How Important are Peer Effects in Group Lending? Estimating a Static Game of Incomplete Information

by

Shanjun Li[1], Yanyan Liu[2] and Klaus Deininger[2]

[1]Department of Economics at SUNY - Stony Brook

shlli@notes.cc.sunysb.edu

[2]Development Research Group, World Bank
1818 H Street N.W., Washington DC 20433
kdeininger@worldbank.org
yliu3@worldbank.org

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association 2009 AAEA & ACCI Joint Annual Meeting, Milwaukee, Wisconsin, July 26-29, 2009

How Important are Peer Effects in Group Lending? Estimating a Static Game of Incomplete Information

Shanjun Li, Yanyan Liu, and Klaus Deininger*

First Draft: November 2008

This Draft: April 2009

Abstract

We quantify the importance of peer effects in group lending by estimating a static game of incomplete information. In our model, group members make their repayment decisions simultaneously based on their household and loan characteristics as well as their expectations on other members' repayment decisions. Exploiting a rich data set of a microfinance program in India, our estimation results suggest that the likelihood of a member making a full repayment would be 15 percent higher on average if all the other follow members make full repayment compared to the case where none of the other members repay in full. We also find that large inconsistencies exist in the estimated effects of other variables in models that do not incorporate peer effects and control for unobserved heterogeneity.

*Affiliations: Li is an assistant professor in the Department of Economics at SUNY - Stony Brook, Stony Brook, NY. Liu and Deininger are a consultant economist and a lead economist in the Development Research Group, World Bank, Washington DC. Correspondences: shlli@notes.cc.sunysb.edu, yliu3@worldbank.org, and kdeininger@worldbank.org.

1 Introduction

This paper provides, to our knowledge, the first structural analysis of peer effects in group lending by estimating a static game of incomplete information based on a rich data set from a microfinance program in India. Since the establishment of the Grameen Bank in Bangladesh (Grameen means "rural" or "village" in Bangla language) in 1976, microfinance has been widely adopted in developing countries as an important tool to provide credit to the poor in order to fight poverty. Different from conventional banking system, microfinance programs employ group lending (or joint liability) practice whereby the loan is made to a group of borrowers and the whole group is liable for the debt of any single member in the group. This practice allows microfinance programs to mainly rely on accountability and mutual trust among group members rather than financial collateral to insure against default. Given that the poor often do not have appropriate financial collateral to offer, group lending programs offer a feasible and even profitable channel to extend credit to the poor who are usually kept out of traditional banking system.

There exist numerous theoretical studies that aim to explain the success of group lending. Most of these studies employ a game-theoretical framework where members in a group are assumed to make their repayment decisions strategically. The success of group lending has been attributed to, among other things, the ability of such groups to mitigate adverse selection and moral hazard through peer selection, peer monitoring, as well as peer pressure, all of which are less costly than the tools available to formal institutions to achieve the same goals (Stiglitz (1990); Banerjee et al. (1994); Besley and Coate (1995); de Aghion (1999); Morduch (1999); Conning (2005)). The process of peer selection (or group formation) tends to screen more risky households out of the group lending program. Through peer monitoring, members in a group can effectively monitor the usage of a loan thus reduce ex-ante moral hazard. Peer pressure refers to the fact that peers can exert pressure to enforce repayment and mitigate ex-post moral hazard. The effectiveness of these channels hinges on the premise that people in the same community know each other well and can identify and punish deliberate defaulters more effectively than lenders when financial collateral cannot be applied.[1]

Despite a rich theoretical literature, empirical work on microfinance is scant. Although the strategic interaction among borrowers in a group is a key element in group lending programs, it has not been modeled explicitly in existing empirical studies. Most empirical studies treat a group as a decision maker and employs a single-agent choice model such as a logit or a tobit model to examine how group level characteristics affect the probability of the repayment of a group (e.g., Zeller (1998); Paxton et al. (2000); Wydick (1999); Ahlin and Townsend (2007)). Karlan (2007) is probably the only paper to explore determinants of the repayment decisions of individual members. In all these papers, peer pressure is not estimated directly but is proxied by different measures of social ties, such as how close the group members live with each other, how well they know each other, and how close is the ethnic and cultural background among members. The approach undertaken thus far in the literature is probably due to the following two reasons. First, incorporating strategic interactions into a discrete choice model is empirically challenging because it inevitably induces a nonlinear model with an endogenous variable that characterizes the repayment decision of other members in the group. Second, data of group lending programs with detailed member information that are suitable for a game-theoretical framework are not easy to obtain.

Different from previous empirical studies, we explicitly model and quantify strategic interactions in the repayment stage among group members by estimating a static game of

[1]There are also some theoretical literatures that point out potential pitfalls of group lending such as bad members can "free ride" off of good clients and may exhibit bad influence on others, e.g., when many of the members default, some members would choose to default even when they would have repaid under individual lending (Besley and Coate (1995)).

incomplete information. Because of the nature of joint liability in group lending programs, the payoff of one member depends not only on her repayment decision but on the decisions of other fellow members. We model the repayment decisions of group members in a static game of incomplete information where members make their repayment decisions simultaneously based on their individual characteristics (part of which is unobserved to other members) as well as their expectations on other members' repayment decisions. We estimate the game using the simulated maximum likelihood estimation (SMLE) method with a nested fixed point algorithm. The fixed point algorithm recovers equilibrium repayment probabilities for each member in the game and these repayment probabilities are then used to form the likelihood function. Our estimation strategy follows advances in estimating discrete choice games such as entry games in industrial organization where one firm's payoff from entry is affected by other firms' entry decisions (e.g., Bresnahan and Reiss (1991), Berry (1992), Tamer (2003), Seim (2006), Bajari et al. (2006)).

Exploiting a rich data set from a group lending program in the Indian state of Andhra Pradesh (AP), our structural estimation is able to quantify the importance of peer effects as well as some member and loan characteristics studied in the previous literature. We find strong peer effects in the repayment decisions of program participants: the likelihood of a group member making a full repayment would be 15 percent higher if the member is in a group where all the follow members repay in full than a group where none of the follow members makes full repayment, *ceteris paribus*. Since the empirical model takes group formation as given, our estimate of peer effects capture the functioning of peer monitoring as well as peer pressure, both of which mitigates the moral hazard problem in the credit market as discussed above. Moreover, without taking into account group formation, our estimate of peer effects should be interpreted as an average treatment effect on program participants (i.e., the treated). Our empirical results also highlights the importance of explicitly modeling peer effects and controlling for unobserved heterogeneity in empirical studies of group lending programs by showing that without doing so, large inconsistencies could arise in the estimated effects of other variables on repayment decisions.

The remainder of the paper is organized as follows. Section 2 discusses the background of the microfinance program under study as well as the data. Section 3 presents the empirical model and estimation strategy. Section 4 reports estimation results and robustness analysis. Section 5 concludes.

2 Background and Data

In this section, we start by discussing the history of microfinance and the microfinance program under study. We describe mechanisms through which peer effects work. The data from the program are then presented.

2.1 Microfinance and Peer Effects

The origin of microfinance can be traced back to 1976 when the 2006 Nobel Peace Prize winner, Muhammad Yunus, started a (Grameen Bank) project in several villages in Bangladeshi to examine the feasibility of a credit delivery system targeted to the rural poor who often do not have financial collateral and cannot obtain credit from conventional banks. Instead of requiring collateral, the project employs a group-based credit approach and relies on peer pressure within groups to ensure repayment. The project achieved great success in delivering credit to the poor while ensuring an almost 100 percent repayment rate. The success of Grameen Bank in Bangladeshi has inspired similar projects in more than 40 developing countries including its neighbor, India.

In 1992, India's National Bank for Agricultural and Rural Development organized 500 self-help groups (SHG) composed of only women as a pilot program for delivering credit to the poor. Since then, the SHG program has witnessed tremendous growth that brought about one of the world's largest and fastest-growing networks for microfinance. In 2007, some 40 million households were organized in more than 2.8 million SHGs that borrowed more than US$ 1 billion of credit from banks in 2006/7 alone (Reserve Bank of India 2008). Cumulative credit disbursed to SHGs amounted to some US$ 4.5 billion (or about 10% of total rural credit) in India (Garikipati (2008)).

The SHG model in India combines savings generation and micro-lending with social mobilization. In this model, women who live in the same village voluntarily form SHGs with the understanding of joint liability mechanism. A typical SHG consists of 10-20 members who meet regularly to discuss social issues and activities and, during these meetings, deposit a small thrift payment into a joint bank account. Once enough savings have been accumulated, group members can apply for internal loans that draw on accumulated savings at an interest rate to be determined by the group. Having established a record of internal saving and repayment, the group can become eligible for loans through a commercial bank, normally at a fixed ratio (normally starting at 4:1) to its equity capital.

The microfinance groups under study in this paper are located in Andhra Pradesh (AP) of India. Besides thrift savings and obtaining credits, SHGs in AP also work as local institutions that take over implementation of a variety of government programs such as distributing subsidized rice credit, life and property insurance, pension, and so on. In AP, the State Bank and Andhra Bank are the two major banks that provide credits to these groups. They share their group-lending information and only allow a group to have one outstanding loan from both of them. Once a loan is obtained by a group, it is immediately allocated among the members (mostly in an equal sense) with the repayment terms (such as interest rate, length, number of installments, etc.) set by the bank. The group cannot obtain loans from the two banks in the future unless the group have fully repaid her loan.

Since we only have information on program participants, we focus on peer effects that arise after groups have been formed. Previous literatures have discussed several mechanisms through which peer effects influence members' repayment decisions (see, for example, Besley and Coate (1995), Morduch (1999), and Karlan (2007)). Peer effects can lead to better repayment rates through the following channels: increasing the cost of defaulting, encouraging more diligent work ethics, and inspiring reciprocity and solidarity within groups. Members in a group are neighbors who know each other well. So they can observe each other's usage of the funds and distinguish deliberate default and default due to irresponsible behaviors (such as investing in too risky projects, spending on drinking and smoking, etc.) from default due to unexpected negative shocks. The repaying members can thus impose social penalties to increase the cost of deliberate default and default due to irresponsible behaviors. Social penalties can take the form of despise, not providing help in their production and other activities in the future, etc. These penalties are severe in close-knit poor communities where people rely on each other in their daily life and to a larger extent, in times of distress (see Coate and Ravallion (1993)). On the other hand, a member who defaults due to unexpected negative shocks is likely to be forgiven and covered by her peers, which can give her high incentive to pay back if her situation gets better.

All three previous mechanisms lead to positive peer effects. The fourth mechanism, raised by the literature (e.g., Besley and Coate (1995)), can nevertheless result in negative peer effects, implying that a higher repayment rate of other members decreases one's own repayment likelihood. The mechanism suggests that some "bad" members can "free ride" off of good members. That is, some members may rely on other members' help to repay the loan even if they have the ability to repay on their own, i.e., they would repay in individual lending. The fact that the SHGs in AP also serve as the organization base for other programs and activities than group lending implies that the potential social penalties can be very severe and that the free-rider problem is likely to be small. This is because free-riders are likely to be kept out of the groups through intensive peer selection process. In addition, intensive interactions among group members also provide larger incentive for members to repay their own part even if their peers do not: they can build or maintain a good reputation which would allow them to join other groups in the same village later should the group fail.[2] In our empirical estimation, we do not restrict the direction of peer effects a prior. The positive and significant peer effects found from our estimation implies that a higher repayment (default) rate of other members increases one's own repayment (default) likelihood. This finding confirms that the free-rider problem is dominated by others if exist at all.

2.2 Data

The data are from an SHG survey of 815 groups in AP in India. In this survey, all loans taken by each group and by each member of a group between June 2003 and June 2006 are recorded from account books of each group. Thus, we have information on each loan taken by a group as well as how the loan was allocated among members. We also have information on terms of each loan and whether a loan had been fully repaid by each member by the time the survey was conducted. This survey also contains demographic information on group members including poverty status,caste, occupation, housing condition, and education background.

We investigate 1,008 "expired" group loans from commercial banks. Panel 1 of Table 1 presents summary statistics for member characteristics of the 815 groups while Panel 2

[2]There are about 20-40 SHGs in each village in AP.

summarizes terms of the 1,008 loans. An SHG has 12 members on average while the smallest group having 7 members and the largest 20 members. About 26% members are from very poor households, 52 percent from poor households, and 22 percent from middle-class households.[3] The very poor households refer to those who can eat only when they get work and who lack shelter, proper clothing, respect in society, and cannot send their children to school; The poor have no land, live on daily wages, and need to send school going children to work in times of crisis. The "not poor" refer to middle and rich classes who have land and proper shelter, send their children to schools, are recognized in society, and have access to bank credit as well as public services. About 31 percent members belong to scheduled tribe or scheduled caste, and 25 percent are literate. About 6.5 percent members are disabled or have family members who are disabled. 41 percent of members live in pucca houses while 26 percent live in kutch houses.[4] 64 percent members are agricultural labors (i.e., do not own land but perform agricultural work for others). It is clear that most SHG members are from poor and vulnerable households. This is in line with the program's goal to target the rural poor.

We define "default" as failure to make a full repayment at the survey time if the loan was past-due by then. Among the 1,008 "expired" loans, 76 percent were fully repaid by all members to whom the loan was allocated, 7.5 percent were fully repaid by some of the members but defaulted by the others, and 16.3 percent were defaulted by all members. The average loan size is 34,000 rupees (about USD 682) and a loan is, on average, allocated to 11 members. The average annual rate of interest is 12.7 percent, and the average

[3]A household's poverty category was assigned by the state's 2001 "below poverty line" census complemented by "participatory identification of the poor" that added vulnerability and social exclusion to quantitative census indicators.

[4]A pucca house has walls and roof made of material such as burnt bricks, stones, cement concrete, and timber while a kutcha house use less sophisticated material such as hays, bamboos, mud, grass, hays. A semi-pucca house uses a combination of material for the other two types.

duration of a loan is about one year. The majority of loans (97 percent) require the groups to make repayment at least as frequently as monthly.

3 Model and Estimation

In this section, we first lay out a theoretical model to characterize household decisions in group lending. We then present our estimation strategy.

3.1 Model

In a group lending program, households form groups in order to get loans from a lender such as a commercial bank. The loan is extended to the group and divided among members and the group as a whole is held liable should one of the members fail to make the repayment. We index a group loan by g and member (i.e., a household) by i. Denote the choice set of a member in group loan g by $A_{gi} = \{0, 1\}$, where 1 represents a full repayment by the member and 0 otherwise. Let the Cartesian product $A_g = \times_i A_{gi}$ denote the possible actions of all borrows and define $a_g = (a_{g1}, a_{g2}, \ldots, a_{gN_g})$ as an element in A_g, where N_g is the number of members that participated in group loan g. Let x_{gi} be the characteristics of member i and $x_g = \left\{x_{g1}, x_{g2}, \ldots, x_{gN_g}\right\}$ denote the characteristics of all participating members in the loan. We assume that x_g is observed by all members in the group.

In the following presentation, however, we suppress group loan index g for brevity. The utility of member i after the realization of repayment decisions by all members in the loan is:

$$U_i(a_i, a_{-i}, x, \epsilon_i) = U_i(a_i, a_{-i}, x_i) + \epsilon(a_i), \tag{1}$$

where a_i is the action taken by member i while a_{-i} is a vector of actions of other members in the same loan. $\epsilon(a_i)$ is a stochastic preference shock observed only by member i as in a standard random utility model. This term can also be interpreted as unobserved individual characteristics. The key feature of the utility function is the presence of actions taken by others in the loan, a_{-i}. With $\epsilon(a_i)$ being private information, the above model is a static game with incomplete information. A pure-strategy Bayesian Nash equilibrium in such a game is defined by $a^* = (a_1^*(\epsilon_1), a_2^*(\epsilon_2), \ldots, a_N^*(\epsilon_N))$, where $a_i^*(\epsilon_i)$ maximizes the expected utility:

$$\max_{a_i \in \{0,1\}} U_i(a_i, x, \epsilon_i) = \int U_i(a_i, a_{-i}^*(\epsilon_{-i}), x) f(\epsilon_{-i}) d\epsilon_{-i} + \epsilon_i. \tag{2}$$

To take the model to the data, we normalize the utility of member i from loan default to be zero, and assume that the normalized ϵ_i (i.e., $\epsilon(a_i = 1) - \epsilon(a_i = 0)$ in previous notations) has a logistic distribution. We further specify the utility function to take the following linear form:

$$U_i(a_i = 1, a_{-i}, x, \epsilon_i) = \gamma \frac{1}{N-1} \sum_{j \neq i} a_j + x_i \beta + \epsilon_i. \tag{3}$$

Because of the normalization, the above function captures how utility differences between the two choices: repay in full and default, are related to the explanatory variables. The actions of other members in the loan are summarized in a single variable $\frac{1}{N-1} \sum_{j \neq i} a_j$, the proportion of members other than i who make full repayments. We use this term to captures peer effects that arise through multiple channels discussed earlier. For example, since the default of member i hinders the ability of other members to obtain credit in the future, other members may impose social penalties to member i in various forms to enforce repayment. Or if member i is subject to some unexpected shock, she may be able to borrow from other members to make her repayment. In both cases, the cost of default (or the benefit of repayment) of member i is higher when more other members choose to repay, *ceteris paribus*. Although the above channels suggest positive peer effects and hence complimentary among group members in making full repayment, the free-rider problem as discussed in the previous section implies the opposite. In the estimation, we do not restrict the direction of the coefficient on the peer effect term, γ.

Given the above utility function, the expected utility (or *ex ante* utility with respect to others' decisions) of member i becomes:

$$\begin{aligned} U_i(a_i = 1, x, \epsilon_i) &= E_{a_{-i}}[U_i(a_i = 1, a_{-i}, x, \epsilon_i)|x] \\ &= \gamma \frac{1}{N-1} \sum_{j \neq i} E(a_j|x) + x_i\beta + \epsilon_i \\ &= \gamma \frac{1}{N-1} \sum_{j \neq i} \text{Prob}(a_j = 1|x) + x_i\beta + \epsilon_i. \end{aligned} \quad (4)$$

Therefore, household i will choose to fully repay the loan if and only if $U_i(a_i = 1, x, \epsilon_i) > 0$. The optimal choice by member i implies that the *ex ante* probability of a full repayment (before the realization of private shock of ϵ_i) is given by

$$P_i = \frac{\exp(\gamma \frac{1}{N-1} \sum_{j \neq i} P_j + x_i\beta)}{1 + \exp(\gamma \frac{1}{N-1} \sum_{j \neq i} P_j + x_i\beta)}, \quad (5)$$

where $P_i = \text{Prob}(a_i = 1|x)$. Denote the probabilities of full repayment for all members in the group loan by $P = (P_1, P_2, \ldots, P_N)$. These probabilities that are consistent with the Bayesian Nash equilibrium are therefore defined by the fixed point of the mapping $P_g = M(P_g)$ where $M(.) : [0,1]^{Ng} \rightarrow [0,1]^{Ng}$ is a continuous function whose single dimension is represented by equation (4). These probabilities also correspond to the Quantal Response Equilibrium defined by (McKelvey and Palfrey (1995)). The existence of a fixed point to the above function follows directly from Brouwer's fixed point theorem. Nevertheless, the uniqueness of the fixed point is not guaranteed and the implication on estimation will be discussed below.

3.2 Estimation Method

There are several challenges in taking the choice probabilities defined by equation (5) to the data. First, loan-level or group-level variables unobservable to the researchers could exist that affect individual payment decisions. These unobservables may include group solidarity, reciprocity, and work ethics as well as weather conditions. Failure to control for them would lead to the over-estimation of the importance of the peer effect in increasing the repayment rate. In our estimation, we allow the common unobservables to be represented by a single variable ξ. With group loan index g re-introduced, the expected utility function of member i can be written as:

$$u_{gi}(a_{gi}=1, x_g, \xi_g, \epsilon_{gi}) = \gamma \frac{1}{N_g - 1} \sum_{j \neq i} P_{gj} + x_{gi}\beta + \xi_g + \epsilon_{gi}, \tag{6}$$

where x_{gi} includes observed household variables as well as group level variables. The *ex ante* choice probability of member i that can be taken to the data becomes:

$$P_{gi} = \frac{\exp(\alpha \frac{1}{N_g-1} \sum_{j \neq i} P_{gj} + x_{gi}\beta + \xi_g)}{1 + \exp(\gamma \frac{1}{N_g-1} \sum_{j \neq i} P_{gj} + x_{gi}\beta + \xi_g)}. \tag{7}$$

Second, one of the explanatory variables, member i's expectation about the average repayment rate among all the other fellow members $E(P_{g,-i}) = \frac{1}{N_g-1} \sum_{j \neq i} P_{gj}$, is unobserved. Although the observed outcome, $\frac{1}{N_g-1} \sum_{j \neq i} a_{gj}$, is a natural choice for the expectation variable, it is correlated with the individual error term, ϵ_{gi} (and ξ_g as well). Due to the nonlinear nature of the model, standard instrumental variable method cannot be applied to deal with the endogeneity problem. Bajari et al. (2006) propose a two-step estimator to address this problem. The key idea is to note that in the absence of unobserved heterogeneity, the choice probabilities are determined by x_g only in the equilibrium, albeit via a non-analytical form. In principle, a consistent estimate of the choice probabilities can be obtained based on x_g through flexible estimation method (e.g., nonparametrically) in the first step and these estimates can then be plugged into the right side of the equation (5) in place of $\frac{1}{N_g-1} \sum_{j \neq i} P_{gj}$ to form likelihood function. However, this method cannot be applied when there exist group-level unobservables because consistent estimates of choice probabilities cannot be obtained based on only x_g in that case. In order to make the two-step method applicable in the presence of unobserved heterogeneity, Bajari et al. (2006) make the assumption that the group level unobservable has a fixed effect presentation and is an unknown but smooth function of the observe variables. However, this assumption could be too strong for our data. For example, local weather condition variations may not have much correlation with observed household demographics.

Instead, we assume that the common unobservable ξ_g is uncorrelated with observed variables x_g, and that $\xi_{gi} \sim N(0, \sigma^2)$ and is i.i.d. across loans. It is worth noting that, different from the random effect assumption in models without strategic interactions, the common unobservable ξ_g in our model is correlated with the key explanatory variable $E(P_{g,-i})$ because it is an equilibrium outcome. With this assumption on the unobserved heterogeneity, we employ a maximum simulated likelihood method with a nested fixed point algorithm. For a given set of parameters and a random draw of ξ_g for each group loan g, the fixed point algorithm, based on equation (7), recovers the choice probabilities in equation (7) for all the members in the group. These probabilities can then be used to form the likelihood function. Because the fixed point algorithm has to be done as many times as the number of random draws for each ξ_g in each parameter iteration, this approach, with the benefit of being more efficient, is much more computationally demanding than the two-step approach.

The third empirical challenge arises from the possibility of multiple equilibria, which are more likely to happen when peer effects are positive and strong.[5] With multiple equilibria, the probability of an observed outcome is undefined without a specification of the equilibrium mechanism. In principle, one can compute all (and finite) fixed points to the system of equations defined by equation (7) via an all solution homotopy method (see Ba-

[5]See Brock and Durlauf (2001) and Bayer and Timmins (2007) for the equilibrium property in the context of social interactions where the reference group is large.

jari et al. (2006)). The likelihood function can then be formed based on all the recovered equilibria and a specified selection mechanism. However, this method is computationally infeasible given the large number of random draws to deal with common unobservables as well as the large number of groups. Instead, we follow the literature and assume that only one equilibrium is observed in the data if multiple equilibria do arise (Seim (2006), Zhu and Singh (2009), Ellickson and Misra (2008)). Robustness analysis with respect to this assumption is provided below.

To illustrate our estimation strategy, let y_{gi} denote the repayment outcome of gi and $\xi_g = \sigma * \nu_g$, where ν has an i.i.d. (across g) standard normal distribution and σ is the standard deviation of a normal distribution. The joint probability of the observed outcome for group g conditional on a realization of ν is:

$$\begin{aligned} & P(y_{g1}, y_{g2}, \ldots, y_{gN_g} | x_g, \nu_g) \\ = \; & P(a_{g1} = y_{g1}, a_{g2} = y_{g2}, \ldots, a_{gN_g} = y_{gN_g} | x_g, \nu_g) \\ = \; & P(a_{g1} = y_{g1} | x_g, \nu_g) P(a_{g2} = y_{g2} | x_g, \nu_g) \ldots P(a_{gN_g} = y_{gN_g} | x_g, \nu_g), \end{aligned} \tag{8}$$

where $P(a_{gi} = y_{gi} | x_g, \nu_g)$ can be obtained based on the fixed points recovered from system of N_g equations defined as (7). The joint probability for group g without conditioning on the unobservable is:

$$P(y_{g1}, y_{g2}, \ldots, y_{gN_g} | x_g) = \int P(y_{g1}, y_{g2}, \ldots, y_{gN_g} | x_g, \nu_g) f(\nu_g) d\nu_g. \tag{9}$$

The above joint probability can be approximated by:

$$\tilde{P}(y_{g1}, y_{g2}, \ldots, y_{gN_g} | x_g) = \sum_{r=1}^{R} P(y_{g1}, y_{g2}, \ldots, y_{gN_g} | x_g, \nu_g^r) w^r, \tag{10}$$

where R the total number of draws and w^r the weight of the r^{th} draw. Define $\vartheta = (\gamma, \beta, \sigma)$. The objective function to be maximized is

$$LL(\vartheta) = \sum_{g=1}^{G} \log \sum_{r=1}^{R} P(y_{g1}, y_{g2}, \ldots, y_{gN_g} | x_g, \nu_g) \tag{11}$$

where G is the total number of group loans. Note that the fixed point algorithm has to be carried out $R * G$ times for each parameter iteration.

To understand the identification of the peer effect coefficient γ, imagine that there are two otherwise identical households except being in different group loans and assume there are no common unobservables. Their repayment decisions may be different solely due to the fact that the repayment rate of their peers is different in the two loans. Peer effects are identified from the difference in the two households' repayment decisions in relation to other members' repayment decisions in the two loans. In the presence of common unobservables, the group loans where members make different repayment decisions (7.5 percent of the loans in the data) are essential: without these loans, the model would not be identified.

4 Results and Robustness Analysis

In this section, we first present our estimation results for several different specifications including the preferred specification. We then discuss caveats in our study and carry out robustness analysis with respect to several assumptions employed in the preferred specification.

4.1 Results

We estimate our empirical model defined by equations (6) and (7) using the simulated maximum likelihood method with a nested fixed point algorithm. For a given set of parameters and a random draw of ν_g for each g, the fixed point algorithm recovers the equilibrium repayment probabilities of each member in a group loan based on equation (7). These probabilities are then used to evaluate the likelihood function defined by equation (11). To reduce computation burden, we use Gauss-Hermite quadrature to approximate the joint probabilities in equation (10), where ν_g^r and w^r are predetermined node and weight whose values depend on the number of nodes used for approximation. Because the choice probabilities can be highly nonlinear, we use as high as 64 points for the approximation in equation (10), recognizing the trade off between approximation accuracy and computation burden. Robustness checks are performed with respect to approximation and are discussed in the next section.

Table 2 presents the parameter estimates as well as their standard errors (in parenthesis) for several specifications. The results for the preferred specification are in the last column where both peer effects and unobserved heterogeneity are included in the model. To investigate the importance of modeling peer effect and unobserved heterogeneity, we also estimate three alternative models. The first alternative model is a logit model with neither peer effects nor unobserved heterogeneity. The estimation results for the model are reported in the second column of Table 2. The second alternative model has the peer effect term but no unobserved heterogeneity while the third alternative model controls for unobserved heterogeneity but not peer effects. In all the four specifications, we control for member characteristics (including poverty status, caste, disability, literacy, land and livestock ownership, housing condition, and occupation), loan characteristics (including loan size and repayment terms), and year and location fixed effects. The likelihood and pseudo R^2 values in the second and third models show that controlling for unobserved heterogeneity can dramatically improve the model fit. This perhaps is not surprising given that in about 84 percent of all the group loans, members make same repayment choices. The peer effect term also improves the model fit and its coefficient estimate is positive and statistically significant in both the second and fourth specifications.

Because the parameter estimates cannot be compared directly across the models, we compute the (sample) average partial effects of the explanatory variables and present them in Table 3.[6] For the two models with the peer effect term, we report two types of partial effects - the direct partial effect and the total partial effect - of the explanatory variables. The difference between the two is that the total partial effect incorporates the feedback/indirect effect transmitted through the peer effect term. That is, a change in the characteristics of household i will not only have a direct effect on her repayment propensity, but also have an indirect effect through her influence on other households in the loan. For instance, the direct and total partial effects of being a very poor household on loan repayment are estimated at -0.005 and -0.015, respectively in the full model. This means, a change of household i's status from being very poor to being poor (the base group) would increase the repayment probability by 0.5 percent, holding all other explanatory variables including other households repayment probabilities constant. However, a change in household i's repayment decision would change repayment decisions of others in the same group loan due to the presence of peer effects, which would in turn affect the repayment decision of household i. Therefore, the total partial effect is the partial effect when the new equilibrium has been achieved and should be larger than the direct partial effect. Based on our model estimation, the total partial effect of the wealth status changed from being poor to being very poor is -0.015, three times as large as the direct partial effect. The larger the peer effect coefficient γ is, the larger the difference between the total partial effect and the direct partial effect should be. The total partial effects for other variables are also about three times as large as the direct partial effects in the full model.

In order to gauge the importance of peer effects in group lending, we conduct two analysis based on parameter estimates. First, we compute the total partial effect of the peer effect variable $E(P_{-i})$ on repayment probability. The estimated total partial effect of the

[6] We compute the partial effects for each observation in the data and the averages of these estimates across all observations are presented.

peer effect variable is 0.154, comparing the direct partial effect of 0.051. To understand this estimate, imagine a group with 11 members and that group members 1 to 10 receive positive shocks (e.g., an increase in ϵ_{gi}) such that each of their repayment probabilities increases by 0.1 holding other factors constant. Therefore, for group member 1, $E(P_{-1})$ increases by 0.1. As a result, the repayment probability of member 1 in the new equilibrium will increase by 1.54 percent. The second way to quantify the importance of peer effects is to look at what would be the change in a member's repayment probability if she is in a group with no other members repaying in full, compared to a group with all other members making full repayment while keeping other factors the same across the two groups. Based on the parameter estimates in the full model, the average repayment rate across all observations would be 71.5 percent if $E(P_{-i}) = 0$, comparing to 86.3 percent if $E(P_{-i}) = 1$. The difference is about 15 percentage points, which provides a similar quantification of the importance of peer effects to the first method. Because our data only include information about participants in group lending programs and our analysis takes group formation as given, we refrain from interpreting these estimates as the difference in repayment rate between group lending and individual lending for all borrowers. Instead, we consider these effects as an average treatment effects among the treated (ATT), i.e., the participants of group lending programs.

The comparison of the partial effects between the second and fourth models highlights the importance of controlling for unobserved heterogeneity. In the second model where unobserved heterogeneity is not controlled for at the loan level, the total partial effect of peer effects on repayment is 0.439, comparing to 0.154 in the fourth model. The average treatment effect is 0.383 in the second model while it is 0.148 in the fourth model. The estimates of the (total) partial effects of other variables can also differ dramatically across the four models. For example, the estimated partial effect of whether poverty status being very poor in the three alternative models is -0.045, -0.059, and -0.006, comparing to

-0.015 from the full model. In addition, qualitative differences exist for some variables across the four models. The results from the first two models show that high repayment frequency is associated with higher repayment rate while the third model and the full model show the opposite. This suggests that without controlling for peer effect and unobserved heterogeneity, there may exist large inconsistency in the estimated effects of observed household demographics as well as loan characteristics.

The estimated effects of most other variables on repayment rate are intuitively signed from the full model. The results in tables 2 and 3 show that that being very poor, belong to lower tribe or caste, and living in a kutcha house (e.g., a house made of dry grass) are associated with lower probability of full repayment, while being self-employed agricultural worker, smaller loan size, lower interest rate as well as shorter loan duration are all associated with higher probability of full repayment.

4.2 Caveats and Robustness Analysis

Two caveats are worth mentioning regarding our empirical analysis. The first one, common in empirical studies of games, concerns possible multiple equilibria. As discussed in section 3, the possibility of multiple equilibria poses significant empirical challenge because without an equilibrium selection mechanism, the likelihood is not well-defined in the presence of multiple equilibria. Moreover, incorporating the algorithm of finding all possible multiple equilibria (e.g., all solution homotopy method) in the estimation could a daunting task because it has to be done for each random draw for each loan in each parameter iteration. We follow the literature and assume that only one equilibrium is played in the data. In practice, we draw the starting values (the length of the vector equals to the number of participating households in the group) for the fixed point algorithm randomly from the uniform distribution. Nevertheless, the starting values are fixed across parameter iterations. The algorithm stops once it reaches a fixed point, which is assumed to be the equilibrium played in the data. To check the robustness of the solution to the starting value (hence the equilibrium selected in case of multiple equilibria), we re-estimate the model twice with the starting value being a vector of ones as well as a vector of zeros. The parameter estimates and the estimated total partial effects are reported in columns 2 and 3 in Table 4. They are almost identical to the results reported in Table 3. In light of the simulation result in Bajari et al. (2006) that the likelihood of multiple equilibria decreases dramatically with the number of players, our robust analysis suggests that the effect of multiple equilibria on our empirical results is likely to be insignificant.

The second caveat is with respect to the assumption that the group-level common unobservable is uncorrelated with observed variables such as household characteristics and loan characteristics. The causal interpretation of these variables on the repayment rate hinges on this assumption. However, the assumption could be violated if for example, group formation is based on some unobservables and these unobservables also affect the repayment rate directly (i.e., not through peer effect term). Recognizing that modeling group formation necessitates richer data (such as non-participants of group lending) than we have and that our main interest in this paper is in peer effect, a conservative approach is to take the estimated relations as correlation and view these variables just as controls of individual as well as group-level (observed and unobserved) characteristics.

In addition to the robustness analysis regarding possible multiple equilibria, we also perform the following robustness checks. The results for the full model reported in Table 3 are based on 64 points Gauss-Hermite approximation for the joint probabilities defined in equation (9). The results based on 56 points approximation, listed in column 4 of Table 4, are very similar to those in Table 3. We note in passing that we find that the 64 points Gauss-Hermite approximation for the joint probability is closer to the simulated joint probability based on 5000 randomized Halton draws (i.e., could be viewed as the truth) than the approximation based on 150 randomized Halton draws for some randomly selected groups with the estimated parameters. These findings suggest that the simulated method exhibits good numerical properties.

The last robustness check is with respect to the assumption about the unobserved heterogeneity. In previous estimations, we have assumed that households participating in each loan face a common unobservable. In our data, we observe multiple loans for some groups, although the loans are not necessarily among same households. We re-estimate the model assuming a common unobservable among the households in the same group even if they may participate in different loans. That is, we now assume the unobservable is at the group-level rather than at the loan-level. The estimation results are listed in the last column of Table 4. With unobservables being at the group level, the total partial effect of $E(P_{-i})$ is now estimated at 0.193 instead of 0.154 while the average treatment effect is 0.209 instead of 0.148 when unobservables are assumed to be at the loan level.

5 Conclusion

Despite the common belief that peer effects play an important role in group lending by mitigating the moral hazard problem, how big the effects are has remained to be an answered question. We address this question by modeling members' repayment decisions in group lending as a static game of incomplete information where group members make their repayment decision simultaneously based on their individual characteristics, loan characteristics, as well as the expectation on other members' repayment decisions. We estimate the empirical model using a simulated maximum likelihood method with a nested fixed point algorithm. Using a rich member-level data set from a microfinance program in India, we find large and positive peer effects: everything else being equal, the likelihood of a member making a full repayment would be 15 percent higher on average if all the other members in the group repay in full compared to the case where none of the other members makes full repayment. Since our empirical model takes group formation as given, the above effect can be interpreted as an average treatment effect on the treated, i.e., those who participate in group lending.

This paper is a first attempt to use a game-theoretical framework to empirically investigate the effects of different mechanisms on the performance of group lending programs. Our structural analysis demonstrates the importance of implicit modeling of strategic interactions inherent in group lending programs as well as how recent empirical advances in estimating discrete choice games can be employed in this line of research. There are many interesting questions yet to be answered that necessitate either richer data or modeling, such as peer selection, possible heterogeneity in peer effect across groups, and the implication of such heterogeneity on group survival as well as on the design of group lending programs.

Table 1: Summary statistics for SHG and loan characteristics

Variable	Mean	S.D.
Panel 1: SHG characteristics (815 SHGs)		
number of members	12.4	2.38
percent of members who are poorest of the poor	0.261	0.337
percent of members who are poor	0.516	0.37
percent of members who are not poor	0.223	0.326
percent of members who belong to scheduled tribe/caste	0.305	0.433
percent of members who belong to other castes	0.695	0.433
percent of literate members	0.253	0.238
percent of members who have some disabled family members	0.064	0.13
percent of members who own land	0.615	0.356
percent of members who own livestocks	0.44	0.328
percent of members living in pucca house	0.405	0.351
percent of members living in semi-pucca house	0.336	0.365
percent of members living in kutcha house	0.255	0.287
percent of members who are self-employed ag. workers	0.166	0.3
percent of members who are ag. labors	0.637	0.39
percent of members who take other occupations	0.197	0.313
Located in Telangana	0.261	0.44
Located in Rayalaseema	0.378	0.485
Located in Coastal AP	0.36	0.48
Panel 2: Loan characteristics (1008 loans)		
if fully repaid by all members	0.762	
if fully repaid by some of the members	0.075	
if fully repaid by none of the members	0.163	
amount of loan (1000 rupees)	34.05	28.32
number of members who received loan	10.95	3.7
annual rate of interest	12.7	2.82
length of loan (year)	1.065	0.408
if repayment frequency at least monthly	0.974	0.159
if due in 2005	0.49	0.5
if due in 2006	0.426	0.495

Table 2: Parameter estimates

	Logit Model		Peer Effects Only		Unobservable Only		Full Model	
Member characteristics								
Dummy for poorest family	-0.315	(-0.06)	-0.269	(-0.021)	-0.352	(-0.35)	-0.387	(-0.195)
Dummy for not being poor	0.314	(-0.076)	0.252	(-0.027)	0.434	(-0.337)	0.201	(-0.223)
If scheduled tribe/caste	-0.138	(-0.06)	-0.069	(-0.013)	-1.728	(-0.284)	-0.849	(-0.216)
Any household member disabled	0.088	(-0.105)	0.129	(-0.049)	-0.33	(-0.467)	-0.272	(-0.513)
If literate	0.017	(-0.061)	-0.012	(-0.024)	-0.355	(-0.307)	-0.15	(-0.265)
If own land	0.014	(-0.059)	0.008	(-0.017)	-0.202	(-0.283)	-0.296	(-0.199)
If own livestock	-0.024	(-0.057)	-0.035	(-0.019)	-0.04	(-0.282)	-0.022	(-0.213)
If live in pucca house	-0.043	(-0.065)	-0.029	(-0.019)	0.58	(-0.311)	0.125	(-0.212)
If live in kutcha house	-0.263	(-0.067)	-0.262	(-0.025)	-0.061	(-0.356)	-0.421	(-0.249)
If self-employed ag. worker	0.211	(-0.097)	0.199	(-0.029)	0.2	(-0.476)	0.666	(-0.37)
If ag. Labor	0.118	(-0.065)	0.082	(-0.018)	-0.356	(-0.343)	0.285	(-0.276)
Loan characteristics								
Amount of loan (1000Rs)	-1.189	(-0.093)	-0.765	(-0.05)	-1.041	(-0.319)	-0.627	(-0.253)
Annual rate of interest	-0.064	(-0.01)	-0.041	(-0.003)	-0.514	(-0.045)	-0.194	(-0.038)
Length of loan (year)	-0.272	(-0.062)	-0.149	(-0.014)	-4.839	(-0.352)	-2.283	(-0.361)
Repay monthly or weekly	-0.403	(-0.198)	-0.307	(-0.049)	1.422	(-0.866)	0.954	(-0.502)
If due in 2005	-0.305	(-0.117)	-0.287	(-0.029)	-0.022	(-0.933)	0.113	(-0.696)
If due in 2006	-1.087	(-0.119)	-0.793	(-0.038)	-7.908	(-1.032)	-3.129	(-0.877)
Group location								
Located in Telangana	0.151	(-0.074)	0.068	(-0.015)	6.545	(-0.404)	3.124	(-0.552)
Located in Rayalaseema	-0.106	(-0.061)	-0.052	(-0.013)	0.855	(-0.387)	0.655	(-0.236)
Unobservables and peer effects								
s.d. of ξ					14.223	(0.778)	7.119	(1.155)
$E(P_{-i})$			2.018	(-0.176)			4.083	(-0.427)
Log-likelihood	-4999.7		-4989.4		-1064.1		-1045.2	
Pseudo R^2	0.074		0.076		0.803		0.806	

Note: In the last two specifications where common unobservables are controlled for, 64 points Gauss-Hermite quadrature are used to approximate the joint probabilities defined in equation (10).

Table 3: Partial effects

	Logit Model		Peer Effects Only			Unobservable Only		Full Model		
	PE		DPE	TPE		PE		DPE	TPE	
Household characteristics										
Dummy for poorest family	-0.045	***	-0.039	-0.059	***	-0.006		-0.005	-0.015	**
Dummy for not being poor	0.045	***	0.036	0.055	***	0.008		0.003	0.008	
If scheduled tribe/caste	-0.02	***	-0.01	-0.015	***	-0.03	***	-0.011	-0.032	***
Any household member disabled	0.013		0.018	0.028	***	-0.006		-0.003	-0.01	
If literate	0.002		-0.002	-0.003		-0.006		-0.002	-0.006	
If own land	0.002		0.001	0.002		-0.004		-0.004	-0.011	
If own livestock	-0.003		-0.005	-0.008	*	-0.001		0	-0.001	
If live in pucca house	-0.006		-0.004	-0.006		0.01	*	0.002	0.005	
If live in kutcha house	-0.037	***	-0.038	-0.057	***	-0.001		-0.005	-0.016	*
If self-employed ag. worker	0.03	**	0.029	0.043	***	0.003		0.008	0.025	*
If ag. Labor	0.017	*	0.012	0.018	***	-0.006		0.004	0.011	
Loan characteristics										
Amount of loan (1000 rupees)	-0.169	***	-0.11	-0.166	***	-0.018	***	-0.008	-0.024	**
Annual rate of interest	-0.009	***	-0.006	-0.009	***	-0.009	***	-0.002	-0.007	***
Length of loan (year)	-0.039	***	-0.021	-0.032	***	-0.083	***	-0.029	-0.086	***
Repayment frequency at least monthly	-0.057	**	-0.044	-0.067	***	0.025	*	0.012	0.036	*
If due in 2005	-0.043	***	-0.041	-0.062	***	0		0.001	0.004	
If due in 2006	-0.155	***	-0.114	-0.172	***	-0.136	***	-0.039	-0.118	***
Group location										
Located in Telangana	0.022	**	0.01	0.015	***	0.113	***	0.039	0.118	***
Located in Rayalaseema	-0.015	*	-0.007	-0.011	***	0.015	**	0.008	0.025	***
$E(P_{-i})$			**0.289**	**0.439**	***			**0.051**	**0.154**	***
ATT of peer effects				**0.383**					**0.148**	

Note: PE represents the partial effect. DPE is the direct partial effect that does not take into account the multiplier/feedback effect present in the model. TPE is the total partial effect that takes into account the multiplier effect. All partial effects are the sample averages of individual partial effects. *** indicates the parameter estimate being significant at 1 percent level while ** and * indicate the parameter estimate being significant at 5 percent and 10 percent level, respectively.

Table 4: Robustness analysis

	Robust Check 1			Robust Check 2			Robust Check 3			Robust Check 4		
	Para.	**S.E.**	**TPE**	**Para.**	**S.E.**	**TPE**	**Para.**	**S.E.**	**TPE**	**Para.**	**S.E.**	**TPE**
Household characteristics												
Dummy for poorest family	-0.387	0.245	-0.005	-0.387	0.245	-0.005	-0.373	0.197	-0.005	0.164	0.117	0.003
Dummy for not being poor	0.203	0.234	0.003	0.201	0.223	0.003	0.251	0.223	0.003	0.57	0.138	0.01
If scheduled tribe/caste	-0.849	0.22	-0.011	-0.849	0.217	-0.011	-0.866	0.214	-0.011	-0.893	0.126	-0.015
Any household member disabled	-0.272	0.464	-0.003	-0.272	0.495	-0.003	-0.291	0.203	-0.004	-0.942	0.118	-0.016
If literate	-0.155	0.259	-0.002	-0.15	0.268	-0.002	-0.021	0.211	0	-0.013	0.139	0
If own land	-0.296	0.194	-0.004	-0.296	0.2	-0.004	-0.238	0.27	-0.003	0.094	0.136	0.002
If own livestock	-0.022	0.22	0	-0.022	0.215	0	-0.262	0.457	-0.003	-0.216	0.391	-0.004
If live in pucca house	0.125	0.249	0.002	0.125	0.214	0.002	0.135	0.222	0.002	0.089	0.135	0.002
If live in kutcha house	-0.421	0.287	-0.005	-0.421	0.251	-0.005	-0.32	0.237	-0.004	-0.293	0.131	-0.005
If self-employed ag. worker	0.666	0.367	0.008	0.666	0.368	0.008	0.66	0.361	0.008	0.086	0.209	0.002
If ag. Labor	0.284	0.29	0.004	0.285	0.279	0.004	0.331	0.26	0.004	0.067	0.142	0.001
Loan characteristics												
Amount of loan	-0.627	0.248	-0.008	-0.627	0.256	-0.008	-0.635	0.235	-0.008	-1.629	0.166	-0.028
Annual rate of interest	-0.194	0.038	-0.002	-0.194	0.038	-0.002	-0.193	0.038	-0.003	-0.279	0.018	-0.005
Length of loan (year)	-2.283	0.361	-0.029	-2.283	0.361	-0.029	-2.304	0.356	-0.029	-0.875	0.085	-0.015
Repayment frequency	0.954	0.917	0.012	0.954	0.604	0.012	0.987	1.173	0.013	-0.355	0.226	-0.006
If due in 2005	0.113	0.702	0.001	0.113	0.694	0.001	0.174	0.704	0.002	-1.843	0.299	-0.031
If due in 2006	-3.13	0.886	-0.039	-3.129	0.879	-0.039	-3.191	0.87	-0.041	-3.621	0.344	-0.062
Group location												
Located in Telangana	3.124	0.592	0.039	3.124	0.554	0.039	3.182	0.557	0.041	3.404	0.189	0.058
Located in Rayalaseema	0.657	0.245	0.008	0.655	0.238	0.008	0.623	0.208	0.008	0.424	0.098	0.007
s.d. of ξ	7.119	1.163	0.09	7.119	1.16	0.089	6.854	1.067	0.087	5.221	0.218	0.089
$E(P_{-i})$	4.082	0.428	0.051	4.083	0.429	0.051	4.056	0.406	0.052	4.118	0.145	0.07
Log-likelihood	-1045.2			-1045.2			-1047.9			-1328.2		
Pseudo $\mathbf{R}^2$	0.806			0.806			0.806			0.754		
ATT of peer effects	0.148			0.148			0.146			0.209		

Note: TPE is the sample average of the total partial effect. Robust checks 1 and 2 use different starting values for the fixed point algorithm than those used to obtain the results in Table 3. Robust check 3 uses 56 points Gauss-Hermite approximation instead of 64 points. Robust check 4 assumes unobserved heterogeneity is at the group level instead of at the loan level.

References

Ahlin, C. and R. Townsend, "Using Repayment Data to Test Across Models of Joint Liability Lending," *The Economic Journal*, 2007, *117*, F11–F51.

Bajari, P., H. Hong, J. Krainer, and D. Nekipelov, "Estimating Static Models of Strategic Interactions," 2006. Working Paper.

Banerjee, A., T. Besley, and T. Guinnane, "The Neighbor's Keeper: The Design of a Credit Cooperative with Theory and a Test," *Quarterly Journal of Economics*, 1994, *109*, 491–515.

Bayer, P. and C. Timmins, "Estimating Equilibrium Models of Sorting Across Locations," *Economic Journal*, 2007, *117* (518), 353–374.

Berry, S., "Estimation of a model of entry in the airline industry," *Econometrica*, 1992, *60* (4), 889–917.

Besley, T. and S. Coate, "Group Lending, Repayment Incentives and Social Collateral," *Journal of Development Economics*, 1995, *46*, 1–18.

Bresnahan, T. and P. Reiss, "Entry and competition in concentrated markets," *Journal of Political Economy*, 1991, *99*, 977–1009.

Brock, William and Steven Durlauf, "Discrete Choice with Social Interactions," *Review of Economic Studies*, 2001, *68*, 235–260.

Coate, S. and M. Ravallion, "Reciprocity without Commitment: Characterization and Performance of Informal Credit Markets," *Journal of Development Economics*, 1993, pp. 1–24.

Conning, J., "Monitoring by Delegates or by Peers? Joint Liability Loans Under Moral Hazard," 2005. Hunter College Department of Economics Working Paper.

de Aghion, B. Armendariz, "On the Design of a Credit Agreement with Peer Monitoring," *Journal of Development Economics*, 1999, *60*, 79–104.

Ellickson, P. and S. Misra, "Supermarket Pricing Strategies," *Marketing Science*, 2008, *27:5*, 811–828.

Garikipati, S., "The Impact of Lending to Women on Household Vulnerability and Womens Empowerment: Evidence from India," *World Development*, 2008, pp. 2620–2642.

Karlan, D., "Social Connections and Group Banking," *Economic Journal*, 2007, *117*, F52–84.

McKelvey, R.D. and T.T. Palfrey, "Quantal Response Equilibrium for Normal Form Games," *Games and Economic Behavior*, 1995, pp. 6–38.

Morduch, J., "The Microfinance Promise," *Journal of Economic Literature*, 1999, *37*, 1569–1614.

Paxton, J., D. Graham, and C. Thraen, "Modeling Group Laon Repayment Behavior: New Insights from Burkina Faso," *Economic Development and Cultural Change*, 2000, *48* (3), 639–655.

Seim, Katja, "An Empirical Model of Firm Entry with Endogenous Product-Type Choices," *Rand Journal of Economics*, 2006, *37:3.*

Stiglitz, J., "Peer Monitoring and Credit Markets," *World Bank Economic Review*, 1990, pp. 351–366.

Tamer, Elie, "Incomplete Simultaneous Discrete Response Model with Multiple Equilibria," *Review of Economic Studies*, 2003, *70* (1).

Wydick, B., "Can Social Cohesion be Harnessed to Repair Market Failure? Evidence From Group Lending in Guatemala," *The Economic Journal*, 1999, *109*, 463–475.

Zeller, M., "Determinants of Repayment Performance in Credit Groups: The Role of Program Design, Intragroup Risk Pooling, and Social Cohesion," *Economic Development and Cultural Change*, 1998, *46* (3), 599–620.

Zhu, T. and V. Singh, "Spatial Competition with Endogenous Location Choices - An Application to Discount Retailing," *Quantitative Marketing and Economics*, 2009, *7* (1), 1–35.