

MANCHESTER
1824

The University
of Manchester

Economics
Discussion Paper Series
EDP-1019

**Does Microfinance Reduce Poverty in
Bangladesh? New Evidence from
Household Panel Data**

Katsushi Imai

Md. Shafiul Azam

October 2010

Economics
School of Social Sciences
The University of Manchester
Manchester M13 9PL

Does Microfinance Reduce Poverty in Bangladesh? New Evidence from Household Panel Data*

Katsushi S. Imai

Economics, School of Social Sciences, University of Manchester, UK & Research Institute for Economics & Business Administration (RIEB), Kobe University, Japan

&

Md. Shafiul Azam

Economics, School of Social Sciences, University of Manchester, UK

30th September 2010

Abstract

The purpose of the present study is to examine whether microfinance reduces poverty in Bangladesh drawing upon the nationally representative household panel data covering 4 rounds from 1997 to 2005. A special attention was drawn to the issue of endogeneity by applying treatment effects model and propensity score matching (PSM) for the participants and non-participants of microfinance programmes. It has been confirmed by treatment effects model applied to panel data that household access to loans for productive purposes from microfinance institutions (MFIs) significantly increased per capita household income, while simple household access to general loans from MFIs did not. This suggests that purpose and monitoring of how clients use the loans is important for increasing household income, and thus decreasing household poverty. However, the application of treatment effects model and PSM to each cross-sectional component of the panel data shows that the poverty reducing effect of MFI on poverty was significantly reduced over the years. This suggests the need of more attention to be drawn to the primary purpose of microcredit, that is, poverty reduction, and also to monitoring loan usages in the situations where the profits of MFIs became increasingly squeezed and their activities became more commercialised under severe competitions among MFIs in recent years.

Key words: microfinance, MFI (microfinance institution), microcredit, poverty, Bangladesh

JEL codes: C30, C31, G21, I32

*Corresponding Author:

Katsushi Imai (Dr)

Department of Economics, School of Social Sciences

University of Manchester, Arthur Lewis Building,

Oxford Road, Manchester M13 9PL, UK

Phone: +44-(0)161-275-4827

Fax: +44-(0)161-275-4928

E-mail: Katsushi.Imai@manchester.ac.uk

Acknowledgement

This study is funded by IFAD (International Fund for Agricultural Development). The authors are grateful to Raghav Gaiha and Ganesh Thapa for their support and guidance throughout this study. The first author wishes to thank RIEB, Kobe University for generous research support during his stay in 2010 and acknowledge valuable comments and advice from Shoji Nishijima, Takahiro Sato and seminar participants at Kobe University. The paper has greatly benefited from comments from Thankom Arun and Samuel Annim. The views expressed are our personal views and not necessarily of the organisations to which we are affiliated.

Does Microfinance Reduce Poverty in Bangladesh? New Evidence from Household Panel Data*

I. Introduction

The idea that microfinance helps poor people build businesses, increase their income and exit poverty has turned into a global movement, so called ‘microfinance revolution’, to fight against poverty over the last three decades. This is reflected in the significant increase of donor countries’ investment in microfinance sector in recent years. The poor tend to have limited access to services from formal financial institutions in less developed countries due to, for example, (i) the lack of physical collateral of the poor; (ii) the cumbersome procedure to start transaction with formal banks, which would discourage those without education from approaching the banks; and (iii) lack of supply of credit in the rural areas related to urban biased banking networks and credit allocations. The hallmark of microfinance revolution is the system of group lending based on the joint liability or ‘social capital’ of communities which would guarantee to repay loans. Here the poor with no physical collateral are allowed to form a group to gain access to credit and the repayment rate is kept high because of, for example, mutual monitoring, sanction against non-repayment of the member or incentives to retain the individual reputation or credit within a community (e.g. Armendáriz and Morduch, 2005, Besley and Coate, 1995, Ahlin and Townsend, 2007).¹

The last thirty years witnessed a phenomenal growth in microfinance sector serving about 40 million clients with an outstanding loan portfolio of US\$17 billion in mid-2006 and the projected market size could be around US\$250-300 billion in near future (Ehrbeck, 2006). However, the argument that microfinance responds to the derived demand for borrowing to support self-employment and small business has come under intense scrutiny in recent years. Even the hard core of pro-microfinance researchers now broadly agree that attention should be drawn to both supply and demand sides of microfinance in order for the sector to have a

noticeable poverty reducing effects. As Robert Pollin (2007, p.2) notes, micro-enterprises “need a vibrant, well functioning domestic market itself that encompasses enough people with enough money to buy what these enterprises have to sell”. Moreover, as noted by Bateman and Chang (2009), microfinance neglects the crucial role of scale economies and it produces an oversupply of inefficient micro-enterprises that could undermine the development of more efficient small and medium industries (SMEs) that would be potentially able to reduce unit costs and register productivity growth in the long run. However, shifting the donor’s fund away from very small groups or enterprises (target of microfinance institutions) to SMEs could imply the neglect of the very poor who are credit constrained and could increase poverty in the country given the recent evidence that has shown a negative and statistically significant association between the MFI loans and poverty based on cross-country data (Imai et al. 2010). The development agencies of donor countries or government will have to make sure whether the benefits to programme participants are sustainable and large enough to make a dent in the poverty of participants and society at large.

Bangladesh has recorded a modest 4-6 % growth within a stable macroeconomic framework in recent years. The poverty trend has shown a consistent decline in poverty incidence over the years, especially in rural areas. However, aggregate poverty rates still remain dauntingly high. According to the estimates based on the Household Income and Expenditure Surveys (HIES) of the Bangladesh Bureau of Statistics, poverty head count ratio declined from 58.8 % in 1991 to 48.9 % per cent in 2000 and it further declined to 40.0 % in 2005. So poverty has declined on average just above one percentage point a year since the 1990s. The observed improvement holds true for the distributionally sensitive poverty measures: the poverty gap ratio reduced from 17.2 % to 12.9 % and the squared poverty gap ratio from 6.8 % to 4.6 % during the same period from 2000 to 2005. This indicates that the situation of the poorest also improved during this period, though there existed the very poor

as well as inequality among the poor even in 2005. The head count ratio in rural area reduced from 52.3 % in 2000 to 43.8 % in 2005. However, the absolute number of people living below poverty line was in fact on the rise –a staggering 56 million people were found to be poor in 2005. The corresponding figure was 55 million in 2000. Similarly, hard core poverty remains almost same during the period 2000-2005 (18.8 % and 18.7 % in 2000 and 2005 respectively). So poverty reduction remains the most daunting challenge for Bangladesh.

Bangladesh, the birthplace of microfinance, is credited with the largest and most vibrant microcredit sector in the world. Microcredit programmes are implemented in Bangladesh by host of formal financial institutions, specialized government organizations and semi-formal financial institutions (nearly 1000 NGOs-MFIs). Furthermore, with a view to coordinating the flow of funds to appropriate use and NGOs-MFI activities, the Palli Karma Sahayak Foundation (the Bengali acronym PKSf and can be translated into English as “Rural Employment Support Foundation”) came into being in 1990. The growth in the MFI sector, in terms of the number of MFIs as well as total membership, was phenomenal during the 1990s and after 2000. The effective coverage would be around 17.32 million borrowers. The total amount is 24.25 million due to overlapping –one borrower taking loan form more than one MFI and the extent of overlapping may be as high as 40% (PKSF, 2006). Out of 17.32 million borrowers covered by micro credit programmes, about 62% were below the poverty line, that is, 10.74 million poor borrowers were covered by MFI programmes. 56 million people were estimated to be poor in 2005. 53% of those or 29.26 million were supposed to be economically active and were potentially the target group of microfinance operation. Therefore, there was still scope for further extending the coverage of microcredit programmes in 2005 to an approximate 18.52 million borrowers who were poor and economically active but not covered by MFI programmes (Ahmed, 2007).

The main purpose of the present study tests whether microfinance reduces poverty in Bangladesh drawing upon the nationally representative household panel data covering 4 rounds, 1997-98, 1998-99, 1999-2000, and 2004-05. A special attention is drawn to the issue of endogeneity on participation in microfinance by applying treatment effects model and propensity score matching for the participants and non-participants of microfinance programmes.

The rest of the paper is organized as follows. The next section surveys the literature on poverty and microfinance in Bangladesh. Section III describes briefly the survey design and data. Section IV explains the underlying econometric intuition of treatment effect model and Section V summarizes the econometric results and findings. The final section offers concluding observations.

II. The Literature Review on Poverty and Microfinance

Despite the data limitations and methodological problems, e.g. on dealing with the sample selection bias associated with microfinance participation, there are a few rigorous studies to assess the impact of microfinance on poverty. The findings of a set of studies summarised by Hulme and Mosley (1996) are somewhat provocative: households with initial higher income above the poverty line benefited from microfinance and enjoyed sizeable positive impacts, while poorer households below the poverty line did not. A majority of those with their initial income below the poverty line actually ended up with less incremental income after obtaining microcredit, as compared to a control group which did not get any loans from MFI. Pitt and Khandker (1998) carried out a survey in 1991/92 involving about 1800 households in Bangladesh and found that for every 100 taka borrowed by a woman, household consumption expenditure increased by 18 taka. For a male borrower, the figure is 11 taka. They estimated the poverty reducing effect of three major microfinance institutions in Bangladesh namely –

Bangladesh Rural Advancement Committee (BRAC), Grameen Bank, and Bangladesh Rural Development Board (BRDB). Moderate and ultra poverty was reduced by about 15 % and 25 % for households who were BRAC members for up to three years. Similar results are found for Grameen Bank and BRDB members.

Drawing upon the follow up survey in 1998/99, Khandker (2005) found resounding results at both micro and aggregate levels: microcredit continued to contribute to reducing poverty among poor borrowers and within local economy. The impact appears to be greater for households who were initially the extremely poor (18 percentage point drop in extreme poverty in seven years) compared to moderate poor households (8.5 percentage point drop). These results differ from earlier evidence that pointed to moderate poor borrowers having benefited more than extremely poor borrowers who tended to have a number of constraints (e.g. fewer income sources, worse health and education) which prevent them from investing the loan in a high-return activity (Wood and Sharif 1997). The finding that better off households benefiting more was also borne out by detailed case-study evidence (Farashuddin, and Amin,1998) and by comparing participants of credit programmes who cater to different socio-economic groups (Montgomery et al., 1996).

The general conclusions of Pitt and Khandker (1998) and Khandker (2005) about the impact of microcredit on poverty include: (i) microcredit was effective in reducing poverty generally, (ii) this is especially true when borrowers were women, and (iii) the extremely poor benefit most in 1998/99. However, the last point has been contested and questioned by Morduch (1998) and Roodman and Morduch (2009). Morduch (1998) using the same data set but a different way of correcting sample selection bias, finds that microcredit had a consumption smoothing effect for households who were at risk, that is, microcredit helped families smooth their consumption expenditures and lessen the pinch of hunger in lean periods. But the study broadly failed to find any significant impact on household

consumption levels and on income poverty. A recent study by Roodman and Morduch (2009) found similar results and pointed to the methodological flaws and econometric issues on the absence of robust and decisive statistical evidence in these literatures. Consumption data from 1072 households in one district of Bangladesh were used to show that the largest effect on poverty occurs when a moderate-poor BRAC client borrows more than tk10,000 (US\$200) in cumulative loans (Zaman, 1998). In other words, there may be a threshold level of credit above which a household gains most in terms of increases in income.

The relationship between poverty and microfinance is unclear outside Bangladesh. Two recent studies that attempted to overcome the sample selection problem by using randomized sample selection methods also came up with not so resounding evidence in favour of microcredit. Banerjee, Duflo, Glennerster and Kinnan (2009) did not find much strong average impact; i.e., the impact on measures of health, education, or women's decision-making among the slum dwellers in the city of Hyderabad, India was negligible. The study by Karlan and Zinman (2009) took a similar method to the Philippines, with a focus on the traditional microcredit for small business investment. Profits rise, but largely for men and particularly for men with higher incomes. Moreover, the increases in profits appear to arise from business contractions that yielded smaller, lower-cost (and more profitable) enterprises. Imai et al. (2010), however, found that the loans from MFI for productive purposes reduced significantly multifaceted household poverty, which was defined in terms of assets, employment, health facilities, and food security, using the survey data in India in 2000.

Given the inconclusive and ambiguous nature of evaluation outcomes and increasing involvement of MFIs both in terms of number of institutions and resources in poverty reduction efforts, it is important to have a deeper look into the relationship between microfinance or microcredit and poverty. The present study aims to provide new evidence on the impact of microfinance on poverty in rural Bangladesh using a large and nationally

representative panel data. The indicator for wellbeing/poverty is per capita household income. This paper seeks to answer the question –whether access to loans from MFIs for general purposes (or loans from MFIs for productive purposes) reduced poverty in rural Bangladesh. Ideally, the impact of microfinance should be ascertained by a counterfactual approach- what would have happened to a person who took a loan from a MFI if she or he had not done so. However, such a counterfactual is never observed in reality. The easiest and intuitive method is to compare the welfare or income of borrowers and non-borrowers. But such comparison is problematic for a number of reasons. First, MFIs are not distributed across regions randomly due to endogenous programme placement where MFIs generally target poorer households, or the constituent of core group of clientele for the services of MFIs are poorer households. Second, there is a self selection problem, that is, whether an individual participates in the MFI programme is determined by herself, not by chance. That is, within the area where the MFI programme is available, individuals sharing similar socio-cultural backgrounds (e.g., education, age or religion) might have different levels of entrepreneurial skills and latent ability leading to different probabilities to their participating in certain programme. Hence, it is essential to take into account the endogeneity or self-selection problems in assessing the impact of microfinance.

III. Design of Survey and Data

(a) Details of Survey

The four-round panel survey was carried out by the Bangladesh Institute of Development Studies (BIDS) for Bangladesh Rural Employment Support Foundation (PKSF) with funding from the World Bank. All four rounds of the survey were conducted during the December-February period in 1997-98, 1998-99, 1999-2000, and 2004-05. The survey covered a sample of 13 PKSF's Partner Organization (PO) and over 3000 households in each round distributed

evenly throughout Bangladesh so as to obtain a nationally representative data set for the evaluation of microfinance programmes in the country (different districts spanning 91 villages from around 23 thanas).

A sample of villages under each of the selected MFI was drawn through stratified random sampling. The stratification was based on the presence or absence of microfinance activities. The non-programme or control villages were selected from the neighbouring villages. At each PO, six to eight villages were selected depending on the availability of control villages. In selecting survey households, the universe of households in the programme villages drawn from the census was grouped according to their eligibility status. A household is said to be eligible if it owns 50 decimals (half an acre) or less of cultivable land. Participation status of the household is defined using the net borrowing from a MFI. If a household is not a participant in a given round, the net borrowing is zero for that household. From the village census list, 34 households were drawn from each of the programme and non-programme villages. The proportion of eligible and non-eligible households was kept at around 12:5 and the sample size within the programme and control villages was determined accordingly. The ratio is chosen to reflect the average participants to non-participants ratio of the population in the village. This is the largest and the most comprehensive data of its kind so far in Bangladesh collected with detailed information on a number of socio economic variables, including household demographics, consumption, assets and income, health and education and participation in microcredit programmes.

(b) Descriptive Statistics and Definition of Variables

The study uses two different definitions of access to Microfinance Institutions: first, whether a household is a client of any MFI and takes loans for general purposes or not, and second, whether a household has actually taken a loan from any MFI for productive purpose or not.

The first definition is used to observe the effect of taking general loans from MFI on per

capita household income and thus on poverty. The second is concerned with whether the household has taken loans for productive activities (and has an outstanding balance of loans at the time of survey) leading to an increase in production, for example, starting a small business or other self employment activities, like small scale poultry or cattle rearing. Loans used for consumption or other non-productive activities like marriage or dowry are excluded from this category.

Appendix provides the descriptive statistics of the variables for the sample households with access to loans from MFI and for those without. As shown by the number of observations, more than a half of the sample household have access to MFI loans. About a half of them have access to loans from MFI for productive purposes. In general, there is a relatively negligible difference between the descriptive statistics of each variable for the households with and without access to loans from MFIs (or with access to loans from MFIs for productive purposes) and for those without.

The average household size is about 6 for both categories of households. Head of the households are categorised into four groups depending on their educational level – illiterate, completing primary education, secondary education, or higher education. Similarly, occupation of the head of the households is grouped into six distinct categories – farmers, agricultural wage labourers, non-agricultural wage labourers, small business, professionals (which comprises of teachers, lawyers, doctors and other salaried employees), and others (beggars, students, retired persons, disabled, unemployed etc.). However, per capita income is generally higher for those who do not take MFI loan or participate in MFI programmes. This does not necessarily imply that taking loans from MFIs reduces per capita income due to the aforementioned sample selection bias. About 93 per cent of the households are male headed, mainly due to the sample design where households in a village are selected randomly even though a majority of the MFI clients are female.

IV. Methodology

(a) Treatment Effects Model

To address the self-selection problem, the present study applies the treatment effects model, a version of the Heckman sample selection model (Heckman, 1979). The treatment effect model estimates the probit model in the first stage and in the second stage, per capita income, our indicator for poverty, is estimated by OLS while sample selection is corrected by using the estimates of the probability of participation in the microfinance programme in the first stage. The model is fitted by a full maximum likelihood (Maddala 1983). The merits of the treatment effects model include – (i) the degree of sample selection bias is explicitly taken into account and (ii) the determinants of the dependent variables in the second stage are fully identified. However, the treatment effects model imposes strong distributional assumptions for the functions in both stages and the final results are highly sensitive to the choice of explanatory variables and the instrument.

In the first stage, access to loans from MFIs is estimated by the probit model where a dependent variable is whether a household had a member who took loans from a MFI for general purposes (or for productive purposes). In the second, the model estimates log of per capita income after controlling for the inverse Mills ratio which reflects the degree of sample selection bias. Distance from nearest ‘Upzilla’, the business and administrative hub where most of the local services including marketing and financial are available, is used as an instrument. This satisfies the exclusion condition as it correlated with participation in a microfinance programme, but not with income of the households. People living nearby should have better business opportunities leading to higher demand for credit than those living far away. But this does not directly affect per capita income.

The merit of treatment effects model is that sample selection bias is explicitly estimated by using the results of probit model. However, the weak aspects include (i) strong

assumptions are imposed on distributions of the error terms in the first and the second stages, (ii) the results are sensitive to choice of the explanatory variables and instruments, and (iii) valid instruments are rarely found in the non-experimental data.

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

$$D_i^* = \gamma X_i + u_i \quad (1)$$

and $D_i^* = 1$ if $D_i^* = \gamma X_i + u_i > 0$

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

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

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

D_i^* is a latent variable. In our case, D_i takes 1 if a household has access to and 0 otherwise and X_i is a vector of household characteristics and other determinants. Φ denotes the standard normal cumulative distribution function.

The linear outcome regression model in the second stage is specified below to examine the determinants of poverty, denoted as W_i . That is,

$$W_i = \beta' Z_i + \theta D_i + \varepsilon_i \quad (2)$$

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

where θ is the average net wealth benefit of accessing loans from MFIs.

Using a formula for the joint density of bivariate normally distributed variables, the expected poverty for those with access to MFI loans is written as:

$$E[W_i | D_i = 1] = \beta' Z_i + \theta + E[\varepsilon_i | D_i = 1]$$

$$= \beta' Z_i + \theta + \rho \sigma_\varepsilon \frac{\phi(\gamma' X_i)}{\Phi(\gamma' X_i)} \quad (3)$$

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

Expected poverty for non-clients is:

$$\begin{aligned} E[W_i | D_i = 0] &= \beta'Z_i + E[\varepsilon_i | D_i = 0] \\ &= \beta'Z_i - \rho\sigma_\varepsilon \frac{\phi(\gamma'X_i)}{1 - \Phi(\gamma'X_i)} \end{aligned} \quad (4)$$

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

$$E[W_i | D_i = 1] - E[W_i | D_i = 0] = \theta + \rho\sigma_\varepsilon \frac{\phi(\gamma'X_i)}{\Phi(\gamma'X_i)[1 - \Phi(\gamma'X_i)]} \quad (5)$$

If ρ is positive (negative), the coefficient estimate of θ using OLS is biased upward (downward) and the sample selection term will correct this. Since σ_ε is positive, the sign and significance of the estimate of $\rho\sigma_\varepsilon$ (usually denoted as β_λ) will show whether there exists any selection bias. To estimate the parameters of this model, the likelihood function given by Maddala (1983, p. 122) is used where the bivariate normal function is reduced to the univariate function and the correlation coefficient ρ . The predicted values of (3) and (4) are derived and compared by the standard t test to examine whether the average treatment effect or poverty reducing effect is significant.

The results of treatment effects model will have to be interpreted with caution because the results are sensitive to the specification of the model or the selection of explanatory variables and/or the instrument. Also important are the distributional assumptions of the model.

(b) Propensity Score Matching

As a robustness check, we will apply Propensity Score Matching (PSM) to the same set of the data to see whether the pattern of the results derived by treatment effects model is same. Our hypothesis is same: the access of MFI general loans or MFI productive loans increases per capita household income. The statistical matching has been widely used in the medical

study where dose response of patients is analysed. The first stage 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 in the second stage (Foster, 2003). Merits of using statistical matching over the IV (instrumental variable) estimation or treatment effects model 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 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), Ravallion (2008), Smith and Todd (2005), and Todd (2008). While there are some advantages in using PSM to estimate the impact of the policy, the derived impact depends on the variables used for matching and the quantity and quality of available data and the procedure to eliminate any sample selection bias is based on observables (Ravallion 2008). If there are important unobservable variables in the model, the bias is still likely to remain in the estimates. For example, if the selection bias based on unobservables counteracts that based on observables, then eliminating only the latter bias may increase aggregate bias, while the replication studies comparing non-experimental evaluations, such as PSM, with experiments for the same programmes do not appear to have found such an example in practice (ibid. 2008).

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

$$p(X) = Pr\{D = 1|X\} = E\{D|X\} \quad (6)$$

where $D = \{0, 1\}$ is the binary variable on whether a household had access to MFIs (1) or not (0) and X is a 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:

$$\begin{aligned}
\tau &\equiv E\{W_{1i} - W_{0i} | D_i = 1\} \\
&= E\{E\{W_{1i} - W_{0i} | D_i = 1, p(X_i)\}\} \\
&= E\{E\{W_{1i} | D_i = 1, p(X_i)\} - E\{W_{0i} | D_i = 0, p(X_i)\} | D_i = 1\}
\end{aligned} \tag{7}$$

where i denotes the i -th household, W_{1i} is the potential outcome (per capita household income) 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 per capita household income 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 per capita household income 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.

Under certain conditions², the policy effect can be estimated by the procedures described in Becker and Ichino (2002) and Smith and Todd (2005). Each procedure involves estimating probit or logit model:

$$\Pr\{D_i = 1 | X_i\} = \Phi(h(X_i)) \tag{8}$$

where Φ denotes the logistic (or normal) cumulative distribution function (cdf) and $h(X_i)$ is a starting specification. We use the probit model whereby whether a household has access to MFI loans is estimated by household and socio-economic characteristics.

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*.³ *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 Becker and Ichino, 2002, for details).

V. Results

The first and second stage results of the treatment effect model are reported in Table 1. They correspond to the equations (1) and (2) in the previous section. Table 2 and Table 3 show the final results of treatment effects in comparison with those of propensity score matching for the current and lagged access to loans from MFIs for general or productive purposes. Each table comparatively presents the results in which a dependent variable in the first stage is whether a household had access to general loans from MFIs (Case (a)) and those in which a dependent variable is replaced by whether a household had access to loans from MFIs for productive purposes (Case (b)). The first stage probit results in the first panel of Table 1 reflect the determinants of access to MFI general loans, or access to MFI loans for productive

purposes. The second panel of Table 1 presents the results of treatment effects model. The final result in Table 3, the first row (denoted as ‘panel data’) of Case (a) and that of Case (b) show that the loans from MFI for productive purposes increased per capita household income significantly, but general MFI loans did not. This suggests the importance of loan purpose and monitoring.

(Table 1 to be inserted around here)

As shown by Case (a) of the first panel of Table 1, the coefficient estimate of age of the head of the household is positive and significant, which implies that a household with older head is more likely to have a member taking a general loan from MFIs, but the statistically significant and negative coefficient estimate of ‘age squared’ suggests a non-linear effect of age of the head. The positive and significant coefficient estimate of household size implies that larger households have higher probability of having members who participated in microfinance programmes. In the participation equation, the coefficient estimate of sex of the head of the household, whether a head is female or not, is positive and significant. Given that microfinance targets women, the result implies that a household headed by a woman is more likely to have a participant in the MFI programmes than a male headed household. The coefficient estimates of all the non-MFI sources of borrowing are negative and significant, which reflects the fact that those who do not have access to, or are excluded from the traditional sources of credit tend to get loans from MFI.⁴ The coefficient of distance from the nearest *Upzilla* (a business hub), an instrument for the treatment effects model, is negative and significant. This indicates that a household living closer to the nearest town with *Upzilla* are more likely to participate in a microcredit programme than those who live far away. This makes sense because *Upzilla* provides banking, marketing and other essential services for micro businesses and enterprises to market their products.

The coefficient estimates of the education dummies are all negative and significant except for primary education. This means the reference category, i.e., illiterate households, are more likely to have a member of participating in microfinance programmes. Coefficient estimates of different occupational categories reveal that a household whose head's occupation is the non-agricultural wage labourer or runs the small business is more likely to have a member of participating in microfinance programmes. This makes sense as these two categories form the core clientele of MFIs. Case (b) of Table 1 shows the results of probit model in which the dependent variable is whether a household has taken loans for productive purposes from MFI. Broadly similar results are obtained and we will not mention these to avoid clustering the text.

The second stage results where log of per capita household income is estimated are shown in the second panel of Table 1. Most of the results are expected for Case (a) and Case (b). Age of the head is positive and significant and its square is negative and significant. Household size is non-significant. Among the loans from non-MFI sources, the coefficient estimate of 'loans from family and friends' is positive and significant. As expected, households headed by a female member tend to have much lesser per capita household income, implying that female headed households are economically more disadvantaged than male headed households. Year dummies show that per capita household income is the smallest in a default case (1997-1998) and it is the largest in 2004-2005 after controlling for inflation. The results of a set of dummy variables on educational achievement implies that a household with the head least educated (or illiterate) tends to have the lowest per capita household income and that with the head most highly educated (who completed higher education) tends to have the highest level of income. Dummy variables on occupational categories of head are also expected- a household headed by an agricultural wage labourer has the lowest average per capita household income, while the household headed by a person working as a professional or in small business has higher income. Infrastructure proxied by

electricity availability is positive and highly significant. Whether a household has access to MFI (general loans or productive loans) is negative and significant, but this should not be interpreted as a policy effect due to the sample selection bias. Treatment effects should be derived by the equation (5) after controlling for the sample selection bias.

A summary of policy effects derived by treatment effects model and propensity score matching (PSM) is presented in Table 2. Based on treatment effects model, we have derived the treatment effects using the equation (5) for the panel data covering all the rounds and for each round of cross-sectional data (i.e., for 1997-1998, 1998-1999, 1999-2000 and 2004-2005). Regression results corresponding to the treatment effects based on each round of cross-sectional data are broadly similar to those for panel data in Table 1 and are not presented here.⁵ Average treatment effects for the treated (ATT) have been derived by PSM using *Nearest Neighbour Matching* and *Kernel Matching* for each round of cross-sectional data.⁶

(Table 2 to be inserted around here)

We have found that simple household access to general loans from MFIs did not increase log per capita household income significantly as the average treatment effect for panel data is negative and non-significant as shown by the first row of the first panel, Case (a). However, it is confirmed by the same panel data that household access to loans for productive purposes from MFIs significantly increased log per capita household income as in the first row of the second panel, Case (b). This suggests that monitoring how clients use the loans is important for increasing household income, and thus decreasing poverty.

However, taking a close look at the policy effects derived by each cross-sectional component of panel data, we have found that the policy effects have changed dramatically over the years, positive and significant effects of MFI loans on per capita household income

in the first round in 1997-1998 to negative and significant, or non-significant effects in the last round in 2004-2004 for both Case (a) and Case (b). That is, income-enhancing or poverty-reducing effects of MFI loans have deteriorated over the years. It is also noted that a broadly similar pattern of the results has been obtained by treatment effects model and PSM. That is, the PSM has served as a robustness check.

In 1997-1998, the access to general loans from MFIs significantly increased per capita household income Case (a) irrespective of whether we have used treatment effects model or PSM, while in Case (b) the MFI loans for productive purposes significantly increased income in the case of treatment effects model and of PSM when kernel matching is applied. That is, the significant income enhancing effects were observed for both Cases (a) and (b) in 1997-1998. In both 1998-1999 and 1999-2000, the policy effects of access to MFI general loans became non-significant (Case (a)), whilst positive and significant effects were observed for MFI productive loans (Case (b)) for both treatment effects model and PSM except the case of PSM based on *Nearest Neighbour Matching* where the policy effect was positive and non-significant. In contrast, in 2004-2005, the policy effect of MFI loans became *negative* and significant in Case (a) (except the case of PSM based on *Nearest Neighbour Matching* where it was positive and non-significant). In the same year, in Case (b), the policy effect of MFI productive loans was negative and significant in the case where treatment effects model was applied, whilst it is non-significant for PSM.

One could argue that there is a time lag from the time when a household member took MFI loans for general purposes or productive purposes and the time when a household actually enjoyed any income increase. For example, It may take a year or more for the agricultural production assets purchased by productive loans from MFI to have any income generating effects. Even if the MFI loan was used for consumption purposes, the household income could increase in the long run if the loan was used to avoid the hardships arising from

short-run shocks, such as floods. Dercon and Christiansen (2008) showed using the Ethiopian Household panel data that failure to reduce consumption fluctuations causes inefficiency in agricultural production choices and increases the risk for the household trapped into chronic poverty. Those who obtained MFI loans for productive purposes might see increase in the household income in the future by the improved productivity, not necessarily observed at the time when they obtained loans, but a year or a few years later.

(Table 3 to be inserted around here)

Table 3 shows that the overall pattern of the results on the relationship between the lagged MFI participation and log of per capita household income is not much different from those for the current MFI participations presented in Table 2. However, in Case (a) where the MFI participation is defined in terms of access to general loans, household access to MFI has a significant and positive impact in 1998-1999 and 1999-2000 when treatment effects model is employed. The results in the corresponding cases were non-significant in Table 2. Despite a few changes, the results in Table 3 are broadly consistent with those in Table 2 and support our conclusion that access to loans for productive purposes significantly increased log per capita household income, but MFI loans for productive purposes did not and that the policy effects of MFIs have deteriorated over the years.

Why the policy effects of MFIs have been weakened over the years is not clear. However, it is surmised that severer competition among MFIs have made MFI loans more commercialised, have squeezed the profits MFIs and have weakened the poverty-reducing effects at household level in recent years after 2000. Another possibility is fungibility, that is, some part of MFI loans was used for the purposes which do not increase income, such as consumption. While the reasons are not obvious, our results suggest that more attention should be drawn to the poverty reducing effects of microcredit and monitoring the purpose and use of loans even in Bangladesh where microfinance has most flourished.

VI. Concluding Observations

The main purpose of the present study was to examine whether microfinance reduced poverty in Bangladesh drawing upon the nationally representative household panel data covering 4 rounds, 1997-98, 1998-99, 1999-2000, and 2004-05. A special attention was drawn to the issue of endogeneity by applying treatment effects model and propensity score matching (PSM) for the participants and non-participants of microfinance programmes.

It has been confirmed by treatment effects model applied to panel data that household access to loans for productive purposes from microfinance institutions (MFIs) significantly increased per capita household income, while simple household access to general loans from MFIs did not. The results will hold regardless of whether we define access to MFI loans in terms of current access, or lagged access. This suggests that the monitoring of how clients use the loans is important for increasing household income, and thus decreasing household poverty. However, the application of treatment effects model and PSM to each cross-sectional component of the panel data shows that (i) the policy effect of household access to MFI general loans on per capita household income turned from positive and significant in 1997-1998 (and positive and significant in 1998-1999 and 1999-2000 in the cases of treatment effects model where the access to loans from MFI is lagged) to negative and significant in 2004-2005 and (ii) the effect of household access to MFI loans for productive purposes on per capita household income also turned from positive and significant in 1997-1998, 1998-1999, and 1999-2000 to negative and significant (in case of treatment effects model) or non-significant (in case of PSM) in 2004-2005. Why the income enhancing or poverty reducing effects became weak in 2004-2005 was not clear, but our results suggest that a greater attention should be drawn to guaranteeing the sizable poverty reducing effects through the MFI's better systems of monitoring of loan usages in the situations where the

profits of MFIs became increasingly squeezed and their activities became more commercialised under severe competitions among MFIs in recent years.

Table 1. Regression Results of Treatment Effects Model
Results of Probit model on the determinants of participation in microfinance
programme (1st stage)

	Case (a) Dependent variable: whether a household has access to MFI	Case (b) Dependent variable: whether a household has taken a productive MFI loan
	Coefficient Estimate (z value) ^{**1}	Coefficient Estimate (z value) ^{**1}
Age of the head of the hh	0.0497 (8.18)**	0.0444 (6.84)**
Age_squared	-0.0005 (-8.92)**	-0.00049 (-7.47)**
Household size	0.0200 (4.21)**	0.0153 (3.08)**
Formal bank loan	-0.0000054 (-1.72)†	-0.0000037 (1.12)
Loans from family and friends	-0.0000020 (-1.93)†	-0.0000027 (2.21)*
Loan from village money lender	-0.00000643 (-2.84)**	-0.0000013 (-0.57)
Distance from nearest Upazilla (a business hub)	-0.0078	-0.0048
(an instrument)	(-3.74)**	(-2.25)*
Sex of head of household (whether a head is female)	0.2054 (3.53)**	0.1884 (3.02)**
Whether in 1998-1999 (2 nd round)	-0.0900 (-2.52)*	-0.2994 (-8.34)**
Whether in 1999-2000 (3 rd round)	-0.2237 (-6.28)**	-0.5516 (-15.04)**
Whether in 2004-2005 (4 th round)	-0.3072 (-7.92)**	-0.4700 (-11.86)**
Education of head of household– completed primary school	-0.0273 (-0.79)	-0.0432 (-1.21)
Education of head of household– completed secondary school	-0.2513 (-7.17)**	-0.2351 (-6.44)**
Education of head of household– completed higher education	-0.4511 (-5.76)**	-0.4438 (-5.20)**
Occupation of head of household- Agricultural wage labourer	-0.0561 (-1.22)	-0.2260 (-4.72)**
Occupation of head of household- Non-Agricultural wage labourer	0.1618 (3.62)**	0.0194 (0.43)
Occupation of head of household- small business	0.3380 (9.17)**	0.2817 (7.67)**
Occupation of head of household- professionals	-0.0855 (-1.47)	-0.2036 (-3.28)**
Occupation of head of household- others	-0.0844 (-1.99)*	-0.1702 (-3.79)**
Whether a household has electricity or not	-0.1283 (-4.31)**	-0.0268 (-0.87)
Constant	-1.007 (6.25)	-1.12 (6.58)
Observations	10163	10163
Joint Significant Test	LR Chi ² (20)=560.37** Prob> Chi ² =0.0000	LR Chi ² (20)=647.94** Prob> Chi ² =0.0000

Log likelihood=-6747.09

Log likelihood=-6270.73

Results on the determinants of per capita household income (2nd stage)

	Case (a) Dependent variable: log of per capita income (1 st stage: whether a household has access to MFI (general loans))	Case (b) Dependent variable: log of per capita income (1 st stage: whether a household has taken a productive MFI loan)
	Coefficient Estimate (z value) ⁻¹	Coefficient Estimate (z value) ⁻¹
Age of the head of the household	0.0050 (5.39)**	0.0049 (5.14)**
Age squared	-0.000013 (-2.76)**	-0.000012 (-2.53)*
Household size	0.00053 (0.17)	-0.00092 (-0.29)
Formal bank loan	0.0000003 (0.57)	0.0000004 (0.74)
Loans from family and friends	0.0000028 (4.67)**	0.0000028 (4.36)**
Loan from village money lender	0.0000018 (1.31)	0.0000031 (2.24)*
Sex of head of household (whether a head is female)	-0.1521 (-4.13)**	-0.1549 (-4.07)**
Whether in 1998-1999 (2 nd round)	0.0885 (3.99)**	-0.0207 (-0.87)
Whether in 1999-2000 (3 rd round)	0.0733 (3.21)**	-0.0264 (-1.08)
Whether in 2004-2005 (4 th round)	0.2583 (10.27)**	0.1954 (7.47)**
Education of head of household- completed primary school	0.0885 (3.99)**	0.0836 (3.64)**
Education of head of household- completed secondary school	0.0733 (3.21)**	0.0757 (3.25)**
Education of head of household- completed higher education	0.2446 (4.90)**	0.2490 (4.86)**
Occupation of head of household- Agricultural wage labourer	-0.0594 (-2.00)*	-0.1145 (-3.72)**
Occupation of head of household- Non-Agricultural wage labourer	0.2826 (9.83)**	0.2404 (8.11)**
Occupation of head of household- small business	0.3790 (15.65)**	0.3746 (15.33)**
Occupation of head of household- professionals	0.3488 (9.38)**	0.3137 (8.13)**
Occupation of head of household- others	0.0255 (0.95)	0.0026 (0.09)
Whether a household has electricity or not	0.3296 (17.45)**	0.3579 (18.41)**
Whether a household has access to MFI (general loans or productive loans)	-0.7634 (-14.77)**	-0.8771 (-24.20)**
Inverse Mills Ratio (β_x)	0.4704 (14.95)**	0.5695 (27.12)**

Constant	6.18 (103.60)	-1.05 (-6.94)
Observations	10163	10163
Joint Significant Test	Wald $\chi^2(20)=1733.88^{**}$ Prob> $\chi^2=0.0000$ Log likelihood=-17890.89	Wald $\chi^2(20)=1996.67^{**}$ Prob> $\chi^2=0.0000$ Log likelihood=-17361.54

Note: † t values in brackets: ** significant at 1%; * significant at 5%; † significant at 10%.

Table 2 Policy Effects (current effects) of Microfinance on per capita household income: Derived by Treatment Effects Model and Propensity Score Matching

Case (a) Whether a household has access to MFI loans

		Log per capita Household Income (mean)		Policy Effect (A-B)	(t value) ^{1,2}	No. of obs.
Model		With access to MFI loans: A	Without access to MFI loans: B	ATT: Average treatment effect		
Panel Data						
	Treatment Effects Model	6.2077	6.2104	-0.0027	(-0.60)	10162
Cross-sectional Data						
1997-1998	Treatment Effects Model	6.0767	6.0176	0.0591	(7.01)**	2580
	PSM (Nearest Neighbour Matching)	-	-	0.1000	(2.14)*	Treat: 1515, Control: 672
	PSM (Kernel Matching)	-	-	0.0690	(2.44)*	Treat: 1515, Control: 1061
1998-1999	Treatment Effects Model	6.1276	6.1362	-0.0085	(-1.07)	2602
	PSM (Nearest Neighbour Matching)	-	-	0.0170	(0.39)	Treat: 1444, Control: 707
	PSM (Kernel Matching)	-	-	0.0090	(0.31)	Treat: 1444, Control: 1150
1999-2000	Treatment Effects Model	6.2308	6.2254	0.0054	(0.64)	2619
	PSM (Nearest Neighbour Matching)	-	-	-0.0110	(-0.25)	Treat: 1318, Control: 685
	PSM (Kernel Matching)	-	-	0.0060	(0.03)	Treat: 1318, Control: 1295
2004-2005	Treatment Effects Model	6.4000	6.4950	-0.0945	(-10.58)**	2594
	PSM (Nearest Neighbour Matching)	-	-	-0.0610	(-1.43)	Treat: 1194, Control: 704
	PSM (Kernel Matching)	-	-	-0.0770	(-2.92)**	Treat: 1194, Control: 1387

Notes: ¹ t value is calculated by Bootstrapped Standard Errors for PSM.

² t values in brackets: ** significant at 1%; * significant at 5%.

Case (b) Whether a household has access to MFI productive loans

		Log per capita Household Income (mean)		Policy Effect (A-B)	(t value) ^{1,2}	No. of observations
Model		With access to MFI loans	Without access to MFI loans	ATT: Average treatment effect		
Panel Data						
	Treatment Effects Model	6.2501	6.1851	0.0649	(14.20)**	10162
Cross-sectional Data						
1997-1998	Treatment Effects Model	6.0958	6.0123	0.0835	(9.97)**	2580
	PSM (Nearest Neighbour Matching)	-	-	0.0530	(1.27)	Treat: 1218, Control: 714
	PSM (Kernel Matching)	-	-	0.0780	(2.96)**	Treat: 1218, Control: 1357
1998-1999	Treatment Effects Model	6.1993	6.0960	0.1032	(12.42)**	2602
	PSM (Nearest Neighbour Matching)	-	-	0.0680	(1.40)	Treat: 937, Control: 667

	PSM (Kernel Matching)	-	-	0.0900	(2.56)*	Treat: 937, Control: 1655
1999-2000	Treatment Effects Model	6.2835	6.1970	0.0865	(8.05)**	2619
	PSM (Nearest Neighbour Matching)	-	-	0.0860	(1.73)†	Treat: 717, Control: 601
	PSM (Kernel Matching)	-	-	0.0650	(2.37)*	Treat: 717, Control: 1894
2004-2005	Treatment Effects Model	6.4130	6.4759	-0.0628	(-7.10)**	2594
	PSM (Nearest Neighbour Matching)	-	-	0.0180	(0.34)	Treat: 770, Control: 634
	PSM (Kernel Matching)	-	-	-0.0290	(-1.01)	Treat: 770, Control: 1812

Notes: ¹. t value is calculated by Bootstrapped Standard Errors for PSM.

² t values in brackets: ** significant at 1%; * significant at 5%; † significant at 10%.

**Table 3 Policy Effects (lagged effects) of Microfinance on per capita household income:
Derived by Treatment Effects Model and Propensity Score Matching**

(a) Whether a household has access to MFI loans						
Panel Data	Model	Log per capita Household Income (mean)		Policy Effect	(t value) ^{1,2}	No. of observations
		With access to	Without access to	(A-B)		
		MFI loans: A	MFI loans: B	ATT: Average treatment effect		
	Treatment Effects Model	6.2597	6.2634	-0.0040	(-0.79)	7494
Cross-sectional Data						
1998-1999	Treatment Effects Model	6.1455	6.1150	0.0304	(3.754)**	2554
	PSM (Nearest Neighbour Matching)	-	-	0.0240	(0.51)	Treat: 1507, Control: 1043
	PSM (Kernel Matching)	-	-	0.0480	(1.48)	Treat: 1507, Control: 675
1999-2000	Treatment Effects Model	6.2344	6.2187	0.0157	(2.06)*	2570
	PSM (Nearest Neighbour Matching)	-	-	0.0370	(0.82)	Treat: 1433, Control: 718
	PSM (Kernel Matching)	-	-	0.0190	(0.70)	Treat: 1433, Control: 1133
2004-2005	Treatment Effects Model	6.4007	6.4661	-0.0659	(-7.12)**	2370
	PSM (Nearest Neighbour Matching)	-	-	-0.0490	(-1.06)	Treat: 1205, Control: 669
	PSM (Kernel Matching)	-	-	-0.0420	(-1.34)	Treat: 1205, Control: 1154

Notes: ¹ t value is calculated by Bootstrapped Standard Errors for PSM.

² t values in brackets: ** significant at 1%; * significant at 5%; + significant at 10%.

(b) Whether a household has access to MFI productive loans						
Panel Data	Model	Log per capita Household Income (mean)		Policy Effect	(t value) ^{1,2}	No. of observations
		With access to	Without access to	(A-B)		
		MFI loans	MFI loans	ATT: Average treatment effect		
	Treatment Effects Model	6.2823	6.2517	0.0307	(5.90)**	7494
Cross-sectional Data						
1998-1999	Treatment Effects Model	6.1497	6.1188	0.0308	(3.79)**	2554
	PSM (Nearest Neighbour Matching)	-	-	0.0270	(0.62)	Treat: 1208, Control: 689
	PSM (Kernel Matching)	-	-	0.0490	(1.44)	Treat: 1208, Control: 1340
1999-2000	Treatment Effects Model	6.2704	6.2025	0.0679	(8.03)**	2570
	PSM (Nearest Neighbour Matching)	-	-	0.0000	(0.008)	Treat: 930, Control: 676
	PSM (Kernel Matching)	-	-	0.0490	(1.65)†	Treat: 930, Control: 1630
2004-2005	Treatment Effects Model	6.4073	6.4752	-0.0444	(-4.92)**	2370
	PSM (Nearest Neighbour Matching)	-	-	0.0160	(0.31)	Treat: 641,

					Control: 585
					Treat: 641,
					Control: 1725
PSM (Kernel Matching)	-	-	-0.0070	(-0.24)	

Notes: ¹ t value is calculated by Bootstrapped Standard Errors for PSM.

² t values in brackets: ** significant at 1%; * significant at 5%; † significant at 10%.

Appendix

Variable	With access to MFI			Without access to MFI			With access to MFI loan for Productive Purposes			Without access to MFI loan for Productive purposes		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Age of Head of HH (age)												
Pooled	5526	45.40	12.38	4954	47.32	15.50	3675	45.17	12.17	6805	46.93	14.82
Round 1	1545	43.86	12.28	1078	45.42	14.77	1237	43.73	12.07	1386	45.19	14.42
Round 2	1463	44.70	12.41	1170	46.62	14.49	948	44.53	12.11	1685	46.12	14.05
Round 3	1327	45.85	12.47	1312	47.26	14.25	721	45.55	12.32	1918	46.93	13.77
Round 4	1209	47.80	12.03	1420	49.43	17.56	778	47.82	11.79	1851	49.04	16.53
Sex of Head of HH (sex_hh)												
Pooled	5528	0.95	0.22	4957	0.92	0.27	3676	0.95	0.21	6809	0.93	0.26
Round 1	1545	0.96	0.20	1078	0.93	0.25	1237	0.96	0.20	1386	0.94	0.25
Round 2	1463	0.95	0.21	1170	0.94	0.24	948	0.96	0.19	1685	0.94	0.24
Round 3	1327	0.95	0.20	1312	0.93	0.24	721	0.96	0.18	1918	0.94	0.23
Round 4	1209	0.93	0.29	1422	0.89	0.37	779	0.93	0.32	1852	0.90	0.35
Size of the HH (hh_size)												
Pooled	5528	6.23	2.75	4957	6.27	3.16	3676	6.21	2.83	6809	6.27	3.02
Round 1	1545	5.73	2.20	1078	5.52	2.44	1237	5.66	2.12	1386	5.62	2.45
Round 2	1463	5.88	2.28	1170	5.88	2.60	948	5.82	2.26	1685	5.92	2.52
Round 3	1327	6.08	2.34	1312	6.10	2.66	721	6.08	2.37	1918	6.09	2.55
Round 4	1211	7.42	3.78	1423	7.32	4.08	779	7.66	4.05	1855	7.25	3.90
Dependency ratio (d_ratio)												
Pooled	5526	0.98	0.70	4944	0.94	0.77	3676	0.97	0.69	6794	0.96	0.76
Round 1	1545	0.98	0.68	1076	0.88	0.68	1237	0.98	0.68	1384	0.91	0.68
Round 2	1463	0.99	0.67	1169	0.92	0.67	948	0.98	0.66	1684	0.94	0.68
Round 3	1327	0.93	0.66	1311	0.88	0.65	721	0.93	0.66	1917	0.89	0.65
Round 4	1209	1.02	0.81	1414	1.07	0.96	779	1.00	0.78	1844	1.07	0.95
Per capita Income (pcy)												
Pooled	5528	638.15	1224.67	4957	823.70	2541.04	3676	664.04	1420.76	6809	759.24	2199.64
Round 1	1545	541.48	485.61	1078	579.27	623.34	1237	552.64	506.98	1386	560.90	579.90
Round 2	1463	577.15	647.30	1170	677.01	771.89	948	604.84	725.24	1685	630.84	696.55
Round 3	1327	633.41	1349.08	1312	701.10	762.11	721	688.43	1785.16	1918	659.03	678.64

Variable	With access to MFI			Without access to MFI			With access to MFI loan for Productive Purposes			Without access to MFI loan for Productive purposes		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Round 4	1211	826.00	2006.94	1423	1225.70	4578.39	779	875.71	2347.42	1855	1111.76	4053.84
Log of per capita income (lpcy)												
Pooled	5528	6.17	0.71	4957	6.26	0.86	3676	6.19	0.71	6809	6.22	0.83
Round 1	1545	6.05	0.70	1078	6.02	0.86	1237	6.07	0.70	1386	6.01	0.82
Round 2	1448	6.10	0.76	1154	6.17	0.86	940	6.15	0.73	1662	6.12	0.84
Round 3	1324	6.19	0.67	1302	6.24	0.80	720	6.24	0.66	1906	6.20	0.76
Round 4	1211	6.38	0.66	1423	6.52	0.86	779	6.41	0.67	1855	6.48	0.82
Productive NGO loans (nl_prod)												
Pooled	5528	8274.55	21739.83	4957	105.41	1822.62	3676	12585.50	25687.42	6809	0.00	0.00
Round 1	1545	18505.53	37656.36	1078	200.92	3574.95	1237	23288.32	40838.83	1386	0.00	0.00
Round 2	1463	4139.04	5639.96	1170	124.60	1067.35	948	6541.35	5845.09	1685	0.00	0.00
Round 3	1327	3396.04	5156.92	1312	44.38	563.57	721	6331.19	5538.54	1918	0.00	0.00
Round 4	1211	5488.87	9716.99	1423	71.63	810.70	779	8663.62	10945.31	1855	0.00	0.00
Non-productive NGO loans (nl_nprod)												
Pooled	5528	2574.08	13832.51	4957	24.77	440.40	3676	2368.82	15820.98	6809	828.98	4693.11
Round 1	1545	3267.84	17997.61	1078	11.64	307.84	1237	2620.46	17846.45	1386	1313.02	8999.78
Round 2	1463	2357.83	4113.11	1170	35.25	427.70	948	2329.26	3814.28	1685	761.20	2798.14
Round 3	1327	2328.31	19663.10	1312	7.69	220.83	721	2652.60	26393.51	1918	619.00	2560.33
Round 4	1211	2238.30	4234.92	1423	41.40	638.83	779	1730.95	3664.54	1855	766.08	2794.69
Formal bank loans (fbl_tot)												
Pooled	5528	376.26	3615.70	4957	848.57	20363.00	3676	385.46	4013.81	6809	715.14	17430.35
Round 1	1545	194.22	1735.18	1078	470.96	4132.29	1237	188.41	1496.01	1386	414.64	3827.35
Round 2	1463	396.77	2712.55	1170	772.65	4667.90	948	409.32	2621.24	1685	650.70	4205.15
Round 3	1327	369.17	2516.35	1312	1562.59	38801.45	721	280.31	2294.18	1918	1218.93	32128.97
Round 4	1211	596.65	6329.83	1423	585.94	5232.52	779	777.59	7698.03	1855	512.45	4718.14
Loans from friends and family (ffl_tot)												
Pooled	5528	2258.52	10024.06	4957	2970.09	16144.27	3676	2138.78	10314.13	6809	2841.20	14625.54
Round 1	1545	2515.75	11259.95	1078	3300.98	13033.71	1237	2513.46	11988.29	1386	3128.52	12053.55
Round 2	1463	2571.42	9321.90	1170	3816.14	18025.69	948	2226.29	8493.35	1685	3629.88	16134.47
Round 3	1327	2410.36	8732.30	1312	3938.79	22638.89	721	2381.82	8815.89	1918	3466.60	19353.00
Round 4	1211	1516.01	10961.81	1423	1201.90	6336.88	779	1416.42	11523.49	1855	1316.87	7316.42

Variable	With access to MFI			Without access to MFI			With access to MFI loan for Productive Purposes			Without access to MFI loan for Productive purposes		
	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Loans from village money lenders (vml_tot)												
Pooled	5528	486.51	4301.19	4957	818.06	7443.37	3676	624.81	5101.62	6809	653.22	6429.93
Round 1	1545	561.08	5036.03	1078	737.06	7547.03	1237	608.50	5477.44	1386	655.63	6767.78
Round 2	1463	408.36	2714.25	1170	1095.08	9792.01	948	515.43	3205.77	1685	824.95	8205.16
Round 3	1327	351.79	3588.69	1312	613.10	4468.81	721	523.48	4514.05	1918	466.00	3864.57
Round 4	1211	642.73	5420.97	1423	849.58	7281.99	779	896.08	6655.58	1855	695.01	6423.82
Distance to nearest Upzilla (dist_uz)												
Pooled	5526	7.38	6.03	4956	7.71	6.28	3674	7.40	5.97	6808	7.61	6.25
Round 1	1545	7.18	5.83	1078	8.06	6.58	1237	7.40	5.85	1386	7.67	6.43
Round 2	1463	7.29	5.97	1170	7.83	6.38	948	7.36	5.98	1685	7.62	6.25
Round 3	1327	7.28	5.98	1312	7.79	6.32	721	7.41	6.03	1918	7.57	6.20
Round 4	1209	7.80	6.37	1422	7.28	5.92	777	7.41	6.10	1854	7.57	6.15
whether household has electricity or not (elec_hh)												
Pooled	5503	0.27	0.44	4944	0.34	0.47	3662	0.28	0.45	6785	0.32	0.46
Round 1	1537	0.25	0.43	1074	0.26	0.44	1231	0.24	0.43	1380	0.26	0.44
Round 2	1455	1.77	0.42	1166	1.71	0.45	944	1.76	0.42	1677	1.73	0.44
Round 3	1326	1.74	0.43	1312	1.66	0.47	721	1.73	0.44	1917	1.69	0.46
Round 4	1203	1.63	0.48	1418	1.56	0.50	775	1.60	0.49	1846	1.59	0.49

Endnotes

¹ It is noted that joint liability payment may not be imposed on the group, for example, in case of lending by Grameen Bank, but repayment performance of the group is closely monitored by the communities and the Bank. To maintain reputations in the community, a member has an incentive to build skills and work hard to keep repaying the instalments. See definitions and salient features of microcredit at http://www.grameen-info.org/index.php?option=com_content&task=view&id=28&Itemid=108 (accessed on 30th September 2010).

² There are two hypotheses necessary for validating PSM, (i) Balancing Hypothesis, related to balancing of pre-treatment variables given the propensity score, which implies that given a specific probability of having access to MFI, a vector of household characteristics, is uncorrelated to the access to MFI and (ii) Unconfoundedness Hypothesis which postulates that given a propensity score, log per capita household income is uncorrelated to the access to a MFI (Rosenbaun and Rubin, 1983).

³ We did not use *Radius Matching* as the results are sensitive to the predetermined radius.

⁴ The possibility cannot be ruled out that the household decisions to take loans from the traditional sources or to take loans from MFIs are made simultaneously and thus these variables may not be entirely exogenous. It has been found that dropping these variables will not change the final results dramatically. We have decided to keep these variables to put more importance on avoiding any bias from omitting these important explanatory variables, the factors which had long existed well before microfinance programmes were implemented.

⁵ Regression results will be furnished on request.

⁶ PSM is not applied for the panel data because of the difficulty in matching the data over the years. We have used logit model in the first stage which shows a broadly similar pattern of the results to those derived by probit model presented in Table 1.

References

- Ahlin, C. and Townsend, R. (2007) Using Repayment Data to Test Across Models of Joint Liability Lending, *The Economic Journal*, 117, pp. F11-F51.
- Ahmed S. (2007) Microfinance Programmes in Bangladesh: Experiences and Issues, in I. Simorangkir (ed.) *Macroeconomic Stability towards high Growth and Employment. :Proceedings on an International seminar held in Denpasar* (Bali: Indonesia).
- Armendáriz, B., and Morduch, J. (2005) *The Economics of Microfinance* (Cambridge, MA: The MIT Press).
- Banerjee, A., Duflo, E., Glennerster, R. and Kinnan, C. (2009) The Miracle of Microfinance? Evidence from a Randomised Evaluation, Department of Economics, Massachusetts Institute of Technology (MIT) Working Paper, May 2009.
- Bateman, M., and Chang, H. (2009) The Microfinance Illusion, mimeo., Cambridge, Faculty of Economics, University of Cambridge, available from <http://www.econ.cam.ac.uk/faculty/chang/pubs/Microfinance.pdf>.
- Becker, S. and Ichino, A. (2002) Estimation of Average Treatment Effects based on Propensity Scores, *The Stata Journal*, 2(4), pp.358-377.
- Besley, T., and Coate, S. (1995) Group lending, repayment incentives and social collateral, *Journal of Development Economics*, 46 (1), pp.1-18.
- BBS (2008) *Report On The Household Income and Expenditure Survey 2005* (Dhaka: Bangladesh Bureau of Statistics).
- Dehejia, R. (2005) Practical Propensity Score Matching: a Reply to Smith and Todd, *Journal of Econometrics*, 125, pp.355-364.
- Dehejia, R. and Wahba, S. (2002) Propensity Score Matching Methods for Nonexperimental Causal Studies, *Review of Economics and Statistics*, 84 (1), pp.151-161.

-
- Dercon, C., and Christiansen, L. (2008) Consumption risk, technology adoption and poverty traps: evidence from Ethiopia, World Economy & Finance Research Programme Working Paper Series WEF0035, University of London, Birkbeck.
- Ehrbeck, T. (2006) Optimizing capital supply in support of microfinance industry growth. Presentation at microfinance investor roundtable, Washington, DC, October 24-25. McKinsey&Co.
- Farashuddin, F. and Amin, N. (1998) Poverty Alleviation and Empowerment: An Impact Assessment Study of BRAC's RDP - Ten Qualitative Case Studies. Mimeo, (Dhaka: BRAC Research and Evaluation Division).
- Foster, M. (2003). Propensity Score Matching: An Illustrative Analysis of Dose Response, *Medical Care*, 41(10), pp.1183-1192.
- Greene, W. H. (2003). *Econometric Analysis 5th Edition* (Upper Saddle River, NJ: Prentice-Hall).
- Heckman, J. (1979). Sample selection bias as a specification error, *Econometrica*, 47, pp.153-161.
- Hulme, D. and P. Mosley (1996). *Finance against Poverty*. Routledge, London.
- Imai, K. S., Arun, T. and Anim, S. K. (2010) Microfinance and Household Poverty Reduction: New evidence from India, *World Development*, forthcoming.
- Karlan, D. and Zinman, J. (2009) Expanding Microenterprise Credit Access: Using Randomized Supply Decisions to Estimate the Impacts in Manila. Working Paper. Yale University, Dartmouth College, and Innovations for Poverty Action.
- Khandker, S. R. (2005) Microfinance and Poverty: Evidence Using Panel Data from Bangladesh, *The World Bank Economic Review*, 19(2), pp.263-286.
- Maddala, G. S. (1983) *Limited dependent and qualitative variables in econometrics* (Cambridge, Cambridge University Press).

-
- Montgomery R., D. Bhattacharya and D. Hulme (1996) Credit for the Poor in Bangladesh: The BRAC Rural Development Programme and the Government Thana Resource Development and Employment Programme, in D. Hulme and P. Mosely, *Finance against Poverty*. Vols. I and 2 (London: Routledge).
- Morduch, J. (1998) Does Microfinance Really Help the Poor: New Evidence from Flagship Programs in Bangladesh, Mimeo, Department of Economics and HIID, Harvard University and Hoover Institution, Stanford University.
- Pitt, M., and Khandker, S. R. (1998) The Impact of Group-Based Credit on Poor Households in Bangladesh: Does the Gender of Participants Matter?, *Journal of Political Economy*, 106(5), pp.958–96.
- PKSF (2006) *MAPs on Microcredit Coverage in Upazilas of Bangladesh* (Dhaka, Bangladesh, Palli Karma Sahayak Foundation).
- Pollin, R. (2007) Microcredit: False Hopes and Real Possibilities. Foreign Policy Focus, available from <http://www.fpif.org/fpiftxt/4323>.
- Ravallion, M. (2008) Evaluating Anti-Poverty Programme, Chapter 59 in *Handbook of Development Economics, Volume 4*, P. Schultz and J. Strauss (eds) (New York: North Holland) .
- Roodman, D., and J. Morduch (2009) The Impact of Microcredit on the Poor in Bangladesh: Revisiting the Evidence, CGD Working Paper 174 (Washington, D.C.: Center for Global Development).
- Rosenbaum, P. R., and Rubin, D. B. (1983) The Central Role of the Propensity Score in Observational Studies for Causal Effects, *Biometrika*, 70(1), pp.41-55.
- Smith, J. A., and Todd, P. E. (2005) Does Matching Overcome LaLonde’s Critique of Nonexperimental Estimators?, *Journal of Econometrics*, 125, pp.305-353.

Todd, P. E. (2008). 'Evaluating Social Programs with Endogenous Program Placement and Selection of the Treated', Chapter 60 in *Handbook of Development Economics, Volume 4*, P. Schultz and J. Strauss (eds) (New York, North-Holland).

Wood, G. and Sharif, I. (eds) (1997) *Who needs credit? Poverty and finance in Bangladesh*. (London, Zed Books).

Zaman, H. (1998) Who benefits and to what extent? An evaluation of BRAC's micro-credit program, University of Sussex, D.Phil thesis.