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How Important are Peer Effects in Group Lending?

Estimating a Static Game of Incomplete Information

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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 of other members' repayment decisions. By exploiting a rich data set of a group lending program in India, our estimation results suggest that the probability of a member's making a full repayment would be 15 percentage points higher if all the fellow members were to make full repayment, compared with a scenario in which none of the fellow members were to 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 group heterogeneity.

Keywords: group lending, microfinance, peer effects, repayment

1. INTRODUCTION

This paper provides, to our knowledge, the first structural analysis of peer effects in group lending programs. We model repayment decisions of group members using a static game of incomplete information and estimate the game based on a rich data set from a microfinance program in India. Since the establishment of the Grameen Bank in Bangladesh in 1976, the practice of group lending has been widely adopted in microfinance programs in developing countries as an important tool to provide credit to the poor. Different from conventional individual lending, in group lending (or joint liability) a loan is granted to a group of borrowers and the whole group is liable for the debt of any individual 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 systems.

Numerous theoretical studies exists that aim to explain the success of group lending, most of which 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 effects. Peer effects have been intensively studied in the literature of education and social interactions, in which they are generally defined as how one's performance is affected by her peers (e.g., Henderson et al. 1978, Evans et al. 1992, Angrist and Lang 1994). Peer effects in the group lending context arise from the joint liability arrangement in which a member's utility (in terms of payoff) is determined not only by her own action but also by the fellow members' actions. Peers can affect a member's repayment decision through peer selection, peer monitoring, and peer pressure, all of which are believed to be less costly than the tools available to formal institutions in achieving 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 the more risky households out of a group lending program. Through peer monitoring, members in a group can effectively monitor others' usage of a loan and reduce ex-ante moral hazard (e.g., risky investment). Peer pressure refers to the fact that peers can exert pressure to enforce repayment and mitigate ex-post moral hazard (e.g., deliberate default). The effectiveness of these channels hinges on the premise that group members who live in close-knit poor communities can effectively identify as well as punish irresponsible members and deliberate defaulters through social penalties.[1]

Despite a rich theoretical literature, empirical work on microfinance is scant. Although researchers recognize that strategic interactions among members are a critical element in group lending programs, it has not been modeled explicitly in existing empirical studies. Most of these studies treat a group as a decision maker and employ a single-agent choice model such as a logit or a tobit model to examine how group-level characteristics affect the probability of repayment by the whole group (e.g., Sharma and Zeller 1997; Zeller 1998; Paxton et al. 2000; Wydick 1999; Ahlin and Townsend 2007). Karlan (2007) is probably the only one to explore determinants of the repayment decisions of individual members. In all these papers (including Karlan), peer effects are not estimated directly but are proxied by different measures of social ties, such as how close the group members live to one another, how well they know each other, and how closely related the members' ethnic and cultural backgrounds are.

The approach undertaken thus far in the empirical literature can probably be attributed to the following two reasons. First, incorporating strategic interactions into a discrete choice model is empirically challenging because, as to be discussed in more detail in the model and estimation section, it inevitably produces 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.

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[1] Theoretical literature also points out potential pitfalls of group lending such as bad members who get a "free ride" off good clients and may exhibit a bad influence on others, for example, 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).

Different from previous empirical studies, we explicitly model and quantify strategic interactions among group members in the repayment stage. That is, we take group formation as given and focus on peer effects that arise from peer monitoring and peer pressure. We model the repayment decisions of group members in a static game of incomplete information in which members make their repayment decisions simultaneously based on their individual characteristics (some of which are unobserved by other members) as well as their expectations of other members' repayment decisions. We estimate the game using the simulated maximum likelihood estimation method with a nested fixed-point algorithm, which recovers equilibrium repayment probabilities for all members in the game. These repayment probabilities are then used to form the likelihood function. Our estimation strategy follows the growing literature in estimating discrete choice games such as entry games in industrial organizations where one firm's payoff from entry is affected by other firms' entry decisions.[2]

By exploiting a rich data set from a group lending program in Andhra Pradesh in India, our structural estimation quantifies 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 probability that a group member would make a full repayment would be 15 percentage points higher if the member were in a group where all the fellow members repay in full than in a group where no fellow members make full repayment, *ceteris paribus*. Because the empirical model takes group formation as given, our estimate of peer effects captures the functioning of peer monitoring and peer pressure but not peer screening. Our empirical results also highlight the importance of explicitly modeling peer effects and controlling for unobserved group 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. We conclude our discussion in section 5.

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[2] To name just a few, Bresnahan and Reiss (1990) and Berry (1992) are two of the earlier studies in estimating static, discrete choice games. Recent studies include Seim (2006), Ellickson and Misra (2008), Jia (2008), and Bajari et al. (2009b).

2. BACKGROUND AND DATA

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

Group Lending and Peer Effects

The origin of group lending can be traced back to 1976 when the 2006 Nobel Peace Prize winner, Muhammad Yunus, started the Grameen Bank Project, a lending project in several villages in Bangladesh. The goal of the project is to examine the feasibility of a credit delivery system (Grameen Bank) specifically targeted to the rural poor, who often do not have financial collateral and cannot obtain credit from conventional banks. Instead of requiring collateral, this new system employs a group-based credit approach and relies on peer effects within groups to ensure repayment. The project has achieved great success in delivering credit to the poor while attaining an almost 100 percent repayment rate. The achievement of Grameen Bank in Bangladesh has inspired similar endeavors in more than 40 developing countries, including one of Bangladesh's neighbors, India.

In 1992, India's National Bank for Agriculture and Rural Development organized 500 self-help groups (SHGs) 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 2006–2007 alone (Reserve Bank of India 2008). Cumulative credit disbursed to SHGs amounted to some US$4.5 billion (or about 10 percent of total rural credit) in India (Garikipati 2008).

The SHG model in India combines savings generation and microlending with social mobilization. In this model, women who live in the same village voluntarily form SHGs with the understanding of a 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 those 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 are located in Andhra Pradesh of India. Besides thrift savings and obtaining credit, SHGs in Andhra Pradesh also work as local institutions that take over implementation of government programs in a variety of areas such as distributing subsidized rice credit, life and property insurance, pension, and so on. In Andhra Pradesh, banks carry out microfinance business in nonoverlapped territories so that a group can only borrow from one bank.[3] Moreover, a bank only allows a group to have one outstanding loan. Once a loan is obtained by a group, it is immediately allocated among the members (mostly on an equal basis) with the repayment terms (such as interest rate, length, number of installments, etc.) set by the bank. The group cannot obtain loans from the bank in the future until the group has fully repaid the 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 peers influence a member's repayment decisions (see, for example, Besley and Coate 1995; Morduch 1999; and Karlan 2007). Positive peer effects, which implies that a higher repayment rate of other members increases one's own repayment likelihood, can derive from 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 one another's usage of the funds and distinguish deliberate default from default due to irresponsible behaviors (such as investing in projects that are too risky, spending on alcohol and tobacco, etc.) from default due to unexpected negative shocks. The repaying

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[3] Only when a group cannot obtain a loan from the bank that specializes in the area where the group is located can the group apply for a loan from another bank. However, the group's chances of obtaining a loan from other banks are rather slim.

members can thus impose social penalties to increase the cost of deliberate default and default due to irresponsible behaviors. Social penalties can take the forms of despise, not providing help in their production and other activities in the future, and so on. These penalties are severe in close-knit, poor communities, where people rely on each other in their daily life and, to an even larger extent, during 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.

Nevertheless, another mechanism that has been raised in the literature (e.g., Besley and Coate 1995) can result in negative peer effects. The mechanism suggests that some "bad," nonpaying members can "free ride" off good, paying members by relying on the paying members' help to repay the loan even though they have the ability to repay on their own, that is, they would repay in individual lending. The fact that the SHGs in Andhra Pradesh also serve as the organization base for programs and activities other than group lending implies that the potential social penalties can be very severe and that the free-rider problem is likely to be small: Free-riders are likely to be kept out of the groups through the intensive peer selection process and thus lose access to other programs implemented by the groups.[4] 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.[5] In our empirical estimation, we do not restrict the direction of peer effects a priori. 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 other mechanisms if it even exists at all.

Data

The data are from an SHG survey of 815 groups in Andhra Pradesh in India. In this survey, all loans taken by each group and by each member of the 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 a whole, as well as how the loan was allocated among group 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 which had passed their due date by the time of the survey. Panel 1 of Table 1 presents summary statistics for member characteristics of the 815 groups, and Panel 2 summarizes terms of the 1,008 loans. The SHGs have 12 members on average, with the smallest group having 7 members and the largest having 20 members. About 26 percent of the members are from very poor households, 52 percent from poor households, and 22 percent from middle-class households.[6] About 31 percent of the members belong to scheduled tribe or scheduled caste, and 25 percent are literate. About 6.5 percent are disabled or have family members who are disabled; 41 percent live in pucca houses, 33 percent live in semi-pucca houses, and 26 percent live in kutcha houses.[7] About 64 percent are agricultural laborers (i.e., they do not own land or own such a small amount of land

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[4] These programs include the Rice Credit Line program that provides in-kind credit for subsidized rice, pension program, job training program, and so forth.

[5] There are about 20–40 SHGs in each village in Andhra Pradesh.

[6] 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. The manual used in the process defines very poor as those who can eat only when they get work; lack shelter, proper clothing, and 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 middle class have some land and proper shelter, are recognized in society, have access to bank credit as well as public services, and can send their children to school.

[7] A pucca house has walls and a roof made of material such as burnt bricks, stones, cement concrete, and timber; but a kutcha house use less-sophisticated material such as hays, bamboos, mud, and grass.

that they have to provide agricultural labor 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.

Table 1. Summary statistics of dependent and explanatory variables

Variable	Mean	SD
Panel 1: SHG characteristics (815 SHGs)		
Number of members	12.40	2.38
Percent of members who are poorest of the poor	0.261	0.337
Percent of members who are poor	0.516	0.370
Percent of members who are of middle class	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	0.130
Percent of members who own land	0.615	0.356
Percent of members who own livestock	0.440	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 agricultural workers	0.166	0.300
Percent of members who are agricultural laborers	0.637	0.390
Percent of members who take other occupations	0.197	0.313
Located in Telangana	0.261	0.440
Located in Rayalaseema	0.378	0.485
Located in Coastal Andhra Pradesh	0.360	0.480
Panel 2: Loan characteristics (1,008 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 (1,000 rupees)	34.05	28.32
Number of members who received loan	10.95	3.70
Annual rate of interest	12.70	2.82
Length of loan (year)	1.065	0.408
If repayment frequency at least monthly	0.974	0.159
If due in 2005	0.490	0.500
If due in 2006	0.426	0.495

Note: S.D., standard deviation.

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 group loans, 76 percent were fully repaid by all members to whom the loan was allocated, 7.5 percent were fully repaid by some members but defaulted by others, and 16.3 percent were defaulted by all members. The average loan size is 34,000 rupees (about US$682), and a loan is allocated to 11 members, on average. The average annual rate of interest is 12.7 percent, and the average duration of a loan is about a year. The majority of loans (97 percent) require the groups to make repayment at least monthly if not more frequently.

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.

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 or more members fail to make repayment. We index group loan by g and member (i.e., a household) by i. We denote the choice set of a member in group loan g by $A_{gi} = \{0,1\}$, where 1 represents a full repayment and 0 otherwise. Let the Cartesian product $A_g = \times_i A_{gi}$ denote the possible actions of all borrowers 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 $x_g = \{x_{g1}, x_{g2}, \ldots, x_{gN_g}\}$ denote the characteristics of all participating members in the loan. We assume that x_g is observed by all members in the group. However, we allow that some components of x_g are not observed by researchers.

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

$$U_i(a_i, a_{-i}, x_i, \varepsilon_i) = U_i(a_i, a_{-i}, x_i) + \varepsilon(a_i),$$
(1)

where a_i is the action taken by member i, and a_{-i} is a vector of actions of other members in the same loan. $\varepsilon(a_i)$ is a stochastic preference shock that is additively separable in the utility function as in a standard random utility model. We assume that $\varepsilon(a_i)$ is observed only by member i. 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 $\varepsilon(a_i)$ 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 $a^* = (a_1^*(\varepsilon_1), a_2^*(\varepsilon_2), \ldots, a_N^*(\varepsilon_N))$, where $a_i^*(\varepsilon_i) \in \{0,1\}$ maximizes the expected utility,

$$U_i(a_i, x, \varepsilon_i) = \int U_i(a_i, a_{-i}^*(\varepsilon_{-i}), x) f(\varepsilon_{-i}) d\varepsilon_{-i} + \varepsilon_i,$$
(2)

for any $i \in \{1, 2, \ldots, N\}$.

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., $\varepsilon(a_i = 1) - \varepsilon(a_i = 0)$ in previous notations) has a logistic distribution. We further specify the utility function to take the following linear form:

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

Because of the normalization, the above function captures how member i's utility difference between the two choices—repay in full or default—is 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 repayment. Following the literature of education and social interactions (e.g., Brock and Durlauf 2001; Cooley 2006), we use this term to capture peer effects that arise through multiple channels as discussed earlier. For example, since the default of member i can hinder 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. The cost of default (or the benefit of repayment) of member i should be higher when more other members choose to repay, *ceteris paribus*. Although this suggests positive peer effects and hence complementarity among group members in making full repayment, the free-rider problem 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:

$$U_i(a_i = 1, x, \varepsilon_i) = E_{a_{-i}}[U_i(a_i = 1, a_{-i}, x, \varepsilon_i) \mid x]$$

$$= \gamma \frac{1}{N-1}\sum_{j\neq i} E(a_j \mid x) + x_i\beta + \varepsilon_i$$

$$= \gamma \frac{1}{N-1}\sum_{j\neq i} \text{Prob}(a_j = 1 \mid x) + x_i\beta + \varepsilon_i.$$

(4)

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

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

(5)

where $P_i = \text{Prob}(a_i = 1 \mid x)$. Note that the logit form of the choice probability as in a logit model follows the assumption that ε_i has a logistic distribution. 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 $M(.):[0,1]^{N_g} \rightarrow [0,1]^{N_g}$ 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.

Estimation Strategy

There are several challenges in taking the choice probabilities defined by equation (5) to the data. First, some variables that affect individual payment decisions (e.g., components of x_g), though observed by group members, could be unobserved by researchers. These unobservables may include group solidarity and

reciprocity, as well as weather conditions. It is important to incorporate these unobservables in the empirical analysis for the following reasons. The information advantage of group members over outsiders and lenders, in addition to being plausible, is essential in justifying the idea of group lending (i.e., versus individual lending). More importantly, failure to control for these unobservables would lead to overestimation of the importance of peer effects in increasing the repayment rate. For example, in the event of a group's suffering from a common negative shock (e.g., an adverse weather condition), we would wrongly attribute the lowered repayment of a member to peer effects without controlling for the common shock. In our estimation, we allow loan-level or group-level unobservables to be represented by a single variable, ξ_g. With group loan index g reintroduced, the expected utility function of member i can be written as

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

(6)

where $x_{gi} = \{z_{gi}, \xi_g\}$. z_{gi} is the part of x_{gi} that is observable to researchers. It includes both household characteristics and group- and loan-level variables. The ex ante choice probability of member i becomes

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

(7)

Since ξ_g is unobservable to researchers, the above choice probabilities cannot be directly taken to the data. As it turns out, the way to deal with the common unobservable is closely related to the next empirical challenge.

The second empirical challenge is fundamental in incorporating strategic interactions into the discrete choice model, and it lies in the fact that one of the explanatory variables is unobserved: member i's expectation about the average repayment rate among all the fellow members $E(P_{g,-i}) = \frac{1}{N_g-1}\sum_{j \neq i} P_{gj}$. 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, the standard instrumental variable method cannot be applied to deal with the endogeneity problem. Bajari et al. (2009b) propose a two-step estimator to address this problem. The key idea is to note that in the absence of unobserved group heterogeneity (ξ_g), the choice probabilities are determined by z_g only in the equilibrium, albeit via a nonanalytical form. In principle, a consistent estimate of the choice probabilities can be obtained based on z_g through a flexible estimation method (e.g., nonparametrically) in the first step, and these estimates can then be plugged in to the right side of 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 group-level unobservables exist, because consistent estimates of choice probabilities cannot be obtained based on only z_g in that case. In order to make the two-step method applicable in the presence of unobserved heterogeneity, Bajari et al. (2009b) make the assumption that the group-level unobservable has a fixed effects presentation and is an unknown, but smooth, function of the observed 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 z_g, and that $\xi_{gi} \sim N(0, \sigma^2)$ is independent and identically distributed across loans. It is worth noting that,

different from the random effects model without strategic interactions where the unobservable is assumed to be uncorrelated with all explanatory variables, the common unobservable ξ_g in our model is nevertheless correlated with the key explanatory variable $E(P_{g,-i})$, which is an equilibrium outcome. For a given set of parameters and a random draw for each group loan g, a fixed-point algorithm based on equation (7) can be used to recover the choice probabilities for all the members in the group. These probabilities can then be used to form the (simulated) likelihood function. The estimation strategy is a maximum simulated likelihood method with a nested fixed-point algorithm. 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.[8] 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 Bajari et al. 2009b). The likelihood function can then be formed based on all the recovered equilibria and a specified equilibrium selection mechanism. However, this method is very computationally intensive, if not practically infeasible for our data, given the significant time needed to find all equilibria especially in games with a small number of players, the large number of random draws to deal with common unobservables, and the large number of groups. Instead, we follow one of the approaches in 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). This approach specifies which type of equilibrium (such as random or extremal equilibria) is picked in the empirical model. Robustness analysis with respect to this assumption is provided below.

We note in passing that two alternative empirical approaches to deal with multiple equilibria have been proposed recently, both in the context of discrete games of complete information. As an alternative to point identification, Tamer (2003) develops bounds estimation based on the necessary conditions for pure strategy Nash equilibria. Bajari et al. (2009a) proposes an approach where an equilibrium selection mechanism is estimated together with utility parameters and all equilibria including those of mixed strategies are computed. Although both approaches are very promising, the computational burden can become prohibitive as the number of players becomes larger than 5 (the number of players ranges from 2 to 25, with the mean being 12 in our data). For example, Ciliberto and Tamer (2009) apply the bounds approach to examine the strategic behavior of four airlines. Bajari et al. (2009a) find that it takes up to 20 minutes for the central processing unit on a 3.0 GHz single processor workstation to compute all Nash equilibria and focus on four large firms in their empirical example.[9] From an alternative angle, Goldfarb and Xiao (2009) provide a strategy to avoid multiple equilibria in empirical work. Following cognitive hierarchy models in behavior game theory, they allow for heterogeneity in the ability of players to correctly conjecture competitor behavior in entry games. By revising the behavioral assumption from complete to limited rationality in decision making, their empirical model yields a unique outcome.

To illustrate our estimation strategy, let y_{gi} denote the repayment outcome of gi and $\xi_g = \sigma * v_g$, where v has an independent and identically distributed (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 v is:

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

[9] It is interesting to note that the simulation results in Bajari et al. (2009b) show that the number of equilibria decreases with the number of players in static games of incomplete information.

$$P(y_{g1}, y_{g2}, \ldots, y_{gN_g} \mid z_g, v_g)$$
$$= P(a_{g1} = y_{g1}, a_{g2} = y_{g2}, \ldots, a_{gN_g} = y_{gN_g} \mid z_g, v_g)$$
$$= P(a_{g1} = y_{g1} \mid z_g, v_g) P(a_{g2} = y_{g2} \mid z_g, v_g) \ldots P(a_{gN_g} = y_{gN_g} \mid z_g, v_g), \tag{8}$$

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

$$P(y_{g1}, y_{g2}, \ldots, y_{gN_g} \mid z_g) = \int P(y_{g1}, y_{g2}, \ldots, y_{gN_g} \mid z_g, v_g) f(v_g) dv_g. \tag{9}$$

The above joint probability can be approximated by

$$\widetilde{P}(y_{g1}, y_{g2}, \ldots, y_{gN_g} \mid z_g) = \sum_{r=1}^{R} P(y_{g1}, y_{g2}, \ldots, y_{gN_g} \mid z_g, v_g^r) w^r, \tag{10}$$

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

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

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, imagine that there are two households that are identical except for a difference in group loans, and further assume there are no common unobservables to ease exposition. The repayment decisions of the two households may be different solely due to a difference in the repayment rate of the peers in the two loans. Intuitively, peer effects are identified from the difference in the two households' repayment decisions in relation to other members' repayment decisions. In the presence of common unobservables, the group loans with members who make different repayment decisions (7.5 percent of the loans in the data) are essential because the model would not be identified without these loans. For example, drivers of any given group's members making the same decisions in the data could be very large positive shocks for the groups with full repayment and very large negative shocks for the groups that default, even for different sets of parameters θ. Similarly, if we were to allow group-level or loan-level fixed effects, these fixed effects could perfectly predict the outcomes.

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.

Results

We estimate our empirical model defined by equations (6) and (7) using the simulated maximum likelihood estimation method with a nested fixed-point algorithm. For a given set of parameters and a random draw of v_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 computational burden, we use Gauss–Hermite quadrature to approximate the joint probabilities in equation (10), where v_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 tradeoff between approximation accuracy and computational 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 parentheses) for several specifications. The results for the preferred specification are in the last column, labeled Full Model, 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 is a logit model with neither peer effects nor unobserved heterogeneity. The second alternative model has the peer effect term but no unobserved heterogeneity (see Peer Pressure Only column), and the third alternative model controls for unobserved heterogeneity but not peer effects (Unobservables Only column). In all 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 Peer Pressure Only and Unobservables Only 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 the same repayment choices. The peer effect term also improves the fitness of the model, and its coefficient estimate is positive and statistically significant in both the Peer Effect Only Model and Full Model.

      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.[10] For the two models with the peer effect term, Peer Pressure Only and Full Model, 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 (the 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 its repayment propensity but also have an indirect effect through its influence on other households in the loan. For instance, the direct and total partial effects of a very poor household on loan repayment are estimated at –0.005 and –0.015, respectively, in the full model.

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

Table 2. Parameter estimates (and standard errors)

	Logit Model		Peer Pressure Only		Unobservables Only		Full Model	
Member characteristics								
Dummy for poorest family	−0.315	(0.06)	−0.269	(0.021)	−0.352	(0.350)	−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)	−0.330	(0.467)	−0.272	(0.513)
If literate	0.017	(0.061)	−0.012	(0.024)	−0.355	(0.307)	−0.150	(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)	−0.040	(0.282)	−0.022	(0.213)
If live in pucca house	−0.043	(0.065)	−0.029	(0.019)	0.580	(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 agricultural worker	0.211	(0.097)	0.199	(0.029)	0.200	(0.476)	0.666	(0.37)
If agricultural laborer	0.118	(0.065)	0.082	(0.018)	−0.356	(0.343)	0.285	(0.276)
Loan characteristics								
Amount of loan (1,000 rupees)	−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								
Standard deviation of common unobservables					14.223	(0.778)	7.119	(1.155)
$E(P_{-i})$			2.018	(0.176)			4.083	(0.427)
log-likelihood	−4999.74		−4989.38		−1064.05		−1045.21	
Pseudo_R2	0.074		0.076		0.803		0.806	

Table 3. Partial effects

	Logit Model		Peer Pressure Only			Unobservables 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	−0.020	***	−0.01	−0.015	***	−0.030	***	−0.011	−0.032	***
Any household member disabled	0.013		0.018	0.028	***	−0.006		−0.003	−0.010	
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		0.000	−0.001	
If live in pucca house	−0.006		−0.004	−0.006		0.010	*	0.002	0.005	
If live in kutcha house	−0.037	***	−0.038	−0.057	***	−0.001		−0.005	−0.016	*
If self-employed agricultural worker	0.030	**	0.029	0.043	***	0.003		0.008	0.025	*
If agricultural laborer	0.017	*	0.012	0.018	***	−0.006		0.004	0.011	
Loan characteristics										
Amount of loan (1,000 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	***
Repay monthly or weekly	−0.057	**	−0.044	−0.067	***	0.025	*	0.012	0.036	*
If due in 2005	−0.043	***	−0.041	−0.062	***	0.000		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$_{-i}$)			**0.323**					**0.0895**		

Note: PE, partial effect; DPE, direct partial effect, which does not take into account the multiplier/feedback effect present in the model; TPE, total partial effect, which takes into account the multiplier effect. All partial effects are the sample averages of individual partial effects.

* parameter estimate significant at 10 percent level

** parameter estimate significant at 5 percent level

*** parameter estimate significant at 1 percent level

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 the 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. It should be larger than the direct partial effect if the peer effect term has a positive coefficient and lower than the direct partial effect otherwise. Based on our model estimation, the total partial effect of the wealth status changing from poor to 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 analyses 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 peer effect variable is 0.154, comparing the direct partial effect of 0.051. To understand this estimate, imagine a group with 11 members: Members 1 to 10 receive positive shocks (e.g., an increase in ε_{gi}) such that each one's repayment probabilities increases by 0.1 holding other factors constant; therefore, for Member 11, $E(P_{-1})$ increases by 0.1. As a result, the repayment probability of Member 11 in the new equilibrium will increase by 1.54 percent according to our estimate.

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 fellow members repaying in full, compared with her being 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 $E(P_{-i}) = 0$, compared with 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 include information only 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.

The comparison of the partial effects between the Peer Pressure Only model and the Full Model highlights the importance of controlling for unobserved heterogeneity. In the Peer Pressure Only model, where unobserved heterogeneity is not controlled for, the total partial effect of peer effects on loan repayment is 0.439, compared with 0.154 in the Full Model. Similarly, the average treatment effect is 0.383 in the Peer Pressure Only model, while it is estimated at 0.148 in the Full 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 a poverty status of very poor in the three alternative models is –0.045, –0.059, and –0.006, compared with –0.015 in the Full Model. In addition, qualitative differences exist for some variables across the four models. The results from the Logit Model and the Peer Pressure Only model show that high repayment frequency is associated with higher repayment rate, while the Unobservables Only Model and the Full Model show the opposite. This suggests that without controlling for peer effect and unobserved heterogeneity, a large inconsistency may exist 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 being very poor, belonging to a scheduled tribe or caste, and living in a house of low quality (kutcha house) are associated with lower probability of full repayment; but being a self-employed agricultural worker and having a smaller loan size, lower interest rate, and shorter loan duration are all associated with higher probability of full repayment.

Discussion 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 a 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 methods) in the estimation will be prohibitive because it has to be done for a large number of random draws for each loan. 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 equal 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. This amounts to assuming that only extremal equilibrium (i.e., the one with the highest or lowest group repayment rate) will be selected. 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. (2009b) that the likelihood of multiple equilibria decreases dramatically with the number of players, our robustness analysis suggests that the effect of multiple equilibria on our empirical results is likely to be insignificant.

The second caveat regards 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. Therefore, a cautious approach is to interpret the estimated effects of observed household and loan characteristics on repayment decisions as correlation rather than causality. However, since our main interest in this paper is in peer effect, we re-estimate the model using different sets of explanatory variables to check the robustness of our estimate for peer effect term. All of them yield very close results.[11]

In addition to the robustness analysis regarding possible multiple equilibria and various sets of explanatory variables, 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 5,000 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, though the loans are not necessarily among the 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 when unobservables are assumed to be at the loan level.

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[11] The estimates of the total partial effect of the peer effect term range from 0.140 to 0.160 for four different sets of explanatory variables. Estimation results are available upon request.

Table 4. Robustness analysis

	Start Value 1			Start Value 0			56 Points' Approximation			Group-level Heterogeneity		
	Coeff.	S.E.	TPE	Coeff.	S.E.	TPE	Coeff.	S.E.	TPE	Coeff.	S.E.	TPE
Member 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 agricultural 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 agricultural laborer	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 (1,000 rupees)	−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
Repay monthly or weekly	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

Table 4. Continued

	Start Value 1			Start Value 0			56 Points' Approximation			Group-level Heterogeneity		
	Coeff.	S.E.	TPE	Coeff.	S.E.	TPE	Coeff.	S.E.	TPE	Coeff.	S.E.	TPE
Unobservables and peer effects												
Standard deviation of common unobservables	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_R2	0.806			0.806			0.806			0.754		

Note: Coeff, coefficient; S.E., standard error; TPE, total partial effect.

5. CONCLUSION

Despite the common belief that peer effects play a significant role in mitigating the moral hazard problem in group lending, how quantitatively important those effects are has remained an unanswered 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 decisions simultaneously based on their individual characteristics and loan characteristics, as well as the expectation of other members' repayment decisions. Using a rich member-level data set from a group lending program in India, we find large and positive peer effects: Everything else being equal, the probability of a member's making full repayment would be 15 percentage points higher on average if all the other members in the group repay in full compared with a scenario in which none of the other members makes full repayment.

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 explicit 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 dynamic modeling. These questions include peer selection, possible heterogeneity in peer effects across groups, and the implication of such heterogeneity on group survival as well as on the design of group lending programs.

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