Chapter-4

Poverty Outreach and Impact of Microfinance on Poverty in India

CHAPTER 4

POVERTY OUTREACH AND IMPACT OF MICROFINANCE ON POVERTY IN INDIA

4.1 Introduction

Microfinance has evolved as a potential means for providing financial services to poor households in the recent past. From a small experiment in Bangladesh this alternative financial approach is now playing a significant role in financial inclusion in almost every developing and underdeveloped country. There is an agreement among various stakeholders that MFIs are targeting those clients, mainly women, who have no collateral to access finance from formal sources. Hence MFIs as semi-formal-institution provides a viable alternative for the poor who were previously dependent on informal sources at exorbitant terms and condition. Further, the recovery rate shown by these MFIs is sometimes higher than formal Banks. Looking at these facts, it can be presumed that microfinance is an effective delivery mechanism as it targets poor clients and recovering loan successfully. But this is a narrow approach of seeing the success of microfinance; a broader approach looks at the outcomes of the financial services to recipients (Morduch, 2000). Proponents of this approach want to know whether provision of financial services through microfinance institutions makes any difference in the social and economic condition of poor clients (Hossain, 1988; Khandker, 1998; Coleman, 2006).

Expansion of MFIs during recent years is due to the large scale involvement of Development Institutions, NGOs, Donors, Government, etc., who believe microfinance is an effective way of reducing poverty. A Lot of funds are poured into the sector in the form of donation and subsidies to propel the holistic mission of microfinance. There is a need of strong evidences suggesting the impact of microfinance on the economic and social well-being for justifying subsidies and donations (Navajas et al., 2000). If microfinance does not improve the condition of the poor such fund must be used in other approaches directed towards poverty alleviation.

Practitioners of microfinance provide anecdotal evidences to show the positive impact on various economic and social dimensions of the clients. Such anecdotes lack any statistical foundation and the reliability of such evidences is rather weak. During recent times MFIs are measuring 'Moving out of Poverty Index' for assessing the effectiveness of microfinance in reducing poverty. Moving out of Poverty Index assumes that change in the outcome is solely due to microfinance over a period of time. Such methods exaggerate the true impact as there may be various other factors responsible for a better outcome. Evaluating the impact of any intervention on the outcome of target group requires rigorous statistical methods.

Inadequacy of formal finance in reaching a lower segment of the population and exorbitant terms and conditions of informal finance led to the emergence of microfinance in developing countries like India. The prime objective of microfinance is to serve the under-served segment. In an early stage of development, microfinance was mainly funded by donors, subsidies and grants and there was little emphasis towards financial sustainability. But during the last two decades, two different approaches emerged with respect to the functioning of MFIs. The first approach known as poverty targeting approach emphasizes poverty outreach of MFIs as the main objective while the second approach known as financial sustainability school focuses on financial sustainability of MFIs as a means for achieving poverty outreach. Looking at the Indian microfinance scenario during last decade, it can be observed easily that MFIs have shifted their focus towards financial sustainability. There is a rush towards financial orientation as many MFIs have converted themselves into NBFCs to attract more funds from commercial sources.

Historical evidence suggests that one of most important reason for failure of various development programmes in the past is poor targeting mechanism (Ghaiha, 1990; Ravallion, 1991). There are only few MFIs which are using some sort of targeting mechanism for identifying the poor. Generally it is believed that self-targeting mechanism will work in microfinance and non-poor clients will opt themselves out of microfinance due to availability of formal finance at easy terms and conditions. At the same time there is a concern that existing mechanism of MFIs excludes hard core poor or poorest of the poor (Weiss & Montgomery, 2005; Mosley, 2001).

Understanding depth of outreach of Indian MFIs is an unexplored area. The current research tried to understand who is participating in microfinance. The current study also aims at ascertaining the impact of microfinance on poverty by using large scale household level data by applying rigorous statistical methods.

4.2 Data Sources and Methodology

4.2.1 Data Source

For accessing poverty outreach of MFIs and impact of microfinance on poverty the study relies on nationally representative household level data collected by EDA-rural[1] for longitudinal impact assessment study conducted by SIDBI in 2002-03. SIDBI conducted an impact assessment study of MFIs lying under SIDBI Foundation for Microcredit (SFMC). The study by SIDBI was a longitudinal study for which the first round survey was conducted in 2002-03 and the second round was conducted in 2007-08.

Analysis of this study is based on baseline survey conducted in 2002-03. Baseline sample used in the current study draws from 20 MFIs in nine States covering 83 clusters (Appendix Table 1). The sample includes 3,900 client households and 1,400 non-client households. At each MFI, 2-6 clusters (villages or urban areas) are randomly selected from village/area lists representing typical operational areas in terms of rural/urban location, development context, and women/men clients – and having at least 20 clients. All MFI clients within a cluster are surveyed for a client sample size of at least 130 per MFI. The sample covers 83 clusters in nine states: 71 rural clusters and 12 urban clusters. The rural clusters reflect varying market contexts, categorized as accessible, remote and semi-rural/semi-urban:

- 'accessible' - usually on a pucca road and close to a main road , well connected by public transport (bus/jeep) to nearest main market (at a distance of 3-12 km); market area sometimes within the village; have primary and secondary schools (government, sometimes private too), and some health facilities (primary health centre, regular visits from government nurse).
- 'remote' - usually kuchcha access road, connected with public transport once or twice a day often from outside the village, nearest market at a distance of 5-20

1 EDA Rural Systems Pvt Ltd, established in 1983, is a leading development sector consultancy providing professional services in research and capacity building. Focus areas are microfinance and micro-enterprise. EDA rural provided household level raw data.

km or more; have government schools at primary level only, no health care centres within the area.

- 'semi-rural' - market towns, with population of 4,000 up to 25,000; substantial levels of nonfarm activity.

Urban Clusters

The urban clusters are located mainly in slum areas of cities – smaller cities such as Tirupati and Guntur in the South, and the larger ones such as Kanpur, Jodhpur and Howrah in the North/East

Poverty assessment is critical for analysis of outreach and of impact. Broadly, there are three approaches to poverty assessment: participatory wealth ranking[2], a scored index[3], household income/expenditure[4]. Each has strengths and some drawbacks – in terms of practicality, validity and standardization.

The methodology used for wealth ranking in this research has evolved by using a combination of the three approaches to generate data, which may be analysed across different regions, compared with an official 'poverty line', and still reflect multiple dimensions of poverty. The study integrates the three approaches. This allows to cross check the results of each approach, and to standardize the wealth ranks across different areas. On the basis of community level indicators emerging from PRA exercises and other studies of poverty indicators, key dimensions of economic status were identified and indicators 'standardized' across 5 wealth rank categories – 3 poor, 2 non-poor. This was further developed into a scored index (Index Based Ranking, IBR), covering selected production/employment and consumption/quality of life indicators (Table 4.2). IBR index captures various dimensions of poverty. IBR scores are created as a weighted sum of scores for different categories with a maximum score of 60. Households are grouped into five categories, viz. "Very Poor"

---

2 Participatory or community wealth ranking reflects local indicators, perceptions and relative ranking, resulting in non-standardised categories; PRA works well with small, rural clusters; but it can be very time consuming in larger clusters, may lead to fights and resentment, and could be unworkable in urban areas where neighbours are unable to comment on each other.

3 Scored index on selected indicators – enables a standardised ranking, but usually still relative to local conditions; can be very effective as a targeting tool but may be less effective for impact assessment when the selected indicators tend to reflect output indicators of the programme under study (assets, housing, increase in income sources).

4 Household income or expenditure measurement – single dimensional standard but enables comparison with national and international 'poverty lines'. Yet, measurement within the informal economy is both complex and prone to inaccuracy.

(with IBR score of 8 or less), "Poor" (IBR- 9-18), "Borderline" (IBR- 19-29), "Self-Sufficient" (IBR- 30-40), and "Surplus" (IBR- 41-60).

Poverty assessment is based on wealth rank categories that are comparable across different areas whilst reflecting local perceptions and a range of indicators of economic status (including housing quality, assets, type of employment, incidence of ill health and alcoholism). The assessment therefore includes more than income poverty. But the categories are close enough to per capita income levels to provide an assessment which is comparable to national and international measures of poverty (Table 4.1).

Table 4.1 Wealth Rank Categories

Wealth Ranks	Official Poverty Line	Characteristics
Very Poor	~Below local poverty line	• Irregular incomes, often landless • poor quality small housing, periphery location • very basic utensils • children go to primary school if free and easily accessible
Poor	~corresponds to local poverty line	• Casual labour, small business activities, periods of unemployment (urban), may own unirrigated land • kuccha or mixed houses, usually small • basic utensils – maybe a bicycle and/or radio • send children mostly to primary schools (Govt.) or secondary (South India); health problems, more girl children (anticipated high marriage costs)
Borderline	~Around the international poverty line (US$-a-day at ppp)	• Alternate livelihoods: occasional casual/skilled labour work; micro-enterprise, low paid wage employment; marginal land holding • mixed or pucca houses • own bicycle, radio, wrist watch, some have electric fan, B&W TV (maybe second hand) • children attend school at least up to secondary level; some problems of ill health and high indebtedness
Self-sufficient	~ Non-poor	• Smooth household economy: more than one regular source of income – productive agriculture/business or salaried employment • own medium to large pucca house • scooter/motorbike, TV • regular family diet

Source: EDA Rural Systems, 2005.

4.2.2 Methodology

4.2.2.1 Poverty Outreach of Microfinance Institutions

For assessing poverty outreach of MFIs, the study uses the data collected by Small Industries Development Bank of India (SIDBI) as part of the impact assessment study. For assessing targeting efficiency the study compares recent clients with non-clients. First, only those clients are taken which have spent less than 2 years with MFIs. Further, those clients are dropped from the sample which have spent less than 2 years with MFI but taken more than one loan (all loans MFI+SHG). Recent clients are those clients which have spent less than two years with MFIs and have taken maximum of one loan. The study sample includes 1218 client households and 1357 non-client households. Among 1218 client households, 427 have just joined the program and 791 have completed one year with the MFI. Further, under Grameen model there are 468 client households and 479 non-client households while in SHG-model there are 377 client households and 628 non-client households.

The study adopted both parametric and non-parametric approaches for determining the probability of participation of different wealth rank categories of households in microfinance. First, Probit model of participation has been estimated by using participation in microfinance as dependent variable and its possible determinants. After estimating participation model probability of participation of various wealth rank categories has been estimated and plotted as probability plot. To check the robustness of the parametric approach the study also uses non parametric method (locally weighted regression) for estimating probability of participation.

Probit Model of Participation

If dependent variable y is dichotomous and it takes on values 0 and 1 then we can define latent variable y^* such that

$$y^* = X_i \beta + u_i$$

We do not directly observe y^*, but rather y, which takes on values 0 and 1 according to the following rule:

$$y_i = \begin{cases} 1 & if\ y_i^* > 0 \\ 0 & otherwise \end{cases}$$

Disturbance term $u_i = N(0, \sigma^2)$

The log likelihood function for probit model is

$$logL = \sum_{j \varepsilon S} w_j \, ln\phi(x_j \, \beta) + \sum_{j \notin S} w_j \, ln\{1 - \phi(x_j \, \beta)\}$$

Where ϕ is commutative normal and w_j denotes the optional weights.

Table 4.3: Description of Variables included in the Participation Model for Poverty Outreach

Variable Name	Definition
Dependent Variable	
Participation Dummy	Dummy variable = 1 if household participates in microfinance, = 0 otherwise.
Independent Variables	
I. Household Characteristics	
Age	Age of the head of household
Household size	Size of the Household
Dependency ratio	
Gender	Gender of the head of household = 1 if female, = 0 otherwise
II. Education splines	
Illiterates	Dummy variable =1 if education of household head is illiterate, = 0 otherwise
Up to primary	Dummy variable =1 if education of household head is up to primary level, = 0 otherwise
Up to secondary	Dummy variable= 1 if education of household head is up to secondary level, = 0 otherwise
III. Availability of business opportunity and formal finance	
Availability of business	Dummy variable =1 if household has business opportunity, =0 otherwise
Availability of formal finance	Dummy variable = 1 if household has access to formal finance, =0 otherwise
IV. Religion and Caste	
Hindu	Dummy variable = 1 if religion of head of household is Hindu, =0 otherwise
Muslim	Dummy variable = 1 if religion of head of household is Muslim, =0 otherwise
V. wealth rank categories	
Very Poor	Poor =1 if household is very poor, = 0 otherwise
Poor	Poor =1 if household is poor, = 0 otherwise
Borderline	Poor =1 if household is borderline, = 0 otherwise
Non-poor	Poor =1 if household is Non-poor, = 0 otherwise

It is assumed that there are differences in poverty outreach of different models of microfinance. Individual/ sector based MFIs are purposefully targeting non-poor clients and hence the study tried to understand poverty outreach of only SHG-model and Grameen model. The MFIs following Grameen methodology are generally using poverty targeting criterion but there is no targeting criterion in SHG-models. It is believed a priori that poverty outreach of Grameen model is better than SHG-Model.

Locally Weighted Regression

Local regression is an approach for fitting curves and surfaces to the data by smoothing: the fit at x is the value of a parametric function fitted only to those observations in a neighborhood of x. The study uses locally weighted scatterplot smoothening. The method creates a new variable for each y_i which contains a smoothed value. The smoothed values are obtained by running a regression of y variable on x variable by using only the data (x_i, y_i) and few of the data near this point. The estimated regression line is then used to predict the smoothed value for y_i. The procedure is repeated to obtain the remaining smoothed values; a separate weighted regression is performed for every point in the data.

If x_i and y_i are two variables and data are ordered so that $x_i \leq x_{i+1}$ for i= 1,2,3, ...N -1. For each y_i a smoothed value y_i^s is calculated. The subset used in calculating y_i^s is indices $i_- = \max(1, i-k)$ through $i_+ = \max(i+k, N)$ where k = [(N×bwidth-0.5)/2]. The weights for each of observations between $j=i_-,\ldots\ldots,i_+$ are either 1 or the tricube,

$$\omega_j = \left\{1 - \left(\frac{|x_j - x_i|}{\Delta}\right)^3\right\}^3$$

Where $\Delta = 1.0001 \max(x_{i_+} - x_i, x_i - x_{i_-})$. The smoothed value y_s^i is then the weighted mean or the weighted regression prediction at x_i.

4.2.2.2 Impact of Microfinance on Poverty

The impact of any intervention (Microfinance) on target group (Microfinance clients) is the difference between current outcome with the intervention and current outcome without the intervention. In ex-post impact evaluation, though the current status of the individual after being treated is known; it is impossible to observe the same individual without the intervention at the same point of time. Hence for valid assessment we need to know what would have happened to the individual without intervention. This issue known as counterfactual in literature makes the task of impact assessment a tedious exercise. The problem of evaluation is that while the program's impact (independent of other factors) can truly be assessed only by comparing actual and counterfactual outcomes, the counterfactual is not observed. So the challenge of an impact assessment is to create a convincing and reasonable comparison group for beneficiaries in light of this missing data.

Suppose Y is the outcome and T is treatment. Treatment T is a binary variable equal to one for participants and zero for non-participants. Let Y_{i1} denotes outcome of the *i-th* individual with the intervention and Y_{i0} outcome of *i-th* individual without intervention. Then the impact of intervention on targeted individual may be define as

$$Impact = (Y_{i1}/T = 1) - (Y_{i0}/T = 1) \qquad (1)$$

And the average impact of the program, known as Average Treatment Effect on Treated (ATT) might be represented as follows

$$ATT = E(Y_{i1}/T = 1) - E(Y_{i0}/T = 1) \qquad (2)$$

$Y_{i1}/T = 1$ is outcome of participants (microfinance clients) after being treated (taking loan from MFIs) and $Y_{i0}/T = 1$ is hypothetical outcome of the participants in the absence of treatment. But as mentioned above the same individual cannot be observed in two different situations at the same point of time. Impact evaluation is thus a missing data problem where $E(Y_{i0}/T = 1)$ is unobserved and needs to be estimated.

In practice, we observe $Y_{i1}/T=1$ i.e. outcome of the participants with treatment and $Y_{i0}/T=0$ outcome of the non-participants without treatment. Impact evaluation studies attempt to estimate ATT defined in equation 2 by

$$D = E(Y_{i1}/T=1) - E(Y_{i0}/T=0) \qquad (3)$$

If we add and subtract $E(Y_{i0}/T=1)$ in equation 3

$$D = E(Y_{i1}/T=1) - E(Y_{i0}/T=0) + E(Y_{i0}/T=1) - E(Y_{i0}/T=1)$$

$$D = [E(Y_{i1}/T=1) - E(Y_{i0}/T=1)] + [E(Y_{i0}/T=1) - E(Y_{i0}/T=0)]$$

$$D = ATT + B \qquad (4)$$

Where $B = E(Y_{i0}/T=1) - E(Y_{i0}/T=0)$ is known as sample selection bias. If the treatment group (clients of MFIs) and the control group does not differ in various attributes (motivation to do business, greater freedom to women etc.) then sample selection bias will not be significant. In case of microfinance participation is voluntary; clients may possess certain pre-treatment attributes and may differ systematically from non-clients. Existence of such attributes will make $E\ (Y_{i0}/\ T=0)$ a poor estimate of $(Y_{i0}/\ T=1)$ and there will be significant sample selection bias.

Various alternative approaches are available for estimating counterfactual outcome $E\ (Y_{i0}/\ T=1)$. These methods have different assumptions about the nature of potential selection bias in program targeting and participation, and the assumptions are crucial to developing the appropriate model to determine program impacts (Khandker et. al., 2010). Major approaches of addressing the problem of counterfactual are:

1. Randomization
2. Propensity Score Matching Method
3. Double Difference Method
4. Instrumental Variable Method
5. Regression Discontinuity Design

There are two broad approaches of measuring impact, the first is experimental approach and second is non-experimental approach. Randomization or randomized control trial (RCTs) is an experimental approach while other methods listed above are non-experimental.

Propensity Score Matching Method

To eliminate selection bias, the best approach would be to assign the program randomly. Then participants and non-participants will have the same expected outcome in the absence of the program, i.e., $E\ (Y_{i0}/\ T=1) = E\ (Y_{i0}/\ T=0)$. The outcome of non-participants will then correctly reveal the counterfactual, i.e., the outcome that we would have observed for participants had they not had access to the program (Baker, 1999). Randomization guarantees that there is no sample selection bias in estimating equation 3. With randomization non-participants are valid control group for identifying the counterfactual outcome and mean impact can be consistently estimated by the difference between the sample means of the observed values of $(Y_{i0}/\ T=1)$ *and* $(Y_{i0}/\ T=0)$ (Ravallion, 2008).

Although randomized evaluation provides unbiased impact, practical implication of this approach has certain ethical and political issues. Deliberately excluding certain section of population from accessing benefits of developmental programmes is unethical and politically unfeasible. Time and cost involved in randomized controlled methods also make it less attractive.

The matching method is a non-parametric approach to the problem of identifying the treatment impact on outcomes. Using observational data propensity score matching (PSM) methods tried to prepare a statistically similar control group as treatment group. This approach can significantly reduce bias in observational study (Rosenbaum, 1987, 2004; Rosenbaum & Rubin, 1985; Dehejia & Wahba, 2002).

Propensity score matching constructs a statistical comparison group that is based on a model of the probability of participating in the treatment, using observed characteristics. Participants are then matched on the basis of this probability, or propensity score, to nonparticipants. The average treatment effect of the program is then calculated as the mean difference in outcomes across these two groups. The validity of PSM depends on two conditions (Smith & Todd, 2005):

(a) Assumption of conditional independence states that unobserved factors do not affect participation. Given a set of observable covariates X that are not affected by treatment, potential outcomes Y are independent of treatment assignment T. If $Y_{i1}/ T=1$ is outcome of the participants with treatment and $Y_{i0}/ T=0$ outcome of the non-participants without treatment, conditional independence implies

$$(Y_{i1}/ T=1,\ Y_{i0}/ T=0) \perp T_i \mid X_i$$

To estimate the TOT as opposed to the ATE, a weaker assumption is needed:

$$(Y_{i0}/ T=0) \perp T_i \mid X_i$$

(b) Assumption of common support states that there should be sizable common support or overlap in propensity scores across the participant and nonparticipant samples. $0 < P\ (T_i = 1|X_i) < 1$. For estimating the ATE, this assumption can be relaxed to P $(T_i= 1|X_i) < 1$.

The rationale behind this assumption is to create a comparison group to be as similar as possible to the treatment group in terms of observables. In forming the comparison group, one should eliminate those observations from the set of non-participants which have lower propensity score than any of participants. One should also exclude those non-participants for whom the probability of participating is zero. It is advisable to trim a small proportion of the sample, say 2 per cent, from the top and bottom of the non-participant distribution in terms of the propensity scores (Baker, 1999).

Once propensity scores are estimated using logit or probit model different algorithm can be applied to estimate treatment effect on treated which can be expressed as (Smith and Todd, 2005).

$$ATT = \frac{1}{N_T}\left[\sum_{i \epsilon T} Y_i^T - \sum_{j \epsilon C} w(i,j) Y_j^C\right] \qquad (5)$$

Where, Y_i^T represents the outcome of participants and Y_j^C outcome of non-participants. N_T is the number of participants i and *w (i, j)* is the weight used to aggregate outcomes for the matched nonparticipants j.

1. Nearest-neighbour Matching

For each control unit this method assigns a weight equal to one for the nearest comparison unit in terms of the balancing score and zero to all the other comparison observations. Nearest-neighbour matching can be applied 'with' or 'without' replacement. In the former case, an untreated individual can be used more than once as a match, whereas in the latter case it is considered only once. It is also suggested to use more than one nearest neighbour ('oversampling'). Oversampling results in reduced variance of estimator at the cost of increased bias that results from on average poorer matches. Denote by *C (i)* the set of control units matched to the treated unit i with an estimated value of the propensity score of pi. Nearest-neighbour matching sets

$$C(i) = \min_j \left\| P_i - P_j \right\|$$

That is, non-participant with propensity score P_j that is closest to P_i is selected as the match. *C (i)* is singleton set unless there are multiple nearest neighbours.

2. Caliper Matching

This estimator chooses the nearest neighbour inside a caliper or tolerance width *r*. This is an alternative way of imposing the common support condition. A possible drawback of caliper matching is that it is difficult to know a priori what choice for the tolerance level is reasonable (Smith and Todd, 2005). In caliper matching,

$$C(i) = \{P_j \| \|P_i - P_j\| < r\}$$

Hence a match for person i is selected only if $\|P_i - P_j\| < r$ where r is pre-specified tolerance level.

By denoting the number of controls matched with observation $i \in T$ by N_i^C weights can be defined for both nearest neighbour and caliper matching as $w(i,j) = \frac{1}{N_i^C}$ if $j \in C(i)$ and $w(i,j) = 0$ otherwise. Matching estimators for both nearest neighbour and caliper matching can be written as

$$ATT_{NN\ or\ CM} = \frac{1}{N_T}\sum_{i \in T}\left(Y_i^T - \sum_{j \in C(i)} w(i,j)Y_j^C\right)$$

$$= \frac{1}{N_T}\left(\sum_{i \in T} Y_i^T - \sum_{i \in T}\sum_{j \in C(i)} w(i,j)Y_j^C\right)$$

$$= \frac{1}{N_T}\sum_{i \in T} Y_i^T - \frac{1}{N_T}\sum_{j \in C} w(j)Y_j^C$$

Where $w_j = \sum_i w(i,j)$

3. Kernel Matching and Local Linear Matching

Kernel matching and Local Linear Matching use a weighted average of all nonparticipants to construct the counterfactual match for each participant. The weighting function is a (Gaussian) kernel density. All the observations in the comparison group inside the common support region are used, the farther the comparison unit from the control unit the lower the weight. Local-linear matching is similar to the kernel estimator but includes a linear term of the balancing score, which is helpful when the data are asymmetric.

The Kernel matching estimator is given by

$$ATT_{KM} = \frac{1}{N_T}\left[\sum_{i \in T} Y_i^T - \sum_{j \in C}\left\{\frac{K\left(\frac{P_j - P_i}{a_n}\right)}{\sum_{k \in C} K\left(\frac{P_k - P_i}{a_n}\right)}\right\} Y_j^C\right] \qquad (2)$$

Where $K(\cdot)$ is a kernel function and a_n is a bandwidth parameter.

The local linear weighting function to be used with equation (1) is given by

$$w(i,j)_{LLR} = \frac{K_{ij}\sum_{k\epsilon C}K_{ik}(P_k-P_i)^2-[K_{ij}(P_j-P_i)]\sum_{k\epsilon C}K_{ik}(P_k-P_i)}{\sum_{j\epsilon C}K_{ij}\sum_{k\epsilon C}K_{ik}(P_k-P_i)^2-[\sum_{k\epsilon C}K_{ik}(P_k-P_i)]^2} \quad (3)$$

4. Stratification or Interval Matching

Stratification matching partition the common support of propensity score into intervals, known as strata and calculate the impact within each interval by taking the mean difference in outcomes between treated and control observations. A weighted average of the interval impact estimates provides an overall impact estimate. Let q index the blocks defined over intervals of propensity score then Stratification matching method within each block estimates

$$ATT_q^S = \frac{\sum_{i\epsilon I(q)} Y_i^T}{N_q^T} - \frac{\sum_{j\epsilon I(q)} Y_j^C}{N_q^C}$$

Where $I(q)$ is the set of units in block q and N_q^T and N_q^C are the numbers of treated and control units in block q.

Finally overall impact estimator is given by

$$ATT^S = \sum_{q=1}^{Q} ATT_q^S \frac{\sum_{i\epsilon I(q)} D_i}{\sum_i D_i}$$

Where weight for each block is given by the corresponding fraction of treated units and Q is the number of blocks.

Decision about the number of intervals (Strata) for estimating impact is difficult. One suggestion is to check balancing property of propensity score (and covariates) within each stratum. If propensity score is not balanced then the number of stratum should be increased and if covariates are not balanced then specification of the model to estimate the propensity score has to be changed by adding higher order and cross product terms.

Table 4.4: Description of Variables included in Propensity Score Analysis

Variable Name	Definition
Probability of Participation Model	
Dependent Variable	
Participation Dummy	Dummy variable = 1 if household participates in microfinance, = 0 otherwise.
Independent Variables	
I. Household Characteristics	
Age	Age of the head of household
Household size	Size of the Household
Female	Gender of the head of household = 1 if female, = 0 otherwise
II. Education splines	
Illiterates	Dummy variable =1 if education of household head is illiterate, = 0 otherwise
Up to primary	Dummy variable =1 if education of household head is up to primary level, = 0 otherwise
Up to secondary	Dummy variable= 1 if education of household head is up to secondary level, = 0 otherwise
III. Availability of business opportunity and formal finance	
Availability of business	Dummy variable =1 if household has business opportunity, =0 otherwise
IV. Religion and Caste	
Christian	Dummy variable = 1 if religion of head of household is Christian, =0 otherwise
Muslim	Dummy variable = 1 if religion of head of household is Muslim, =0 otherwise
Caste	Dummy variable = 1 if household belongs to SC or Schedule Tribe group, =0 otherwise
V. Outcome Indicator	
IBR Score	Index based measure of well-being of household ranges from 0 to 60.

4.3 Results and Discussion

4.3.1 Poverty Outreach of Microfinance Institutions in India

As whole enthusiasm for microfinance among various stakeholders is due to its holistic objective of targeting poor households, it is worthwhile to understand the poverty outreach of MFIs. Karlan & Goldberg (2007) emphasize importance of measurement of poverty outreach as a part of impact evaluation.

In this section we have tried to understand poverty outreach of MFIs by estimating different probability of participation models for rural and urban areas. Further, different models for two broad groups[5] of MFIs (based on credit delivery approach) viz. SHG- model and Grameen-model have been estimate to explore participation in different type of MFIs. First, Probit model of participation has been estimated for all these groups by including various household specific determinants, various social factors, education level and poverty level of the clients. There are four different categories of poverty level, extreme poor, poor, borderline and non-poor. Regression model includes three dummy variables for poverty level where the category 'extreme poor' is a base category. After probability of selection model, probability of participation according to poverty level has been estimated and plotted.

Composition of Study Sample

Status	Rural		Urban	
	SHG	Grameen	SHG	Grameen
Clients	209	280	168	188
Non Clients	431	370	197	109
Total	640	650	365	297

Table 4.5 provides estimation results of Probit model of participation of the rural market. The first column of Table 4.5 provides results of the overall rural market while the second and the third columns give results of Rural-SHG and Rural-Grameen model respectively. Estimated rural-overall model shows probability of participation of borderline and non-poor households is high in comparison to base category- very poor. Estimated coefficient of wealth rank category- poor- is also positive but insignificant so there is no difference in participation of poor and very poor households. In estimated model, there are few other control variables whose significance shed throw light on poverty outreach of MFIs. Gender of head of the household and education splines are important in this respect. It is found that, as household headed by females have higher probability of participation into

5 There are three different models of MFIs in India viz., SHG, Grameen and Individual model. Study includes only first two models for analysis as Individual model exclusively focuses on wealthier clients.

programme. Two educational splines (*Upto Primary* and *Upto Secondary & Higher*) have been included in models with *Illiterate* as base category. We found as education level increases probability of participation decreases as evidenced by negative coefficients of both educational dummies. Hence poverty outreach of rural market is low by looking at estimated coefficients of wealth rank categories but participation of women is satisfactory. Schedule castes and tribes have a low probability of participation in rural microfinance market

Result of the Rural-SHG model also gives similar results, where estimated coefficients of wealth rank categories indicate high participation of wealthier clients in the programme. Further, the coefficient of the dummy variable *Gender of Household Head* is positive but insignificant and educational dummy *Primary* is positive and significant. In this model, educational dummy Secondary & Higher has been dropped due to collinearity problem. There is no significant difference in participation of female and male headed household in case of Rural-SHG model. Participation of Schedule castes & Tribes and Muslims is low.

Estimation results of Rural-Grameen model reported in last column of Table 4.5 gives optimistic picture as far as poverty outreach is concerned. Estimated coefficients of wealth rank categories are positive but statistically insignificant. There is no significant difference in probability of participation of various wealth rank categories. Female headed household are participating more in comparison to male counterparts. Education level is inversely related with probability of participation as coefficients of two educational dummies are negative and significant. Also, marginalized groups, Muslims and Schedule Castes & Tribes have equal chance of participation into the programme. For all the three models, coefficient of variable *Availability of Business* has positive and significant coefficient which means availability of business increases the chances of participation in all rural models. Availability of formal finance decreases the chances of participation in all models.

Table 4.6 provides results of the urban market. For urban market we have merged two wealth rank categories (Poor and Borderline) hence there are two wealth rank categories *Poor & Borderline* and *Non-Poor*. Estimated signs of two wealth rank categories for overall model show higher participation of wealthy households. The estimated coefficient of *Borderline* is significant at 7 per cent level while the coefficient of *Non-Poor* is positive and highly significant. Female headed households have a higher probability of participation as in case of the rural market. Due to collinearity urban market model includes only one dummy of education level, *Secondary & Higher*. Education level has no effect on participation in urban microfinance. Estimated coefficients of religion and caste dummy variables are insignificant. Looking at the overall urban market results, we can conclude poverty outreach in unsatisfactory.

In case of Urban-SHG model estimated coefficients of two wealth rank categories are positive and highly significant; which shows a higher probability of participation of less poor households. Women headed households again have a higher probability of participation while marginalized religious and social groups have less probability of participation. Availability of formal finance has negative but statistically insignificant effect on participation. Further, availability of business opportunity has no effect on the chance of participation as indicated by the insignificance of the estimated parameter.

Estimated model of Urban Grameen MFIs provided in Table 4.5 gives some encouraging picture as far as depth of outreach is concerned. It shows there is no significant difference in the participation of different wealth rank category households in microfinance. The estimated coefficient of the two included wealth rank categories is negative (even though it is insignificant) which means poorest of the poor are participating more than others. By looking at significance of other included covariates, we found that availability of business opportunity significantly increases the chances of participation. Marginalized groups are also participating well in this model.

Table 4.5: Probit Model of Participation (Rural)

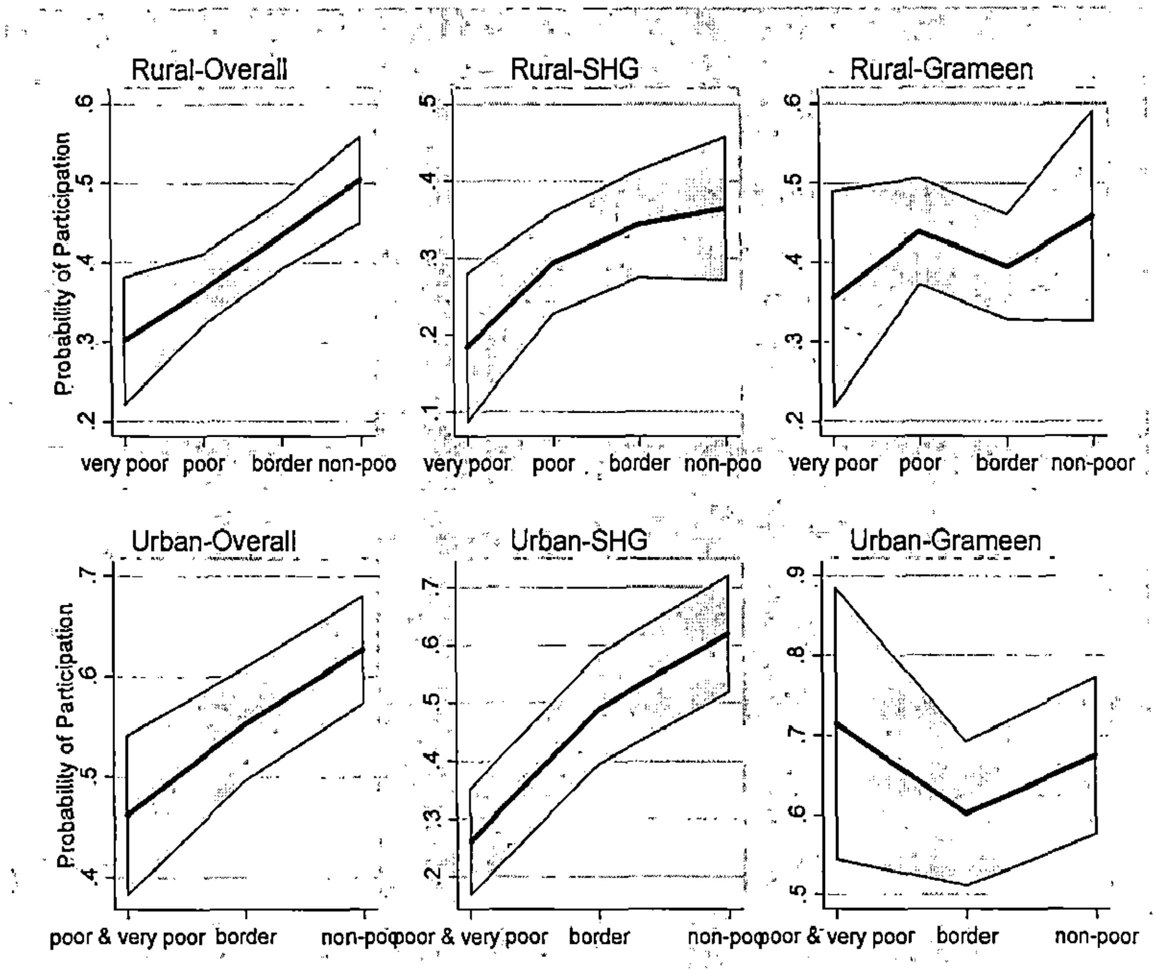
Variables	Rural Overall	Rural SHG	Rural Grameen
Age of the head of household	0.01	0.02	-0.04
	0.44	*0.39*	*0.10*
Square of age	0.00**	0.00	0.00
	0.02	*0.13*	*0.55*
Household size	-0.02	0.07**	-0.05
	0.34	*0.02*	*0.13*
Dependency Ratio	-0.59***	0.11	-1.19***
	0.00	*0.65*	*0.00*
Gender of household head	0.32**	0.30	0.44**
	0.01	*0.16*	*0.03*
Primary education	-0.46***	0.62***	-1.22***
	0.00	*0.00*	*0.00*
Secondary education	-0.46***		-1.07***
	0.01		*0.00*
Availability of Business	0.43***	0.22	0.27**
	0.00	*0.12*	*0.04*
Availability of formal finance	-0.23***	-0.28**	-0.25**
	0.00	*0.02*	*0.05*
Hindu	-0.31***	-0.25	-0.81***
	0.00	*0.21*	*0.00*
Muslim	0.02	-0.51	-0.20
	0.88	*0.12*	*0.41*
Schedule cast or tribe	-0.27***	-0.49***	0.24
	0.00	*0.00*	*0.12*
Wealth Rank Categories			
Poor	0.17	0.36*	0.22
	0.17	*0.07*	*0.27*
Borderline	0.35***	0.5**	0.10
	0.01	*0.02*	*0.62*
Non-Poor	0.53***	0.55**	0.27
	0.00	*0.02*	*0.31*
Constant	0.88**	-1.3**	3.36***
	0.02	*0.05*	*0.00*
Number of Observations	1666	640	650
Log likelihood	-1028.61	-365.61	-373.61
chi2	181.44	62.02	119.01
Prob > chi2	0.00	0.00	0.00
Pseudo R2	0.09	0.10	0.16

Table.4.6 Probit Model of Participation (Urban)

Variables	Urban Overall	Urban SHG	Urban Grameen
Age of the head of household	-0.03	0.08*	-0.07
	0.14	*0.06*	*0.18*
Square of age	0.00	0.00**	0.00
	0.58	*0.01*	*0.35*
Household size	0.02	0.02	-0.04
	0.53	*0.75*	*0.49*
Dependency Ratio	-0.62***	-0.53**	-1.48***
	0.00	*0.05*	*0.00*
Gender of household head	0.48***	0.74***	0.43
	0.00	*0.00*	*0.18*
Secondary education	0.11	___	0.40
	0.70		*0.21*
Availability of Business	0.36***	-0.15	0.56***
	0.00	*0.32*	*0.00*
Availability of formal finance	-0.15*	-0.11	-0.07
	0.10	*0.48*	*0.67*
Hindu	-0.27	-5.3***	5.45***
	0.74	*0.00*	*0.00*
Muslim	-0.45	-5.86***	5.56***
	0.58	*0.00*	*0.00*
Schedule cast or tribe	-0.07	-0.26	0.16
	0.51	*0.15*	*0.45*
Wealth Rank Categories			
Borderline	0.23*	0.62***	-0.31
	0.07	*0.00*	*0.28*
Non-Poor	0.42***	0.95***	-0.11
	0.00	*0.00*	*0.71*
Constant	1.08	4.23***	-2.98***
	0.26	*0.00*	*0.01*
Number of Observations	909	365	297
Log likelihood	-587.15	-221.46	-168.89
chi2	71.68	500.11	513.59
Prob > chi2	0.00	0.00	0.00
Pseudo R2	0.06	0.12	0.13

Probability of participation according to various wealth rank categories has been plotted in Figure 4.1. Visual inspection of plots shows that poorest of the poor are participating well in the programme. There is no significant difference in participation probability of different wealth rank categories, especially in the case of Urban-Grameen model. For urban model poorest of poor have highest probability of participation. In case of SHG model (both for Urban and Rural) probability of participation significantly differs for different categories.

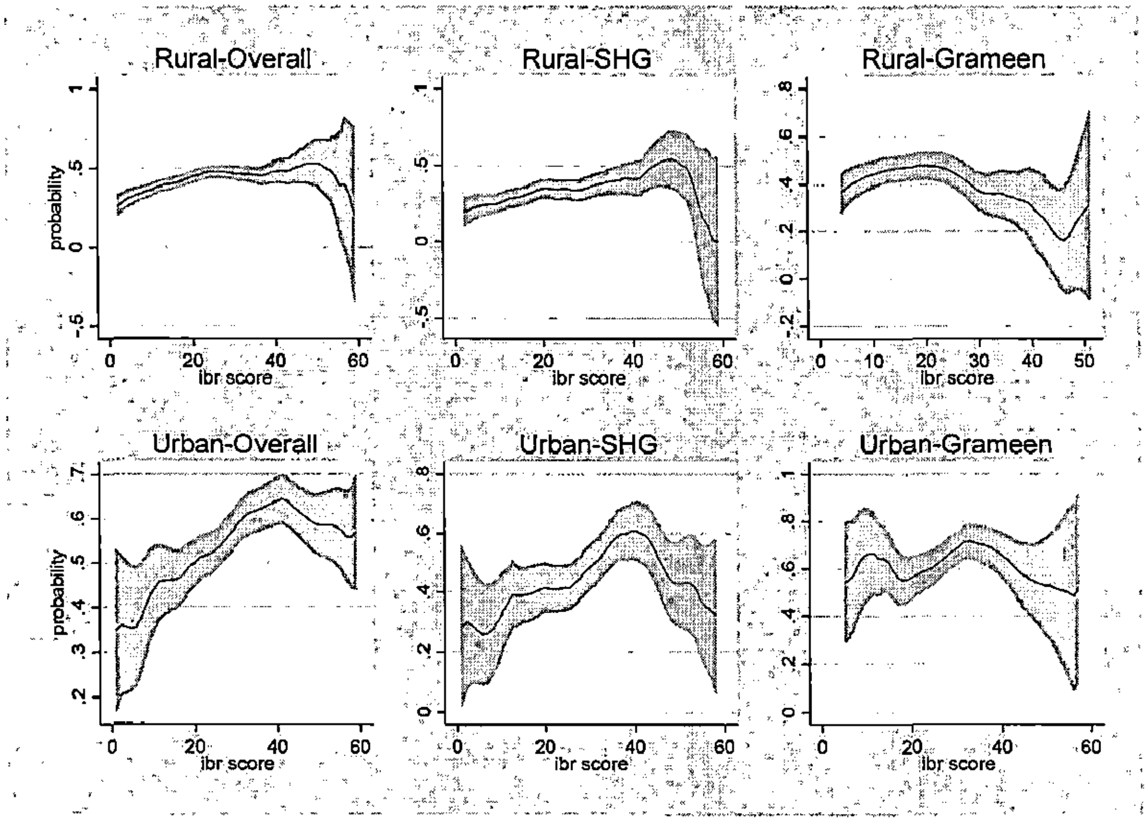
Figure.4.1 Probability of Participation according to Wealth Rank Categories



Parametric estimates of probability of participation clearly indicate the Grameen model of MFI has better poverty outreach in comparison to SHG model. The estimated Probit model indicates that Grameen model has better poverty outreach not only with respect to income level of households but also with respect to various other dimensions like, gender, education, cast and religion.

To check the sensitivity of parametric method we have also estimated probability of participation by non-parametric method (locally weighted regression) by using IBR Scores (continuous variable) as a measure of wellbeing of households. Visual inspection of probability plots shows that probability of participation decreases at high level of IBR scores for all the models. In case of SHG model probability of participation increases continuously with IBR score; then at a very high level, it tampers off. In case of Grameen model (both rural and urban) there is a clear evidence of better poverty outreach. Non parametric method shows Rural Grameen model is the best performing model.

Figure 4.2 Probability of Participation by Locally Weighted Regression



Better outreach of Grameen model may be due to the proper targeting mechanism adopted by these MFI. MFIs following Grameen approach generally use some targeting criterion for screening poor clients. Grameen model exclusively focuses on the targeting poor clients and ultimately reducing poverty of targeted groups. Some MFIs in India following Grameen model, like Cashpore and Bandhan use Housing index[6] for targeting poor clients. On the other hand, SHG model runs on self- selection philosophy. Proponents of this approach have strong belief that the concept of microfinance has inbuilt mechanism to exclude non-poor households. It is

6 Housing index is generally used for identifying poor household by many MFIs. It is an index based on the height of the wall and material used in the wall and roof of a house. The logic of this index is based on the premise that poor people spend their money on basic necessities, while surplus is invested in their house. Therefore, the quality of house is a reflection of prosperity of the household.

argued that small amount of loans, weekly meetings, progressive lending and focus on women makes microfinance unattractive to better-off households, who can access formal financial services at better terms and conditions. Findings of this study contradict the widely held belief of appropriateness of self-targeting mechanism in the microfinance sector.

4.3.2 Impact Evaluation of Microfinance

Propensity score matching (PSM) constructs a statistical comparison group that is based on a model of the probability of participating in the treatment using observed characteristics. Participants are matched on the basis of this probability, or propensity score, to nonparticipants. The average treatment effect of the program is calculated as the mean difference in outcomes across these two groups. The validity of PSM depends on two conditions: (a) conditional independence which requires that unobserved factors do not affect participation and (b) sizable common support or overlap in propensity scores across the participant and nonparticipant samples (Khandker, 2010)

Matching is a method of sampling from a large reservoir of potential controls in which the goal is to select a subset of the control sample that has covariate values similar to those in the treated group. One can attempt to match on all covariates, but this may be difficult to implement when the set of covariates is large. In order to reduce the dimensionality of the matching problem, Rosenbaum & Rubin (1983) suggested an alternative method which is based on matching on the propensity score. Recent papers by Dehejia and Wahba (1999, 2002) have generated great interest among researchers towards the ability of propensity score matching methods to potentially produce unbiased estimates of a social program's impact.

Propensity score matching is a method that arguably improves on the ability of regression to generate accurate causal estimates by virtue of its nonparametric approach to the balancing of covariates between the "treatment" and the "control" group, which removes bias due to observable variables. However, matching methods are not robust against "hidden bias" arising from the existence of unobserved variables that simultaneously affect assignment to treatment and the outcome variable (DiPrete & Markus, 2004).

There are three basic models of MFIs based on credit delivery mechanism in India. According to Karlan & Goldberg (2007) each model possesses differences in potential impacts. Following Karlan & Goldberg (2007) we have estimated separate impact evaluation models for different types of MFIs (SHG, Grameen & Individual).

First, the samples of participants and nonparticipants have been pooled, and then participation model (Probit model)[7] has been estimated on all the observed covariates X in the data that are likely to determine participation. Probit model of participation have been estimated with subsamples for different market context (rural and urban model) and different credit delivery of MFIs (Grameen, Self-Help Group & Individual model). After the participation equation is estimated, the predicted values of participation from the participation equation have been derived. The predicted outcome represents the estimated probability of participation or propensity score. To impose common support conditions, observations in the treatment group with propensity scores higher than the maximum or lower than the minimum of the control group are dropped.

We performed balancing test on the differences in means based on t-statistics. These were calculated for each independent variable to investigate whether the matched control households had characteristics similar to the matched treatment households. If the difference between the matched treatment and control households was statistically insignificant, it could be safely claimed that there was no systematic difference between these two groups, at least in terms of observable characteristics.

Once conditional independence and a sizable overlap in propensity scores between participants and matched nonparticipants have met, the PSM average treatment effect is equal to the mean difference in outcomes over the common support, weighting the comparison units by the propensity score distribution of participants.

Different approaches are used to match participants and nonparticipants on the basis of the propensity score. They include one to one matching, nearest-neighbor (NN) matching, caliper matching, kernel matching and local linear matching (LLM)

---

7 There are two models for estimating probability of participation viz., Logit and Probit models. After estimating both Logit and Probit we find better fit of Probit model.

Unlike traditional regression methods, the estimated variance of the treatment effect in PSM should include the variance attributable to the derivation of the propensity score, the determination of the common support, and (if matching is done without replacement) the order in which treated individuals are matched (Khander, 2010; Caliendo and Kopeinig 2008). Failing to account for this additional variation beyond the normal sampling variation will cause the standard errors to be estimated incorrectly (Heckman, Ichimura and Todd 1998).

One can use bootstrapping where repeated samples are drawn from the original sample, and properties of the estimates (such as standard error and bias) are re-estimated with each sample. Each bootstrap sample estimate includes the first steps of the estimation that derive the propensity score, common support, and so on (Khandker, 2010). Standard errors of matching models used in the study have been estimated by bootstrapping.

Table 4.7 Probit Model of Participation by Market Context

Variables	**Overall**		**Rural**		**Urban**	
	Coeff.	**P value**	**Coeff.**	**P value**	**Coeff.**	**P value**
Age of the head of household	0.021***	*0.01*	0.025***	*0.01*	0.011*	*0.07*
Square of Age	0.000***	*0.00*	0.000***	*0.00*	0.000	*0.16*
Household Size	0.045***	*0.00*	0.032***	*0.01*	0.082***	*0.00*
Primary	-0.051	*0.70*	-0.107**	*0.02*	0.496***	*0.00*
Secondary and higher	0.033	*0.80*	-0.024	*0.86*		
Female	0.263***	*0.00*	0.226***	*0.01*	0.363***	*0.01*
Muslim	-0.001	*0.99*	0.033	*0.66*	-0.165	*0.22*
Christian	0.140*	*0.07*	0.146**	*0.07*	0.696	*0.18*
Cast	0.009	*0.84*	0.044***	*0.01*	-0.032*	*0.09*
Availability of business	-0.151***	*0.00*	-0.195***	*0.00*	-0.048	*0.50*
Constant	0.186	*0.37*	0.189	*0.43*	0.263	*0.41*
Number of obs	5075		3466		1609	
LR chi2(10)	99.58		74.03		48.09	
Prob > chi2	0.00		0.00		0.00	
Pseudo R2	0.02		0.02		0.03	
Log likelihood	-2896.98		-2005.30		-878.27	

Table 4.7 provides estimation results of Probit model of participation by market context, viz. overall market, rural market and urban market. There is no need

to discuss probability models in detail as we have already estimated probability of participation model with a different set of data for ascertaining determinants of participation. All the three Probit models reported in Table 4.7 show better bit by individual significance as well as by the overall significance test (LR test shows overall significance of estimated models).

After probability model, balancing test has been conducted to investigate whether the matched control households have characteristic similar to the matched treatment households. Balancing test results for the three market context (overall, rural and urban) have been reported respectively in Table 4.8, Table 4.9 and Table 4.10. As shown by Table 4.8, without matching, there is a significant difference in the mean value of different covariates included in Probit model. After matching, there is no systematic difference in the mean value of different covariates. LR test statistics, overall median and mean bias before and after matching have also been reported along with balancing test results. From Table 4.8 we can observe median and mean bias decreases significantly after performing matching. Table 4.9 and Table 4.10 provide balancing test results for rural and urban models. In both cases matching results in less bias in the sample. Most of the variables balanced after matching as shown by the t-value of mean difference.

After calculating propensity scores and balancing test treatment effect on treated have been estimated for different market context and reported in Table 4.11. Table 4.11 gives treatment effect results by using different matching methods. A cursory look at table 4.11 shows the treatment effect on treated is significant for all the three samples. There are variations in the magnitude of treatment effect by different matching methods but all are highly significant.

Empirical exercise shows there is a significant positive impact of microfinancial services on the overall economic wellbeing of the households. The result remains same for different market context. It can be concluded that microfinance is an effective means of reducing poverty of beneficiary households.

Table 4.8 Balancing Test Overall Sample

Variable	Unmatched-Matched	Mean		t-value	p>t
		Treated	Control		
Age of the head of household	Unmatched	38.93	41.26	-5.81	0.00
	Matched	38.56	38.49	0.25	0.80
Square of Age	Unmatched	1662.00	1899.10	-6.57	0.00
	Matched	1619.50	1612.40	0.31	0.76
Household Size	Unmatched	5.05	4.88	2.54	0.01
	Matched	5.00	4.99	0.30	0.77
primary	Unmatched	0.41	0.43	-1.53	0.13
	Matched	0.41	0.42	-0.45	0.65
Secondary and higher	Unmatched	0.57	0.54	1.70	0.09
	Matched	0.57	0.57	0.09	0.93
female	Unmatched	0.10	0.07	2.98	0.00
	Matched	0.09	0.09	0.65	0.52
muslim	Unmatched	0.12	0.11	0.88	0.38
	Matched	0.12	0.11	0.88	0.38
christian	Unmatched	0.08	0.06	1.91	0.06
	Matched	0.08	0.07	0.63	0.53
cast	Unmatched	0.67	0.68	-0.46	0.65
	Matched	0.67	0.77	-2.73	0.0.68
Availability of business opportunity	Unmatched	0.38	0.44	-3.67	0.00
	Matched	0.38	0.37	0.77	0.44
Sample	Pseudo R2	LR chi2	p>chi2	Mean Bias	Median Bias
Raw	0.02	99.58	0.00	8.80	7.10
Matched	0.00	18.75	0.04	1.90	1.30

Table 4.9 Balancing Test Rural Sample

Variable	Unmatched-Matched	Mean		t-value	p>t
		Treated	Control		
Age of the head of household	Unmatched	39.64	42.03	-4.91	0.00
	Matched	39.29	39.63	-1.04	0.30
Square of Age	Unmatched	1720.00	1971.00	-5.63	0.00
	Matched	1679.40	1701.30	-0.77	0.44
Household Size	Unmatched	5.11	5.03	0.99	0.32
	Matched	5.09	5.06	0.65	0.52
primary	Unmatched	0.57	0.60	-1.67	0.10
	Matched	0.58	0.60	-1.54	0.18
Secondary and higher	Unmatched	0.39	0.36	1.84	0.07
	Matched	0.39	0.37	1.29	0.20
Female	Unmatched	0.10	0.07	2.31	0.02
	Matched	0.09	0.08	0.91	0.36
Muslim	Unmatched	0.14	0.12	1.22	0.22
	Matched	0.14	0.14	0.08	0.94
Christian	Unmatched	0.11	0.09	2.04	0.04
	Matched	0.10	0.10	1.00	0.32
Cast	Unmatched	0.65	0.64	0.32	0.75
	Matched	0.65	0.67	-1.48	0.14
Availability of business opportunity	Unmatched	0.34	0.41	-3.78	0.00
	Matched	0.34	0.32	1.97	0.05
Sample	Pseudo R2	LR chi2	p>chi2	Mean Bias	Median Bias
Raw	0.02	74.03	0.00	9.30	7.50
Matched	0.00	17.00	0.07	3.00	2.70

Table 4.10 Balancing Test Urban Sample

Variable	Unmatched / Matched	Mean Treated	Mean Control	t-test	p>t
Age of the head of household	Unmatched	37.47	39.43	-2.81	0.05
	Matched	37.40	37.50	-0.20	0.84
Square of Age	Unmatched	1541.40	1727.10	-3.08	0.00
	Matched	1534.50	1527.70	0.17	0.86
Household Size	Unmatched	4.91	4.53	3.53	0.00
	Matched	4.85	4.81	0.53	0.60
primary	Unmatched	0.07	0.03	3.28	0.00
	Matched	0.06	0.05	1.61	0.11
Secondary and higher	Unmatched	0.93	0.97	-3.28	0.00
	Matched	0.94	0.95	-1.61	0.11
female	Unmatched	0.10	0.07	1.89	0.06
	Matched	0.10	0.11	-0.54	0.59
muslim	Unmatched	0.08	0.08	-0.09	0.93
	Matched	0.08	0.04	3.54	0.00
christian	Unmatched	0.01	0.00	1.44	0.15
	Matched	0.01	0.01	-0.69	0.41
cast	Unmatched	0.72	0.76	-1.70	0.09
	Matched	0.72	0.73	-0.83	0.41
Availability of business opportunity	Unmatched	0.46	0.50	-1.39	0.16
	Matched	0.46	0.49	-1.40	0.16
Sample	Pseudo R2	LR chi2	p>chi2	Mean Bias	Median Bias
Raw	0.03	48.09	0.00	13.50	13.50
Matched	0.01	21.12	0.01	4.50	3.30

Table 4.11 Treatment Effect on Treated by Market Context

Matching Methods	Treated	Controls	Difference	Boot. S.E.	z	P>z
Overall Sample						
One to One Matching	25.08	23.18	1.90***	0.56	3.37	0.00
K-nearest Neighbours Matching	25.08	23.10	1.98***	0.33	5.97	0.00
Caliper Matching	25.08	22.94	2.14***	0.31	6.95	0.00
Kernel Matching	25.08	23.20	1.88***	0.29	6.60	0.00
Local Linear Regression Matching	25.08	22.62	2.46***	0.37	6.60	0.00
Rural Sample						
One to One Matching	21.99	20.14	1.85***	0.57	3.22	0.00
K-nearest Neighbours Matching	21.99	19.90	2.09***	0.45	4.66	0.00
Caliper Matching	21.99	20.02	1.97***	0.35	5.56	0.00
Kernel Matching	21.99	20.36	1.63***	0.37	4.45	0.00
Local Linear Regression Matching	21.99	19.86	2.13***	0.32	6.64	0.00
Urban Sample						
One to One Matching	31.67	29.57	2.11**	0.93	2.27	0.02
K-nearest Neighbours Matching	31.67	29.59	2.08***	0.67	3.09	0.00
Cliper Matching	31.67	29.38	2.29***	0.61	3.74	0.00
Kernel Matching	31.67	29.56	2.11***	0.53	4.00	0.00
Local Linear Regression Matching	31.67	28.94	2.73***	0.68	4.04	0.00

As discussed above, there are three major delivery models of MFIs in India, viz. Grameen, SHG and Individual. We have made an attempt to understand the differential impact of these different models of MFIs. Probit models of participation are reported in Table 4.12. Likelihood ratio test of overall significance for all three models indicate good fit of all these estimated models.

Balancing tests have been conducted after estimating Probit models of participation and results of Grameen, SHG and Individual models are reported in Table 4.13, Table 4.14 and Table 4.15 respectively. Most of the variables are balanced after matching. Overall median and mean bias decreases considerably after matching in all three models reported in Table 4.13, Table 4.14 and Table 4.15.

After calculating propensity score by estimated probability of participation models and success of balancing tests, treatment effect on treated has been estimated for three different models of MFIs. Table 4.16 reports impact results of three models by using various matching methods. Bootstrapped standard errors are also reported in Table 4.16. Some interesting results emerge from impact results reported in Table 4.16. In case of Grameen model there is week impact of microfinance on household poverty. All matching techniques give insignificant impact. For other two models (SHG and Individual) there is significant positive impact of microfinance on household poverty.

Hence analysis of impact of microfinance on household multidimensional poverty index by credit delivery methodologies of MFIs shows Grameen model does not perform well when it comes to impact on poverty. Microfinance provided through two other models of MFIs (SHG and Individual) has been an effective instrument for reducing poverty.

Table 4.12 Probit Model of Participation Model by Different Delivery Schemes

Variables	Grameen		SHG		Individual	
	Coeff.	**P value**	**Coeff.**	**P value**	**Coeff.**	**P value**
Age of the head of household	-0.007**	*0.02*	0.043***	*0.00*	0.019	*0.27*
Square of Age	0.000	*0.82*	-0.001***	*0.00*	0.000*	*0.06*
Household Size	0.019*	*0.07*	0.058***	*0.00*	0.078***	*0.00*
Primary	-0.323	*0.14*	0.097*	*0.10*	-0.002	*0.99*
Secondary and higher	-0.056***	*0.00*			0.102	*0.60*
Female	0.174	*0.18*	0.366***	*0.00*	0.123**	*0.02*
Muslim	0.291***	*0.00*	-0.398***	*0.00*	-0.232	*0.11*
Christian	-0.018	*0.88*	0.326**	*0.01*	0.908*	*0.07*
Cast	-0.053	*0.51*	-0.073	*0.25*	0.115*	*0.07*
Availability of business	-0.231***	*0.00*	-0.169**	*0.01*	-0.067*	*0.07*
Constant	1.060***	*0.00*	-0.326	*0.23*	0.016	*0.97*
Number of obs	1836		2269		970	
LR chi2(10)	51.63		88.33		35.88	
Prob > chi2	0.00		0.00		0.00	
Pseudo R2	0.02		0.03		0.03	
Log likelihood	-1028.03		-1294.27		-535.61	

Table 4.13 Balancing Test of Grameen Model

Variable	Unmatched / Matched	Mean Treated	Mean Control	t-test	p>t
Age of the head of household	Unmatched	37.62	39.84	-3.37	0.00
	Matched	37.49	37.62	-0.30	0.77
Square of Age	Unmatched	1561.70	1757.80	-3.38	0.00
	Matched	1545.00	1553.50	-0.21	0.83
Household Size	Unmatched	5.03	4.99	0.32	0.75
	Matched	5.01	4.95	0.86	0.39
primary	Unmatched	0.33	0.42	-3.36	0.00
	Matched	0.33	0.30	1.97	0.15
Secondary and higher	Unmatched	0.64	0.56	3.03	0.00
	Matched	0.64	0.69	-2.84	0.01
female	Unmatched	0.08	0.06	1.16	0.25
	Matched	0.08	0.07	0.74	0.46
muslim	Unmatched	0.22	0.14	3.57	0.00
	Matched	0.21	0.18	1.75	0.18
christian	Unmatched	0.09	0.09	-0.02	0.98
	Matched	0.09	0.11	-1.23	0.22
cast	Unmatched	0.62	0.60	1.00	0.32
	Matched	0.62	0.59	1.71	0.09
Availability of business opportunity	Unmatched	0.31	0.40	-3.27	0.00
	Matched	0.31	0.30	0.42	0.68
Sample	Pseudo R2	LR chi2	p>chi2	Mean Bias	Median Bias
Raw	0.02	51.63	0.00	11.90	16.60
Matched	0.01	27.62	0.00	4.60	4.10

Table 4.14 Balancing Test of SHG Model

Variable	Unmatched / Matched	Mean Treated	Mean Control	t-value	p>t
Age of the head of household	Unmatched	39.33	41.33	-3.40	0.00
	Matched	39.02	38.95	0.18	0.85
Square of Age	Unmatched	1685.60	1909.40	-4.27	0.00
	Matched	1650.70	1654.90	-0.12	0.90
Household Size	Unmatched	4.89	4.73	1.75	0.08
	Matched	4.88	5.04	-2.39	0.02
primary	Unmatched	0.55	0.52	1.36	0.17
	Matched	0.54	0.59	1.06	0.01
Secondary and higher	Unmatched	0.45	0.48	-1.36	0.17
	Matched	0.46	0.41	1.16	0.01
female	Unmatched	0.13	0.09	3.01	0.00
	Matched	0.13	0.09	2.87	0.00
muslim	Unmatched	0.04	0.08	-3.67	0.00
	Matched	0.04	0.03	1.12	0.26
christian	Unmatched	0.09	0.06	2.10	0.04
	Matched	0.08	0.07	0.72	0.47
cast	Unmatched	0.66	0.71	-2.47	0.01
	Matched	0.65	0.64	0.96	0.34
Availability of business opportunity	Unmatched	0.33	0.39	-2.92	0.00
	Matched	0.33	0.32	0.56	0.57
Sample	Pseudo R2	LR chi2	p>chi2	Mean Bias	Median Bias
Raw	0.03	88.33	0.00	12.10	12.70
Matched	0.01	22.55	0.01	4.80	3.30

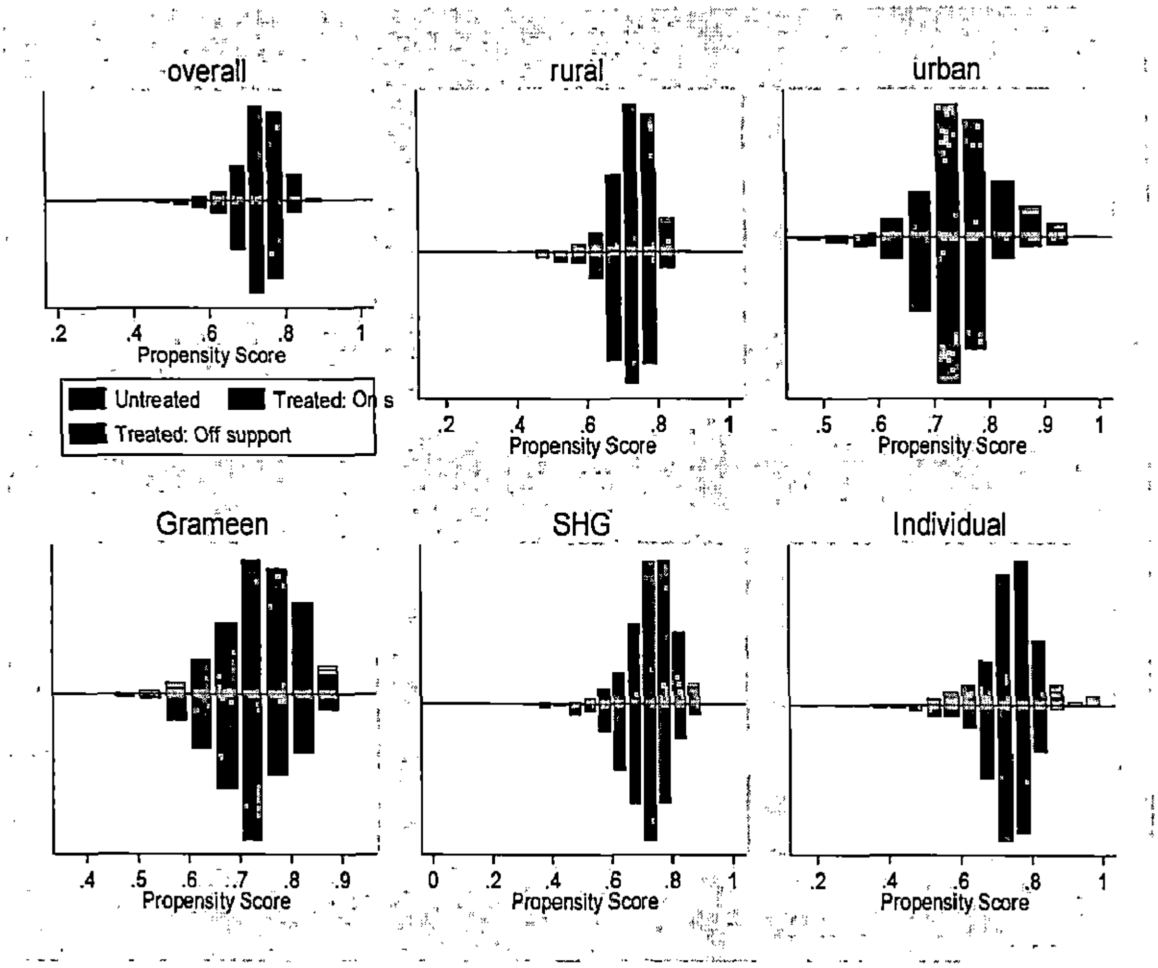
Table 4.15 Balancing Test of Individual Model

Variable	Unmatched / Matched	Mean Treated	Mean Control	t-test	p>t
Age of the head of household	Unmatched	40.50	43.84	-3.45	0.00
	Matched	40.41	41.22	-1.22	0.22
Square of Age	Unmatched	1797.00	2144.10	-3.82	0.00
	Matched	1784.10	1841.70	-0.96	0.34
Household Size	Unmatched	5.44	5.08	2.50	0.01
	Matched	5.33	5.30	0.30	0.76
primary	Unmatched	0.24	0.26	-0.53	0.59
	Matched	0.25	0.24	0.44	0.66
Secondary and higher	Unmatched	0.69	0.64	1.51	0.13
	Matched	0.68	0.68	-0.12	0.91
female	Unmatched	0.07	0.06	0.52	0.60
	Matched	0.06	0.05	1.07	0.29
muslim	Unmatched	0.11	0.13	-0.60	0.55
	Matched	0.12	0.10	1.04	0.30
christian	Unmatched	0.03	0.00	2.15	0.03
	Matched	0.00	0.00	-1.42	0.16
cast	Unmatched	0.80	0.75	1.50	0.13
	Matched	0.80	0.81	-0.68	0.50
Availability of business opportunity	Unmatched	0.61	0.61	-0.02	0.98
	Matched	0.61	0.61	-0.06	0.96
Sample	Pseudo R2	LR chi2	p>chi2	Mean Bias	Median Bias
Raw	0.03	35.88	0.00	12.20	10.90
Matched	0.00	7.59	0.58	3.20	3.00

Table 4.16 Treatment Effect on Treated by Delivery Models

Matching Methods	Treated	Controls	Difference	Boot. S.E.	z	P>z
Grameen Model						
One to One Matching	21.78	20.87	0.90	0.83	1.08	0.28
K-nearest Neighbours Matching	21.78	21.03	0.75	0.59	1.26	0.21
Radius Matching	21.78	20.88	0.90*	0.48	1.87	0.06
Kernel Matching	21.78	20.66	1.11**	0.48	2.33	0.02
Local Linear Regression Matching	21.78	20.68	1.10**	0.50	2.22	0.03
SHG Model						
One to One Matching	23.76	21.45	2.31***	0.66	3.50	0.00
K-nearest Neighbours Matching	23.76	21.24	2.51***	0.63	3.97	0.00
Radius Matching	23.76	21.57	2.19***	0.53	4.16	0.00
Kernel Matching	23.76	21.91	1.85***	0.53	3.49	0.00
Local Linear Regression Matching	23.76	21.56	2.19***	0.65	3.35	0.00
Individual Model						
One to One Matching	34.37	30.09	4.28***	1.33	3.21	0.00
K-nearest Neighbours Matching	34.37	30.82	3.55***	0.92	3.87	0.00
Radius Matching	34.37	30.78	3.58***	0.85	4.20	0.00
Kernel Matching	34.48	30.26	4.22***	0.64	6.61	0.00
Local Linear Regression Matching	34.48	30.94	3.54***	0.73	4.84	0.00

Figure 4.3 Distribution of Propensity Scores



4.4 Conclusions

Expansion of MFIs during recent years is due to the large scale involvement of Development Institutions, NGOs, Donors, Government, etc., who believe microfinance is an effective way of reducing poverty. A Lot of funds are poured into the sector in the form of donation and subsidies to propel the holistic mission of microfinance. There is a need of strong evidences suggesting the impact of microfinance on the economic and social well-being for justifying subsidies and donations. If microfinance does not improve the condition of the poor such fund must be used in other approaches directed towards poverty alleviation.

The current research tried to understand who is participating in microfinance and also aims at ascertaining the impact of microfinance on poverty by using large scale household level data by applying rigorous statistical methods. For accessing poverty outreach of MFIs and impact of microfinance on poverty the study relies on nationally representative household level data collected by EDA-rural for longitudinal impact assessment study conducted by SIDBI in 2002-03.

Our analysis indicates, poverty outreach of rural market is low but participation of women is satisfactory. Schedule castes and tribes have a low probability of participation in rural microfinance market. Result of the Rural-SHG model also gives similar results, where participation of wealthier clients is high in the programme. Estimation results of Rural-Grameen model gives optimistic picture as far as poverty outreach is concerned. There is no significant difference in probability of participation of various wealth rank categories in Rural- Grameen model. Looking at the overall urban market results, we can conclude poverty outreach in unsatisfactory. For Urban-SHG model estimated coefficients of two wealth rank categories are positive and highly significant; which shows a higher probability of participation of less poor households. For Urban- Grameen MFIs, there is no significant difference in the participation of different wealth rank category households in microfinance. The estimated coefficient of the two included wealth rank categories is negative (even though it is insignificant) which means poorest of the poor are participating more than others. The study concluded Grameen model is best as far as poverty outreach is concerned. Better outreach of Grameen model may be due to the proper targeting mechanism adopted by these MFI. MFIs following Grameen approach generally use some targeting criterion for screening poor clients. Grameen model exclusively focuses on the targeting poor clients and ultimately reducing poverty of targeted groups.

Impact analysis shows there is a significant positive impact of microfinancial services on the overall economic wellbeing of the households. The result remains same for different market context. It can be concluded that microfinance is an effective means of reducing poverty of beneficiary households. Further, analysis of impact of microfinance on household multidimensional poverty index by credit delivery methodologies of MFIs shows Grameen model does not perform well when it comes to impact on poverty. Microfinance provided through two other models of MFIs (SHG and Individual) has been an effective instrument for reducing poverty.