Discussion Paper Series

RIEB

Kobe University

DP2010-24

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Revised November 1, 2011

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23rd June 2011

Abstract

The purpose of the present study is to examine whether loans from microfinance institutions (MFI) reduce poverty in Bangladesh drawing upon the nationally representative household panel data covering 4 rounds from 1997 to 2004. Our aim is to estimate the effects of general microfinance loans as well as loans for productive purposes on household income, food consumption and women's Body Mass Index (BMI). It has been found by different versions of household fixed-effects model that overall effects of MFI's loans on income and food consumption in 1997-2004 were positive and that the purpose of the loan is important in predicting which household welfare indicator is improved. As a supplementary analysis, we have carried out Difference-In-Difference Propensity Score Matching (DID-PSM) and have confirmed a positive impact of MFI's general loans on food consumption's growth in 1999-2004. It can be concluded that loans provided by MFIs had significant poverty reducing effects particularly on income and consumption in Bangladesh.

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

JEL codes: C30, C31, G21, I32

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Acknowledgements

We acknowledge valuable comments and advice from Samuel Annim, Thankom Arun, Raghav Gaiha, Shoji Nishijima, Takahiro Sato, seminar participants at Kobe University and two anonymous referees. The first author wishes to thank RIEB, Kobe University for generous research support during his stay in 2010. Only the authors are responsible for any errors.

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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; (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 groups which would guarantee to repay loans.[1] 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).

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. 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 a 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 from 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. Out of estimated 56 million poor people in 2005, 29.26 million (53% of 56 million) were supposed to be economically active and potential target of microfinance operations. 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 is to test whether microfinance reduces poverty in Bangladesh drawing upon a nationally representative household panel data covering 4 rounds, 1997-98, 1998-99, 1999-2000, and 2004-05. Special attention is drawn to the issue of sample selection or endogeneity associated with participation in microfinance, by applying different versions of household fixed effects model as well as difference in difference and propensity score matching (DID-PSM)[2] to the sample which consists of 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 emphasises the underlying intuition of econometric models 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 was 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 were found for Grameen Bank and BRDB members.[3]

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 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 benefited most in 1998/99. 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.

Using the same household data set in 1991/2 used by Pitt and Khandker (1998) and Morduch (1998) and overcoming the limitations of the previous studies (e.g. the problem related to identification for the former and the problem not taking account of endogenous programme placement for the latter), Chemin (2008) applied the propensity score matching (PSM) technique to evaluate the impact of participation in microfinance programmes on a number of outcome indicators. He found that microfinance had a positive impact on participants' expenditure, supply of labour and male/female school enrolment. The present study attempts to extend Chemin (2008) in the following three ways. First, we have used more recent and rich data for a panel of households in Bangladesh from 1997 to 2005 and have examined the effects of microfinance participation on household welfare, in terms of log per capita household income, food consumption and women's body mass index (BMI). Second, while we also apply PSM to each cross-sectional component of the panel, we utilise the longitudinal nature of the data by applying different versions of household fixed effects model as well as DID-PSM. Third, we have focused on the effects of purpose of loans from MFIs (i.e. productive purposes or not)[4]on per capita household income, food consumption and women's BMI.

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 (2010) 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 (i) per capita household income, (ii) per capita food consumption, and (iii) women's BMI. 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 a 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, food consumption and women's BMI and thus on poverty. It is noted that unlike the first, third and fourth rounds, the second round consumption data are highly aggregated and not comparable with the other rounds. In case of BMI, comprehensive data are available only for the first and the last rounds, while the data on household income are available for all four rounds. 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.

Online Appendix 1 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. Heads 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 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. Methodologies

(1) Panel Data Model

Fixed Effects (FE) Model

First, we have applied different versions of household fixed effects model to take account of the amount of MFI's general or productive loans whilst PSM or DID-PSM can consider only binary classification of participation status. The standard fixed effect model is estimated as:

$$W_{it} = \beta_0 + X_{it}\beta_1 + L_{it}\,\beta_2 + Y_t\beta_3 + \mu_i + \varepsilon_{it} \qquad (5)$$

where W_{it} is the outcome variable (namely, log household income per capita, log food consumption per capita or women's BMI), X_{it} is a vector of variables of household and socio-economic characteristics as well as other control variables, and L_{it} is either a total amount of MFI's loans or a vector consisting of MFI's productive and non-productive loans (sum of which is equal to the total amount of MFI's loans). We are interested in the sign of coefficient of L_{it}, β_2 which represents the effects of MFI's loan on the outcome variable.[5] Y_t is a vector of year dummies to take account of time specific effects, μ_i is a household-specific unobservable fixed effect (e.g. unobserved entrepreneurship), and ε_{it} is an error term, *i.i.d.* (see, e.g. Greene, 2003). For the income equation, we use household characteristics (X_{it}), such as arable land and its square, age of the household head and its square, household size, sex of the household head, education of the head, occupational categories, and whether a household has access to electricity. For the equations for food consumption and BMI, we replace arable land and its square by a set of prices (for rice, potatoes and milk).

Fixed Effects Model with PSM (FE-PSM)

Initial household characteristics as well as pre-existing socio-economic and area attributes are likely to influence the programme placement and the subsequent growth paths of outcome variables. Controlling for these potential sources of selection bias would bring us a more credible estimate of the policy effect. To deal with these sources of bias, we need to control for the initial conditions as well as time-varying factors that would influence the programme placement and growth rates. One possible way of correcting for these biases is to use PSM to select appropriate counterfactuals from the sampled non-participants (Ravallion and Chen 2005, Chen et al. 2008). Matching methods or PSM will construct the control groups that are as similar as possible except for the access to microfinance programmes. PSM will trim the sample of control group with propensity scores that do not overlap with those for the treatment groups. More specifically, we carry out PSM for each round and match the participating households with non-participating ones.[6] Second, we drop all the households which are not matched, or outside the common support region.[7] In order to control for the initial conditions and any time-varying factors, we have carried out the fixed-effects model for the reconstructed panel data in which participating households have been matched with controls.

Fixed Effects (FE) Model with control for initial characteristics

In the FE or FE-PSM estimation, some of the explanatory variables have either a linear time trend or little variation over time and they are swept away in the process of first-differencing. However, these variables may have a significant effect on the change in outcome variables and eliminating them from the model might bias the policy effect. To circumvent this problem, using only the data of the first and last rounds, we implement an alternate version of the fixed effects model where initial characteristics of households (e.g. age of household head and its square; household size; sex of head of the household; education; occupation; access to electricity) are used along with the first differenced variables. The purpose of these models is also to correct any possible bias due to pre-existing initial heterogeneity of households and time-varying factors.

(2) DID-PSM

There is a huge empirical literature where the policy effects are estimated by PSM. The method is applied, in many cases, to cross-sectional data because of the limitations of IV models (e.g. assuming linearity; requiring a valid instrument; sensitivity of the results to specifications). PSM matches a participating household in MFIs with a non-participating household by using the propensity score, the estimated probability of participating in the microfinance programmes. We can then obtain average treatment effect (ATT) of the policy by comparing the averages of outcome variables for participants and non-participants. In PSM, 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). 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. Models and methodological issues for propensity score matching estimation are discussed in details, for example, by Becker and Ichino (2002), Dehejia (2005), Dehejia and Wahba (2002), Heckman et al. (1997), Ravallion (2008), Smith and Todd (2005), and Todd (2008).[8] In the first stage logit model of PSM[9], we include the same set of explanatory variables which we use for the panel data model.

While there are some advantages in using PSM to estimate the impact of policy, the derived impact depends on the variables used for matching and the quantity and quality of available data and the procedure to eliminate any sample selection bias 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. 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 (Heckman et al., 1997, Ravallion, 2008). However, there may be systematic differences between participants and non-participant outcomes even after conditioning on household's observable characteristics, which could lead to the violation of the identification condition required for PSM (Smith and Todd, 2005). Because bias cannot be completely eliminated if there are important unobservable variables in the model, the results of PSM for cross-sectional data will have to be interpreted with caution. Therefore, the present study reports the PSM results in Online Appendix 3 and provide only a summary of the results.

To overcome the limitations of PSM using cross-sectional data, we apply the DID-PSM method which utilises the longitudinal nature of the data. The DID-PSM estimator requires, as specified by (Smith and Todd, 2005), that

$$E(W_{0i}^{t} - W_{0i}^{t'} \big| p_i(X_i),\ D_i = 1) = E(W_{0i}^{t} - W_{0i}^{t'} \big| p_i(X_i),\ D_i = 0)$$

where t and t' are time periods (where t=1 and t'=0, or after and before the programme). W_{0i}^{t} is the outcome at time t for non-participant, $p_i(X_i)$ is a propensity score, the probability of participation at time t, and D_i is whether a household participated in a microfinance programme between t' and t (1 if participated, 0 otherwise). In the PSM applied to the cross-sectional data, the mean of the outcome of a household at a particular point of time is compared between participants and non-participants conditional on the probability of participation estimated by observable household characteristics, whilst in the DID-PSM, the time-series or temporal *change* of outcome of a household is compared at time *t* (after the programme) conditional on the propensity score. The results of the latter are *not* subject to the existence of unobservable household characteristics in the model. In our context, DID-PSM implies that PSM is applied to 'the first difference' (from *t'* to *t*) of the outcome variable (e.g. log per capita income) of a household with access to MFI loans at *t*, but not at *t'*, the previous round, is compared with that of a household with the same characteristics (with respect to the propensity score), but without any access to MFI loans at both *t'* and *t*, along the lines of Smith and Todd (2005).

V. Results

(1) Results of Fixed-effects models

Table 1 reports the results of different versions of fixed effects models where we estimate either the effect of MFI's general loan or that of MFI's productive loan and non-productive loans on log household income per capita, log food consumption per capita, and BMI of a female member.

(Table 1 to be inserted around here)

The results of the simple fixed effects model show that MFI's general loan tends to significantly increase household income (the columns (1)). If MFI's loan is disaggregated into the productive component and the non-productive component in the column (4), it is found that the positive effect of the total loan is associated only with the productive component. In fact, the non-productive component tends to reduce household income per capita. We have obtained a very similar pattern of the results in case of fixed effects model with PSM and fixed effects model with control for initial characteristics (the columns (2), (3), (5) and (6)). That is, our results are robust to use of alternative models in which initial household characteristics are taken account of. However, the magnitude of these effects is not so large – even 100% increase of net change of total loan raises household income per capita only by 0.51% to 0.54% on average *ceteris paribus*. However, 100% increase of net change of productive loan raises household income per capita by 0.69% to 1.09% on average *ceteris paribus*.

On the contrary, the non-productive component is positive and significant and the productive component is non-significant in the case where food consumption is estimated (columns (7) and (10)). The results are once again similar in the cases where alternative versions of fixed-effects model are used (columns (8), (9), (11) and (12)). MFI's general loan has a significant and positive effect on food consumption. 100% increase of net change of total loan raises household food consumption per capita by 0.52% to 1.02% on average *ceteris paribus*. On the other hand, 100% increase of net change of non-productive loan increases household food consumption per capita by 0.74% to 1.11% on average *ceteris paribus.*

While the aggregate component of MFI loans is not a significant determinant of women's BMI in any version of fixed-effects models (columns (13), (14) and (15)), non-productive loans show a significant and positive effect on women's BMI as in the case of food consumption(columns (16), (17) and (18)). The absolute impact seems substantial as, for example, 10% increase of change in non-productive loans raises women's BMI by 0.44 point in columns (16) and (17), while it is only 0.017 in column (18) where initial household characteristics are included in the model. The results are different from those of PSM and DID-PSM to be discussed in the next sub-section, but it is conjectured that having access to a larger amount of the non-productive component of MFI loans, rather than simply accessing MFI's loans, is important in raising BMI for women.

(2) Results of DID-PSM [10]

The results of logit model reported in Online Appendix 2 reflect the determinants of access to MFI's general loans, or access to MFI's loans for productive purposes. Corresponding to PSM or DID-PSM, we present the results of logit model for all the rounds as well as each round. To briefly summarise the results, the coefficient estimate of age of head of the household is positive and significant in all cases, which implies that a household with an 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. 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 in a majority of the cases. 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 estimate of distance from the nearest Upzilla (a business hub) is negative and significant only in the first column. A negative sign indicates that a household living closer to the nearest town with Upzilla is more likely to access MFI's loans 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 number of village money lenders is negative and either statistically significant in a few cases.

The coefficient estimates of the education dummies are all negative and significant except for most of the cases of 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.

Table 2 presents the results of DID-PSM. It is noted that in DID-PSM *the first difference* of the dependent variable (e.g. log of household income per capita) of the households which accessed the MFI loans in the present round, but *not* in the previous round, is compared with that of the household which did *not* access MFI loans in either the previous round or the present round and had similar characteristics in terms of the propensity score. Because both the objective variable is in log term, policy effect (or the average treatment effects) denotes the growth of household income per capita (or food consumption/ women's BMI) achieved by accessing general loans (or productive loans). While DID-PSM is superior to PSM in correcting for sample selection biases, because of the relatively small sample size of treatment groups in our context, the estimated average treatment effect tends to be generally non-significant. Case (a) is the case where DID-PSM is applied to see if household access to

MFI's general loans increases the growth of household income per capita, food consumption, and women's BMI. Only a significant policy effect is observed for food consumption per capita *growth* from 1999-2000 to 2004-5. That is, a household which had access to MFI loans in 2004-5, but not in 1999-2000 had 10.4% a higher per capita food consumption growth on average than the household with the same characteristics (in terms of propensity score) which did not access to MFI loans in either of these years. It is noted that the former (new participants in 2004-5) did not see increase in their household income in 2004-5, or actually decreased per capita income growth by 5.9%, though it is statistically non-significant. That is, it is probably safe to conclude that the new participants in 2004-05 used microfinance loans for food consumption, but not for income-increasing activities. In Case (b), we focus on household access to MFI's productive loans, but the policy effects are non-significant. It is non-significant for the case of food consumption growth from 1999-2000 to 2004-5.

(Table 2 to be inserted around here)

Though the average treatment effects are statistically non-significant except one case in Table 2, it is generally observed that the effects of both general loan and productive loans on household income growth turned negative in the last period (1999-2000 to 2004-5), while those on food consumption remained positive in the last period. To see why, we have disaggregated DID-PSM by income groups based on the household per capita income of the first round of each pair for 0-25%, 25-50%, 50-75% and 75-100%. The average treatment effects of general loan on food consumption growth of relatively poor income groups (0-25% and 25-50%) are consistently positive (with the effects statistically significant for the 25-50% group for both '1997-8 to 1999-2000' and '1999-2000 to 2004-5'), while the effects on relatively richer income groups (50-75% and 75-100%) become negative and non-significant for '1999-2000 to 2004-5'. That is, the effect of MFI loans in increasing food consumption growth was strong for poorer groups, confirming the poverty-reducing role of MFI's general loan. Second, the effects of MFI's general loans on household income are non-significant for most of the groups for all the cases ('1997-8 to 1998-9', '1998-9 to 1999-2000'and '1999-2000 to 2004-5') except one case where the loans had a significant and negative average impact on income growth of the 50-75% group for '1999-2000 to 2004-5'. That is, the negative (and non-significant) effect of general MFI loans on income growth in the last round Table 2 is mainly associated with their negative effect on the non-poor households.[11]

VI. Concluding Observations

The main purpose of the present study is to examine whether microfinance reduced poverty – defined in terms of household income, food consumption and women's BMI - in Bangladesh drawing upon the nationally representative household panel data covering 4 rounds, 1997-98, 1998-99, 1999-2000, and 2004-05. Special attention was given to the issue of endogeneity by applying different versions of fixed effects model as well as DID-PSM proposed by Smith and Todd (2005), following a recent contribution by Chemin (2008) who thoroughly analysed the Bangladesh household data in 1991-92 for the participants and non-participants of microfinance programmes. Another contribution of the present study is that it distinguishes between the effects of different purposes of loans from microfinance institutions (MFIs) on household income, i.e., whether loans were used for the purposes of enhancing agricultural productivity or for general purposes, such as consumption.

We applied household fixed-effects models - with or without control for initial household characteristics - to the panel data in order to estimate the effects of amount of aggregate MFI loans as well as their subcomponents, the productive and non-productive loans. A positive and significant effect of the aggregate component of MFI loans is found for both household income and food consumption, but this positive effect is due to the positive effect of the productive component in case of income, and that of the non-productive component in case of food consumption. That is, income poverty tends to be alleviated by offering productive loans for households and consumption poverty is likely to be reduced by non-productive loans. It is also found that MFI's non-productive loans will reduce BMI. These results are broadly consistent with the past studies which have confirmed poverty reducing effects of microfinance programmes in Bangladesh (e.g. Pitt and Khandker, 1998, Khandker, 2005 and Chemin, 2008). DID-PSM confirms that the households which accessed MFI's general loans in 2004-05, but not in 1999-2000, had a higher food consumption growth than those which did not access to microfinance loans in either of these years. The effect on women's BMI is non-significant and mostly negative.

It can be concluded that loans provided by microfinance institutions had significant poverty reducing effects particularly on income and consumption in Bangladesh, which is consistent with earlier studies, for example, Pitt and Khandker (1998), Khandker (2005), Chemin (2008) and Pitt (2011 a, b). More evidence is needed, however, to confirm our results, for example, by randomised control trials (RCTs) [12] or econometric estimations using more recent household data.

Table 1 Panel Data Models for Income, Food Consumption and women's BMI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dependent Variable	**log household income per capita**						**log food consumption per capita**					
Model Chosen	Fixed-Effects	Fixed-Effects with PSM	Fixed-Effects :Control for initial Character-istics	Fixed-Effects	Fixed-Effects with PSM	Fixed-Effects :Control for initial Character-istics	Fixed-Effects	Fixed-Effects with PSM	Fixed-Effects :Control for initial Character-istics	Fixed-Effects	Fixed-Effects with PSM	Fixed-Effects :Control for initial Character-istics
Explanatory Variables												
MFI loan amount (aggregate)	**0.0051***[1]	**0.0054***	**0.0054**	-	-	-	**0.0052+**	**0.0048+**	**0.0102****	-	-	-
(log)	**(2.37)**	**(2.46)**	**(1.59)**	-	-	-	**(1.88)**	**(1.70)**	**(2.77)****	-	-	-
MFI's productive loan amount	-	-	-	**0.0069****	**0.0072****	**0.0109****	-	-	-	**0.00213**	**0.00177**	**0.00053**
(log)	-	-	-	**(3.22)**	**(3.30)**	**(3.08)**	-	-	-	**(0.77)**	**(0.63)**	**(0.01)**
MFI's non-productive loan amount	-	-	-	**-0.0054***	**-0.0053***	**-0.0079+**	-	-	-	**0.00747***	**0.00742***	**0.0111***
(log)	-	-	-	**(-2.22)**	**(-2.17)**	**(-1.78)**	-	-	-	**(2.24)**	**(2.21)**	**(2.35)**
Arable land area	0.318	0.284	0.021*	0.321	0.284	0.0207	-	-	-	-	-	-
(log)	(0.90)	(0.80)	(1.66)	(0.91)	(0.80)	(1.61)	-	-	-	-	-	-
Initial Arable land area	-	-	0.704	-	-	0.683	-	-	-	-	-	-
(log)	-	-	(0.95)	-	-	(0.92)	-	-	-	-	-	-
Arable land area^2	-0.152	-0.135	-	-0.153	-0.135	-	-	-	-	-	-	-
(log)	(-0.86)	(-0.75)	-	(-0.86)	(-0.76)	-	-	-	-	-	-	-
Initial Arable land area^2	-	-	-0.360	-	-	-0.350	-	-	-	-	-	-
(log)	-	-	(-0.97)	-	-	(-0.94)	-	-	-	-	-	-
Age of the head of the hh	0.00146	0.0010	0.0015	0.00145	0.0010	0.0014	-0.00217	-0.00154	-0.00081	-0.00222	-0.00159	-0.00083
	(0.86)	(0.58)	(0.56)	(0.86)	(0.58)	(0.52)	(-1.10)	(-0.76)	(-0.28)	(-1.12)	(-0.78)	(-0.29)
Initial Age of the head of the hh	-	-	0.023*	-	-	0.024	-	-	0.0079			0.0073
	-	-	(2.43)	-	-	(2.51)	-	-	(0.78)			(0.78)
Age_squared	-5.54e-06	-4.71e-06	-6.02e-06	-5.58e-06	-4.71e-06	-5.69e-06	2.05e-07	-9.44e-07	-1.79e-06	3.71e-07	-7.75e-07	-1.26-06
	(-1.13)	(0.95)	(0.87)	(-1.14)	(0.96)	(-0.82)	(0.036)	(-0.17)	(-0.25)	(0.07)	(0.14)	(-0.17)
Initial Age_squared	-	-	-0.0002*	-	-	-0.0002	-	-	-0.0001			-0.0001
	-	-	(-2.02)	-	-	(2.10)	-	-	(-1.07)			(-0.99)
Household size	-0.025**	-0.024**	-0.037**	-0.0251**	-0.024**	-0.037**	0.0504**	0.0501**	0.0336**	0.0505**	0.0503**	0.0350**
	(-4.73)	(-4.56)	(-5.30)	(-4.75)	(-4.59)	(-5.34)	(8.79)	(8.66)	(4.54)	(8.82)	(8.69)	(4.73)
Initial Household size	-	-	0.059**	-	-	0.059	-	-	0.1753**			0.1738**
	-	-	(6.28)	-	-	(6.34)**	-	-	(17.36)			(17.18)
Sex of head of household	-0.308**	-0.301**	-0.348**	-0.313**	-0.306**	-0.357**	0.00629	0.00829	0.0619	0.0120	-0.0023	0.0679
(female or not)	(-5.17)	(-5.01)	(-4.30)	(-5.25)	(-5.09)	(-4.42)	(0.092)	(0.12)	(0.74)	(0.18)	(-0.03)	(0.81)
Initial Sex of head of household	-	-	0.059	-	-	-0.260**	-	-	0.009			0.0139
	-	-	(6.28)**	-	-	(2.56)**	-	-	(0.08)			(0.13)

Education of head of household	0.0622	0.062	0.067	0.0611	0.061	0.069	0.0405	0.0441	0.0314	0.0419	0.045	0.0307
– completed primary school	(1.57)	(1.53)	(1.98)*	(1.54)	(1.50)	(2.05)*	(0.88)	(0.94)	(0.88)	(0.91)	(0.97)	(0.86)
Education of head of household	0.0834	0.0771	-	0.0816	0.0753	-	0.0123	-0.007	-	0.0109	-0.086	-
– completed secondary school	(1.59)	(1.43)	-	(1.56)	(1.40)	-	(0.21)	(0.12)	-	(0.18)	(-0.14)	-
Education of head of household	-0.0684	-0.063	-	-0.0666	-0.062	-	0.156	0.136	-	0.153	0.133	-
– completed higher education	(-0.64)	(-0.58)	-	(-0.62)	(-0.57)	-	(1.36)	(1.17)		(1.34)	(1.15)	
Initial education of head	-	-	0.030	-	-	0.033	-	-	-0.0750			-0.0756
– completed primary school	-	-	(0.56)	-	-	(0.61)	-	-	(-1.30)			(-1.31)
Initial education of head	-	-	0.121*	-	-	0.117*	-	-	-0.0250			-0.0269
– completed secondary school	-	-	(2.15)	-	-	(2.10)	-	-	(-0.42)			(-0.45)
Initial Education of head	-	-	0.431	-	-	0.420	-	-	-0.1025			-0.1023
– completed higher education	-	-	(3.49)**	-	-	(3.41)**	-	-	(-0.81)			(-0.81)
Farmer	-0.228**	-0.245**	0.011	-0.225**	-0.243**	0.012	-0.0202	-0.0211	0.005	-0.0220	-0.023	-0.004
	(-3.93)	(-4.18)	(1.21)	(-3.89)	(-4.14)	(1.31)	(-0.30)	(-0.31)	(0.53)	(-0.32)	(-0.33)	(0.44)
Agricultural wage labourer	-0.110+	-0.132*	-	-0.105	-0.136+	-	0.162*	0.159*	-	0.157*	0.154+	-
	(-1.68)	(1.98)	-	(-1.60)	(1.90)	-	(2.07)	(2.01)	-	(2.00)	(1.94)	-
Non-Agricultural wage labourer	-0.125*	-0.141*	-	-0.121*	-0.136*	-	0.0541	0.0458	-	0.0487	0.0432	-
	(-2.08)	(-2.32)	-	(-2.01)	(-2.25)	-	(0.77)	(0.68)	-	(0.69)	(0.61)	-
small business	0.00533	-0.010	-	0.00744	-0.008	-	0.0563	0.0518	-	0.0542	0.0500	-
	(0.09)	(-0.18)	-	(0.13)	(-0.14)	-	(0.82)	(0.75)	-	(0.79)	(0.72)	-
professionals	-0.0572	-0.068	-	-0.0526	-0.063	-	-0.0821	-0.0874	-	-0.0864	-0.0917	-
	(-0.87)	(1.02)	-	(-0.80)	(0.95)	-	(-1.07)	(-1.130)	-	(-1.12)	(-1.18)	-
others	-0.146*	-0.161**	-	-0.141*	-0.156**	-	0.0343	0.0238	-	0.0304	0.0204	-
	(-2.57)	(-2.80)	-	(-2.49)	(-2.71)	-	(0.51)	(0.350)	-	(0.45)	(0.30)	-
Farmer (Initial)	-	-	0.063	-	-	0.066	-	-	-0.1735+			-0.17658
	-	-	(0.83)	-	-	(0.86)	-	-	(-1.93)			(-1.96)
Agricultural wage labourer (Initial)	-	-	-0.062	-	-	-0.066	-	-	-0.2096*			-0.2013*
	-	-	(0.77)	-	-	(0.81)	-	-	(-1.97)			(-1.89)+
Non-Agricultural wage labourer	-	-	-	-	-	-	-	-	-0.1548			-0.1412
(Initial)	-	-	-	-	-	-	-	-	(-1.50)			(-1.36)
small business (Initial)	-	-	-0.219**	-	-	-0.208**	-	-	-0.094			-0.094
	-	-	(2.94)	-	-	(2.80)	-	-	(-1.06)			(-1.05)
Professionals (Initial)	-	-	-0.091	-	-	-0.095	-	-	-			-
	-	-	(0.92)	-	-	(0.96)	-	-	-			-
Others (Initial)	-	-	0.063	-	-	0.063	-	-	-0.062			-0.061
	-	-	(0.65)	-	-	(0.65)	-	-	(-0.58)			(-0.57)
Whether a household	0.0830**	0.0845**	0.0731	0.0840**	0.0854**	0.0703	-0.00926	-0.00930	0.0039	-0.00884	-0.009	0.0068
has electricity or not	(3.12)	(3.15)	(1.63)	(3.16)	(3.18)	(1.57)	(-0.29)	(-0.28)	(0.08)	(-0.27)	(-0.26)	(0.14)

Whether a household	-	-	0.006	-	-	0.009	-	-	0.0275			0.0279
has electricity or not (Initial)	-	-	(0.12)	-	-	(0.17)	-	-	(0.51)			(0.52)
price of rice	-	-	-	-	-	-	-0.0778	-0.0668	0.2213	-0.0703	-0.0617	0.2628
(log)	-	-	-	-	-	-	(-0.38)	(-0.32)	(0.80)	(-0.35)	(-0.30)	(0.95)
price of potatoes	-	-	-	-	-	-	0.260**	0.260**	0.488**	0.262**	0.265**	0.4968**
(log)	-	-	-	-	-	-	(3.60)	(3.60)	(4.59)	(3.63)	(3.63)	(4.66)
price of milk	-	-	-	-	-	-	-0.0287	-0.027	-0.064	-0.0271	-0.026	-0.063
(log)	-	-	-	-	-	-	(-0.80)	(-0.75)	(-1.53)	(-0.75)	(-0.70)	(-1.48)
Whether in 1998-9	0.0936**	0.0899**	-	0.102**	0.0985**	-	-	-	-	-	-	-
	(5.35)	(5.09)	-	(5.77)	(5.50)	-	-	-	-	-	-	-
Whether in1999-2000	0.189**	0.190**	-	0.195**	0.195**	-	-0.220**	-0.224**	-	-0.228**	-0.232**	-
	(10.44)	(10.36)	-	(10.70)	(10.61)	-	(-4.08)	(-4.13)	-	(-4.22)	(-4.27)	-
Whether in 2004-5	0.446**	0.443**	-	0.451**	0.449**	-	-0.275**	-0.279**	-	-0.283**	-0.288**	-
	(19.06)	(18.67)	-	(19.24)	(18.85)	-	(-4.71)	(-4.72)	-	(-4.85)	(-4.85)	-
Constant	6.445	6.471	0.176	6.449**	6.475	-0.192	5.438**	5.399	-0.375	5.415**	5.382	-1.398
	(59.59)	(58.66)	(0.73)	(59.72)	(58.78)	(0.80)	(8.44)	(8.26)	(4.93)	(8.40)	(8.23)	(5.00)
Observations	10,388	10,076	2,484	10,388	10,388	2,484	5,991	5,812	2,174	5,991	5,812	2,174
Number of hhid	2,669	2545	1,242	2,669	2,545	1,242	2,634	2,519	1,087	2,634	2,519	1,087
Joint Significance	F(20,7699)	F(20,7511)	F(24,2459)	F(21,7698)	F(21,7510)	F(25,2458)	F(20,3337)	F(20,3273)	F(24,2149)	F(21,3336)	F(21,3272)	F(24,2148)
	39.46**	38.52**	7.71**	38.01**	37.11**	7.79**	8.196**	7.88**	20.71**	7.92**	7.64**	19.77**

Notes 1. t-statistics in parentheses, ** p<0.01, * p<0.05, + p<0.1.

Table 1 Panel Data Models for Income, Food Consumption and women's BMI (Cont.)

	(13)	(14)	(15)	(16)	(17)	(18)
Dependent Variable	**Women's BMI**					
Model Chosen	Fixed-Effects	Fixed-Effects with PSM	Fixed-Effects :Control for initial Character-istics	Fixed-Effects	Fixed-Effects with PSM	Fixed-Effects :Control for initial Character-istics
Explanatory Variables						
MFI loan amount (aggregate)	**0.0136**	**0.0130**	**0.0004**	**-**	**-**	**-**
(log)	**(1.09)**	**(1.04)**	**(0.62)**	**-**	**-**	**-**
MFI's productive loan amount	**-**	**-**	**-**	**0.00509**	**0.00555**	**0.00017**
(log)	**-**	**-**	**-**	**(0.41)**	**(0.45)**	**(0.28)**
MFI's non-productive loan amount	**-**	**-**	**-**	**0.0442****	**0.0443****	**0.0017***
(log)	**-**	**-**	**-**	**(2.87)**	**(2.78)**	**(2.30)**
Age of the head of the hh	0.00382	0.00322	-0.00030	0.00319	0.00261	-0.00030
	(0.40)	(0.33)	(0.62)	(0.34)	(0.27)	(0.56)
Initial Age of the head of the hh	-	-	-0.0029	-	-	-0.0027
	-	-	(-1.60)	-	-	(-1.48)
Age_squared	-1.59e-05	-1.43e-05	-1.55e-05	-1.43e-05	-1.28e-05	-1.76e-07
	(-0.71)	(-0.63)	(-0.13)	(-0.64)	(-0.56)	(-0.15)
Initial Age_squared	-	-	0.00002	-	-	0.00003
	-	-	(1.17)	-	-	(1.07)
Household size	-0.074**	-0.074**	-0.0042**	-0.074**	-0.074**	-0.0041**
	(-2.66)	(-2.66)	(-2.96)	(-2.66)	(-2.66)	(-2.94)
Initial Household size	-	-	0.0039*	-	-	0.0036*
	-	-	(2.16)	-	-	(2.01)
Sex of head of household	-0.343	-0.333	-0.0278+	-0.317	-0.308	-0.0270+
(female or not)	(-1.11)	(-1.06)	(-1.81)	(-1.03)	(-0.98)	(-1.76)
Initial Sex of head of household	-	-	-0.1320**	-	-	-0.1299**
	-	-	(-4.21)	-	-	(-4.15)
Education of head of household	0.284	-0.277	0.002	-0.291	-0.284	0.002
– completed primary school	(1.42)	(-1.37)	(0.32)	(-1.46)	(-1.41)	(0.26)
Education of head of household	-0.0322	0.018	-	-0.0624	0.011	-
– completed secondary school	(-0.12)	(0.07)	-	(-0.24)	(0.04)	-
Education of head of household	0.498	0.354	-	0.438	0.294	-
– completed higher education	(0.84)	(0.59)	-	(0.74)	(0.49)	-
Initial education of head	-	-	0.023**	-	-	0.023**
– completed primary school	-	-	(2.45)	-	-	(2.49)
Initial education of head	-	-	0.010	-	-	0.010
– completed secondary school	-	-	(1.04)	-	-	(1.04)
Initial Education of head	-	-	0.012	-	-	0.013
– completed higher education	-	-	(0.56)	-	-	(0.61)
Farmer	-0.251	-0.294	-1.66e-6	-0.275	-0.318	-1.71e-6
	(-0.90)	(-1.03)	(-0.00)	(-0.98)	(-1.12)	(-0.11)
Agricultural wage labourer	-0.352	-0.385	-	-0.392	-0.420	-
	(-1.09)	(-1.18)	-	(-1.21)	(-1.29)	-
Non-Agricultural wage labourer	-0.299	-0.337	-	-0.346	-0.383	-
	(-1.02)	(-1.14)	-	(-1.18)	(-1.30)	-
small business	-0.297	-0.329	-	-0.324	-0.354	-
	(-1.03)	(-1.14)	-	(-1.13)	(-1.23)	-
professionals	-0.691*	-0.703*	-	-0.739*	-0.749*	-
	(-2.13)	(-2.15)	-	(-2.28)	(-2.29)	-
others	-0.246	-0.281	-	-0.288	-0.321	-
	(-0.88)	(-0.100)	-	(-1.03)	(-0.14)	-
Farmer (Initial)	-	-	0.015	-	-	0.015
	-	-	(0.97)	-	-	(0.94)
Agricultural wage labourer (Initial)	-	-	0.031	-	-	0.030
	-	-	(1.72)+	-	-	(1.70)+
Non-Agricultural wage labourer	-	-	0.018	-	-	0.019

(Initial)	-	-	(1.02)	-	-	(1.07)
small business (Initial)	-	-	0.021	-	-	0.020
	-	-	(1.32)	-	-	(1.25)
Professionals (Initial)	-	-	0.037	-	-	0.036
	-	-	(1.96)*	-	-	(1.93)+
Others (Initial)	-	-	-	-	-	-
	-	-	-	-	-	-
Whether a household	0.193	0.196	0.017*	0.189	0.191	0.016*
has electricity or not	(1.35)	(1.36)	(2.14)	(1.32)	(1.34)	(2.10)
Whether a household	-	-	0.016*	-	-	0.016+
has electricity or not (Initial)	-	-	(1.81)	-	-	(1.76)
price of rice	-0.394	-0.310	0.016	-0.319	-0.244	-0.013
(log)	(-0.43)	(-0.34)	(1.81)+	(-0.35)	(-0.26)	(0.30)
price of potatoes	-0.872*	-0.870*	-0.043*	-0.843*	-0.842*	-0.041*
(log)	(-2.50)	(-2.25)	(-2.51)	(-2.42)	(-2.41)	(-2.43)
price of milk	0.371**	0.403**	0.018**	0.379**	0.411**	0.019**
(log)	(2.70)	(2.89)	(2.77)	(2.76)	(2.95)	(2.80)
Whether in 1998-9	-	-	-	-	-	-
	-	-	-	-	-	-
Whether in1999-2000	-	-	-	-	-	-
	-	-	-	-	-	-
Whether in 2004-5	1.965**	1.947**	1.947**	1.915**	1.901**	1.947**
	(7.21)	(7.11)**	(7.11)**	(6.99)	(6.92)**	(7.11)**
Constant	20.98	20.70	0.260	20.72	20.47	0.251
	(7.18)	(7.07)	(5.17)	(7.10)	(7.07)	(5.00)
Observations	3,988	3,881	1532	3,988	3,881	1532
Number of hhid	2,444	2,349	766	2,444	2,349	766
Joint Significance	F(19,1525)	F(19,1513)	F(24,1507)	F(20,1524)	F(20,1512)	F(25,1506)
	28.82**	28.51**	2.91**	27.87**	27.55**	3.01**

Notes 1. t-statistics in parentheses,
** p<0.01, * p<0.05, + p<0.1.

Table 2 Effects of microfinance loans on growth of household income, food consumption and BMI (DID- Propensity Score Matching: *Kernel Matching*[*3, 4, *5])

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

Model	Log per capita Household Income (mean) or First difference of Log per capita Household Income: With access to MFI loans: A	Without access to MFI loans: B	Policy Effect (A-B) ATT: Average treatment effect	(t value)[*1, 2]	No. of obs.
1. Growth rate of household income per capita					
1997-1998 to 1998-1999	0.09883	0.07449	**0.02434**	**(0.38)**	Treat: 140, Control: 1081
1998-1999 to 1999-2000	0.12951	0.1007	**0.02881**	**(0.43)**	Treat: 151, Control: 1270
1999-2000 to 2004-2005	0.20182	0.26111	**-0.05929**	**(-1.14)**	Treat: 424, Control: 1250
2. Growth rate of food consumption per capita					
1997-1998 to 1999-2000	-0.31527	-0.4055	**0.09026**	**(1.49)**	Treat: 144, Control: 1061
1999-2000 to 2004-2005	0.36292	0.25854	**0.10438**	**(2.25)***	Treat: 406, Control: 1171
3. Change of BMI of a woman (spouse of household head or household head)					
1997-1998 to 2004-2005	-0.07358	-0.0402	**-0.03341**	**(-0.27)**	Treat: 102, Control: 357

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

Model	With access to MFI loans: A	Without access to MFI loans: B	Policy Effect (A-B)	(t value)	No. of obs.
1. Growth rate of household income per capita					
1997-1998 to 1998-1999	0.09876	0.06876	**0.03**	**(0.14)**	Treat: 163, Control: 1180
1998-1999 to 1999-2000	0.10625	0.08882	**0.01743**	**(0.33)**	Treat: 187, Control: 1435
1999-2000 to 2004-2005	0.23062	0.25141	**-0.02079**	**(-0.45)**	Treat: 400, Control: 1320
2. Growth rate of food consumption per capita					
1997-1998 to 1999-2000	-0.31603	-0.398	**0.08197**	**(1.04)**	Treat: 113, Control: 1092
1999-2000 to 2004-2005	0.32356	0.26423	**0.05933**	**(1.13)**	Treat: 404, Control: 1351
3. Change of BMI of a woman (spouse of household head or household head)					
1997-1998 to 2004-2005	-0.08243	-0.0408	**-0.04159**	**(-1.25)**	Treat: 97 Control: 404

Notes: [*1]. t value is calculated by Bootstrapped Standard Errors for PSM (100 bootstrap replications)
[*2] t values in brackets: ** significant at 1%; * significant at 5%; † significant at 10%.
[*3] A common support condition is imposed by dropping treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls.
[*4] The bandwidth for kernel is set 0.05.
[*5] The balancing property of explanatory variables is tested by the Stata command *pstest*. In each case, there is no statistically significant difference for *all* the explanatory variables for the treated households and the controls which have been matched.
[*6] ‘0’ stands for the state in which any of the household members did not have any access to MFI general loans or MFI productive loans and ‘1’ is for the state in which one of the household members had access to either MFI general loans or productive loans.

Appendix 1: Descriptive Statistics for MFI participants and non-participants

Variable	With access to MFI			Without access to MFI			With access to MFI loan for Productive Purposes			Without access to MFI laon 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 laon 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 laon 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

Appendix 2: Results of logit model on the determinants of participation in microfinance (or access to productive loans)

	All 4 rounds		1st round		2nd round		3rd round		4th round	
	MFI access	Productive loan access	MFI access	Productive loan access	MFI access	Productive loan access	MFI access	Productive loan access	MFI access	Productive loan access
Age of the head of the hh	0.0915**	0.0763**	0.130**	0.120**	0.105**	0.0844**	0.0919**	0.0554*	0.0515*	0.0498*
	(8.542)	(6.828)	(6.237)	(5.699)	(4.862)	(3.753)	(4.003)	(2.309)	(2.381)	(2.133)
Age_squared	-0.00101**	-0.000856**	-0.00147**	-0.00134**	-0.00116**	-0.000936**	-0.000967**	-0.000622*	-0.000580**	-0.000571*
	(-9.234)	(-7.486)	(-6.695)	(-6.085)	(-5.219)	(-4.038)	(-4.171)	(-2.566)	(-2.700)	(-2.450)
Household size	0.0240**	0.0241**	0.00991	0.0121	0.0185	-0.0110	0.00472	0.0140	0.0341**	0.0402**
	(3.113)	(3.012)	(0.502)	(0.613)	(0.986)	(-0.558)	(0.250)	(0.702)	(3.093)	(3.534)
Sex of head of household (female or not)	0.364**	0.317**	0.673**	0.635**	0.444*	0.212	0.198	0.406	0.293+	0.198
	(3.754)	(3.067)	(3.116)	(2.897)	(1.978)	(0.889)	(0.850)	(1.541)	(1.907)	(1.202)
Distance from nearest Upazilla (a business hub) *2	-0.00683*	-0.00575	-0.00949	-0.00741	-0.0109	-0.00807	-0.00780	-0.00648	0.000673	-0.00158
	(-2.006)	(-1.628)	(-1.430)	(-1.115)	(-1.624)	(-1.155)	(-1.113)	(-0.866)	(0.0965)	(-0.214)
No. of village moneylenders *2	-0.0023+	-0.00254+	-0.00167	-0.000817	-0.00092	-0.00311	-0.00293	-0.00404	-0.00352	-0.00236
	(-1.735)	(-1.836)	(-0.649)	(-0.316)	(-0.353)	(-1.131)	(-1.055)	(-1.333)	(-1.280)	(-0.812)
Education of head of household – completed primary school	-0.107+	-0.0900	0.101	0.0895	-0.0669	-0.0690	-0.0725	-0.0572	-0.383**	-0.350**
	(-1.914)	(-1.551)	(0.892)	(0.794)	(-0.596)	(-0.597)	(-0.624)	(-0.464)	(-3.424)	(-2.954)
Education of head of household – completed secondary school	-0.451**	-0.389**	-0.360**	-0.318**	-0.455**	-0.409**	-0.366**	-0.341**	-0.576**	-0.466**
	(-7.779)	(-6.459)	(-3.159)	(-2.776)	(-3.893)	(-3.369)	(-2.988)	(-2.613)	(-5.049)	(-3.875)
Education of head of household – completed higher education	-0.894**	-0.793**	-0.570*	-0.614*	-1.051**	-0.799**	-0.502+	-0.319	-1.240**	-1.237**
	(-6.617)	(-5.556)	(-2.242)	(-2.346)	(-3.670)	(-2.670)	(-1.760)	(-1.074)	(-4.387)	(-3.950)
Agricultural wage labourer	0.115	0.165	-0.155	-0.0676	0.0390	0.464*	0.0563	0.137	0.0872	0.137
	(0.683)	(0.930)	(-0.923)	(-0.401)	(0.227)	(2.498)	(0.311)	(0.699)	(0.488)	(0.727)
Non-Agricultural wage labourer	0.0255	-0.190	-0.375+	-0.447*	0.0326	0.0458	-0.0708	-0.232	0.739*	0.383
	(0.142)	(-1.001)	(-1.928)	(-2.279)	(0.163)	(0.211)	(-0.334)	(-1.001)	(2.011)	(1.015)
small business	0.375*	0.197	0.162	0.0595	0.220	0.183	0.348+	0.152	0.399+	0.483*
	(2.132)	(1.064)	(0.791)	(0.292)	(1.104)	(0.854)	(1.676)	(0.672)	(1.904)	(2.223)
professionals	0.663**	0.630**	0.351+	0.422*	0.643**	0.985**	0.656**	0.692**	0.537**	0.326
	(3.866)	(3.501)	(1.917)	(2.307)	(3.455)	(4.962)	(3.386)	(3.346)	(2.775)	(1.601)

others	-0.0594	-0.155	-0.487*	-0.492*	-0.329	-0.145	-0.243	-0.244	1.015**	0.909**
	(-0.316)	(-0.782)	(-2.180)	(-2.177)	(-1.394)	(-0.564)	(-0.967)	(-0.897)	(2.991)	(2.657)
Whether a household has electricity or not	-0.0722	-0.0260	-0.0463	-0.0139	-0.0458	-0.00125	-0.176+	-0.128	-0.0146	0.0422
	(-1.491)	(-0.519)	(-0.463)	(-0.139)	(-0.454)	(-0.0120)	(-1.763)	(-1.210)	(-0.161)	(0.444)
Whether in 1998-1999 (2nd round)	-0.343**	-0.488**	-	-	-	-	-	-	-	-
	(-6.004)	(-8.397)	-	-	-	-	-	-	-	-
Whether in 1999-2000 (3rd round)	-0.767**	-0.915**	-	-	-	-	-	-	-	-
	(-13.09)	(-15.11)	-	-	-	-	-	-	-	-
Whether in 2004-2005 (4th round)	-0.618**	-0.759**	-	-	-	-	-	-	-	-
	(-9.786)	(-11.69)	-	-	-	-	-	-	-	-
Constant	-2.283	-2.066	-3.016	-3.059	-2.864	-2.653	-2.824	-2.550	-1.998	-2.212
	(-7.244)	(-6.267)	(-6.048)	(-6.076)	(-5.416)	(-4.799)	(-4.919)	(-4.198)	(-3.467)	(-3.577)
Observations	10,360	10,360	2,591	2,591	2,588	2,588	2,594	2,594	2,587	2,587
Joint Significant Test	LR $Chi^2(19)$= 643.31**	LR $Chi^2(19)$= 658**	LR $Chi^2(15)$= 145.10**	LR $Chi^2(15)$= 136.94**	LR $Chi^2(15)$= 144.70**	LR $Chi^2(15)$= 140.63**	LR $Chi^2(15)$= 101.40**	LR $Chi^2(15)$= 84.31**	LR $Chi^2(15)$= 112.46**	LR $Chi^2(15)$= 95.81**
Prob> Chi2=	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Log likelihood	-6717	-6379	-1722	-1723	-1703	-1622	-1618	-1477	-1644	-1521

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Note z-statistics in parentheses (** p<0.01, * p<0.05, + p<0.1).

Appendix 3: Effects of microfinance loans on level of household income, food consumption and BMI (Propensity Score Matching by Kernel Matching) [*3, 4, 5]:

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

Model	Log per capita Household Income (mean) or First difference of Log per capita Household Income: With access to MFI loans: A	Without access to MFI loans: B	Policy Effect (A-B) ATT:	% change	(t value) [*1, 2]	No. of obs.
1. Effect on log household income per capita (level)						
1997-1998	6.0636	6.0173	**0.0463**	**4.74**	**(1.46)**	Treat: 1344, Control:1247
1998-1999	6.12803	6.0682	**0.05983**	**6.17**	**(1.96)***	Treat: 1127, Control: 1430
1999-2000	6.21238	6.1797	**0.03268**	**3.32**	**(1.33)**	Treat: 890, Control: 1692
2004-2005	6.39602	6.45781	**-0.06179**	**-5.99**	**(-2.06)***	Treat: 949, Control: 1638
2. Effect on log household food consumption per capita (level)						
1997-1998	5.8878	5.8752	**0.0126**	**1.27**	**(0.66)**	Treat: 1344, Control: 1247
1999-2000	5.4996	5.4682	**0.0314**	**3.19**	**(1.45)**	Treat: 875, Control: 1660
2004-2005	5.79482	5.76009	**0.03473**	**3.53**	**(0.74)**	Treat: 930, Control: 1567
3. Effect on BMI of a woman (level) (spouse of household head or household head)						
1997-1998	18.371	18.501	**-0.13**	**-0.70**	**(-1.07)**	Treat: 1205, Control: 1057
2004-2005	19.7805	19.9727	**-0.1922**	**-0.96**	**(-1.11)**	Treat: 788, Control: 1212

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

Model	With access to MFI loans: A	Without access to MFI loans: B	Policy Effect (A-B) ATT:	% change	(t value)	No. of obs.
1. Effect on log household income per capita (level)						
1997-1998	6.0755	6.018	**0.0575**	**5.92**	**(1.62)**	Treat: 1223, Control: 1368
1998-1999	6.15386	6.06382	**0.09004**	**9.42**	**(2.10)***	Treat: 926, Control: 1631
1999-2000	6.24694	6.17971	**0.06723**	**6.95**	**(1.18)**	Treat: 706, Control: 1876
2004-2005	6.41003	6.45213	**-0.0421**	**-4.12**	**(-2.06)***	Treat: 763, Control: 1824
2. Effect on log household food consumption per capita (level)						
1997-1998	5.89383	5.87255	**0.02128**	**2.15**	**(2.40)***	Treat: 1223, Control: 1368
1999-2000	5.51633	5.46927	**0.04706**	**4.82**	**(2.09)***	Treat: 694, Control: 1541
2004-2005	5.81154	5.77621	**0.03533**	**3.60**	**(0.74)**	Treat: 747, Control: 1750
3. Effect on BMI of a woman (level) (spouse of household head or household head)						
1997-1998	18.404	18.472	**-0.068**	**-0.37**	**(-0.63)**	Treat: 1099, Control: 1163
2004-2005	19.8144	19.984	**-0.1696**	**-0.85**	**(-0.92)**	Treat: 633, Control: 1367

Notes: [*1]. t value is calculated by Bootstrapped Standard Errors for PSM (100 bootstrap replications)

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

[*3] A common support condition is imposed by dropping treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the controls.

[*4] The bandwidth for kernel is set 0.05.

[*5] The balancing property of explanatory variables is tested by the Stata command *pstest*. In each case, there is no statistically significant difference for *all* the explanatory variables for the treated households and the controls which have been matched.

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 installments.
[2] We have also briefly summarized the results of propensity score matching (PSM) and report the results in Appendix 3 bearing in mind its limitations.
[3] While Roodman and Morduch (2009) tried to replicate Pitt and Khandker's (1998) results and questioned their validity, recent responses from Pitt (2011 a, b) have shown that Roodman and Morduch's replication of Pitt and Khandker's study was wrong because of their econometric errors in running Tobit model and omission of target/non-target status and they have argued that the original results remain valid.
[4] While this distinction is important in evaluating microfinance programmes (e.g. Imai et al., 2010), the results will have to be interpreted with caution because the funds are fungible, that is, there might be some cases where the borrowers use loans for the purpose which is different from the one initially specified by the lenders.
[5] Here, because L_{it} , while fixed-effects models take partial account of the endogeneity of a loan amount, this can be instrumented by valid instruments, for example, by using fixed-effects IV estimator. We have carried out this estimation as a robustness check. As our base variables for our instruments, we use (i) number of village money lenders and (ii) distance from nearest 'Upzilla', the business and administrative hub where most of the local services including marketing and financial are available. The former proxies the competition of the financial market or the degree of strength of traditional and large money lenders in the village and this is likely to be negatively associated with the supply of microfinance lending. The latter is associated with demand for microfinance loans and demand is likely to be lower if the distance from 'Upzilla' is larger. However, these instruments have little temporal variation over the years and we have used the interactions between year and each of these variables on the assumption that there is a year-to-year variation in the competition of the financial market or in the demand for microfinance, which are not associated with the outcome variables. The coefficient estimate of total loan is positive for income and food consumption and negative for BMI, but as it is non-significant, we avoid reporting the results of IV model in the text. They will be provided on request.
[6] It is noted that PSM for cross-sectional data is based only on observables and thus it cannot control for unobservables. We will thus introduce DID-PSM in the next sub-section.
[7] We have used the Stata command *pscore* to identify common support in estimating fixed-effects PSM model. In carrying out DID-PSM as well as PSM, we have applied a different command, *psmatch2* and thus have obtained different ranges of common support for each round.
[8] See Becker and Ichino (2002) for technical details of PSM. Technically, we adopt *Kernel Matching* for PSM and DID-PSM where 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. We have also tried *Nearest Neighbour Matching* to take each treated unit and search for the control unit with the closest propensity score and have obtained broadly similar results. To save the space, only the results based on *Kernel Matching* are presented.
[9] Use of probit model in the first stage provides very similar results.
[10] A summary of policy effects derived by propensity score matching (PSM) applied for each cross-sectional component of the panel is given in Appendix 3. Case (a) is the case of access to MFI's general loans and Case (b) is of access to MFI's productive loans. The results for all four rounds are shown for log household income per capita, while those for food consumption are only for the first, the third and the last rounds and those for women's BMI for the third and the last rounds due to the problem of missing observations. In case of income, a similar pattern has been observed for both access to MFI's general loans and productive loans. That is, positive policy effects in the first three rounds (where a statistically significant and positive effect is found only in 1998-9) turned negative and significant in the last round in 2004-5. As an extension, we have repeated PSM for four different income groups: 0-25%, 25-50%, 50-75% and 75%-100%. In 1998-9, we have found a positive and

significant policy effect only for the poorest group of households (0-25%), which further supports the policy effectiveness of microfinance programmes. If we disaggregate PSM by income groups for the last round, we find for both general and productive loans a positive and significant average treatment effect on income for the poor group (0-25%) and a negative and significant average treatment effect on the group with the income range of 75-100%. This implies that microfinance programmes continued to have a poverty-reducing effect for the poorest in 2004-5. On food consumption, the effect of access to general loans is positive and non-significant, while that of access to productive loans is positive and significant in 1997-8 and in 1999-2000.The effects of MFI loans on women's BMI are non-significant in the first and the last rounds. All these results have to be interpreted with caution because of the limitations of PSM for cross-sectional data which we discussed in Section IV.

[11] It is not clear why the non-poor group (50-75%) which obtained the loans decreased per capita household income in comparison with (continuous) non-participants with similar characteristics. It might be related to the failure of investment based on MFI loans and a further investigation is needed to investigate the variation of the effects of microfinance on income among different income groups.

[12] However, it is noted that RCTs are not without problems. See the recent critique by Barrett and Carter (2010).

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