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Abstract:
Drawing upon the data in 2001, the present study analyses the effect of Micro Finance Institutions (MFIs) on poverty of households in India. The propensity score matching is employed to estimate the poverty-reducing effects of the access to MFIs and the loans used for productive purposes to take account of the endogeneity problem. Significantly positive effects on the multidimensional poverty indicator suggest the role of MFIs in poverty reduction. We also show that households in rural areas need loans from MFIs for productive purposes to reduce poverty, while simply accessing to MFIs is sufficient for urban households to reduce it.

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

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I. Introduction

The relationship between microfinance and poverty is still an unsettled question, mainly due to the disproportionate focus on financial sustainability of microfinance institutions. This view supports the argument that microfinance institutions should aim for sustainable financial services to low income people, and, reasonably contradicts the potential role of this institutional innovation in poverty reduction and empowerment. Irrespective of these approaches, many organizations have used these institutions to develop a range of services on a continuing basis to address the requirements of the poor people. However, there is an argument that microfinance supports informal activities which have a low market demand and the aggregate poverty impact of microfinance is modest or non existent in a slow growth economy. However, Khandker (2003) addresses this issue using household level panel data in the context of Bangladesh and confirms that microfinance programmes have a sustained impact in reducing poverty among the participants and a positive spill over effect at the village level. The findings of the study indicate that microfinance programmes are helping the poor beyond income redistribution with contribution to local economic growth.

The development of the microfinance sector is based on the concept that the poor possess the capacity to implement income generating activities and is limited by lack of access and inadequate provision of savings, credit and insurance facilities. However, there are apprehensions on the role of microfinance institutions to provide services and products to the poorest of the poor category (Hulme and Mosley, 1996). The real challenge in serving poorest of the poor is to identify the beneficiaries from various categories such as financial services alone, non financial services along with finance, and non financial services before participating in market oriented finance (Meyer,2002). The recent literature suggest the need for microfinance institutions to move away from the perceptions of a products based organization to reflect the heterogeneity of demand structure for financial services/products by the poor people and the complex livelihood need of the poor (Arun and Hulme, 2003). To capture the multi-dimensional dimensions of poverty, such as basic needs, capabilities, social capital or vulnerability, this study used 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 the recent economic growth at national level[1], poverty remains still a serious problem for policy-makers because (i) the growth is mainly driven by growth in a few sectors in urban area, such as industry and service sectors[2] and is unevenly distributed within the urban, and between urban and rural area, (ii) 'trickle down' of the benefits from economic growth to the poor is limited even in the area with high economic growth due to social factors, and (iii) the rural-urban linkages are weak due mainly to the geographical factors. Based on the US1$ a day poverty line, poverty head count ratio was 35.3 per cent in 2000, which had been reduced from 42.3 per cent in 1993. Poverty reduction remains the country's major challenge.

Recently, the Government of India has initiated some targeted interventions such as National Rural Employment Guarantee Scheme has been proposed to extend the Employment Guarantee Scheme (EGS) in Maharashtra to the poorest 150 districts.[3] However, the scheme is not available to those who are old or are physically weak. The EGS potentially has some effects to help the participants cope with various shocks (e.g. drought), but these risk-reducing benefits are limited only to agricultural workers with high wages because the poor cannot afford the high costs of participating in the scheme (Scandizzo et al., 2005). Thus, the potential of this type of intervention to reduce poverty and vulnerability of households is limited if a negative shock occurs frequently and often in the large magnitude as in India. The recent studies on vulnerability in India suggest that a large section of rural households in India is not only poor but also *vulnerable* to both idiosyncratic and aggregate shocks (e.g. Gaiha and Imai, 2004, 2006; Ligon, 2005)[4]. Microfinance schemes play potentially important roles not only in reducing poverty but also in reducing vulnerability with the schemes appropriately designed and instrumented to cover the poorest households.

In India, until the early 1990s, the micro 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. Although many of these bank branches in rural areas were unprofitable, they did play a positive role in financial savings and reducing poverty which is evident in the fact during the 1951-1991 periods; the share of total financial institutions in rural house hold debt has increased from 8.8 per cent to 53.3 percent, and the role of money lenders has declined significantly during this period. However, despite the vast network of banking and cooperative finance institutions and srong micro components in various programmes, the performance of formal financial sector is still far behind in reaching out to reflect and respond the requirements of the poor. This is true to an extent that most of the initiatives in the formal sector are based on the preconceived notion that rural people are not bankable and not reflecting the heterogeneous needs of the poor which led to the growth of several subsidy-linked credit programs in India where the state had a crucial role in identifying the borrowers and in the allocation of credit and subsidy.

In the 1990s, the microfinance schemes or microfinance institutions (MFIs) have become increasingly important in India mainly due to the potential advantages of these schemes such as better access to local knowledge and information at community level and use of peer group monitoring. For example, Microfinance based on SHGs (Self-Help Groups) has become increasingly important in India through its flexible nature (Mosley and Arun, 2003). This distinctive microfinance programme is based on the existing banking network in delivering financial services to the poor. These groups are building on the traditional institution of ROSCA, and provide access to both savings and credit for the asset less poor. The rapid expansion of SHG groups has even generated discussions on formal financial institutions and microfinance institutions, and appropriate policy decisions based on it. A recent study in Pune district in Maharashtra shows that while the targeting performance of microfinance through SHGs was unsatisfactory in terms of income, it was satisfactory in caste, landlessness and illiteracy and thus facilitates empowerment of women (Gaiha and Nandhi, 2005). This study also finds that loans were used largely for health and education of children and argues against confining the impact assessment of microfinance to conventional economic criteria alone.

Despite its increasingly important roles of MFIs in poverty reduction in India, there have been relatively few studies that evaluate the effect of MFIs on poverty in India. The present study aims to provide empirical evidence on the relationship between MFIs and poverty using the large-scale household data set in India which was collected by one of the authors with the aim to assess 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 sanitation facility[5]. Our research question is simple -whether the access to MFI reduces poverty. Simple comparison of the average of IBR indicator of households with access to MFI and that without is not appropriate because MFI is not randomly distributed due to sample selection where MFI targets poor households or poor households tend to take loans from or save at MFIs (EDA Rural Systems, 2005). The commonly used econometric method is the Instrumental Variable (IV) estimation, but the survey data do not necessarily contain data for the valid instruments or the results are not reliable if the instrument is not significant. As an alternative to IV, the present study employs propensity score matching estimators to identify the policy effects as average treatment effects to take into account the sample selection bias.

The rest of the paper is organized as follows. Section II summarises the survey design and data. Section III describes econometric methodology we use to estimate average treatment effects based on propensity score. Section IV provides econometric results and main findings, followed by the conclusions in the final section.

II. Survey Design and Data [6]

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. The two-stage longitudinal socio-economic research was undertaken to assess on a national scale, the development impact of MFI programmes. The study covered a sample of 20 partner Micro Finance Institutions (MFIs) of SIDBI and 5327 households, 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 the study is: 'Microfinance is an effective strategy for extending financial services to the poor and other disadvantaged groups by the formal sector finance,' which was generally supported by the reports (SIDBI, 2005; EDA Systems, 2002, 2005).

Suppositions which have also been corroborated by the survey include: (1) MFI services reach those who have not yet accessed formal sector finance; (2) MFIs' outreach is generally focused on poorer areas; (3) MFIs serve all castes and communities; and (4) majority of clients are women and micro finance has supported increased non-farm employment (SIDBI, 2005). The study confirmed that (a) micro credit has significantly promoted the incidence of borrowing for investment (60% of client households versus 38% of non-client households have borrowed for investment); (b) micro finance has supported increased non-farm employment, especially for poor/borderline clients; (c) MFI involvement has enabled client households to diversify their income sources and reduce dependency; (d) MFIs involvement positively affects children's education, although the client- non-client difference is not too large; (e) MFI involvement helps clients protect against risk through livelihood diversification, asset building and savings and; (f) access to Micro finance has had a significant positive impact on women's economic and social empowerment (SIDBI, 2005).

Five MFIs were selected as representative of 31 MFIs in SFMC's list of current partners – representing different regions, models of microfinance (Self Help Group -SHG, Grameen, Individual Banking and sector/enterprise specific cooperatives), age, and outreach to members and range of services. At each MFI, two to four sample areas (villages or urban wards) were selected purposefully to represent a 'typical' area of the MFI in terms of 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).

Coverage of a microfinance programme is computed on the basis of number of client households compared to the total number of households in sample villages and urban slums. In rural areas, outreach of the sample is to 25% households in smaller villages (<500 households) and 13% in larger villages. The data set has 3320 client households and 1226 non-client households, the latter of which is used as a control. The main objective of this study is to statistically compare poverty defined by the wellbeing ranking for both groups of households using the propensity-score ranking.

Index Based Ranking (IRR) Indicators

Index Based Ranking Indicators were created to overcome the income or consumption based poverty measures and capture non-income or multi-dimensional dimensions of poverty, such as basic needs, capabilities, social capital or vulnerability (Sihna 2002). 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 simple questions) and higher reliability due to lower risk of falsification or error. Respondents are asked about quality of life in several dimensions, including (a) income (e.g. regularity of income, type of employment), (b) productive assets (e.g. land-holding and number and quality of livestock, only for rural area), (c) basic needs (e.g. food security, use of health care services, sanitation), (d) capabilities /human and social capital (e.g. children's schooling, major expenses on health treatment), (e) housing (e.g. material or size, ownership) and (f) household assets (ownership of bicycle or 4-wheeler, TV etc.). Then IBR indicators are created as a weighted sum of scores (as a maximum score of 60) for each category (ranged from 0-6) using different weights different for rural and urban areas in four categories, namely 'very poor', 'poor', 'borderline' 'non-poor' were created (Sinha, 2002). However, to keep continuity of the variable, we use the IBR indicators as they are in the following sections.

III. Methodology

Our main hypothesis is the access of microfinance institutions (MFIs) reduces poverty 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 or there is no sample selection bias. The methodology widely used in the literature is the IV estimation or the Heckman sample selection model where the access to MFIs is estimated in the first stage and the effect of access to MFI on poverty is estimated in the second. While useful, the estimation results are only robust if they are estimated with valid instruments which affect the access to MFIs, but not poverty. In general, it is not necessarily easy to find such valid instruments. Also, if the linear regressions are used, the linear relationship is assumed between dependent variables and explanatory variables and distributional assumptions have to be imposed on the explanatory variables (Foster, 2003).

Because our dependent variable is the IBR indicator which has already incorporated various aspects of wellbeing, it is not easy to find a valid instrument in our context. Hence, we use statistical matching which has been widely used in the medical study where dose response of patients is analysed. This first specifies a function matching the proximity of one household to another in terms of household characteristics and then households are grouped to minimize the distance between matched cases (Foster, 2003). Merits of using statistical matching over the IV estimation includes; 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 details, for example, by Becker and Ichino (2002), Dehejia (2005), Dehejia and Wahba (2002), and Smith and Todd (2005). We will summarise estimation methods for the propensity score matching based on these studies.

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).

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

where $D = \{0, 1\}$ is the binary variable on 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 the 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:

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

where *i* denotes the *i-th* household, W_{1i} is the potential outcome (as 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 of the IBR indicator of the *i-th* household with access to MFI and that for the same household in the counterfactual situation where it would not have had access to MFI. The second line is same as the first line except that the expected policy effect is defined over the distribution of the propensity score. The last line is the policy effect as an 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) the access to MFI. In other words, for a specific propensity score, the MFI is randomly distributed and thus on average households with MFI 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 the 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 logit (or probit) model:

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

where Φ denotes the logistic (or normal) cumulative distribution function (cdf) and $h(X_i)$ is a starting specification.

One possible procedure for statistical matching is *Stratification Matching* whereby the sample is split in *k* equally spaced intervals of the propensity score to ensure that within each interval test the average propensity scores of treated and control households do not differ. We did not use Stratification Matching as observations are discarded when either treated or control units are absent. Instead, we use other variants in matching estimators of the average effect of treatment on the treated, namely, *Nearest Neighbour Matching* and *Kernel Matching.*[7] *Nearest Neighbour Matching* is the method to take each treated unit and search for the control unit with the closest propensity score, while with *Kernel Matching* all 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 the Appendix 1 for details).

IV. Results

This section provides the results for matching estimators to investigate the effects of the access to MFIs on poverty. Because of the fundamental differences of environment, industrial structures, household characteristics or activities between urban and rural areas, we will first derive the estimations for total households and then apply the same specification for urban areas and rural areas separately.

Only having access to MFIs does not necessarily affect household wellbeing particularly if one does not have a long transaction history or has only a zero account. Therefore the present study uses the following two different definitions of the access to MFIs:

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

b) whether a household has taken a loan from MFI for a productive activity ("*mfi_productive*").[8]

The first definition is used to see the effect of simply accessing MFI on poverty and that of utilizing microfinance for any productive purposes

Table 1 provides descriptive statistics used for the estimation. The first two panels show that about three quarters (irrespective of being in rural or in urban areas) in the sample households have access to MFIs, while about a half of them have taken loans for productive purposes. On the latter, the share is higher in rural areas than in urban areas. The higher share of being headed by a female member implies that MFIs are targeted to those households and controls are selected by a similar criterion. Education of household head of most of the households in rural areas is either illiterate or 'completed primary school', while all completed only primary school in urban areas. This reflects only poor households with low levels of education are targeted by MFIs. Household size is about five. About 30% of the sample households are scheduled caste or tribe reflecting that the microfinance targets mainly poor households. The average IBR index of households in rural areas is lower than that in urban areas, implying that poverty is severer in rural areas.

(Table 1 to be inserted around here)

Estimation results of logit model in Table 2 are generally intuitive in the case for the entire households where dependent variable is 'MFI_status' (i.e. Case A-1) (e.g. a household with older household head is more likely to be a client; a household with female household head is more likely to be a client, which reflects the fact that microfinance focuses on women; education has a positive and significant impact; dependency ratio has a negative and significant effect). However, in Case B-1 where 'MFI_productive' is estimated for the entire households, a few changes are observed. The coefficient of 'Age' ceases to be significant, and that for 'Female' is *negative* and significant, that is, a household with male household head is more likely to take a loan for productive purposes. This reflects the fact that while microfinance focuses on women, male-headed households tend to be in a more advantageous position to take loans for productive purposes.

The coefficient of 'Education' is *negative* and significant, and that of 'Caste_dum' is positive and significant. These results imply that relatively poor households whose household head has a lower level of education or is illiterate, or which are in scheduled caste or scheduled tribe tend to take a loan for productive purposes. Cases A-2 and A-3 and Cases B-2 and B-3 in Table 2 show the results of logit model applied separately for urban areas and rural areas. In Cases A-2 and A-3, in urban areas, the coefficient of 'Age' is not significant, while in rural areas it is positive and significant at 10% level, while other results look generally similar to those in Case A-1. The results for rural areas in Case B-3 are generally consistent with those in Case B-1 for total households except that the coefficient of 'Education' is positive and significant.

(Table 2 to be inserted around here)

Based on the results of logit model in Table 2, we derived the propensity scores for each case.[9] With the same specification applied to all the cases, the balancing hypotheses are satisfied in all the cases except case B-1. Only in this case did we try a different specification where the square of age is dropped and then it has been found that the balancing hypothesis is satisfied.[10] It is assumed as in Becker and Ichino (2002) that 'unconfoundedness' is satisfied.

Table 3 and Table 4 provide the results for matching estimators which are based on the equations (3) and (4). Table 3 shows the results which are based on Cases A-1 to A-3 (for 'MFI_status') and Table 4 based on Cases B-1 to B-3 in Table 2 (for 'MFI_productive'). All the results use bootstrapped standard errors. The columns we are interested in those labeled as 'Average Poverty Reducing Effect' and '*t* value'. Both Table 3 and Table 4 generally confirm that the 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 is much higher than those of households with the same propensity score (estimated by household characteristics) without. 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 3.

(Table 3 & 4 to be inserted around here)

Appendix 2 shows some details of propensity score matching. It is noted that even after enforcing common support only a few observations are dropped through the comparison of observations for those MFI supported and for those not supported. 3 observations are dropped in Case A-1; none in Case A-2; 3 in Case A-3; 1 observation is dropped in Case B-1; 3 in Case B-2; 1 in Case B-3. In each case, we first identified the optimal number of blocks which ensures that the mean propensity score is not different for treated and controls in each block.[11] Then, we test the balancing property of the propensity score for each block and for all covariates of the logit model. It should be noted that the balancing property is satisfied for all covariates for all blocks, which validates our choice of the covariates and the results of propensity score matching. Then, we apply Nearest Neighbour Matching and Kernel Matching based on our estimates for propensity score.

Absolute values of the 'Average Poverty-Reducing Effects' show that the extent to which the access to MFIs increased an IBR indicator, i.e., reduced poverty. Table 3 shows that simply being able to have access to MFIs has a larger poverty reducing effect in urban areas than in rural areas. That is, it is not sufficient for poor households in rural areas to have access to MFIs to reduce poverty. However, Table 4 indicates that the 'Average Poverty-Reducing Effect' in rural areas expected from taking loans from MFIs is larger than that in corresponding cases in Table 3 (i.e., 3.755 in Case of Nearest Neighbour Matching and 3.488 in Case of Kernel Matching). These results imply that unless the poor households are able to take loans from MFIs from productive purposes, they cannot substantially escape from poverty, which is consistent with Gaiha and Nandhi's (2005) results based on a survey in Maharashtra. In urban areas, having loans from MFIs for productive purposes has a poverty-reducing effect that is not much different from simply having access to MFIs.

While propensity score matching is a potentially useful method to control for endogeneity, the results have to be interpreted with caution as shown in the recent discourse between Smith and Todd (2005) and Dehejia (2005) particularly with matching based on 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). Thus, sensitivity tests based on small changes in the specification are important (Dehejia 2005). We tried different specifications by including squares of some of the right-hand-side variables (e.g. household size or dependency ratio) in the logit model and have got similar results.

V. Conclusions

Drawing upon a national-level cross-sectional household data set in India in 2001, the present study analyses the effect of Micro Finance Institutions on poverty of households, which is defined by the indexed based ranking (IBR) indicator, a measure reflecting multi-dimensional aspects of poverty, such as basic needs, capabilities, social capital or vulnerability. To take account of sample selection bias problems arising from the household access to MFIs, the propensity score matching is employed to estimate the poverty-reducing effects of the access to MFIs and the loans used for productive purposes. Significantly positive effects are observed on the IBR indicator, which suggests that MFIs play an important role in poverty reduction. If we decompose the results into rural and urban areas, some interesting results emerged. First, for households in rural areas, significant results are observed only in the case where the access to MFIs is defined as household taking loans from MFIs for productive purposes and *not* in the case of simply having access to MFIs. The result implies that monitoring the use of loans as well as increasing the productivities is particularly important in helping the poor escaping from poverty and protecting them from various shocks. In urban areas, such significant poverty-reducing effects are observed in both cases. As the large section of poor households is not only poor bus also *vulnerable*, a stronger emphasis should be placed on microfinance schemes as a policy means of poverty reduction in both urban and rural areas in India.

Table 1 Descriptive Statistics and Definitions of the Variables

Variable	Definition		Obs	Mean	Std. Dev.
MFI_status	Whether any member in the household has access to MFI	(Total)	5327	0.734	0.442
		(Urban)	1385	0.740	0.439
		(Rural)	3942	0.731	0.443
MFI_productive	Whether a hh has taken a loan for productive purposes	(Total)	5327	0.524	0.499
		(Urban)	1385	0.379	0.485
		(Rural)	3942	0.576	0.494
Age	Age of household head	(Total)	5327	39.943	12.792
		(Urban)	1385	37.686	11.861
		(Rural)	3942	40.735	13.012
Female	Whether a hh head is female	(Total)	5327	0.089	0.285
		(Urban)	1385	0.095	0.293
		(Rural)	3942	0.088	0.283
Education	Education of the household head (0= illiterate, 1= completed primary school (5th), 2= completed higher (12th))	(Total)	5327	0.588	0.2852
		(Urban)	1385	1.000	0.000
		(Rural)	3942	0.443	0.555
Hhsize	Household size: number of household members	(Total)	5327	5.032	2.029
		(Urban)	1385	4.691	1.827
		(Rural)	3942	5.152	2.082
Dependency	Dependency Ratio (Ratio of hh members under 15 or over 60 to the total)	(Total)	5326	2.712	1.343
		(Urban)	1385	2.769	1.330
		(Rural)	3941	2.692	1.347
Caste_dum	Whether a household is scheduled caste or tribe (=0) or not (=1) not	(Total)	5327	0.687	0.464
		(Urban)	1385	0.760	0.428
		(Rural)	3942	0.662	0.473
Urban_dum	Whether a household is in urban areas or not	(Total)	5327	0.260	0.439
IBR indicator	Indexed Based Ranking of a household's wellbeing	(Total)	5076	24.704	11.809
		(Urban)	1382	33.218	11.525
		(Rural)	3694	21.519	10.232

Table 2 Results of logit Model on the Determinants of Access to Microfinance

Case A: Dep Variable: whether a household has access to a MFI ("MFI_Status")									
	Case A-1: Total			Case A-2: Urban			Case A-3: Rural		
	Coef.	Z value	1)	Coef.	Z value		Coef.	Z value	
Age	0.023	(1.79)	+	0.007	(0.24)		0.016	(1.84)	+
Age_square	0.000	(-3.24)	**	0.000	(-0.86)		0.000	(-3.14)	**
Female	0.448	(3.68)	**	0.480	(2.02)	*	0.253	(3.08)	**
Education	0.166	(2.80)	**	-	-	2)	0.107	(2.71)	**
Hhsize	0.115	(6.35)	**	0.211	(4.91)	**	0.053	(4.57)	**
Dependency	-0.180	(-7.44)	**	-0.242	(-4.90)	**	-0.098	(-5.88)	**
Caste_dum	0.009	(0.13)		-0.190	(-1.25)		0.039	(0.85)	
Constant	1.127	(3.61)		1.528	(2.40)		0.663	(3.08)	
No. of Obs.	5326			1385			3941		
Joint Significance	LR $Chi^2(7)$=133.28		**	LR $Chi^2(6)$=48.87		**	LR $Chi^2(7)$=94.64		**
Log likelihood	-3020.71			-769.14			-2246.24		
Pseudo R2	0.022			0.038			0.026		

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	0.009	(0.72)		0.005	(0.19)		0.002	(0.23)	
Age_square	0.000	(-1.87)	+	0.000	(-0.64)		0.000	(-1.56)	
Female	-0.293	(-2.88)	**	0.220	(1.09)		-0.208	(-2.81)	**
Education	-0.210	(-3.98)	**	-	-	2)	0.064	(1.72)	+
Hhsize	0.166	(10.28)	**	0.155	(4.50)	**	0.094	(8.58)	**
Dependency	-0.200	(-8.76)	**	-0.398	(-7.67)	**	-0.092	(-5.72)	**
Caste_dum	0.299	(4.91)	**	0.595	(4.23)	**	0.192	(4.45)	**
Constant	-0.447	(-1.58)		-0.689	(-1.14)		-0.206	(-1.01)	
No. of Obs.	5326			1385			3941		
Joint Significance	LR $Chi^2(7)$=138.50		**	LR $Chi^2(6)$=90.33		**	LR $Chi^2(7)$=153.86		**
Log likelihood	-3570.32			-873.92			-2609.37		
Pseudo R2	0.0308			0.0491			0.0286		

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.

Table 3: Results of Propensity Score Matching (based on Case A in Table 2 where dependent variable is 'whether a household has access to a MFI'):
Effects of MFIs in Reducing Poverty (estimation using Bootstrapped Standard Errors, 100 Rps.)

Whether a household is a client of any MFI ("**MFI_status"**)or not

	Households with MFIs	Households without MFIs	**Average Poverty-Reducing Effect**	S.E.	**t value**
Nearest Neighbour Matching					
Total (Case A-1)	3907	1146	**1.693**	0.495	**3.417****
Urban(Case A-2)	1025	303	**3.811**	1.031	**3.697****
Rural (Case A-3)	2882	813	**0.459**	0.529	**0.868**
Kernel Matching					
Total (Case A-1)	3907	1417	**1.668**	0.338	**4.929****
Urban (Case A-2)	1025	360	**3.028**	0.664	**4.832****
Rural (Case A-3)	2882	1057	**0.993**	0.400	**2.485***

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

Table 4: Results of Propensity Score Matching (based on Case B in Table 2 where dependent variable is 'whether a household has taken a loan from MFI or the group for a productive activity):

Effects of MFIs in Reducing Poverty (estimation using Bootstrapped Standard Errors, 100 Rps.)

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	1626	**2.037**	0.494	**4.198****
Urban (Case B-2)	525	428	**2.254**	0.952	**2.368****
Rural (Case B-3)	2296	1109	**3.755**	0.440	**8.538****
Kernel Matching					
Total (Case B-1)	2794	2532	**1.965**	0.311	**6.311****
Urban (Case B-2)	525	857	**3.825**	0.642	**5.962****
Rural (Case B-3)	2269	1109	**3.755**	0.504	**7.455****

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

Appendix 1: Technical Details of Nearest Neighbour Matching and Kernel Matching

Nearest Neighbour Matching

Nearest Neighbour Matching is the method to take each treated unit and search for the control unit with the closest propensity score. Let T be the set of treated units (i.e. households with access to MFIs) and C be the set of control units (*i.e.* households without access to MFIs), and W_i^T and W_j^C be the observed outcomes (i.e. the IBR indicator) of treated and control units. $C(i)$ denotes the set of control units matched to the treated units i with an estimated value of the propensity score of p_i. In *Nearest Neighbour Matching,*

$$C(i) = \min_j \left\| p_i - p_j \right\|$$

Denoting the number of controls matched with observation $i \in T$ by N_i^C and define the weights $\omega_{ij} = \frac{1}{N_i^C}$ if $j \in C(i)$ and $\omega_{ij} = 0$ otherwise. The number of units in the treated group is N^T. Then the formula for a matching estimator is:

$$\begin{aligned}
\tau &= \frac{1}{N^T} \sum_{i \in T} \left[W_i^T - \sum_{j \in C(i)} \omega_{ij} W_j^C \right] \\
&= \frac{1}{N^T} \left[\sum_{i \in T} W_i^T - \sum_{i \in T} \sum_{j \in C(i)} \omega_{ij} W_j^C \right] \\
&= \frac{1}{N^T} \sum_{i \in T} W_i^T - \frac{1}{N^T} \sum_{j \in C} \omega_j W_j^C \qquad (3)
\end{aligned}$$

where $\omega_j = \sum_i \omega_{ij}$.

Kernel Matching

With *Kernel Matching* all 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 (Becker and Ichino, 2002). Then the formula for a matching estimator is:

$$\tau = \frac{1}{N^T}\sum_{i \in T}\left\{W_i^T - \frac{\sum_{j \in C} W_j^C G\left(\frac{p_j - p_i}{h_n}\right)}{\sum_{k \in C} G\left(\frac{p_k - p_i}{h_n}\right)}\right\} \tag{4}$$

where $G(.)$ is a kernel function and h_n is a bandwidth parameter. We use a Kernel Matching Estimator because the results are not subject to a specific radius or a number of stratification.

Appendix 2: Details of Computation of Propensity Score Matching

Case A-1 Total

Region for common support	Min.	Max.	Obs.	No. of blocks
	0.2889	0.9324	**5324**	7

Balancing Hypothesis **: Satisfied for all variables for all blocks.**

Inferior of block of propensity score	With access to MFI	With no access to MFI	Total
0.2	4	6	10
0.4	97	109	206
0.6	360	709	1069
0.7	466	1178	1644
0.75	241	754	995
0.775	130	567	697
0.8	119	584	703
Total	1417	3907	5324

Case A-2 Urban

Region for common support	Min.	Max.	Obs.	No. of blocks
	0.3068	0.9816	**1385**	5

Balancing Hypothesis **: Satisfied for all variables for all blocks.**

Inferior of block of propensity score	With access to MFI	With no access to MFI	Total
0.2	1	1	2
0.4	26	29	55
0.6	128	228	356
0.7	158	501	659
0.8	47	266	313
Total	360	1025	1385

Case A-3 Rural

Region for common support	Min.	Max.	Obs.	No. of blocks
	0.2731	0.9069	**3939**	5

Balancing Hypothesis **: Satisfied for all variables for all blocks.**

Inferior of block of propensity score	With access to MFI	With no access to MFI	Total
0.2	3	7	10
0.4	85	86	171

0.6	249	467	716
0.7	643	1961	2604
0.8	77	361	438
Total	1057	2882	3939

Case B-1 Total

Region for common support	Min.	Max.	Obs.	No. of blocks
	0.123	0.9364	**5326**	8

Balancing Hypothesis	**: Satisfied for all variables for all blocks.**		
Inferior of block of propensity score	With access to MFI	With no access to MFI	Total
0.1220151	7	1	8
0.2	383	201	584
0.4	363	225	588
0.45	458	436	894
0.5	917	1186	2103
0.6	339	573	912
0.7	54	156	210
0.8	11	16	27
Total	2532	2794	5326

Case B-2 Urban

Region for common support	Min.	Max.	Obs.	No. of blocks
	0.0721	0.8518	**1382**	5

Balancing Hypothesis	**: Satisfied for all variables for all blocks.**		
Inferior of block of propensity score	With access to MFI	With no access to MFI	Total
0.0721321	98	21	119
0.2	422	176	598
0.4	328	311	639
0.6	9	16	25
0.8	0	1	1
Total	857	525	1382

Case B-3 Rural

Region for common support	Min.	Max.	Obs.	No. of blocks
	0.2338	0.9111	**3941**	6

Balancing Hypothesis	: Satisfied for all variables for all blocks		
Inferior of block of propensity score	With access to MFI	With no access to MFI	Total
0.4	6	6	12
0.5	233	237	470
0.55	1290	1837	3127
0.6	143	189	332
Total	1672	2269	3941

Endnotes:

[1] For example, real GDP grew by 6.9 percent in 2004/2005.

[2] 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 agricultural sector is 2.0% (based on World Bank Data in 2005 taken from http://devdata.worldbank.org/AAG/ind_aag.pdf).

[3] See Gaiha and Imai (2005).

[4] The relative size of idiosyncratic risks is larger in Gaiha and Imai (2006) than in Ligon (2005) due to the difference in specifications and ways to correct measurement errors.

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

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

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

[8] An extension would be to create a binary variable based on a particular number of transaction years with MFIs to capture the effects of transaction history on poverty. However, households with a long history of transaction are a sub-set of those with any transaction at the time of survey (as we do not have any data on leaving the MFIs in the past), this is unlikely to change our main conclusions.

[9] Details of the distributions of propensity scores will be provided on request.

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

[11] See Becker and Ichino (2002) for details of the computation procedure.

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