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Does Microfinance Reduce Poverty in India?

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Does Microfinance Reduce Poverty in India?[1]

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Abstract

Drawing upon national household data from 2001, the present study analyses the impact of access to Micro Finance Institutions (MFIs) on household poverty in India. Propensity score matching (PSM) and the treatment effects model are employed to estimate the poverty-reducing effects of access to MFIs and loans from them used for productive purposes, such as investment in agriculture or non-farm businesses. These models take into account the endogenous binary treatment effects and the sample selection bias associated with access to MFIs. Despite some limitations e.g. those arising from the unobservability of potentially important determinants of access to MFIs, significantly positive effects of MFI access on the multidimensional welfare indicator were confirmed by both models, implying a poverty reducing role for MFIs. We found that loans for productive purposes were more important in poverty reduction in rural than in urban areas. We also show that, in urban areas, significant poverty reducing effects of MFIs are observed only for the moderately poor, not for the poor , while they are significant for both groups in rural areas.

Key Words: Microfinance, Poverty, Evaluation, India, Propensity Score Matching
JEL Classification: C21, I30, I38, O16, R51

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Does Microfinance Reduce Poverty in India?

I. Introduction

In most parts of the world the microfinance sector is adopting a financial systems approach, either by operating on commercial lines or by systematically reducing reliance on interest rate subsidies and/or aid agency financial support (Hulme and Arun 2009). The financial systems approach supports the argument that microfinance institutions should aim for sustainable financial services to low income people, which may risk undermining the potential of this institutional innovation for poverty reduction and social empowerment. Irrespective of the renewed emphasis on the financial systems approach, over the years, many Micro Finance Institution (MFIs) have developed a range of services to address the requirements of the poor, such as the Income Generation for Vulnerable Group Development (IGVGD) programme of BRAC, Bangladesh. Using household level panel data in Bangladesh, Khandker (2005) confirms that microfinance programmes have a sustained impact in reducing poverty among the participants and a positive spill over effect at village level. The results of this study indicate that microfinance programmes not only help the poor or redistribute income but also contribute to national economic growth.. However, some studies have shown that MFIs have not reached the poorest of the poor in Asian countries (Weiss, Montgomery, and Kurmanalieva 2003) or in Bolivia (Mosley 2001). The relationship between microfinance and poverty is still in question and this paper provides further empirical evidence on the poverty-reducing effects of MFIs.

The development of the microfinance sector is based on the concept that the poor possess the capacity to implement income generating activities but are limited by lack of access to, and inadequate provision of, savings, credit and insurance facilities. However, there are concerns about the ability of microfinance institutions to provide services and products to the poorest of the poor (Hulme and Mosley 1996). The real challenge in serving the poorest of the poor is to identify who might benefit from stand-alone financial services or from non financial services with or without finance, before participating in market oriented finance (Meyer 2002). The recent literature suggests the need for microfinance institutions to move away from being product-based organizations to reflect the heterogeneity of the demand structure for financial services/products by poor people and their complex livelihood needs (Arun and Hulme 2003). To capture the multi-dimensional aspect of poverty, such as basic needs, wealth, type of housing, job security, sanitation and food security, this study uses Index Based Ranking (IBR) Indicators based on a national-level household survey to examine the role of microfinance in poverty reduction in India.

In India, despite recent economic growth at national level[2], poverty remains a serious problem for policy-makers because this growth is mainly driven by growth in a few sectors in urban areas, such as industry and service sectors[3]. The incidence of poverty in India is estimated by quinquennial large sample surveys on household consumption and expenditure and, according to the Uniform Recall Period (URP) consumption distribution data in 2004-05, poverty strands at 28.3 per cent in rural areas , 25.7 per cent in urban areas and 27.5 per cent for the country as a

[2] For example, real GDP grew by 9.4 percent in 2006/2007.

[3] The average annual output growth rates in industry and services sectors in the period 1994-2004 are 5.6% and 8.2% respectively, while that in the agricultural sector is 2.0% (based on World Bank Data in 2005 taken from http://devdata.worldbank.org/AAG/ind_aag.pdf~~)~~. The poverty head count ratio has been much higher in rural areas than in urban areas (e.g. Deaton and Kozel 2005 and Sen and Himanshu 2004).

whole (Government of India, 2008). Although the proportion of persons below the poverty line has declined from around 36 per cent of the population in 1993-94 to 28 per cent in 2004-05, poverty reduction remains the country's major challenge in the 21st century.

Until the early 1990s, financial services were provided through a variety of state sponsored institutions, which resulted in impressive achievements in expanding access to credit particularly among the rural poor (Arun and Mosley 2003). Although many of these commercial bank branches in rural areas were unprofitable, they played a positive role in financial savings and reducing poverty which is evident from the fact that during the period 1951-1991 the financial institutions' total share in rural household debt increased from 8.8 per cent to 53.3 percent and the role of money lenders declined significantly (Arun and Mosley 2003; Basu and Srivastava 2005). However, despite the vast network of banking and cooperative finance institutions and strong micro components in various programmes, the performance of the formal financial sector still fails to adequately reach out to, or reflect and respond to the requirements of, the poor.

In the 1990s, MFIs became increasingly important in India mainly due to their better access to local knowledge and information at community level and their use of peer group monitoring. For example, microfinance programmes involving SHGs (Self-Help Groups), which are based on the existing banking network in delivering financial services to the poor, have become increasingly important in India due to their flexible nature (Mosley and Arun 2003). SHGs are built on the traditional institution of ROSCA (Rotating Savings and Credit Associations) and provide access to both savings and credit for the assetless poor. A recent study in Pune district in Maharashtra showed that while the targeting performance of microfinance through SHGs was unsatisfactory in terms of income, it was satisfactory in terms of caste, landlessness and illiteracy and thus facilitated the empowerment of women (Gaiha and Nandhi

2007). This study also found that loans were used largely for children's health and education and argued against restricting the impact assessment of microfinance to conventional economic criteria alone.

Despite MFIs' increasing involvement in poverty reduction in India, there have been relatively few studies that evaluate their impact. The present study aims to provide empirical evidence on the relationship between MFIs and poverty in India using a large-scale household data set which was collected with the intention of assessing the impact of microfinance. In our study, poverty is defined by the 'IBR (Indexed Based Ranking) Indicator', a composite indicator that captures various aspects of wellbeing, including land holdings, salaried income sources, livestock, transport assets, housing, and access to sanitation facilities[4]. Our research question is simple - whether access to MFIs reduces poverty. A simple comparison of the average of the IBR indicator for households with access to MFIs and those without is not appropriate. Firstly, MFIs are not randomly distributed due to endogenous programme placement where MFIs target poor households or poor households tend to take loans from, or save at MFIs (EDA Rural Systems 2005). Furthermore, there are self-selection problems associated with participation in microfinance programmes. That is, within the area where microfinance is available, individuals with similar characteristics (e.g. education or age) might have different levels of entrepreneurial spirit or ability, which may lead to different probabilities of their participating in the scheme. Hence it is necessary to take into account self-selection problems or the endogeneity associated with participation in microfinance programmes.

To address at least partly the sample selection problem, we apply propensity score matching (PSM) and the treatment effects model, a version of the Heckman sample selection

[4] See Sinha (2003) for the conceptual framework of IBR indicator.

model (Heckman, 1979), to the same household data. PSM first uses a probit or logit model to estimate a function matching the proximity of one household to another in terms of household characteristics and then groups households to minimize the distance between matched cases. While it has some advantages over the IV (instrumental variable) model (e.g. not requiring the instrument or linearity as in the IV model), the sample selection bias would not be entirely corrected if there were important unobservable variables which affected the household decision to participate in the programmes (e.g. health, intra-household bargaining, cultural or psychological factors not found in the data). The treatment effects model also estimates the probit model with the same specification as in the first stage of PSM. In the second stage, the IBR indicator, our proxy for poverty, is estimated by OLS while sample selection is corrected by using estimates of the probability of participation in microfinance programmes. The model is fitted by a full maximum likelihood (Maddala, 1983). The merits of the treatment effects model over PSM include that (i) the degree of sample selection bias is explicitly taken into account and (ii) the determinants of the dependent variable in the second stage are identified. However, the treatment effects model imposes strong distributional assumptions for the functions in both stages and the final results are highly sensitive to the choice of explanatory variables and the instrument. The presence of unobservable variables would also affect the results as in PSM. Given these limitations, applying different models is useful as each model serves to check the robustness of the results derived by the other.

The rest of the paper is organised as follows. Section II summarises the survey design and data. Section III describes the econometric methodologies which we have used to estimate PSM and the Treatment effects model. Section IV provides the econometric results and main findings. The concluding remarks are given in the final section.

II. Survey Design and Data [5]

Details of Survey

The original survey was carried out by EDA Systems for the SIDBI (Small Industries Development Bank of India) in 2001 as a part of SIDBI's impact assessment study of its micro finance programme. This cross-sectional socio-economic research was undertaken to assess, on a national scale, the development impact of MFI programmes. The study covered a sample of 20 of SIDBI's partner Micro Finance Institutions (MFIs) and a sample of 5260 households distributed across different and diverse regions of India, including both clients and non-clients (EDA Systems 2005; SIDBI 2005). Our study is based on the cross-sectional data set for these households.

The hypothesis of our study is: 'access to microfinance institutions (MFIs) reduces poverty'. Five types of MFI were selected as representative of 31 MFIs in SFMC[6]'s list of current partners - representing different regions and models of microfinance (Self Help Group (SHG), Grameen, Individual Banking and sector/enterprise specific cooperatives), age, outreach to members and range of services. At each MFI, two to four sample areas (villages or urban wards) were purposefully selected to represent a typical area of the MFI in terms of the socio-economic context and range of MFI programmes. Within each sample area, a stratified random sample of clients, non-clients and dropouts was drawn using wealth ranking as a basis for stratification (EDA Systems 2002, 2005). The ratio of non-client households to MFI client

5 This section is based on EDA Systems (2002, 2005), SIDBI (2005) and Sinha (2003).

6 It stands for SIDBI (Small Industries Development Bank of India) Foundation for Micro Credit.

households was set at 1:2.75 for most of the villages. This ratio was chosen to reflect the average non-client to client ratio of the population in the village or the urban wards where microfinance programmes were in operation. For each group of clients in the program area, an appropriate number of non-client households with similar characteristics (based on wealth, social group or female-headedness) were chosen in the same program area as a comparison group. It might have been better to choose non-clients outside the programme area because of the indirect effects of MFIs on non-clients, but due to time-constraints this was not possible. However, our approach has advantages, because, for example, clients and non-clients have similar environments as they were sampled in the same area.

Index Based Ranking (IBR) Indicators

Index Based Ranking (IBR) Indicators were created to overcome any limitations of the income or consumption based poverty measures and to capture non-income or multi-dimensional dimensions of poverty, such as basic needs, wealth, type of housing, job or employment security, sanitation, and food security (Sihna 2003). A score index, such as IBR, is useful to capture various dimensions of poverty because of its higher practicality (e.g. less costly than those for expenditure surveys; based on less-sensitive /obtrusive and simpler questions) and higher reliability due to lower risk of falsification or error. Respondents are asked about their quality of life in several dimensions and then IBR indicators are created as a weighted sum of scores for different categories with a maximum score of 60.

The actual scoring is based on quantitative observations of trained researchers using common criteria. The dimensions include (i) agriculture (e.g. area in acres, value of crop sold last year in rupees, and, as a proxy for food security, the number of months the stock of crop would meet family needs); (ii) employment (e.g. regularity of income, type of employment - permanent or ad hoc, binary classification of income level, number of people employed); (iii) animal husbandry (the number of buffalos, cows, goats, pigs, and poultry); (iv) transport and household assets (e.g. the number of bicycles, rickshaws, two or four wheelers; ownership of fridge, TV, or phone); (v) house ownership and housing type (owned, rented, or homeless; house size - large, medium, or small, electrical connection); and (vi) sanitation (with or without access to public, shared or own toilet (inside or not), with or without bath, inside or outside). The IBR indicator thus reflects income or employment or business characteristics, basic needs such as food security, the availability of sanitation facilities, housing and asset characteristics. Households are grouped into five categories, namely 'very poor' (with an IBR indicator of 8 or less; 5.1% of the total sample of 5260), 'poor' (IBR - 9-18; 23.6%), 'moderately poor or borderline' (IBR - 19-29; 33.5%), 'self-sufficient' (IBR - 30-40; 33.5%), and 'surplus' (IBR - 41-60 (Sinha, 2003). While we use the IBR indicator as the dependent variable, we limit the sample to those households who are poor (or below) and those who are moderately poor (or below) in the second stage of PSM as an extension.

Descriptive Statistics and Definitions of the Variables

The present study employs two different definitions of access to MFIs.

a) whether a household is a client of any MFI ("*MFI_Access*") or not, and

b) whether a household has taken a loan from MFI for a productive activity "*MFI_Productive*").

The first definition is used to see the effect of simply accessing MFI on poverty.[7] The second is concerned with whether the household has taken loans for productive activities (and has an outstanding balance of those loans at the time of survey), leading to an increase in production, e.g. buying inputs for agriculture or investment in non-farm business, such as repairing a shop. The binary classification of 'whether the household used the MFI loans for productive purposes' is based solely on the respondents' perception of the nature of their loans and thus the possibility cannot be ruled out that loans were actually used for other purposes. Thus, caution is needed in interpreting the results.

Appendix 1 provides descriptive statistics of the variables for the sample households with access to MFIs and for those without. As shown by the number of observations in two columns, about three quarters of the sample households have access to MFIs in both rural and urban areas. About half of them have access to loans from MFI for productive purposes. In general, there is a relatively small difference between the descriptive statistics of each variable for the households with access to MFIs (or with access to MFI loans for productive purposes) and for those without, except in a few cases (e.g. there are higher proportions of larger households with lower dependency ratios and households with non-farm business opportunities among those receiving MFI loans than among those without). That is partly because of the design of the sample survey where households with relatively similar characteristics are chosen in each village. The higher proportion of female-headed households indicates that these are targeted by MFIs and the controls are selected according to a similar criterion. For most rural households, the household

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7 'Being a client' means that any member of the household has either savings or loan account with MFIs at the time of survey.

head is either illiterate or ‘completed primary school’ only, while all of those in urban areas completed only primary school..

Households typically contain about five people. About 30% of the sample households belong to a Scheduled Caste or Scheduled Tribe. The proportion of Hindus is relatively higher in urban areas, while that of Muslims is relatively higher in rural areas. Other religions include Christianity and Sikhism. We created a variable on ‘business availability’, the availability of non-farm business opportunities for households. It is assumed that more business opportunities will increase the demand for microfinance. This is proxied by the proportion of households engaged in non-farm business in a village. As expected, it is higher in urban areas. The average IBR indicator of households in rural areas is lower than in urban areas, implying that poverty is more severe in rural areas. The IBR indicator is higher for those with access to MFIs (or those with access to MFI loans for productive purposes) than those without. However, this may not necessarily imply that access to MFIs reduces poverty due to sample selection biases. The next section will address the methodologies by which the treatment effects are estimated taking account of sample selection biases.

III. Methodology

We use the propensity score matching (PSM) model and treatment effects model to address the sample selection issues associated with participation in microfinance programmes. In this section, we explain these methodologies.

(1) Propensity Score Matching (PSM)

Our main hypothesis is that access to microfinance institutions (MFIs) reduces poverty as defined by the IBR indicators. Because we have only cross-sectional data, we can compare IBR indicators of households with access to MFIs and those without, as long as MFIs are randomly distributed across the sample. However, we cannot simply statistically compare the average of IBR indicators for those with access to MFIs and those without because of the sample selection bias. The sample selection problem may arise from (1) self selection where the households themselves decide whether or not to participate in MFI programmes, which depends on observable and unobservable household characteristics, and/or (2) endogenous program placement where those who implement microfinance programmes select (a group of) households with specific characteristics (e.g. high poverty rates or reasonably good credit records depending on the programme specifications). Statistical matching, such as PSM and the instrumental variable (IV) model, or the Heckman Sample Selection Model, could be used to compensate for sample selection bias or the endogeneity associated with household access to MFIs.

Statistical matching has been widely used in medical studies where the dose response of patients is analysed. This involves first specifying a function matching the proximity of one household to another in terms of household characteristics and then grouping households so as to minimize the distance between matched cases (Foster 2003). The merits of using statistical matching over IV estimation include; the former does not assume linearity: it is valid even though distributions of explanatory variables of treatment and control groups overlap relatively little, and it does not require a valid instrument. Rosenbaum and Rubin (1983) proposed statistical matching using the propensity score, the predicted probability that an individual receives the treatment of interest (e.g. financial services, such as loans or savings in our case) to make comparisons between individuals with the treatment and those without. Methodological issues and programs for propensity score matching estimation are discussed in detail, by, for example, Becker and Ichino (2002), Dehejia (2005), Dehejia and Wahba (2002), Smith and Todd (2005), Todd (2008) and Ravallion (2008). While there are some advantages in using PSM to estimate the impact of policy, the derived impact depends on the variables used for matching and the quantity and quality of available data and the procedure to eliminate any sample selection bias is based on observables (Ravallion 2008). If there are important unobservable variables in the model, the bias is likely to remain uncorrected. For example, if the selection bias based on unobservables counteracts that based on observables, then eliminating only the latter bias may increase aggregate bias, although replication studies comparing non-experimental evaluations, such as PSM, with experiments for the same programs do not appear to have found such an example in practice (ibid. 2008).

The discourse between Smith and Todd (2005) and Dehejia (2005) further draws our attention to the limitations of PSM, in particular those relating to cross-sectional data. First, unmeasured characteristics or time effects cannot be controlled for by cross-sectional data. Second, bias associated with cross-sectional matching estimators may be large without a good set of covariates or if treated and control households are not strictly comparable, for example, located in different markets (Smith and Todd 2005). To overcome these limitations of PSM to some extent, we also use the treatment effects model.

We summarise below the estimation methods for propensity score matching. The propensity score is the conditional probability of receiving a treatment (or of having access to MFI) given pre-treatment characteristics, X (or household characteristics).

$$p(X) = Pr\{D = 1 | X\} = E\{D | X\} \tag{1}$$

where $D = \{0, 1\}$ is the binary variable indicating whether a household has access to MFIs (1) or not (0) and X is the multidimensional vector of pre-treatment characteristics or time-invariant or relatively stable household characteristics in our context. It was shown by Rosenbaun and Rubin (1983) that if exposure to MFI is random within cells defined by X, it is also random within cells defined by p(X) or the propensity score.

The policy effect of MFI can be estimated in the same way as in Becker and Ichino (2002) as:

$$\begin{aligned}
\tau &\equiv E\{W_{1i} - W_{0i} \mid D_i = 1\} \\
&= E\{E\{W_{1i} - W_{0i} \mid D_i = 1,\ p(X_i)\}\} \\
&= E\{E\{W_{1i} \mid D_i = 1, p(X_i)\} - E\{W_{0i} \mid D_i = 0, p(X_i)\} \mid D_i = 1\}
\end{aligned} \tag{2}$$

where *i* denotes the *i-th* household, W_{1i} is the potential outcome (wellbeing or poverty status captured by IBR indicator) in the two counterfactual situations with access to MFI and without. So the first line of the equation states that the policy effect is defined as the expectation of the difference between the IBR indicator of the *i-th* household with access to MFI and that of the same household in the counterfactual situation without access to MFI. The second line is the same as the first except that the expected policy effect is defined over the distribution of the propensity score. The last line is the policy effect as the expected difference of the expected IBR score for the *i-th* household with access to MFI given the distribution of the probability of accessing MFI and that for the same household *without* MFI given the same distribution.

Formally, the following two hypotheses are needed to derive (2) given (1).

Lemma 1 Balancing Hypothesis (Balancing of pre-treatment variables given the propensity score)

If p (X) is the propensity score, then

$D \perp X \mid p(X)$ This implies that, given a specific probability of having access to MFI, a vector of household characteristics, X, is orthogonal to (or uncorrelated to) access to MFI. In other words, for a specific propensity score, the MFI is randomly distributed and thus on average households with MFI access and those without are observationally identical (given a propensity score). Otherwise, one cannot statistically match households of different categories.

Lemma 2 Unconfoundedness given the propensity score

If treatment (or whether a household has access to MFI) is unconfounded, i.e.

$$W_1, W_2 \perp D \mid X$$

Then, assignment to treatment is unconfounded given the propensity score, i.e.

$$W_1, W_2 \perp D \mid p(X)$$

The latter implies that, given a propensity score, the IBR indicator is uncorrelated to access to a MFI. If the above lemmas are satisfied, the policy effect can be estimated by the procedures described in Becker and Ichino (2002) and Smith and Todd (2005). Each procedure involves estimating a probit or logit model:

$$\Pr\{D_i = 1 \mid X_i\} = \Phi(h(X_i)) \qquad (3)$$

where Φ denotes the logistic (or normal) cumulative distribution function (cdf) and $h(X_i)$ is a starting specification. We use the probit model whereby whether a household has access to MFI is estimated by household and socio-economic characteristics (e.g. age and its square, sex and educational attainment of the household head, household size, dependency ratio, caste, and religion) as well as by access to other financial services (formal banks, money lenders, and borrowing from relatives and friends).

One possible procedure for statistical matching is *Stratification Matching* whereby the sample is split into *k* equally spaced intervals of the propensity score to ensure that within each interval the average propensity scores of treated and control households do not differ. We did not use Stratification Matching as it requires observations to be discarded when either treated or control units are absent. Instead, we used other variants in matching estimators of the average effect of treatment on the treated, namely, *Nearest Neighbour Matching* and *Kernel Matching*.[8] *Nearest Neighbour Matching* involves taking each treated unit and searching for the control unit with the closest propensity score, while with *Kernel Matching* all those treated are matched with a weighted average of *all* controls with weights that are inversely proportional to the distance between the propensity scores of treated and controls (see Becker and Ichino 2002 for details).

(2) Treatment effects Model

We also employ the treatment effects model, a version of the Heckman sample selection model (Heckman, 1979), which estimates the effect of an endogenous binary treatment. This enables us to compensate for sample selection bias associated with access to MFIs. In the first stage, access to MFI is estimated by the probit model. In the second, we estimate the IBR indicator by various household characteristics and a dummy variable on whether the household participates in the MF programme after controlling for the inverse Mill's ratio which reflects the degree of sample selection bias. The instrument is the availability of formal banks at village level (or the proportion of households with access to formal banks), the proxy for the level of local financial services which determines the demand for microfinance, but would not directly affect the poverty level of the household.

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8 We did not use *Radius Matching* as the results are sensitive to the predetermined radius.

The merit of the treatment effects model is that sample selection bias is explicitly estimated by using the results of the probit model. Also, it does not require the two conditions for PSM discussed in the last sub-section. However, its weak aspects include (i) strong assumptions being imposed on distributions of the error terms in the first and the second stages, (ii) the results being sensitive to the choice of explanatory variables and instruments, and (iii) valid instruments rarely being found in the non-experimental data.

The selection mechanism by the probit model above can be more explicitly specified as (e.g. Greene, 2003):

$$D_i^* = \gamma X_i + u_i \qquad (3)'$$

and

$$D_i^* = 1 \quad \text{if } D_i^* = \gamma X_i + u_i > 0$$

$$D_i^* = 0 \quad \text{otherwise}$$

where

$$\Pr\{D_i = 1 | X_i\} = \Phi(\gamma' X_i)$$

$$\Pr\{D_i = 0 | X_i\} = 1 - \Phi(\gamma' X_i)$$

and

$$D_i^* = 1 \quad \text{if } D_i^* = \gamma X_i + u_i > 0$$

D_i^* is a latent variable. In our case, D_i equals 1 if a household has access to MFIs and 0 otherwise, X_i is a vector of household characteristics and the instrument for the participation equation, that is, the proportion of households with access to formal banks, Φ , denotes the standard normal cumulative distribution function.

The linear outcome regression model in the second stage is specified below to examine the determinants of poverty, proxied by IBR (index based ranking) score or W_i. That is,

$$W_i = \beta' Z_i + \theta D_i + \varepsilon_i \qquad (4)$$

$(u_i\ \varepsilon_i) \sim$ bivariate normal $[0, 0, 1, \sigma_\varepsilon, \rho]$.

where θ is the average net wealth benefit of participating in MF programmes. Z_i is the same as X_i except that it does not include instruments for the MFI participation equation.

Using a formula for the joint density of bivariate normally distributed variables, the expected IBR indicator for those with access to MFIs (or clients) is expressed as:

$$\begin{aligned} E[W_i | D_i = 1] &= \beta' Z_i + \theta + E[\varepsilon_i | D_i = 1] \\ &= \beta' Z_i + \theta + \rho\sigma_\varepsilon \frac{\phi(\gamma' X_i)}{\Phi(\gamma' X_i)} \end{aligned} \tag{5}$$

where ϕ is the standard normal density function. The ratio of ϕ and Φ is called the inverse Mill's ratio.

The expected IBR for non-clients is:

$$\begin{aligned} E[W_i | D_i = 0] &= \beta' Z_i + E[\varepsilon_i | D_i = 0] \\ &= \beta' Z_i - \rho\sigma_\varepsilon \frac{\phi(\gamma' X_i)}{1 - \Phi(\gamma' X_i)} \end{aligned} \tag{6}$$

The expected effect of poverty reduction associated with MFI access is computed as (Greene, 2003, 787-789):

$$E[W_i | D_i = 1] - E[W_i | D_i = 0] = \theta + \rho\sigma_\varepsilon \frac{\phi(\gamma' X_i)}{\Phi(\gamma' X_i)[1 - \Phi(\gamma' X_i)]} \tag{7}$$

If ρ is positive (negative), the coefficient estimate θ of using OLS is biased upward (downward) and the sample selection term will correct this. Since σ_ε is positive, the sign and significance of the estimate of $\rho\sigma_\varepsilon$ (usually denoted as β_λ) will show whether any selection bias exists. To estimate the parameters of this model, the likelihood function given by Maddala (1983, 122) is used where the bivariate normal function is reduced to the univariate function and the correlation ρ. The predicted values of (5) and (6) are derived and compared by the standard t test to examine whether the average treatment effect or poverty reducing effect is significant.

The results must be interpreted with caution because they are sensitive to the specification of the model or the selection of explanatory variables and/or the instrument. Also important are the distributional assumptions of the model. However, applying the treatment effects model overcomes the potential limitations of propensity score matching in evaluating the impacts of MFIs.

IV. Results

Propensity Score Matching

We first provide the results for matching estimators to investigate the impacts of access to MFIs on poverty. Because of the fundamental differences of environment, industrial structures, household characteristics and activities between urban and rural areas, we first derive the estimations for total households and then for urban areas and rural areas separately. The results of the probit model imply the sort of characteristics which are the key determinants underlying access to, and use of, microfinance services.

The estimation results of the probit model in Table 1 are generally intuitive in the case of all households where the dependent variable is 'MFI_Access' (i.e. Case A-1). A household with an older household head is more likely to be an MFI client, but the negative coefficient of the age square suggests a non-linear effect, which is significant for both total and rural households. Also, a household with a female head is more likely to be a client, which reflects the fact that microfinance programmes target women. Education variables are not significant. Dependency ratio has a negative and significant effect. The coefficient estimate of 'business availability' is positive and significant in Cases A-1 (total) and A-3 (rural areas). If a household deals with formal banks, it is less likely to be an MFI client. This is significant in Cases A-1 and A-3. The coefficient estimates of loans from formal banks, money lenders, friends and relatives are negative, which reflects the fact that those who cannot obtain loans, or can only obtain smaller loans, tend to use MFI services. The availability of formal banks is positive and significant in urban areas and negative and significant in rural areas. That is, households in areas where formal banks are not available are more (less) likely to be MFI clients in rural (urban) areas.[9]

However, in Case B-1 where 'MFI_Productive' is estimated, a few differences are observed. The coefficient estimate of 'Female' (headedness) is *negative* in Case B-1 (total) and Case B-3 (rural areas), that is, a household with a male head is more likely to take a loan for productive purposes. This may reflect the fact that, although microfinance focuses on women, male-headed households are more likely to take loans for productive purposes. The coefficient estimates of variables on 'Education' are positive and significant. Households with more educated heads are more likely to take MFI loans for productive purposes, while education does not matter for simple access to MFI. The coefficient estimates of 'Caste_dum' are negative and

[9] We estimated the PSM model and the treatment effects model based on the probit without the variables on access to other financial services for both 'MFI-Access' and 'MFI-Productive' noting that these may not be exogenous. The coefficient estimates of variables show similar results in the cases without the variables on access to other financial services. The final results of the PSM model and treatment effects model are also similar. This has the shortcoming, however, of not controlling for the variables on other financial services and thus we decided to present the cases with these variables.

significant in Case B-1 and Case B-3. That is, households which do not belong to Scheduled Castes or Scheduled Tribes are more likely to be MFI clients, suggesting the exclusion of socially disadvantaged groups from MFI loans for productive purposes. The availability of non-farm business is highly significant in all cases as this increases the demand for loans for productive purposes. In rural areas transactions with formal banks and loans from money lenders show positive and significant signs, that is, other financial services serve as complements to MFI loans for productive services. On the other hand, the coefficient estimate of loans from formal banks is negative and significant in Case B-2 for urban areas. That is, those who cannot get loans from the formal banks tend to obtain MFI loans for productive purposes in urban areas. Formal bank availability at village level is negative and significant in Case B-1 (total) and Case B-3 (rural areas). Rural households living in a village with more difficult access to formal banks are more likely to take MFI loans.

(Table 1 to be inserted around here)

Based on the results of the probit model in Table 1, we derived the propensity scores for each case.[10] With the same specification applied to all cases, the balancing hypotheses were satisfied in all cases except Case B-1. Only in this case did we try a different specification where the square of age was dropped and then it was found that the balancing hypothesis was satisfied.[11] It was assumed, as in Becker and Ichino (2002), that 'unconfoundedness' is satisfied.

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[10] Details of the distributions of propensity scores are shown in Appendix 2.

[11] The result of probit where the square of age is dropped is similar to that of Case B-1.

Table 2 and Table 3 provide the results for matching estimators based on equations (3) and (4). Table 2 shows the results based on Cases A-1 to A-3 (for 'MFI_Access') and based on Cases B-1 to B-3 in Table 1 (for 'MFI_Productive') applied for all the sample households. In Table 3, we restrict the sample to only 'The Poor' (below an IBR of 19, that is under the poverty line; 31.5% in total) and the moderately poor (below an IBR of 30, including those above the poverty line but considered 'Borderline' in the survey; 64.9% in total) to see if there was any difference in the effects of microfinance on poverty across sub-groups under poverty thresholds.

All the results use bootstrapped standard errors. The columns which we are interested in are those labelled 'Average Poverty Reducing Effect' and '*t* value'. Both Table 2 and Table 3 generally confirm that access to MFIs has a significant effect on increase of the IBR score, i.e. reduction of poverty, because the IBR indicators of households with access to MFIs are much higher than those of households with the same propensity score (estimated by household characteristics) but without access to MFIs. There is only one exception where a policy effect is positive and not significant, that is, the case for *Nearest Neighbour Matching* applied to Rural Areas in Table 2.

(Table 2 & 3 to be inserted around here)

Absolute values of the 'Average Poverty-Reducing Effects' show the extent to which access to MFIs increased an IBR indicator, i.e. reduced poverty. The first panel of Table 2 shows that simply having access to MFIs has a larger poverty reducing effect in urban areas than in rural areas. However, the second panel of Table 2 indicates that the 'Average Poverty-Reducing Effect' in rural areas expected from taking loans for productive purposes is larger than that in the cases of ‘MFI_Access’. These results imply that unless poor households are able to take loans from MFIs for productive purposes (e.g. for buying agricultural inputs), they cannot substantially increase their welfare, which is consistent with Gaiha and Nandhi (2007). In urban areas, simply having access to MFIs has larger average poverty-reducing effects than taking loans from MFIs for productive purposes.

Table 3 shows the results based on sub-samples, i.e., ‘The Poor’ and ‘The Moderately Poor’. The main conclusion remains the same: microfinance generally has significant poverty reducing effects for both ‘The Poor’ and ‘The Moderately Poor’ except in a few cases. A few important results emerged from Table 3. In urban areas, significant poverty reducing effects are found only for the moderately poor, not for the poor. If households are (very) poor in urban areas, their poverty score will be unchanged irrespective of having access to MFIs or taking productive loans. This implies the limitation of microfinance as a means of helping those who are in severe poverty, while it is effective in improving the welfare of the moderately poor in urban areas.

However, significant poverty reducing effects are observed in all cases in rural areas. It is noted, however, in the second panel of Table 3 (‘MFI_Productive’), that the average poverty reducing effects are significantly larger for ‘The Moderately Poor’, than for ‘The Poor’. This implies that productive loans will have a larger welfare-increasing impact for those above the poverty threshold than for those below it. For those below the poverty line, to simply access MFIs and to take loans for productive purposes are similar in terms of the magnitude of their poverty-reducing (or welfare-improving) effect, while for those above the poverty line, the latter has a larger welfare-improving effect than the former.

Treatment Effects Model

Based on the regression results of the probit model in Table 1, we estimate treatment effects models and present the results in Table 4 for the total sample and for urban and rural areas separately for the cases where whether the household had access to MFI is estimated in the probit model (Cases A-1, A-2, and A-3) and for those where the households obtained a loan for any productive purposes (Cases B-1, B-2, and B-3). The dependent variable is the Indexed Based Ranking (IBR) of a household's wellbeing, our proxy for poverty. Note that the higher value of IBR reflects higher wellbeing or lower poverty. Most of the results are similar irrespective of the areas chosen or the definitions of the dependent variable in the first stage.

(Table 4 to be inserted around here)

Most of the coefficient estimates of dependent variables show the expected signs. Households with older household heads tend to have higher IBR indicators with some non-linear effects, that is, the IBR indicator first increases as the household head gets older and then decreases. Female-headed households are associated with lower IBR indicators. Both completing primary education and higher education are associated with higher IBR indicators, and thus lower poverty. Larger households tend to have higher IBR indicators, but a larger proportion of elderly people or children in a household have a counter effect. If the household belongs to a Scheduled Caste or Scheduled Tribe, it is likely to have a lower IBR. Being Hindu has a positive and significant effect and being Muslim has a negative effect in the cases for total sample and for rural areas, while their coefficient estimates are non-significant for urban areas.

The availability of non-farm business opportunities is significantly and positively associated with a higher IBR Indicator. Variables controlling for access to other sources of financial services (namely, loans from formal banks, money lenders, friends and relatives) show positive and significant coefficients. This implies that a household less financially constrained is less likely to be poor. Our results would remain the same if the variables on having access to other financial services were omitted. The positive coefficient for Θ implies that the net benefit of having access to MFI is significant and positive in urban areas even without controlling for sample selection bias.

The last panel of Table 4 shows the treatment effects or the average poverty reducing effects in accessing MFIs or taking loans for productive purposes. Incidentally, the results on the size and sign of the poverty reducing effects in each case are very similar to those derived by *kernel matching* for PSM. This would support our results based on PSM with the caveat that both methodologies have their own limitations. That is, on average, having access to MFI or taking loans from MFI reduces poverty.

V. Conclusions

Drawing upon a national-level cross-sectional household data set in India in 2001, the present study analyses the impact of Micro Finance Institutions (MFIs) on household poverty, as defined by the Indexed Based Ranking (IBR) Indicator, a measure reflecting multi-dimensional aspects of poverty, such as basic needs, wealth, type of housing, job /employment security, sanitation and food security. The propensity score matching (PSM) model and the treatment effects model, a version of the Heckman sample selection model, are employed to estimate poverty-reducing effects of access to MFIs and loans used for productive purposes, such as investment in agriculture or non-farm businesses. These models compensate for endogenous binary treatment effects or sample selection bias associated with access to MFIs. Despite some limitations e.g. arising from the unobservability of potentially important determinants of participation in microfinance programmes, significantly positive effects of MFI access on the multidimensional welfare indicator were confirmed by both models, a result which suggests that MFIs play a significant role in poverty reduction. We found that the results from the treatment effects model were similar to those derived by *kernel matching* in the PSM model.

If we consider the results for rural and urban areas separately, some interesting observations emerge. For households in rural areas, a larger poverty reducing effect of MFIs is observed when access to MFIs is defined as taking loans from MFIs for productive purposes than in the case of simply having access to MFIs. In urban areas, on the contrary, simple access to MFIs has larger average poverty-reducing effects than taking loans from MFIs for productive purposes.

Significant welfare increasing effects are generally observed for both the poor and the moderately poor. However, in urban areas, these are found only for the moderately poor, that is, if households are very poor, the poverty or welfare score will be unchanged irrespective of their having access to MFIs or taking productive loans from MFIs. In rural areas, while significant poverty reducing effects are observed in all cases, taking loans for productive purposes has a larger impact in raising the IBR indicator for those above the poverty threshold.

These results imply that monitoring the use of MFI loans as well as increasing their number is particularly important in helping the poor escape from poverty and protecting them from various shocks. As a large proportion of poor households is not only poor but also vulnerable, policy should more strongly emphasise the role of microfinance schemes as a means of poverty reduction in both urban and rural areas of India.

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Table 1 Results of Probit Model on the Determinants of Access to Microfinance

Case A: Dep Variable: whether a household has access to a MFI ("MFI_access")	Case A-1: Total			Case A-2: Urban			Case A-3: Rural		
	Coef.	Z value	1)	Coef.	Z value		Coef.	Z value	
Age	0.0138	(1.80)	+	0.0008	(0.05)		0.0167	(1.90)	+
Age_square	-0.0003	(-3.22)	**	-0.0002	(-0.78)		-0.0003	(-3.12)	**
Female	0.2917	(4.09)	**	0.3445	(2.47)	*	0.2721	(3.25)	**
Primary Education	-0.0456	(-0.91)		-	-		-0.0442	(-0.86)	
Higher Education	-0.0532	(-0.40)		-	-		-0.1251	(-0.93)	
Hhsize	0.0116	(1.08)		0.0389	(1.62)		0.0054	(0.44)	
Dependency	-0.6427	(-8.03)	**	-0.7791	(-5.15)	**	-0.5695	(-5.98)	**
Caste_dum	0.0043	(0.10)		0.0937	(1.00)		-0.0629	(-1.20)	
Hindu	-0.2813	(-4.15)	**	-0.5754	(-1.13)		-0.2874	(-4.13)	**
Muslim	-0.2696	(-2.97)	**	-0.7683	(-1.46)		-0.2637	(-2.69)	**
Business Availability	0.4623	(4.99)	**	0.1259	(0.53)		0.5052	(4.91)	**
Formal banks (transaction)	-0.1729	(-4.07)	**	-0.1106	(-1.30)		-0.1965	(-3.95)	**
Formal banks (loan)	-0.7160	(-0.71)		-1.7400	(-1.44)		0.0000	(0.71)	
Money lenders (loan)	-0.1120	(-0.28)		3.1300	(1.53)		0.0000	(-0.38)	
Friends/Relatives (loan)	-1.5200	(-1.70)	+	-2.1500	(-1.16)		0.0000	(-1.45)	
Whether in urban areas	-0.0136	(-0.25)		-	-		-	-	
Formal Bank Availability	0.0305	(0.26)		0.5640	(2.49)	*	-0.2560	(-1.73)	+
Constant	1.2553	(5.86)		1.8643	(2.81)		1.2079	(4.88)	
No. of Obs.	5327			1385			3942		
Joint Significance	LR $Chi^2(11)$=168.16		**	LR $Chi^2(14)$=74.11		**	LR $Chi^2(16)$=154.32		**
Log likelihood	-2987.18			-756.52			-2216.72		
Pseudo R2	0.0325			0.0467			0.0272		

Case B: Dep Variable: whether a household has taken a loan for productive purposes ("MFI_productive")	Case B-1: Total			Case B-2: Urban			Case B-3: Rural		
	Coef.	Z value		Coef.	Z value		Coef.	Z value	
Age	0.0030	(0.40)		0.0047	(0.28)		0.0032	(0.36)	
Age_square	-0.0001	(-1.70)	+	-0.0002	(-0.91)		-0.0001	(-1.48)	
Female	-0.1007	(-1.53)		0.0345	(0.27)		-0.1586	(-2.06)	*
Primary Education	0.1221	(2.52)	*	-	-		0.1029	(2.08)	*
Higer Education	0.5804	(4.58)	**	-	-		0.5714	(4.45)	**

Hhsize	0.0161	(1.56)		-0.0246	(-1.10)		0.0278	(2.37)	*
Dependency	-0.8102	(-10.30)	**	-1.1665	(-7.65)	**	-0.6502	(-7.00)	**
Caste_dum	-0.1119	(-2.60)	**	-0.2173	(-2.39)	*	-0.1003	(-1.99)	*
Hindu	-0.0578	(-0.92)		-0.7196	(-1.83)	+	-0.0249	(-0.38)	
Muslim	-0.0217	(-0.25)		-0.7420	(-1.77)	+	0.0186	(0.20)	
Business Availability	1.5358	(17.01)	**	1.5476	(6.73)	**	1.4843	(14.79)	**
Formal banks (transaction)	0.1123	(2.73)	**	0.0219	(0.27)		0.1239	(2.56)	*
Formal banks (loan)	-1.3700	(-1.32)		0.0000	(-1.84)	+	0.0000	(0.63)	
Money lenders (loan)	2.0900	(4.25)	**	0.0000	(0.48)		0.0000	(4.36)	**
Friends/Relatives (loan)	1.7200	(1.84)	+	0.0000	(1.27)		0.0000	(1.25)	
Whether in urban areas	-0.7122	(-13.59)	**	-	-		-	-	
Formal Bank Availability	-0.3367	(-2.96)	**	0.0932	(0.43)		-0.5536	(-3.89)	**
Constant	0.1755	(0.85)		0.2760	(0.49)		0.0194	(0.08)	
No. of Obs.	5327			1385			3942		
Joint Significance	LR $Chi^2(17)=788.67$		**	LR $Chi^2(14)=175.90$		**	LR $Chi^2(16)=482.92$		**
Log likelihood	-3291.66			-831.14			-2445.7		
Pseudo R2	0.107			0.0957			0.0899		

Notes: 1) ** = significant at 1% level. * = significant at 5% level. + = significant at 10% level.

2) Education is dropped in case of urban areas as there is no variation in the variable.

3) District Dummy Variables are included, but not shown in this table

Table 2: Results of Propensity Score Matching: Effects of MFIs in Reducing Poverty (Estimation using Bootstrapped Standard Errors, 100 Rps.) for Total Sample

Whether a household is a client of any MFI ("MFI_access")

	Households with MFIs	Households without MFIs	**Average Poverty-Reducing Effect**	S.E.	**t value**
Nearest Neighbour Matching					
Total (Case A-1)	3908	1059	**2.084**	0.48	**4.339****
Urban(Case A-2)	1025	275	**4.038**	0.914	**4.420****
Rural (Case A-3)	2883	772	**0.769**	0.574	**1.340**
Kernel Matching					
Total (Case A-1)	3908	1419	**1.705**	0.287	**5.932****
Urban (Case A-2)	1025	360	**3.212**	0.693	**4.635****
Rural (Case A-3)	2883	1058	**1.095**	0.364	**3.011****

Whether a household has taken a loan from MFI or from the group for a productive activity (MFI_Productive)

	Households with MFIs	Households without MFIs	**Average Poverty-Reducing Effect**	S.E.	**t value**
Nearest Neighbour Matching					
Total (Case B-1)	2794	1226	**0.182**	0.475	**3.829****
Urban (Case B-2)	525	311	**0.888**	1.088	**0.816**
Rural (Case B-3)	2269	868	**2.488**	0.501	**4.970****
Kernel Matching					
Total (Case B-1)	2794	2521	**2.29**	0.292	**7.848****
Urban (Case B-2)	525	840	**1.865**	0.525	**3.553****
Rural (Case B-3)	2269	1669	**2.489**	0.357	**6.973****

Note a ** = significant at 1% level. * = significant at 5% level. + = significant at 10% level.

Table 3: Results of Propensity Score Matching: Effects of MFIs in Reducing Poverty (Estimation using Bootstrapped Standard Errors, 100 Rps.) for the Poor and the Moderately Poor

Whether a household is a client of any MFI ("MFI_access")

	Households with MFIs	Households without MFIs	**Average Poverty-Reducing Effect**	S.E.	**t value**
For the Poor					
Nearest Neighbour Matching					
Total (Case A-1)	1184	351	**0.735**	0.331	**2.119***
Urban(Case A-2)	78	24	**0.603**	1.108	**0.544**
Rural(Case A-3)	1106	324	**0.91**	0.359	**2.535***
Kernel Matching					
Total (Case A-1)	1184	495	**0.86**	0.207	**4.149****
Urban (Case A-2)	78	39	**0.682**	0.939	**0.762**
Rural (Case A-3)	1106	449	**0.863**	0.212	**4.071****
For the Moderately Poor					
Nearest Neighbour Matching					
Total (Case A-1)	2493	740	**0.767**	0.394	**1.948***
Urban(Case A-2)	397	127	**2.111**	0.739	**2.854****
Rural(Case A-3)	2096	587	**1.268**	0.428	**2.96****
Kernel Matching					
Total (Case A-1)	2493	960	**1.22**	0.24	**5.079****
Urban (Case A-2)	397	183	**1.574**	0.534	**2.950****
Rural (Case A-3)	2093	775	**1.186**	0.287	**4.125****

Whether a household has taken a loan from MFI or from the group for a productive activity (MFI_Productive)

	Households with MFIs	Households without MFIs	**Average Poverty-Reducing Effect**	S.E.	**t value**
For the Poor					
Nearest Neighbour Matching					
Total (Case A-1)	749	373	**0.869**	0.33	**2.607****
Urban(Case A-2)	11	10	**0.091**	2.501	**0.036**
Rural(Case A-3)	738	384	**0.956**	0.358	**2.667****
Kernel Matching					
Total (Case A-1)	749	914	**1.056**	0.214	**4.941****
Urban (Case A-2)	11	83	**-0.619**	2.031	**-0.305**
Rural (Case A-3)	738	805	**1.088**	0.247	**4.408****
For the Moderately Poor					
Nearest Neighbour Matching					
Total (Case B-1)	1740	794	**1.891**	0.338	**5.59****
Urban(Case B-2)	173	109	**1.827**	0.77	**2.371***
Rural(Case B-3)	1567	675	**2.172**	0.434	**5.001****
Kernel Matching					
Total (Case B-1)	1740	1695	**2.228**	0.244	**9.114****
Urban (Case B-2)	173	408	**2.046**	0.482	**4.241****
Rural (Case B-3)	1567	1303	**2.200**	0.262	**8.385****

Table 4 The Results of Treatment effects Model for Poverty (Indexed Based Ranking of a household's wellbeing) (The First Stage: whether a household has access to productive assets/ whether a household has loan from MFI for productive purposes shown in Table 1)

Case A: Dep. Variable: Index Based Ranking
(the first-stage probit estimates whether a household has access to a MFI ("MFI_Access"))

	Case A-1: Total			**Case A-2: Urban**			**Case A-3: Rural**		
	Coef.	Z value	1)	Coef.	Z value		Coef.	Z value	
Age	0.2210	(3.95)	**	0.3728	(2.93)	**	0.2077	(3.18)	**
Age_square	-0.0009	(-1.42)		-0.0016	(-1.05)		-0.0016	(-2.11)	*
Female	4.7049	(9.54)	**	-4.5313	(-4.60)	**	-3.5385	(-5.72)	**
Primary Education	1.1642	(3.26)	**	-	-		0.6229	(1.73)	+
Higher Education	2.0793	(2.29)	*	-	-		1.6409	(1.82)	+
Hhsize	0.6061	(8.01)	**	1.0662	(6.20)	**	0.4423	(5.18)	**
Dependency	-0.9876	(-1.46)		1.9087	(1.60)		-4.3710	(-4.53)	**
Caste_dum	-3.8773	(-12.54)	**	-4.5531	(-6.67)	**	-3.7885	(-10.76)	**
Hindu	1.4548	(2.68)	**	-1.7161	(-0.60)		1.2874	(2.26)	*
Muslim	-1.4477	(-2.15)	*	-3.0860	(-1.00)		-1.2351	(-1.74)	+
Business Availability	6.4979	(9.96)	**	9.5918	(6.21)	**	7.5205	(9.14)	**
Formal banking sector	6.2691	(21.22)	**	6.7404	(11.56)	**	4.9097	(12.42)	**
Formal banks (loans)	36.1392	(4.87)	**	32.9048	(3.43)	**	55.4760	(3.98)	**
Money lenders (loans)	13.5712	(2.54)	*	-23.3631	(-1.75)	+	24.6858	(4.22)	**
Friends/Relatives(loans)	62.6509	(8.22)	**	80.0072	(5.75)	**	41.7274	(4.38)	**
Whether in urban areas	10.1017	(27.24)	**	-	-		-	-	
Θ	8.5276	(5.76)	**	15.0780	(10.45)	**	-4.9649	(-1.69)	+
λ (the inverse Mill's ratio derived by the probit model)	-4.0009	(-4.63)	**	-0.6988	(-12.33)	**	0.3982	(2.32)	**
Constant	-6.8068	(-3.38)		-10.4329	(-2.33)		8.6273	(2.74)	
No. of Obs.	5076			1382			3694		
Joint Significance	Wald $Chi^2(17)=3442$		**	Wald $Chi^2(14)=801$		**	Wald $Chi^2(16)=1152$		**
Log likelihood	-21145.74			-5714.69			-15359.73		

Case B: Dep. Variable: Index Based Ranking
(the first-stage probit estimates whether a household has taken a loan for productive purposes ("MFI_productive"))

	Case B-1: Total			**Case B-2: Urban**			**Case B-3: Rural**		
	Coef.	Z value		Coef.	Z value		Coef.	Z value	
Age	0.2700	(4.69)	**	0.3770	(2.80)	**	0.1751	(2.89)	**
Age_square	-0.0021	(-3.26)	**	-0.0016	(-1.01)		-0.0011	(-1.65)	+
Female	-4.0562	(-8.23)	**	-3.2461	(-3.15)	**	-4.0785	(-7.56)	**
Primary Education	1.3695	(3.66)	**	-	-		0.7161	(2.02)	*
Higher Education	3.4746	(3.58)	**	-	-		2.1236	(2.19)	*
Hhsize	0.6331	(8.02)	**	1.3532	(7.47)	**	0.4566	(5.49)	**
Dependency	-5.2513	(-7.60)	**	4.3071	(3.32)	**	-3.6995	(-4.26)	**

Caste_dum	-3.9362	(-12.20)	**	-2.8163	(-3.89)	**	-3.7545	(-11.00)	**
Hindu	1.3943	(2.48)	*	0.2542	(0.08)		1.7074	(3.12)	**
Muslim	-1.2643	(-1.80)	+	-2.0580	(-0.63)		-0.8736	(-1.22)	
Business Availability	11.5261	(13.92)	**	3.1718	(1.80)	+	7.5086	(6.56)	**
Formal banking sector	5.9715	(20.06)	**	6.4710	(10.51)	**	5.2984	(16.08)	**
Formal banks (loans)	30.1628	(3.90)	**	35.9048	(3.54)	**	55.0513	(4.07)	**
Money lenders (loans)	16.1221	(2.91)	**	-16.4192	(-1.17)		23.5341	(4.17)	**
Friends/Relatives(loans)	57.8164	(7.33)	**	57.9332	(3.94)	**	45.1227	(5.02)	**
Whether in urban areas	8.3650	(18.04)	**	-	-		-	-	
Θ	-6.6020	(-6.78)	**	15.4018	(12.30)	**	-1.4821	(-0.84)	
λ **(the inverse Mill's ratio derived by the probit model)**	5.4197	(9.41)	**	-8.1994	(-11.51)	**	4.8925	(2.61)	**
Constant	4.5311	(2.75)		-3.8102	(-0.84)		2.3222	(2.17)	
No. of Obs.	5076			1382			3694		
Joint Significance	Wald $Chi^2(17)=3184$		**	Wald $Chi^2(14)=772$		**	Wald $Chi^2(16)=1222$		**
Log likelihood	-21370.03			-5791.19			-15504.9		

Notes: 1) ** = significant at 1% level. * = significant at 5% level. + = significant at 10% level.

2) Education is dropped in case of urban areas as there is no variation in the variable.

Treatment effect (average poverty reducing effect) = $E[W_i | D_i = 1] - E[W_i | D_i = 0]$

Whether a household is a client of any MFI ("**MFI_access**")

	Households with MFIs	Households without MFIs	**Average Poverty-Reducing Effect**	S.E.	**t value**
Based on Treatment effects Model					
Total (Case A-1)	3908	1419	**1.710**	0.148	**11.562****
Urban(Case A-2)	1025	360	**2.829**	0.275	**10.284****
Rural(Case A-3)	2883	1059	**1.273**	0.119	**10.692****

Whether a household has taken a loan from MFI or from the group for a productive activity

	Households with MFIs	Households without MFIs	**Average Poverty-Reducing Effect**	S.E.	**t value**
Based on Treatment effects Model					
Total (Case B-1)	2794	2553	**2.454**	0.148	**16.5926****
Urban (Case B-2)	525	860	**1.619**	0.275	**5.8855****
Rural (Case B-3)	2269	1673	**2.414**	0.115	**21.0712****

Note a ** = significant at 1% level. * = significant at 5% level. + = significant at 10% level.

Appendix 1. Descriptive Statistics and Definitions of the Variables

Variable	Definition	With Access to MFI			With Access to MFI			With Access to MFI loan for productive purposes			Without Access to MFI loan for productive purposes		
		Obs	Mean	S.D.	Obs	Mean	S.D.	Obs	Mean	Std. Dev.	Obs	Mean	S.D.
Age	Age of household fead												
	(Total)	3908	39.341	12.241	1419	41.599	14.072	2794	39.377	12.296	2533	40.567	13.292
	(Urban)	1025	37.300	11.531	360	38.783	12.704	525	37.341	11.475	860	37.897	12.092
	(Rural)	2883	40.067	12.404	1059	42.556	14.388	2269	39.848	12.433	1673	41.940	13.671
Female	Whether a hh head is female												
	(Total)	3908	0.904	0.295	1419	0.929	0.257	2794	0.928	0.258	2533	0.891	0.312
	(Urban)	1025	0.898	0.303	360	0.928	0.259	525	0.914	0.280	860	0.900	0.300
	(Rural)	2883	0.906	0.291	1059	0.929	0.257	2269	0.932	0.252	1673	0.886	0.317
Primary	Education of the household head, 1= completed primary school, 0= otherwise.												
	(Total)	3908	0.552	0.497	1419	0.517	0.500	2794	0.523	0.500	2533	0.565	0.496
	(Urban)*	1025	1.000	0.000	360	1.000	0.000	525	1.000	0.000	860	1.000	0.000
	(Rural)	2883	0.393	0.489	1059	0.352	0.478	2269	0.413	0.492	1673	0.341	0.474
Higher	Education of the household head, 1= completed higher education, 0=otherwise.												
	(Total)	3908	0.022	0.146	1419	0.025	0.155	2794	0.015	0.122	2533	0.031	0.173
	(Urban)*	1025	0.000	0.000	360	0.000	0.000	525	0.000	0.000	860	0.000	0.000
	(Rural)	2883	0.029	0.169	1059	0.033	0.179	2269	0.019	0.135	1673	0.047	0.211
Hhsize	Household size: number of household members												
	(Total)	3908	5.075	2.024	1419	4.913	2.038	2794	5.253	2.053	2533	4.788	1.974
	(Urban)	1025	4.780	1.844	360	4.439	1.756	525	4.798	1.942	860	4.626	1.751
	(Rural)	2883	5.180	2.075	1059	5.075	2.102	2269	5.358	2.064	1673	4.871	2.075
Depratio	Dependency Ratio (Ratio of household members under 15 or												
over 60 to the total) (Total)		3908	0.563	0.253	1419	0.626	0.274	2794	0.536	0.240	2533	0.628	0.273
	(Urban)	1025	0.602	0.262	360	0.702	0.276	525	0.553	0.237	860	0.674	0.277
	(Rural)	2883	0.549	0.249	1059	0.600	0.269	2269	0.531	0.241	1673	0.605	0.269
Caste_dum	Whether a household belongs to scheduled caste or not												
	(Total)	3908	0.685	0.465	1419	0.693	0.462	2794	0.711	0.453	2533	0.660	0.474
	(Urban)	1025	0.748	0.434	360	0.792	0.407	525	0.819	0.385	860	0.723	0.448
	(Rural)	2883	0.663	0.473	1059	0.659	0.474	2269	0.686	0.464	1673	0.628	0.483
Hindu	Whether a household head is Hindu or not												
	(Total)	3908	0.769	0.422	1419	0.792	0.406	2794	0.758	0.429	2533	0.794	0.404
	(Urban)	1025	0.930	0.256	360	0.911	0.285	525	0.926	0.262	860	0.924	0.264
	(Rural)	2883	0.712	0.453	1059	0.752	0.432	2269	0.719	0.450	1673	0.727	0.445

Muslim	Whether a household head is Muslim or not													
		(Total)	3908	0.115	0.319	1419	0.106	0.308	2794	0.137	0.344	2533	0.085	0.279
		(Urban)	1025	0.059	0.235	360	0.086	0.281	525	0.057	0.232	860	0.071	0.257
		(Rural)	2883	0.135	0.341	1059	0.113	0.317	2269	0.156	0.363	1673	0.092	0.289
Business Availability	Whether there is a business opportunity available to the household													
		(Total)	3908	0.412	0.264	1419	0.375	0.263	2794	0.447	0.267	2533	0.353	0.252
		(Urban)	1025	0.548	0.196	360	0.529	0.196	525	0.605	0.165	860	0.505	0.204
		(Rural)	2883	0.364	0.268	1059	0.322	0.262	2269	0.411	0.272	1673	0.274	0.238
Formal Banks	Whether a household has any transaction with the formal bank													
(transaction)		(Total)	3908	0.383	0.486	1419	0.443	0.497	2794	0.419	0.494	2533	0.377	0.485
		(Urban)	1025	0.482	0.500	360	0.497	0.501	525	0.531	0.499	860	0.458	0.499
		(Rural)	2883	0.348	0.476	1059	0.424	0.494	2269	0.393	0.489	1673	0.335	0.472
Formal Banks	The balance of loan of a household from the formal bank													
(loan)		(Total)	3908	0.002	0.018	1419	0.003	0.019	2794	0.002	0.013	2533	0.003	0.022
		(Urban)	1025	0.004	0.027	360	0.006	0.035	525	0.003	0.020	860	0.005	0.034
		(Rural)	2883	0.002	0.013	1059	0.002	0.008	2269	0.002	0.011	1673	0.002	0.012
Money lenders	The balance of loan of a household from Money lenders													
(loan)		(Total)	3908	0.011	0.040	1419	0.012	0.061	2794	0.013	0.055	2533	0.009	0.035
		(Urban)	1025	0.007	0.022	360	0.006	0.016	525	0.007	0.019	860	0.007	0.022
		(Rural)	2883	0.012	0.044	1059	0.014	0.070	2269	0.014	0.060	1673	0.010	0.040
Relatives and friends	The balance of loan of a household from relatives and friends													
(loan)		(Total)	3908	0.004	0.019	1419	0.006	0.023	2794	0.005	0.023	2533	0.004	0.016
		(Urban)	1025	0.005	0.019	360	0.006	0.024	525	0.007	0.025	860	0.004	0.016
		(Rural)	2883	0.004	0.019	1059	0.006	0.023	2269	0.005	0.022	1673	0.004	0.017
Formal Bank Availability (share of the households with access to formal banks at the village level- Excluding microfinance)														
		(Total)	3908	0.398	0.200	1419	0.402	0.194	2794	0.399	0.206	2533	0.399	0.190
		(Urban)	1025	0.494	0.224	360	0.463	0.225	525	0.526	0.230	860	0.462	0.218
		(Rural)	2883	0.364	0.178	1059	0.381	0.177	2269	0.369	0.188	1673	0.367	0.164
Urban_dum	Whether a household is in urban areas or not													
		(Total)	3908	0.262	0.440	1419	0.254	0.435	2794	0.188	0.391	2533	0.340	0.474
IBR indicator	Indexed Based Ranking of a household's wellbeing													
		(Total)	3718	25.14	11.753	1358	23.52	11.88	2643	25.736	11.257	2433	23.58	12.29
		(Urban)	1022	34.057	11.229	360	30.836	12.027	523	35.987	10.529	859	31.532	11.782
		(Rural)	2696	21.757	10.057	998	20.875	10.668	2120	23.207	9.918	1574	19.245	10.211

Appendix 2. Distribution of Estimated Propensity Score in Region of Common Support

Whether a household is a client of any MFI ("MFI_access")					Whether a household has taken a loan from MFI or from the group for a productive activity (MFI_productive)				
(Total)					(Total)				
	Percentiles	Smallest				Percentiles	Smallest		
1%	0.468	0.231			1%	0.155	0.121		
5%	0.585	0.236			5%	0.216	0.123		
10%	0.621	0.254	Obs	5327	10%	0.278	0.123	Obs	5315
25%	0.684	0.261	Sum of Wgt.	5327	25%	0.393	0.125	Sum of Wgt.	5315
50%	0.746		Mean	0.734	50%	0.521		Mean	0.525
		Largest	Std. Dev.	0.087			Largest	Std. Dev.	0.185
75%	0.795	0.916			75%	0.660	0.938		
90%	0.832	0.920	Variance	0.008	90%	0.791	0.981	Variance	0.034
95%	0.850	0.921	Skewness	-1.017	95%	0.839	0.993	Skewness	0.048
99%	0.883	0.923	Kurtosis	5.103	99%	0.891	0.997	Kurtosis	2.293
(Urban)					(Urban)				
	Percentiles	Smallest				Percentiles	Smallest		
1%	0.477	0.306			1%	0.106	0.099		
5%	0.573	0.371			5%	0.133	0.100		
10%	0.608	0.387	Obs	1385	10%	0.159	0.100	Obs	1365
25%	0.673	0.390	Sum of Wgt.	1385	25%	0.256	0.100	Sum of Wgt.	1365
50%	0.759		Mean	0.740	50%	0.372		Mean	0.383
		Largest	Std. Dev.	0.097			Largest	Std. Dev.	0.166
75%	0.812	0.967			75%	0.524	0.847		
90%	0.854	0.968	Variance	0.009	90%	0.605	0.867	Variance	0.028
95%	0.877	0.970	Skewness	-0.607	95%	0.650	0.876	Skewness	0.224
99%	0.914	0.978	Kurtosis	3.314	99%	0.746	0.894	Kurtosis	2.205
(Rural)					(Rural)				
	Percentiles	Smallest				Percentiles	Smallest		
1%	0.461	0.232			1%	0.218	0.155		
5%	0.576	0.234			5%	0.299	0.157		
10%	0.624	0.254	Obs	3941	10%	0.357	0.165	Obs	3938
25%	0.684	0.270	Sum of Wgt.	3941	25%	0.459	0.167	Sum of Wgt.	3938
50%	0.743		Mean	0.731	50%	0.566		Mean	0.576
		Largest	Std. Dev.	0.087			Largest	Std. Dev.	0.166
75%	0.793	0.906			75%	0.705	0.986		
90%	0.831	0.908	Variance	0.008	90%	0.809	0.996	Variance	0.028
95%	0.849	0.911	Skewness	-1.103	95%	0.845	0.998	Skewness	-0.032
99%	0.881	0.919	Kurtosis	5.514	99%	0.895	0.998	Kurtosis	2.316