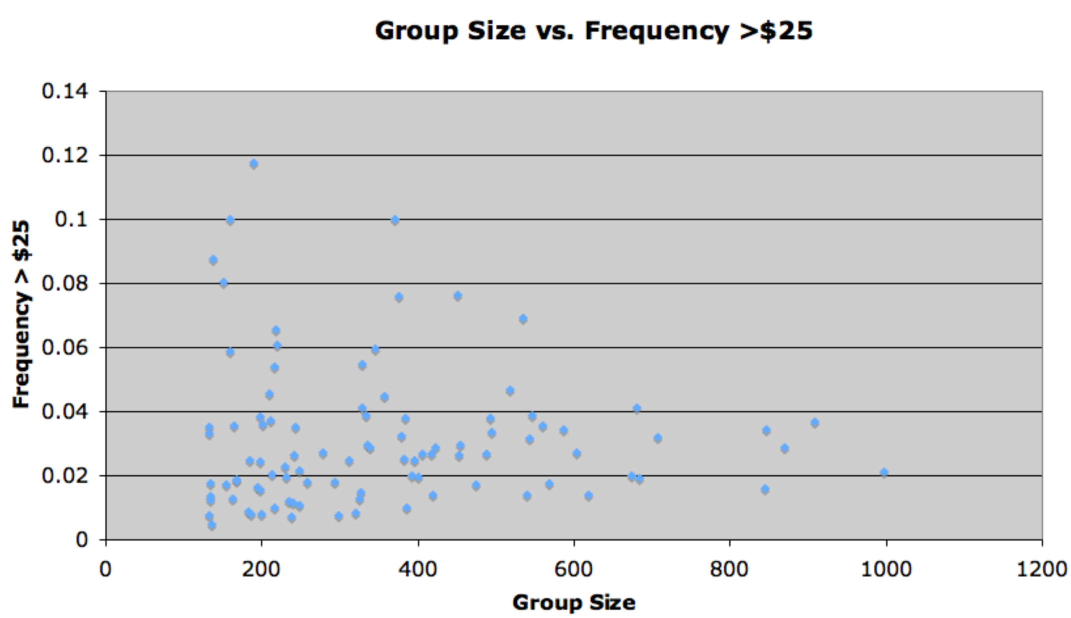
Fig.2:



Linear Regression:
Y=ax + b
a=-0.0179
b=0.843

Fig. 3:



Linear Regression:
Y=ax + b
a=-6.57*10^-5
b=0.0816

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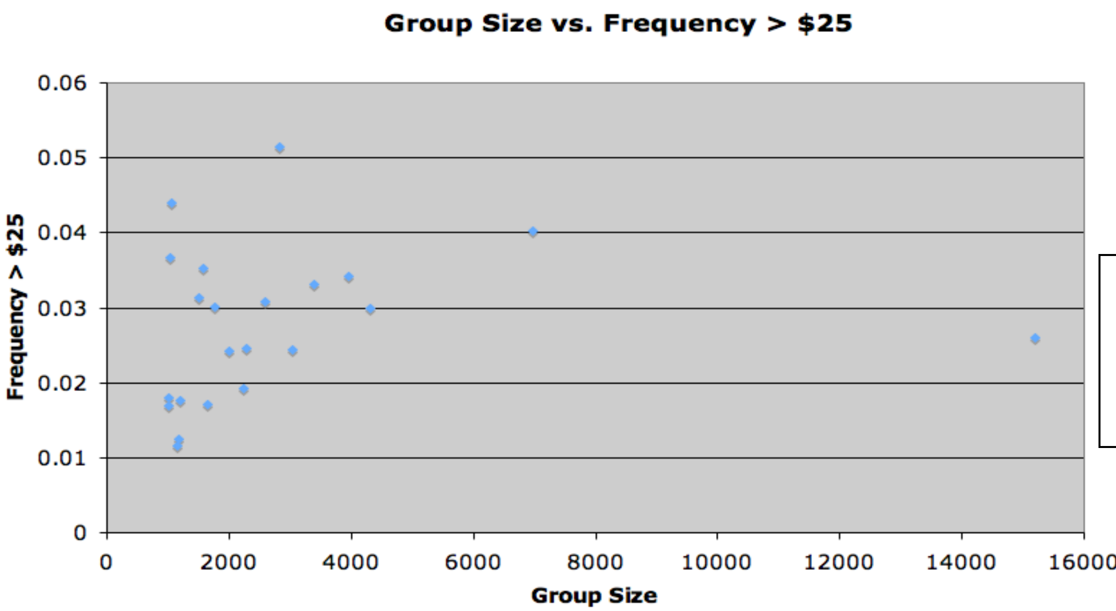
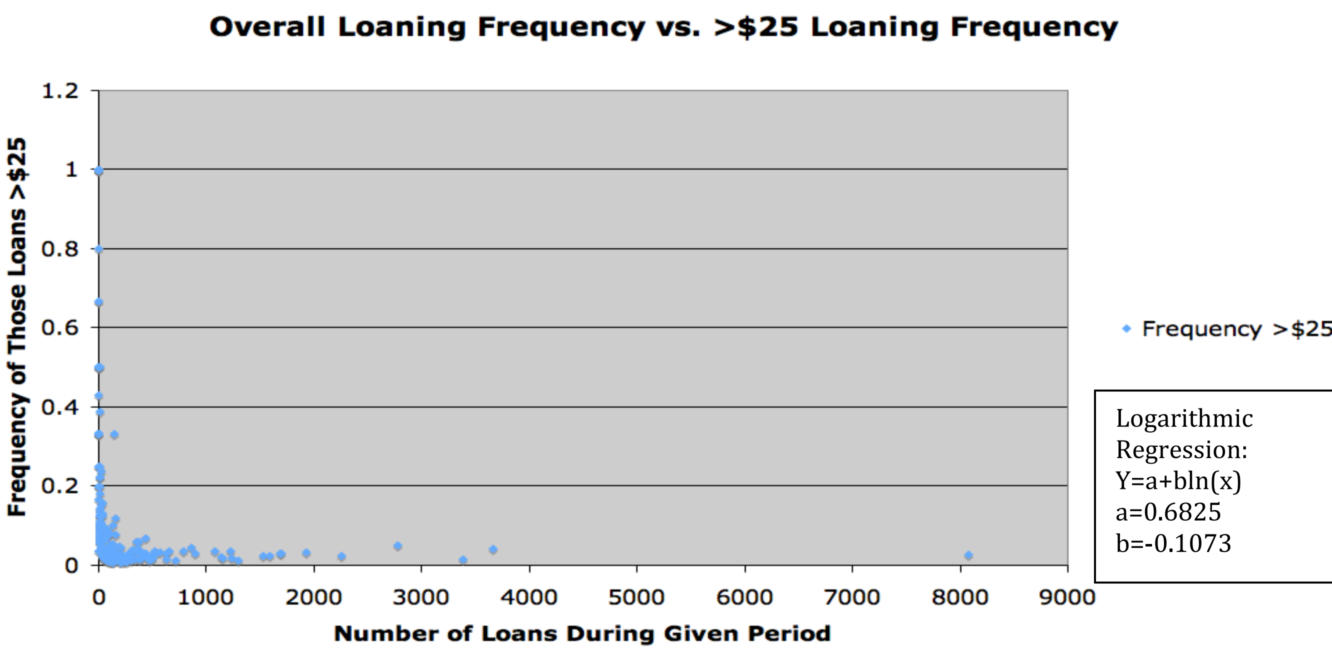
<u>Fig. 4</u>:



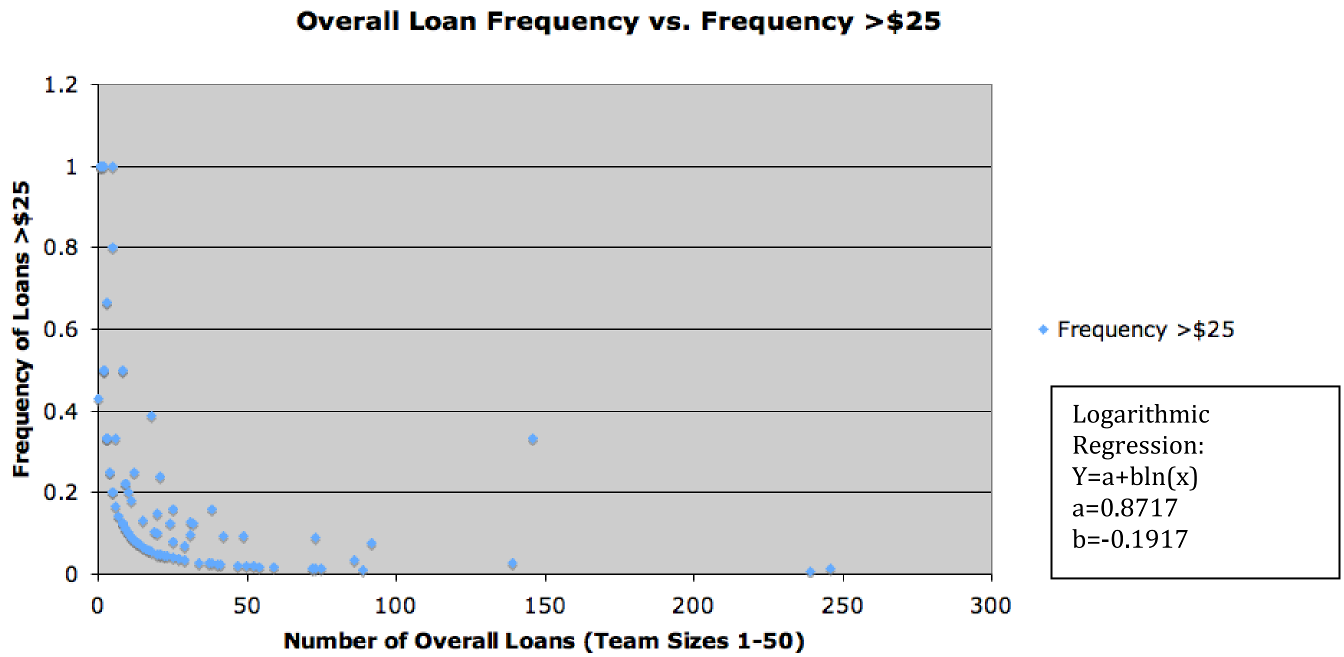
Linear Regression:
Y=ax + b
a=-1.27*10^-7
b=0.0282

<u>Fig. 5</u>:

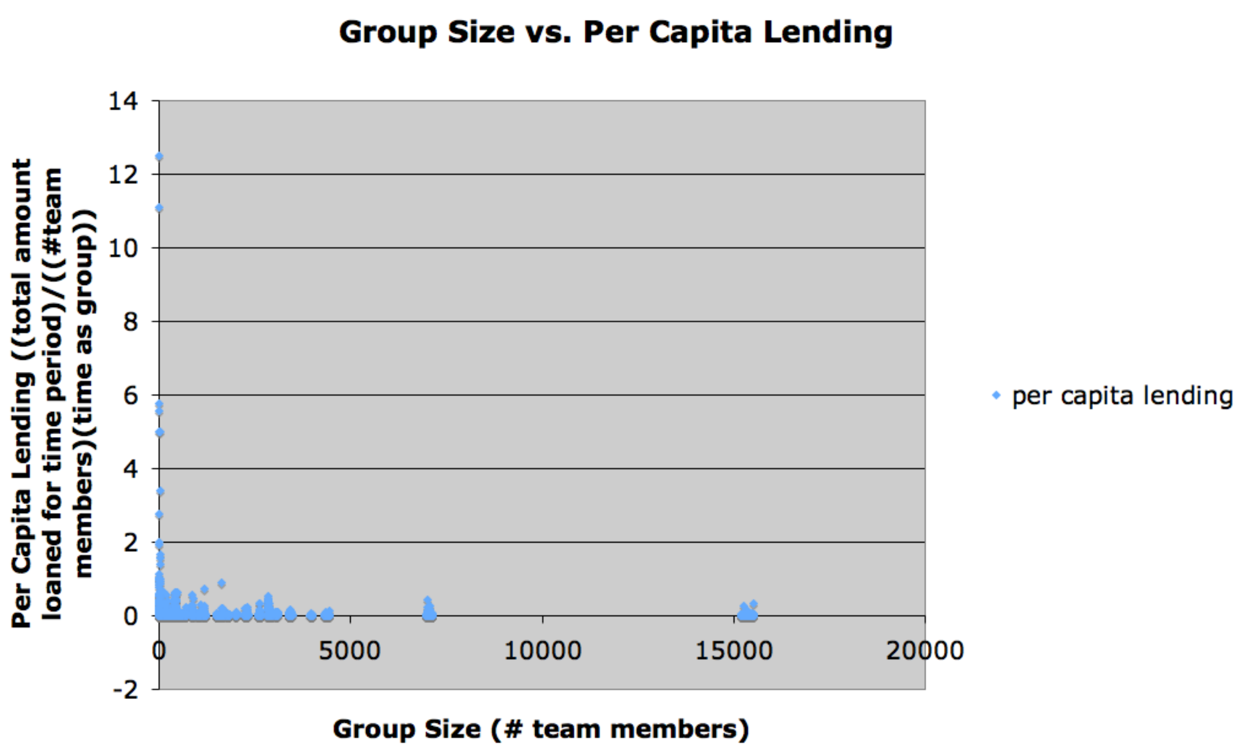


Logarithmic Regression:
Y=a+bln(x)
a=0.6825
b=-0.1073

<u>Fig. 6</u>:



<u>Fig. 7</u>:



Results and Conclusion

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My findings support signaling as an explanation for risky lending behavior on Kiva and for charity in general. It is clear from Figures 5 and 6 that the more frequent loans are in a team, the less likely those loans are to be greater than $25. Greater than $25 loans are an unnecessary risk and so are likely used as an indicator of risk tolerance and the wealth that accompanies it. If greater than $25 loans are meant to be a signal then we should see a non-normal frequency distribution of them along the x-axis since the x-axis is loan frequency. The greater than $25 loans obtain the maximum value as a signal when there is longevity of the signal because this entails more observers of the signal. Given the nature of the "latest activity" section of the teams, a loan will get the most longevity as a signal if frequency of lending within that team is low – frequency of overall lending is on the x-axis of Figures 5 and 6. Combined, if greater than $25 loans are meant to be a signal, then they will be in highest frequency where the value of the signal will be maximized which is at the lowest values on the x-axis.

This predicts a negative sloping function with frequency of greater than $25 loans (y-axis) decreasing as frequency of all loans (x-axis) increases. The y-axis value is frequency rather than absolute value because that normalizes the data against teams that have more loans in general – equivalently the frequency value provides a measure of probability of observing a "greater than $25" loan for any given loan. Again, this is precisely what we see in Figures 5 and 6. The analogy with $u = (x, y\text{-}g)$ is such: given a certain g, lenders want to maximize the lifetime of g so that as many Kiva users as possible will observe g and perceive the lender as possessing wealth "$y\text{-}g$."

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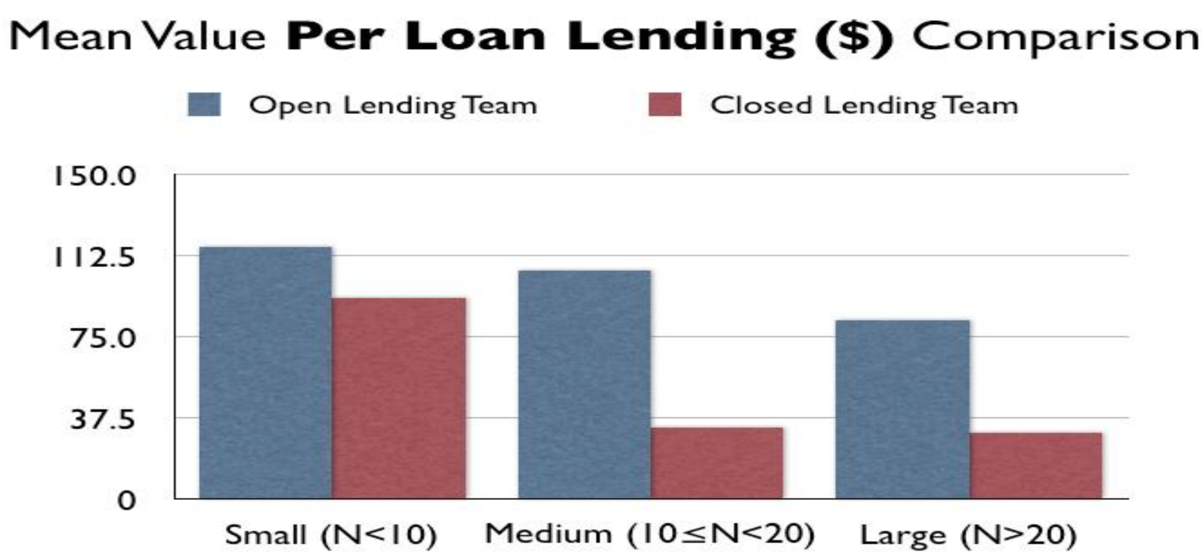
The signaling theory of charity is also supported by Figures 2-4. Comparing the linear regressions between the three figures it is clear that as teams get larger the incremental difference in frequency of loans greater than $25 gets smaller – in other words the slope ("a") value gets smaller as teams get larger. Frequency of lending is directly correlated to team size as implied by Figures 5 and 6. After a certain threshold of frequency is met within a team, any further increase in frequency won't have a significant effect on loans greater than $25 because the threshold frequency is already high enough to discourage signaling loans. This is why the "a" value is so small in Figures 3 and 4, because the teams have high lending frequency (correlated with their large size) in these graphs and the threshold has been crossed.

To further validate the significance of my results econometric analysis would be useful. This would entail making the data more accessible to t-tests and running Wald tests to see which variables are integral in determining frequency of loans greater than $25. With continued data collection it would be possible to run these analyses because there would be extensive data from individual teams showing how they change as they grow in size. Initially this is what I set out to do but more time was required to collect this data than expected (27 days was not enough). The only data I was able to collect was looking at different teams of all different sizes, which makes it impossible to control for different variables and run an econometric analysis. Ideally, I could observe a team grow from a size of one member to a size of 1000 members and see how it changes along the way.

How do my findings reflect on Hartley's paper? Hartley draws the correlation between group size and per capita lending. My results indicate that this is *only* a correlation and not causation. The causation is from frequency of team lending, which is positively correlated with group size, that determines how long a signal will be observable. Below is a plot taken from Hartley's paper that is worth comparing to my findings. Small (N<10, Medium (10<N<20) and Large (N>20) describes the size of the lending teams where N is the number of members. The y-axis of the plot is mean value per loan. Hartley took a small sample of 10 teams for each group range. My sample, shown in Figure 7, is of 6700 teams and shows a similar trend where per capita lending is negatively correlated with group size.



This finding is relevant to signaling economics but how about practical relevance? This study will hopefully help further the microfinance movement. Economists studying microfinance have concluded microfinance for the poorest of the world will not be sustainable in the long run (in a private capital market with no government grants). (Cull, 25) Harnessing the utility that people derive from social interaction on sites like kiva.org may be a sustainable solution to the credit-gap problem.

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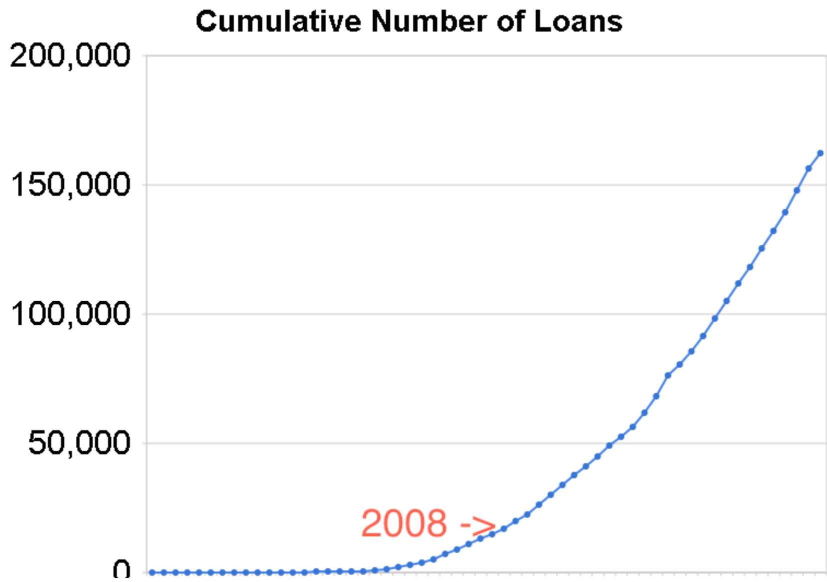

(http://www.kivadata.org/summary.html)

The above graph shows data from kiva.org on cumulative number of loans starting in 2005 and ending in 2010. The graph shows that number of loans is increasing exponentially. It is possibly of significance that this exponential growth in lending began right around the time that team lending was introduced to Kiva in 2008. Of course, I am not strongly asserting that team lending was the source of Kiva's growth but, it very well may be. If the growth of Kiva is due to team lending, this demonstrates the potential in understanding the force of signaling economics in Kiva's online communities.

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Bibliography

Abbink, Klaus, Irlenbusch, Bernd and Renner, Elke, Group Size and Social Ties in Microfinance Institutions (October 2006). Economic Inquiry, Vol. 44, Issue 4, pp. 614-628, 2006. Available at SSRN: http://ssrn.com/abstract=1095969 or doi:10.1093/ei/cbl001

Armendariz de Aghion, Beatriz and Morduch, Jonathan , Microfinance Beyond Group Lending. Economics of Transition, Vol. 8, No. 2, July 2000. Available at SSRN: http://ssrn.com/abstract=264809

Cassar, Alessandra, Crowley, Luke and Wydick, Bruce, The Effect of Social Capital on Group Loan Repayment: Evidence from Field Experiments. Economic Journal, Vol. 117, No. 517, pp. F85-F106, February 2007. Available at SSRN: http://ssrn.com/abstract=976774 or doi:10.1111/j.1468-0297.2007.02016.x

Cull, Robert, Demirguc-Kunt, Asli and Morduch, Jonathan , Microfinance Meets the Market (May 1, 2008). World Bank Policy Research Working Paper Series, Vol. , pp. -, 2008. Available at SSRN: http://ssrn.com/abstract=1149133

Feigenberg, Benjamin, Field, Erica and Ponde, Rahini, Building Social Capital Through Microfinance (June 2010). HKS Faculty Research Working Paper Series: 16018. Available at: http://www.nber.org/papers/w16018

Glazer, Amihai and Konrad, Kai A. “A Signaling Explanation for Charity,” *American Economic Review*, September 1996, Vol. 86, No. 4, pp. 1,019-28

Harbaugh, William T. “The Prestige Motive for Making Charitable Transfers,” *American Economic Review Papers and Proceedings*, May 1998, Vol.88, No.2, pp. 277-82.

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Hartley, Scott E., Kiva.org: Crowd-Sourced Microfinance and Cooperation in Group Lending (March 25, 2010). Available at SSRN: http://ssrn.com/abstract=1572182

http://www.kivadata.org/, Accessed December 15, 2010

Park, J. W. & Zak, P. J. 2007. Neuroeconomics studies. Analyse and Kritik, 29: 47-59

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