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# Abstract

This paper examines the heterogeneous impacts of microfinance intervention in rural Bangladesh using a long panel survey data expanding from 1991/92 to 2010/11. Heterogeneity in program effects may arise due to household (such as landholding, head's education, employment or skills in oral math) and community (electrification and accessibility) endowments. Benefits do vary by such endowments. For example, large and medium holders benefit more than marginal or small holders from microfinance in non-land asset, net worth and labor supply. Beneficiary households whose heads completed primary education experience higher gains in non-land asset and net worth than those whose heads did not complete primary education. Also, having adults with competency in oral math (supposedly helpful in augmenting in entrepreneurial skills) helps the households benefit more. Beneficiaries in villages with electricity and better road access benefit more than those in villages lacking electricity or access. Quantile regression estimates show that, with the exception of the effects of male borrowing, lower income households benefit more than higher income ones. Finally, this paper shows that households with older heads or more adult males are likely to drop out from microfinance, so are those with adults with less competency in oral math. However, program dropouts are not large enough to affect the overall benefits of microfinance.

# Who Benefits Most from Microfinance in Bangladesh?

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## 1. Introduction

There is a large body of literature that estimates the effects of microfinance participation on the welfare of the poor. This is basically an attempt to demonstrate the benefits of microfinance by estimating either the average effect of microfinance program participation or the marginal effect of the amount of borrowing from a microfinance program. An estimation of average or marginal effect of a program or policy intervention such as microfinance is based on the assumption that there is a common effect of a program across all program recipients. One can justify a common effect (either average or marginal) model on the following assumptions: (1) induced total effects increase total welfare of a society; (2) the detrimental effects of a program on certain groups of the population are not important enough or are offset by transfer—either through an over arching social welfare function or from family members or social networks.

However, the assumption of a common effect is not quite plausible for a program such as microfinance where the productive use of capital depends on the entrepreneurial ability of a borrower, and such skills are not equal across borrowers. That is, all participants may not benefit equally via borrowing and other services provided by a microfinance program.

This is why policymakers and researchers often find it important to consider how gains from a program such a microfinance institution might vary by individual ability or individual, household and community characteristics (such as age, education, gender, income or expenditure, or electrification status or road infrastructures). Such a consideration is perhaps of paramount importance to consider the distributional gains of a program even if the average or marginal effect is not statistically significant. Then the question is, who benefits or loses from such a program when the average impact is not statistically significant. In fact, for different reasons, it is very important to consider the distributional or heterogeneous effects of microfinance.

For example, it is argued by critics that microfinance does not reduce poverty and that the poor participants are forced to remain with the programs once they join as there is no mechanism for them to graduate from the program. That is, they keep on borrowing, and hence, become dependent on MFIs. Is this an average situation? Does this mean the program is not benefiting any group at all so that the operations of microfinance programs cannot be justified? On the

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other hand, even if there is a positive effect of participation, this does not mean everybody benefits. If not, who are the beneficiaries among program participants?

Therefore, a study examining only an average effect which finds, say, a negative effect of microfinance, does not necessarily refute the role of microfinance. It is possible that there may be certain groups that benefit from such a program, although their benefits may not be large enough to out weigh the negative effect of others, implying an overall negative or insignificant effect of program participation. There are studies which question the development performance of a targeted program that is captured by better-off households in a society (e.g., Araujo and others 2008; Gugerty and Kremer 2008; Mansuri and Rao 2004; Platteau 2004). Besides, groups benefiting from a microfinance program in the short run may not benefit over time or vice versa (King and Behrman 2009; van de Walle 2009). This means, studying the distributional or heterogeneous effects of microfinance is important which will show who benefits or who is hurt by a microfinance program and why. After all microfinance is not a charity; benefits accrued from microfinance depends on the productive use of borrowing, which in turn depends on the entrepreneurial ability of a borrower as well as local market conditions or a combination of resource endowments. Therefore, when such ability or such resource endowment is not uniformity distributed, it is pertinent that the common effect model is not valid and thus, policymakers ought to know the distributional/heterogeneous effects of microfinance across households and across areas as well as over time. This paper addresses this critical policy issue.

## 2. Data

The data used to address the heterogeneity of the effects of microfinance program is the long panel data set collected by the World Bank with the help of BIDS and InM. The World Bank and the Bangladesh Institute of Development Studies (BIDS) carried out the first survey in 1991/92 to study the role of microfinance in poverty reduction. This was a survey of 1,769 households randomly drawn from 87 villages of 29 upazilas in rural Bangladesh. The households from 87 villages of 29 upazilas were revisited in 1998/99, again with the help of BIDS. However, only 1,638 households were available for the re-survey due to sample attrition. The re-survey included some new households from old villages and a few newly included villages. Altogether 2,599 households were surveyed in 1998/99 out of which 2,226 were from old households (allowing for household split-off) and 373 are new.

The households were resurveyed again in 2010/11, this time jointly with the Institute of Microfinance (InM). The resurvey tried to revisit all the households (2,599) surveyed in 1998/99. However, due to attrition, 2,342 households were located, which spawned to 3,082 households due to split off. The analysis of this study is based on 1,509 households from 1991/92 that are common in all three surveys. Of course, because of household split-off, we have higher number of households in 1998/99 (1,758) and 2010/11 (2,322).

## 2.1 Distribution of Program Benefits: Do Resource Endowments Matter? A Descriptive Analysis

The household surveys used questionnaires asking respondents about microfinance participation over the five years preceding survey interviews. Although we do not have pre-participation baseline information, we use the first survey (1991/92) as the baseline for the follow-up surveys of 1998/99 and 201/11.

We are interested to see how the outcomes of interest such as income, expenditure, asset and net worth vary by resource endowments observed at the individual level (e.g., years of education, occupation, and math skill), household level (e.g., landholding), and community level (e.g., village access to road and electricity and irrigation). Tables 1-6 show descriptive statistics of such outcomes by household and community endowments.

As Table 1 shows that, except for employment, outcome variables increase monotonically as household landholding increase for all survey years. For example in 2010/11, household per capita expenditure of small and medium landholders is 42 percent higher than that of marginal holders, and large holders have 47 percent higher per capita expenditure than medium holders. Marginal holders, however, have the highest labor supply in all three survey years for both males and females, which is not surprising given that they are mostly wage-employed.

We also observe somewhat similar pattern in household outcomes by head's education and oral math skills.[1] Households that are least endowed in education and skill endowments have again the lowest welfare in outcomes, except for labor supply (Tables 2 and 3). For example, compared to the households whose heads completed secondary education, those completed just primary education have almost one-third of the net worth in 2010/2011, and those whose heads did not complete primary education have less than half the net worth of those with primary-educated heads in the same period. Per capita income of the households who have adults with competency in oral math is 43 percent higher than that of those without adults with math competency in 1991/92 and 27 percent higher in 1998/99.

Unlike the observations based on household landholding or education (or skills), we do not see any distinct patterns in household outcomes based on their main occupation (Table 4).[2] That said, households dependent on self-employed nonfarm activities have the highest income and expenditure, with the exception of that in 1998/99. Also, households that are mostly self-employed farmers, have the highest net worth during all three years.

[1] While education (years of schooling) is a good measure of human endowment it does not necessarily imply competency or skills needed for entrepreneurial or material success, especially when the quality of education is questionable as it is in most developing countries. So, we also use skills in oral math of adults as an alternate, and perhaps more practical, measure of competency. Members of the households surveyed in 1991/92 and 1998/99 were subjected to skill tests which were developed specifically to get a measure of their basic literacy and skills in reading, writing, written math and oral math. Based on the scores of such tests, members were adjudged either competent or incompetent. We group households based on whether or not they have adults with competency in math oral. We consider the competency in oral math, among the four basic skills, to be most important to entrepreneurship, even though findings do not vary much for other skills.

[2] Household's main occupation is determined by the activity that brings the highest income.

How do the household outcomes vary by village endowments? To investigate this, we consider two village-level infrastructures: electricity and roads. Villages are grouped based on whether they have electricity and they are accessible through out the year. As Table 5 shows, barring a few exceptions, households in villages with electricity are better off than those in villages without electricity. On the other hand, patterns in outcomes are not uniform by village accessibility (Table 6). Whatever the trends in outcomes are, these descriptive analyses clearly show that the outcomes do vary by household or community endowments. Question is to what extent such variation can be attributed to microfinance borrowing or benefits?

## 2.2 Distribution of Program Benefits: Estimation Using a Non-linear Regression Technique

The underlying assumption is that the source of heterogeneity in program impacts is the differential effects due to resource endowment of households or communities. For instance, similar to the time-varying effects of microfinance participation, we would like to see whether borrowing from a microfinance program works better for households with better resource endowments. We can answer this question by estimating the outcome equation with program participation interacted with resource endowments of households and communities. The estimating equation can help us understand if household and community endowments constrain benefits accrued to households. We would then formally test if treatment effects varies systematically across households. Pitt and Khandker (1998), for example, found that land ownership and schooling were important determinants of the decision to participate in group-based credit programs and of the outcomes they affect (consumption, non-land assets, labor supply, etc.). It may well be that assets, schooling and other observed and unobserved household and individual attributes signal the severity of the constraints felt by households in other credit markets, and consequently are associated with less optimal resource allocations. Relaxing these constraints through participation in group-based credit schemes may thus have large impacts for these households. This goes to the heart of the question of targeting – are the least well off households getting greatest benefit from these programs?

The basic model for estimating the common effect of microfinance participation of $i$-th member from $j$-th household ($P_{ij}$) on household level welfare outcomes ($Y_{ij}$) such as consumption, female and male labor supply, asset holding, net worth, and children's schooling is given below:

$$Y_{ijt} = \beta X_{ijt} + \delta E_{ijt} + \gamma_f P_{ijft} + \gamma_m P_{ijmt} + \mu_{ij} + \eta_{ijt} + \varepsilon_{ijt} \qquad (1)$$

where $X$ is set of household and village level exogenous variables such as age and gender of the household head, and villages-level prices and wage; $E$ is a set of resource endowments considered such as landholding and education of household head as well as village level resources such as access to road and electricity. Here $m$ stands for male membership and $f$ for female membership. This is to differentiate the effects of microfinance participation by gender of program participants. $\gamma_f, \gamma_m, \beta, \delta$ Also are parametersto be estimated. Equation suffers from two sources of unobserved heterogeneity (both at household and at village level); one source is time-invariant heterogeneity ($\mu$) and the other source is time-varying heterogeneity ($\eta$). As we have three rounds of survey (i.e., t>1), we can apply difference-in-difference technique to equation (1) whence we get the following differenced equation:

$$\Delta Y_{ijt} = \beta \Delta X_{ijt} + \delta \Delta E_{ijt} + \gamma_f \Delta P_{ijft} + \gamma_m \Delta P_{ijmt} + \Delta \eta_{ijt} + \Delta \varepsilon_{ijt} \quad (2)$$

Here in equation (2), the time-invariant heterogeneity ($\mu$) cancels out because of differencing over time. The time varying heterogeneity ($\eta$) persists, for which a simple fixed-effect (FE) method cannot resolve sample selection bias and hence, special treatment is needed to resolve this matter.

There are alternative methods to control for the time varying heterogeneity while using fixed effects (FE) method based on panel data (see a discussion of such methods in Khandker, Koolwal, Samad (2010). One such method is the propensity score-weighted fixed-effects method where each household included in the sample irrespective of their participation status receives a propensity score based on a participation equation where the probability of participating in a microfinance program is determined by a host of factors observed in 1991/92 (the first survey period) such as age, education, and gender of household head, landholding assets, and other factors considered exogenous in year 1991/92. Thus, following Hirano, Imbens and Ridder (2003), the weights used in the regression of equation (2) are 1 for the participating households and *P*/(1–*P*) for nonparticipating households in any year where *P* is the predicted probability of participation by the household.[3]

In order to estimate how the common effects of participation by gender vary by resource endowments, we allow for non-linearities in the effect of credit with interactions of some key policy variables such as head's education, household landholding, village access to road or electricity, and so on. That is, credit variables are interacted with household and community endowments (expressed as binary variables) to see if microfinance participation effects vary with changes in resource endowments either at the household or community level. With such interactions the differenced outcome equation (2) can be expressed as follows:

$$\Delta Y_{it} = \beta \Delta X_{it} + \Delta E_{ijt} + \gamma_f \Delta P_{ift} + \gamma_m \Delta P_{imt} + \lambda_f \Delta (P_{ift} * E_{it}) + \lambda_m \Delta (P_{imt} * E_{it}) + \Delta \eta_{it} + \Delta \varepsilon_{it} \quad (3)$$

where $\lambda_m$ and $\lambda_f$ are parameters for the interaction terms of resource endowments with male and female credits, respectively. Resource endowments ($E$),such as head's education, are expressed as dummy variables, so that, for example, $E_{it}$=1 when head has completed primary education and $E_{it}$=0 otherwise. When households do not have the endowments (that is, using the example, head has no primary education, and $E_{it}$=0), equation (3) reduces to the basic differenced equation of (2):

$$Y_{it} = \beta \Delta X_{it} + \delta \Delta E_{ijt} + \gamma_f \Delta P_{ift} + \gamma_m \Delta P_{imt} + \Delta \eta_{it} + \Delta \varepsilon_{it} \quad (4)$$

and $\gamma_m$ and $\gamma_f$ give the estimates of credit effects for households without the resource

[3] An alternate method is the lagged dependent variable (LDV) method, which uses lagged dependent variable as additional regressors. But for only three rounds of survey, we find that P-score weighted FE is a better fit than the LDV method in terms of the number of significant parameters estimated.

endowments (those with heads with no primary education). On the other hand, for households with endowments (that is, head has primary education, and $E_{it}$=1), equation (3) becomes:

$$Y_{it} = \beta \Delta X_{it} + (\gamma_f + \lambda_f)\Delta P_{ift} + (\gamma_m + \lambda_m)\Delta P_{imt} + \Delta\eta_{it} + \Delta\varepsilon_{it} \quad (5)$$

and $(\gamma_m + \lambda_m)$ and $(\gamma_f + \lambda_f)$ give the estimates of credit effects for households withre source endowments (those with heads who have primary education).[4]

Table 7 presents the distributional impacts of microfinance by landownership. There are three groups of households by landownership status—marginal farmers, small and medium farmers, and larger farmers. While male credit increases per capita expenditure for marginal farmers, female credit increases it for both small and medium farmers. Male credit increases male labor supply, non-land assets, and net worth for all three categories of farmers. It also increases female labor supply for small and medium farmers. Female credit also increases labor supply of male and female family workers, non-land asset, and net worth for marginal, and small to medium farmers. For example, a 10 percent increase in female borrowing, while it does not increase net worth for marginal farmers, increases net worth by one percent for small and medium farmers and 1.5 percent for large farmers.

Table 8 presents the heterogeneous impacts of microfinance by household head's education. Credit by both males and females increases non-land asset and net worth for households whose heads did not complete primary education and also for those with heads completing the primary education, more for the latter, without any effects for households whose heads completed secondary level education. For example, a 10 percent increase in male credit increases household net worth by 0.17 percent for households headed by individuals with no primary schooling, compared to 0.37 percent and 0.27 increase for householdswith heads completing primary education and secondary education, respectively. Table 9 presents the estimated credit impacts by competency of household adults in oral math. Competency in oral math increases impacts of female credit on both male and female labor supply. While credit has impacts on non-land asset and net worth, effects are higher for households whose adults have competency in oral math.

Table 10 shows how the benefits accrued to household from microfinance borrowing vary by occupation. Among the households, only the self-employed households were able to gain in income and expenditure from microfinance borrowing. Wage-employed households were, however, gained in employment hours, non-land assets and net worth. For example, a 10 percent gain in female credit increases labor supply by 0.6 percentage points for both men and women. On the other hand, male borrowing increases only men's labor supply for wage-employed households. Households who are self-employed benefit in most of their outcomes from borrowing (either by males or females, or by both). A 10 percent increase in male credit increases non-land asset and net worth by 04. Percent and 0.2 percent, respectively, for self-employed farmers. The corresponding figures for female credit are 0.5

[4] In practice, we measure the credit effects for households with endowments by computing point estimates of the terms ($P_{ift} + P_{ift}*E_{it}$) and ($P_{imt} + P_{imt}*E_{it}$) after running the regression for equation (3).

percent and 0.3 percent, respectively. Female labor supply also decreases male labor supply.

The benefits of microfinance also vary by village attributes. Table 11 shows the heterogeneous effects of credit by whether the village is electrified or not. For both male and female credit, the effects are atleast equal or higher on non-land assets and net worth in villages with electricity than in non-electrified villages. Same is true for labor supply. Similarly, returns to borrowing are higher in villages with all-year access by roads compared to that in villages without such access (see Table 12).

Above analysis clearly demonstrates that impacts of microfinance are not uniform across all types of borrowers; they seem to vary by education, landholding, and occupation of households as well as by the village electrification status and its access status to all weather roads.

## 2.3 Distribution of Program Benefits: A Quantile Regression Technique

Does borrowing from a microfinance program,besides yes-no participation, also work better for households with better existing resource endowments? We can answer this question by re-estimating the outcome equation with credit amount interacted with resource endowment variables of households and communities. The estimating equation can help us understand if household and community endowments constrain benefits accrued to households. We can also formally test whether the effect of credit program participation is different at various points in the conditional distribution of the dependent variables such as per capita consumption, a measure of household welfare. If the findings suggest that returns to borrowing depend on the distribution of income or consumption, this then reflects the view that treatment effects may not be same for all those treated. That is, the variation in treatment effects may vary systematically across households.

We apply the quantile regression model introduced by Koenker and Basssett (1978), and generalized to the censored quantile regression model by Powell (1984, 1986). For example, we can test if there are differential returns to credit in terms of household consumption and income per capita at distinct points in the household consumption or income distribution.

It is potentially important to investigate changes in the outcomes observed at different points in the distribution, as simply investigating changes in the mean may not be sufficient when the entire shape of the distribution changes significantly (Buchinsky 1998). While the objective of ordinary regression is to estimate the mean of dependent variable, the objective of quantile regression is to estimate a quantile value (median or other quantile values such as 0.25, 0.60, etc.) of the dependent variable. Technically a quantile regression minimizes the sum of absolute residuals corresponding to the quantile value in question as opposed to minimizing the sum of squares of the residuals achieved by ordinary regression. Microfinance programs, by design, try to reach the poorest groups, especially women, and so, it is expected that the poorer households may benefit more from these programs than the better-off households. A quantile regression enables us to investigate this issue.

Following the model proposed by Koenker and Basset (1978), assume $Y_i = 1, 2, \ldots n$, is a sample of observations on the outcome, and that $X_i$ is a $K$ x 1 vector comprising the household, and village-level characteristics controlled on the right-hand side of the outcome equation. The quantile regression model can be expressed as:

$$Y_i = X_i^{/}\beta_\theta + \varepsilon_{\theta i}, \; Quant_\theta(y_i|X_i) = X_i^{/}\beta_\theta, \; \theta \in (0,1) \qquad (6)$$

where $Quant_\theta(Y_i|X_i)$ denotes the quantile $\theta$ of log per capita expenditure or income conditional on the vector of covariates. In general, the $\theta$-th sample quantile of $Y$ solves:

$$\min_\beta \frac{1}{n} \sum_{i:Y_i \geq X_i^{'}\beta} \theta |Y_i - X_i^{/}\beta_\theta| + \sum_{i:Y_i < X_i^{'}\beta} (1-\theta)|Y_i - X_i^{/}\beta_\theta| = \min_\beta \frac{1}{n} \sum_{i=1}^{n} \varrho_\theta(\varepsilon_{\theta i}) \qquad (7)$$

where $\rho_\theta(\varepsilon_{\theta i})$ denoted as the “check function” and is defined as:

$$\rho_\theta(\varepsilon_{\theta i}) = \begin{cases} \theta\varepsilon_{\theta i} \;\; if \; \varepsilon_{\theta i} \geq 0 \\ (\theta - 1)\varepsilon_{\theta i} \;\; if \; \varepsilon_{\theta i} < 0 \end{cases} \qquad (8)$$

Parameters are estimated semi-parametrically by minimizing the sum of weighted absolute deviations, which fits medians to a linear function of covariates, and can be performed using linear programming methods (Buchinsky 1998). To account for possible heteroskedasticity in the error term, the variance-covariance matrix of coefficients is estimated using bootstrap re-sampling. Specifically, the quantile’s coefficients can be interpreted as the partial derivative of the conditional quantile of $Y_i$ with respect to one of the regressors $X_i$, namely $\partial Quant_\theta(Y_i|X_i)/\partial X_i$

To estimate quantile regression for panel data, we use a semi-parametric approach to examine the distributional effects of non-random treatment.[5] This method involves a panel quantile regression model that estimates the treatment impact on outcomes $Y$ by distributional quantile. More specifically, we use the quantile regression equations for the two data periods to estimate the distributional effects of electricity connection on household/individual outcomes $Y$, as follows:

$$Q_\tau(Y_{ijt}|Z_{ijt}, E_{ijt}, \eta_{ijt}) = \psi_\tau Z_{ijt} + \delta_\tau E_{ijt} + \eta_{ijt}, \tau \in (0,1) \qquad (9)$$

where $Q_\tau(Y_{ijt}|Z_{ijt}, E_{ijt}, \eta_{ijt})$ denotes the quantile $\tau$ of Y in period $t$, conditional on the fixed effect and household and community covariates in period $t$. Vector $Z$ measures both household ($X$) and village ($V$) exogenous attributes, while $\eta$ subsumes unobserved commune and household heterogeneity. One problem in applying the quantile regression model to panel data is that differencing variables is not generally equal to the difference in the conditional quantiles because quantiles are not linear operators. To overcome this obstacle, we follow Gamper-Rabindran, Khan, and Timmins (2009), which specifies the unobserved effect $\eta$ non-parametrically as an unknown function $\phi(\cdot)$ of the covariates $X$, as follows:[6]

[5] This method is applied in Brazil by Gamper-Rabindran, Khan, and Timmins (2009) in the context of providing piped water.

[6] Abrevaya and Dahl (2008) apply a similar approach based on the correlated fixed-effects model of Chamberlain (1982), where the fixed effect is specified as a parametric (linear) function of the covariates $X$.

$$\eta = \varphi(Z_{ij1}, Z_{ij2,}..., Z_{ijt}) \quad (10)$$

Substituting equation (10) in each conditional quantile in equation (9) allows us to estimate the distributional impact of income on outcomes $Y$.[7] In practice, we transform equation (9), and take the quantile over the difference of the outcome and its mean as shown below:

$$Q_\tau(\Delta Y_{ijt}) = \psi_\tau \Delta Z_{ijt} + \delta_\tau \Delta E_{ijt} + \theta_{1\tau} Z_{ij1} + \theta_{2\tau} Z_{ij2} + \theta_{3\tau} Z_{ij3} + \Delta\varepsilon_{ijt} \quad (11)$$

Table 13 shows the quantile regression results of the contribution of microfinance that vary by percentile groups by income and expenditure. Results for the expenditure quintile show that households in lower expenditure brackets benefit more than those in higher expenditure bracket. This is for both male and female borrowing. For example, a 10 percent increase male borrowing increases per capita expenditure by 0.03 percent for the lower quantile households without any effect on households in the higher expenditure quantiles. Similarly, female borrowing increases per capita income more for the lower income groups than for the higher income groups. For example, a 10 percent increase in female borrowing increases per capita income by 0.11 percent for the $15^{th}$ quantile and $25^{th}$ quantile, and 0.07 percent for the $50^{th}$ quantile, and nothing for highest income groups. But the reverse is true for male borrowing—it is the higher income groups who benefit more from microfinance than for lower income groups. For example, a 10 percent increase in male borrowing increases per capita income by 0.18 percent for the $85^{th}$ quantile, 0.14 percent for the $75^{th}$ quantile, 0.11 percent for the $50^{th}$ quantile, 0.09 percent for the $25^{th}$ quantile and only 0.07 percent for the lowest $15^{th}$ quantile.

The results demonstrate that benefits are not equally distributed for borrowing from microfinance. However, female borrowing is more pro-poor than male borrowing in raising household income and expenditure.

## 2.4 Who Are the Losers in Microfinance?

Microfinance does not benefit all participants equally all as we noticed in earlier sections. We, however, are yet to assess if there are losers in microfinance – those who quit microfinance? How many are the losers in microfinance over the last 20 years in our panel data of 1,530 households? One way to assess the extent of losers is to examine the indebtedness among borrowers. Another way to examine the extent of losers in microfinance is to find out who drops out and why. It is possible that some participants drop out as they graduate; others drop out if they do not benefit from microfinance. It is a matter of empirical issue to determine who drops out because they graduate from microfinance or because they are losers.

Table 14 shows the characteristics of two groups of participating households, one group that

[7] Gamper-Rabindran, Khan, and Timmins (2009) show how the quantile regression (QTE) can be estimated using a two-step procedure. First, $\hat{Q}_\tau(Y_{ijt} | Z_{ijt}, E_{ijt}, \eta_{ijt})$ should be non-parametrically estimated for each period $t$, with $Z$ and $E$ entering linearly in the equation. Second, the differenced fitted values

$$\hat{\hat{Q}}_\tau(Y_{ijt} | Z_{ijt}, E_{ijt}, \eta_{ijt}) - \hat{\hat{Q}}_\tau(Y_{ijt-1} | Z_{ijt-1}, E_{ijt-1}, \eta_{ijt-1})$$

from the estimations can be regressed on the differenced regressors since the proxies for the fixed effects fall out of the estimation.

drops out and the other group who did not. The average dropout rate is 13.8 percent between the surveys, with 11.8 percent in 1998/99 and 13.8 percent in 2010/11. One key difference between this two groups is that the average loans for both male and female borrowers is higher for dropout members than for continuing members: for example, the average loan for female member is Tk. 6,130 for dropouts and Tk. 3,645 for those who did not dropout. The dropout members are older, less educated, and less wealthy (in terms of landholding), compared to those who continued with microfinance membership. More importantly, households who dropped out from a microfinance program are less able in terms of possessing skill in both reading and oral mathematics compared to those who continued.

What determines the dropout rate? Table 15 presents the factors determining who dropped out or not. The model includes the characteristics of 1991/92 survey to explain who dropped out in 1998/99 and 2010/11. There are two models, one with the loan amount as an additional regressor and the other without. We find that higher is the amount borrowed by either male or female from a microfinance program higher the probability of dropout from the program. This means, higher is the amount of borrowing higher is the risk of loan default and consequently, higher is the probability of dropout. However, the more capable people (those with higher competency either in reading or mathematics) are less likely to drop out from a program. Hence, program dropout is not random; both own and household characteristics matter for a member's dropout from a program.

Of course, it is not clear if dropout members are net losers of microfinance and thus, they drop out. We look at the welfare outcomes of those who dropped out and those who did not during the initial year (when the dropouts were participants) and the following year (when the dropouts ceased to participate). As shown in Table 16, those who dropped out from a microfinance program were better off than the continuing members in terms of most outcomes during the initial years (t-statistics of the difference in outcomes between the two groups is statistically significant). However, over time the situation has changed – t-statistics of the difference in outcomes has either lost its statistical significance or changed sign. For example, the dropout members had less non-land asset than the continuing members by the time they dropped out. This trend suggests that dropouts did not do as well as the continuing members. It is possible that the factors that contribute to member dropout (age, education, competency in oral math, etc.) also contribute to diminished outcomes.

Since dropout is not random (as it is determined by human endowments) and outcomes vary over time by dropout phenomenon, it is possible that microfinance impacts also vary by that phenomenon and as such, we need to figure out the differential impacts for dropouts and continuing members. Such impacts can be captured using a Difference-in- Difference-in-Difference or Triple Difference (DDD) estimators. If $DD_r$ is the impact for continuous members and $DD_d$ is the impact for dropout members we would like to find out if $DD_r=DD_d$. In a DDD framework this can be expressed as,

$$Y_{it} = \beta T_t + \lambda_r M^r_{it} + \lambda_d M^d_{it} + \gamma_1 T_t M^r_{it} + \gamma_2 T_t M^d_{it} + \gamma_3 M^r_{it} M^d_{it} + \gamma_4 T_t M^r_{it} M^d_{it} + \varepsilon_{it} \qquad (12)$$

where, $T_t$ is the time control, $M^r_{it}$ is the intervention variable for continuing members, $M^r_{it}$ is the intervention variable for dropout members, and $\varepsilon_{it}$ is the random error, and $\beta$, $\lambda$ and $\gamma$ are parameters to be estimated. The parameter of interest here is $\gamma_4$ which captures the incremental effects for continuing participants over dropout members. In practice, we capture the effects of regular and dropout members by adding dummy variables for each type. Table 17 shows the participation effects on household outcomes for two scenarios: when member dropout is controlled for and when it is not.[8] We can see the controlling for member dropout does not change much the microfinance impacts. For household income and expenditure there is no difference (t-statistics are not significant). Not controlling for member dropout underestimates the credit effects for male labor supply, and overestimates the credit effects for female labor supply and non-land asset. There is no difference in the effects for household net worth and children's schooling.[9] So, we can summarize by saying that change in credit impacts is very little when member dropout is controlled for.

## 3. Conclusion

This paper examines the heterogeneous impacts of microfinance intervention in rural Bangladesh. Heterogeneity in program effects may arise due to household and community endowments. For household resource endowments, we consider household landholding, head's education, competency in oral math (as proxy for entrepreneurial ability), and employment types, and for village endowments we consider village electrification and accessibility. We find that while large holders experience income gain from microfinance, marginal, and small-to-medium holders experience increased no effects on income. For other outcomes (labor supply of males and females, non-land asset and net worth), while all households benefits, it seems large and medium holders benefit more than marginal farmers. Findings for head's education are mixed – for labor supply (of both males and females) there is little variation in impacts by head's education, however, when it comes to non-land asset and net worth, households whose heads have completed primary or secondary education seem to have done better than those whose heads did not complete primary education. Since education in rural Bangladesh may not reflect the true ability to utilize loans, we also look at microfinance impacts by competency of adults in oral math, which is perhaps better proxy for entrepreneurial ability. And expectedly, we see that having adults with competency in oral math helps the households reap more benefits than not having adults with such competency. As for effects of employment on microfinance returns, only self-employed households seem to gain in income and expenditure from microfinance borrowing. Self-employed households also gained more than wage-employed ones in non-land asset and net worth. Speaking of community endowments, findings show that households in villages with electricity and better access benefit more from microfinance than those in villages without electricity or inferior access. Quantile regression estimates show that, except for the effects of male borrowing, households in the

[8] Again, this estimation is done for 1998/99 and 2010/11 observations as dropout information is indeterminate in the first survey year (1991/92)

[9] We also estimated the credit effects using cumulative borrowing amount and did not find any difference in the impacts from that using participation variables.

lower welfare brackets (in terms of income or expenditure) benefit more than those in the higher welfare brackets. This means that microfinance programs are perhaps well-targeted. This is very critical as alleviating poverty is a stated objective of microfinance interventions.

This chapter also tries to identify who the program dropouts are and if they can be called losers of microfinance. Findings show that households with older heads or more adult males are likely to drop out. Most importantly, those with adults with less competency in oral math are more likely to drop out, which may be indicative of lower ability to make productive uses of microloans. These households also borrowed more than their counterpart members who continued to stay with microfinance programs. Perhaps the dropout members, having borrowed more than they could handle and with less entrepreneurial ability, did not fare well. In fact, the trend in their outcomes over time is clearly suggestive of that. While the dropout members were either better off or at least similar to their counterpart continuing members in terms of welfare measures during the participation years, they failed to maintain their prosperity over time. That said, our findings also suggest that the differential impacts of microfinance by program dropouts are not large enough to affect the overall impacts of microfinance.

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**Table 1. Summary Statistics of Household Outcomes by Land Ownership ($N_{HH}$=1,509)**

| Household Landholding | Per Capita Total Income (Tk./month) | Per Capita Total Expenditure (Tk./month) | Male Labor Supply (hours/month) | Female Labor Supply (hours/month) | Non-Land Asset (Tk.) | Net-Worth (Tk.) |
|---|---|---|---|---|---|---|
| **1991/91** | | | | | | |
| Marginal holders (land size<0.5 acre) | 501.2 | 316.1 | 192.8 | 38.6 | 12,312.7 | 33,909.6 |
| Small and medium holders (land size 0.5-2.5 acres) | 587.5 | 381.8 | 178.0 | 22.3 | 31,771.8 | 129,512.0 |
| Large holders (land size>2.5 acres) | 760.9 | 565.8 | 128.3 | 16.0 | 81,698.3 | 499,047.7 |
| **1998/99** | | | | | | |
| Marginal holders (land size<0.5 acre) | 492.8 | 423.5 | 222.4 | 25.3 | 19,292.9 | 68,841.6 |
| Small and medium holders (land size 0.5-2.5 acres) | 610.5 | 510.7 | 175.6 | 19.1 | 30,804.1 | 252,663.7 |
| Large holders (land size>2.5 acres) | 910.0 | 801.0 | 190.3 | 10.8 | 73,866.7 | 1,057,525.0 |
| **2010/11** | | | | | | |
| Marginal holders (land size<0.5 acre) | 1,038.5 | 567.5 | 182.2 | 53.0 | 44,593.7 | 172,988.4 |
| Small and medium holders (land size 0.5-2.5 acres) | 1,437.7 | 807.2 | 143.9 | 50.6 | 100,292 | 728,936.8 |
| Large holders (land size>2.5 acres) | 2,362.0 | 1,193.0 | 162.7 | 51.2 | 197,426.5 | 2,891,637.0 |

**Source:** WB-BIDS Surveys 1991/92 and 1998/99, and WB-InM Survey 2010/11

**Table 2. Summary Statistics of Household Outcomes by Head's Education ($N_{HH}$=1,509)**

| Head's Education | Per Capita Total Income (Tk./ month) | Per Capita Total Expenditure (Tk./ month) | Male Labor Supply (hours/month) | Female Labor Supply (hours/month) | Non-Land Asset (Tk.) | Net-Worth (Tk.) |
|---|---|---|---|---|---|---|
| **1991/91** | | | | | | |
| Did not complete primary level | 451.7 | 328.5 | 184.0 | 34.3 | 17,998.7 | 84,225.7 |
| Completed primary level | 712.8 | 400.4 | 171.5 | 23.3 | 32,795.7 | 133,818.4 |
| Completed secondary level or above | 1,114.2 | 634.3 | 164.2 | 19.0 | 93,592.0 | 444,148.9 |
| **1998/99** | | | | | | |
| Did not complete primary level | 499.3 | 418.3 | 221.2 | 24.9 | 21,495.2 | 149,610.1 |
| Completed primary level | 695.6 | 647.0 | 165.6 | 14.0 | 39,191.0 | 302,995.8 |
| Completed secondary level or above | 1,060.5 | 865.2 | 138.6 | 9.7 | 80,873.5 | 992,323.0 |
| **2010/11** | | | | | | |
| Did not complete primary level | 1,132.1 | 581.8 | 168.9 | 53.7 | 46,824.8 | 269,650.9 |
| Completed primary level | 1,205.4 | 712.8 | 170.8 | 48.6 | 88,825.0 | 586,662.3 |
| Completed secondary level or above | 1,819.2 | 1,103.5 | 195.2 | 52.1 | 152,414.5 | 1,561,825.0 |

**Source:** WB-BIDS Surveys 1991/92 and 1998/99, and WB-InM Survey 2010/11

**Table 3. Summary Statistics of Household Outcomes by Adults' Oral Math Competency ($N_{HH}$=1,509)**

| Adults' Oral Math Competency | Per Capita Total Income (Tk./ month) | Per Capita Total Expenditure (Tk./ month) | Male Labor Supply (hours/month) | Female Labor Supply (hours/month) | Non-Land Asset (Tk.) | Net-Worth (Tk.) |
|---|---|---|---|---|---|---|
| **1991/91** | | | | | | |
| Household has adults with oral math competency | 626.0 | 402.0 | 178.8 | 23.7 | 35,100.0 | 157,349.1 |
| Household has no adults with oral math competency | 439.2 | 305.9 | 181.9 | 44.4 | 13,038.9 | 59,151.9 |
| **1998/99** | | | | | | |
| Household has adults with oral math competency | 615.3 | 522.0 | 214.1 | 17.6 | 32,603.0 | 292,563.2 |
| Household has no adults with oral math competency | 485.6 | 425.3 | 187.9 | 33.1 | 21,576.8 | 115,153.7 |

**Source:** WB-BIDS Surveys 1991/92 and 1998/99

**Table 4. Summary Statistics of Household Outcomes by Head's Main Occupation ($N_{HH}$=1,509)**

| HH's Main Occupation | Per Capita Total Income (Tk./ month) | Per Capita Total Expenditure (Tk./ month) | Male Labor Supply (hours/month) | Female Labor Supply (hours/month) | Non-Land Asset (Tk.) | Net-Worth (Tk.) |
|---|---|---|---|---|---|---|
| **1991/91** | | | | | | |
| Wage employment | 517.1 | 333.8 | 190.6 | 35.7 | 19,726.9 | 71,515.3 |
| Self-employment in farm sector | 405.9 | 425.0 | 143.9 | 16.8 | 39,851.5 | 251,070.5 |
| Self-employment in nonfarm sector | 792.4.2 | 585.4 | 195.6 | 35.8 | 24,516.1 | 91,503.6 |
| Mostly from non-earned activities | 310.4 | 368.1 | 152.9 | 28.3 | 127,015.7 | 250,869.8 |
| **1998/99** | | | | | | |
| Wage employment | 398.4 | 390.4 | 218.0 | 26.9 | 20,904.9 | 114,675.8 |
| Self-employment in farm sector | 443.5 | 507.1 | 150.3 | 13.7 | 35,389.1 | 508,997.9 |
| Self-employment in nonfarm sector | 447.0 | 517.1 | 261.1 | 22.9 | 30,015.6 | 180,753.5 |
| Mostly from non-earned activities | 838.9 | 759.0 | 83.5 | 17.1 | 41,611.2 | 283,338.5 |
| **2010/11** | | | | | | |
| Wage employment | 579.1.1 | 553.1 | 198.7 | 59.2 | 44,623.6 | 287,685.3 |
| Self-employment in farm sector | 573.4.4 | 647.7 | 79.3 | 39.8 | 97,769.8 | 1,001,881.0 |
| Self-employment in nonfarm sector | 2,204.0 | 834.1 | 242.6 | 53.2 | 72,751.4 | 370,296.9 |
| Mostly from non-earned activities | 1,073.3 | 796.8 | 55.0 | 42.5 | 85,425.8 | 476,672.4 |

**Source:** WB-BIDS Surveys 1991/92 and 1998/99, and WB-InM Survey 2010/11

**Table 5. Summary Statistics of Household Outcomes by Village Electrification ($N_{HH}$=1,509)**

| Village Electrification Status | Per Capita Total Income (Tk./month) | Per Capita Total Expenditure (Tk./month) | Male Labor Supply (hours/month) | Female Labor Supply (hours/month) | Non-Land Asset (Tk.) | Net-Worth (Tk.) |
|---|---|---|---|---|---|---|
| **1991/91** | | | | | | |
| Village has electricity | 644.4 | 393.4 | 180.9 | 28.9 | 32,444.4 | 135,168.4 |
| Village does not have electricity | 477.1 | 344.3 | 178.5 | 32.6 | 22,252.7 | 113,898.3 |
| **1998/99** | | | | | | |
| Village has electricity | 607.0 | 512.8 | 202.9 | 20.3 | 30,207.0 | 216,180.0 |
| Village does not have electricity | 532.2 | 465.4 | 207.5 | 24.0 | 27,439.3 | 271,137.4 |
| **2010/11** | | | | | | |
| Village has electricity | 1,274.1 | 667.0 | 173.7 | 51.7 | 69,135.2 | 490,778.1 |
| Village does not have electricity | 433.3 | 502.4 | 146.6 | 60.0 | 40,501.0 | 164,558.2 |

**Source:** WB-BIDS Surveys 1991/92 and 1998/99, and WB-InM Survey 2010/11

**Table 6. Summary Statistics of Household Outcomes by Village Accessibility ($N_{HH}$=1,509)**

| Village accessibility | Per capita total income (Tk./ month) | Per capita total expenditure (Tk./ month) | Male labor supply (hours/month) | Female labor supply (hours/month) | Non-land asset (Tk.) | Net-worth (Tk.) |
|---|---|---|---|---|---|---|
| **1991/91** | | | | | | |
| Village is accessible whole year | 552.7 | 370.3 | 179.7 | 31.7 | 26,535.4 | 117,045.6 |
| Village is not accessible whole year | 721.2 | 348.8 | 181.1 | 13.9 | 42,847.8 | 58,937.2 |
| **1998/99** | | | | | | |
| Village is accessible whole year | 579.1 | 492.3 | 208.1 | 22.3 | 28,688.0 | 191,007.4 |
| Village is not accessible whole year | 559.3 | 499.7 | 184.8 | 18.5 | 31,418.5 | 529,693.3 |
| **2010/11** | | | | | | |
| Village is accessible whole year | 1,106.7 | 659.8 | 171.7 | 51.1 | 70,525.1 | 525,517.3 |
| Village is not accessible whole year | 1,612.9 | 671.5 | 171.9 | 56.8 | 53,948.3 | 246,493.0 |
| **Source:** WB-BIDS surveys 1991/92 and 1998/99, and WB-InM survey 2010/11 | | | | | | |

**Table 7. Impacts of Microfinance Loans on Household Outcomes by Land Ownership: Propensity Score-Weighted HH FE Estimates ($N_{HH}$=1,509)**

| Microfinance Loan Variables | Log Per Capita Total Income (Tk./ month) | Log Per Capita Total Expenditure (Tk./month) | Log MaleLabor Supply (hours/month) | Log Female Labor Supply (hours/month) | Log HH Non-Land Asset (Tk.) | Log HH Net-Worth (Tk.) |
|---|---|---|---|---|---|---|
| **Marginal Holders (land size<0.5 acre)** | | | | | | |
| Log loans of HH males (Tk.) | -0.006<br>(-0.41) | 0.007*<br>(1.73) | 0.047**<br>(2.97) | 0.031<br>(1.40) | 0.036**<br>(2.88) | 0.024*<br>(1.71) |
| Log loans of HH females (Tk.) | 0.013*<br>(1.70) | 0.001<br>(0.43) | 0.045**<br>(4.85) | 0.052**<br>(4.62) | 0.032**<br>(4.71) | -0.002<br>(-0.21) |
| **Small and Medium Holders (land size 0.5-2.5 acres)** | | | | | | |
| Log loans of HH males (Tk.) | 0.008<br>(0.59) | 0.007<br>(0.99) | 0.052**<br>(3.13) | 0.068**<br>(3.07) | 0.065**<br>(5.32) | 0.072**<br>(5.87) |
| Log loans of HH females (Tk.) | 0.002<br>(0.38) | 0.003*<br>(1.80) | 0.027**<br>(2.18) | 0.068**<br>(4.29) | 0.063**<br>(7.22) | 0.095**<br>(9.34) |
| **Large Holders (land size>2.5 acres)** | | | | | | |
| Log loans of HH males (Tk.) | 0.015<br>(0.53) | 0.007<br>(1.31) | 0.100**<br>(3.30) | 0.004<br>(0.11) | 0.054**<br>(2.06) | 0.077**<br>(2.98) |
| Log loans of HH females (Tk.) | 0.042**<br>(2.34) | 0.003<br>(1..06) | -0.009<br>(-0.24) | 0.112**<br>(4.01) | 0.099**<br>(5.41) | 0.151**<br>(6.29) |
| R2 | 0.135 | 0.372 | 0.210 | 0.237 | 0.376 | 0.377 |

**Note:** * and **refer to statistical significance level of 10% and 5% (or less), respectively.Figures in parentheses are t-statistics based on standard errors clustered at the village level. Regressions include more control variables at household- (age, sex, education of head) and village- level (village price of consumer goods; infrastructure such as availability of electricity, and schools; and proportion of village land irrigated).
**Source:** WB-BIDS Surveys 1991/92 and 1998/99, and WB-InM Survey 2010/11

**Table 8. Impacts of Microfinance Loans on Household Outcomes by Head's Education: Propensity Score-Weighted HH FE Estimates ($N_{HH}$=1,509)**

| Microfinance Loan Variables | Log Per Capita Total Income (Tk./ month) | Log Per Capita Total Expenditure (Tk./month) | Log MaleL abor Supply (hours/month) | Log Female Labor Supply (hours/month) | Log HH Non-Land Asset (Tk.) | Log HH Net-Worth (Tk.) |
|---|---|---|---|---|---|---|
| **Did not Complete PrimaryLevel** | | | | | | |
| Log loans of HH males (Tk.) | -0.001<br>(-0.08) | 0.002<br>(0.42) | 0.054**<br>(3.79) | 0.014<br>(0.63) | 0.033**<br>(3.27) | 0.017*<br>(1.79) |
| Log loans of HH females (Tk.) | -0.0004<br>(-0.08) | -0.0001<br>(-0.04) | 0.041**<br>(4.63) | 0.059**<br>(5.40) | 0.034**<br>(5.18) | 0.009*<br>(1.63) |
| **Completed Primary Level** | | | | | | |
| Log loans of HH males (Tk.) | 0.002<br>(0.15) | 0.014**<br>(2.23) | 0.052**<br>(3.83) | 0.046**<br>(2.80) | 0.057**<br>(4.46) | 0.037**<br>(4.44) |
| Log loans of HH females (Tk.) | 0.001<br>(0.19) | 0.005*<br>(1.68) | 0.040**<br>(4.70) | 0.037**<br>(3.35) | 0.036**<br>(4.23) | 0.016*<br>(1.98) |
| **Completed Secondary Level or Above** | | | | | | |
| Log loans of HH males (Tk.) | -0.007<br>(-0.38) | 0.012<br>(1.22) | 0.052**<br>(3.69) | 0.039<br>(0.80) | 0.010<br>(0.68) | 0.027**<br>(2.10) |
| Log loans of HH females (Tk.) | -0.016<br>(-1.35) | 0.017**<br>(3.07) | 0.040**<br>(4.87) | 0.031<br>(0.98) | 0.061**<br>(3.75) | 0.016<br>(1.10) |
| R2 | 0.136 | 0.375 | 0.209 | 0.240 | 0.454 | 0.652 |

**Note:** * and **refer to statistical significance level of 10% and 5% (or less), respectively. Figures in parentheses are t-statistics based on standard errors clustered at the village level. Regressions include more control variables at household- (age, sex, household landholding) and village- level (village price of consumer goods; infrastructure such as availability of electricity, and schools; and proportion of village land irrigated).
**Source:** WB-BIDS Surveys 1991/92 and 1998/99, and WB-InM Survey 2010/11

**Table 9. Impacts of Microfinance Loans on Household Outcomes by Adults' Oral Math Competency: Propensity Score-Weighted HH FE Estimates ($N_{HH}$=1,509)**

| Microfinance Loan Variables | Log Per Capita Total Income (Tk./month) | Log Per Capita Total Expenditure (Tk./month) | Log Male Labor Supply (hours/month) | Log Female Labor Supply (hours/month) | Log HH Non-Land Asset (Tk.) | Log HH Net-Worth (Tk.) |
|---|---|---|---|---|---|---|
| **Household has Adults with Oral Math Competency** | | | | | | |
| Log loans of HH males (Tk.) | 0.029<br>(1.55) | 0.003<br>(0.36) | 0.034<br>(1.16) | 0.044<br>(0.91) | 0.008<br>(0.46) | 0.038**<br>(2.15) |
| Log loans of HH females (Tk.) | -0.001<br>(-0.16) | -0.001<br>(-0.32) | 0.012*<br>(1.83) | 0.036*<br>(1.95) | 0.041**<br>(4.10) | -0.012<br>(-1.05) |
| **Household Has No Adults with Oral Math Competency** | | | | | | |
| Log loans of HH males (Tk.) | 0.035<br>(1.50) | -0.004<br>(-0.36) | 0.019<br>(0.50) | 0.043<br>(0.75) | -0.014<br>(-0.65) | 0.025*<br>(1.79) |
| Log loans of HH females (Tk.) | -0.006<br>(-0.81) | -0.002<br>(-0.36) | -0.005<br>(-0.27) | 0.015**<br>(3.51) | 0.039**<br>(5.86) | -0.004<br>(-0.36) |
| R2 | 0.103 | 0.196 | 0.170 | 0.215 | 0.239 | 0.518 |

**Note:** * and **refer to statistical significance level of 10% and 5% (or less), respectively. Figures in parentheses are t-statistics based on standard errors clustered at the village level. Regressions include more control variables at household- (age, sex, household landholding) and village- level (village price of consumer goods; infrastructure such as availability of electricity, and schools; and proportion of village land irrigated).
**Source:** WB-BIDS surveys 1991/92 and 1998/99, and WB-InM survey 2010/11

**Table 10. Impacts of Microfinance Loans on Household Outcomes by HH's Main Occupation: Propensity Score-Weighted HH FE Estimates ($N_{HH}$=1,509)**

| Microfinance Loan Variables | Log Per Capita Total Income (Tk./month) | Log Per Capita Total Expenditure (Tk./month) | Log Male Labor Supply (hours/month) | Log Female Labor Supply (hours/month) | Log HH Non-Land Asset (Tk.) | Log HH Net-Worth (Tk.) |
|---|---|---|---|---|---|---|
| **Wage Employment** | | | | | | |
| Log loans of HH males (Tk.) | -0.015<br>(-1.35) | 0.002<br>(0.52) | 0.062**<br>(3.08) | 0.038<br>(1.41) | 0.021*<br>(1.75) | 0.018**<br>(1.99) |
| Log loans of HH females (Tk.) | -0.008<br>(-1.30) | -0.002<br>(-0.68) | 0.055**<br>(5.40) | 0.055**<br>(4.32) | 0.025**<br>(3.61) | 0.007<br>(1.12) |
| **Self-Employment in Farm sector** | | | | | | |
| Log loans of HH males (Tk.) | 0.044**<br>(2.26) | 0.011*<br>(1.68) | 0.044**<br>(2.06) | 0.052**<br>(2.35) | 0.043**<br>(3.97) | 0.023**<br>(2.36) |
| Log loans of HH females (Tk.) | 0.061**<br>(6.06) | 0.003<br>(0.75) | -0.031**<br>(-2.11) | 0.052**<br>(2.85) | 0.050**<br>(5.09) | 0.029**<br>(3.61) |
| **Self-Employment in Nonfarm Sector** | | | | | | |
| Log loans of HH males (Tk.) | 0.031**<br>(3.34) | 0.008<br>(1.44) | 0.050**<br>(3.12) | 0.029<br>(1.35) | 0.041**<br>(4.03) | 0.026**<br>(2.57) |
| Log loans of HH females (Tk.) | 0.029**<br>(4.80) | 0.004<br>(1.49) | 0.067**<br>(7.13) | 0.058**<br>(5.41) | 0.042**<br>(5.59) | 0.008<br>(1.31) |
| **Mostly from non-Earned Activities** | | | | | | |
| Log loans of HH males (Tk.) | 0.032<br>(1.59) | 0.003<br>(0.30) | 0.058**<br>(2.34) | 0.039<br>(1.39) | 0.030**<br>(2.01) | 0.019<br>(1.46) |
| Log loans of HH females (Tk.) | 0.007<br>(0.77) | 0.013**<br>(2.53) | -0.120<br>(-1.16) | 0.046**<br>(2.34) | 0.057**<br>(5.50) | 0.018**<br>(2.15) |
| R2 | 0.240 | | 0.269 | 0.238 | 0.459 | 0.652 |

**Note:** Occupation type is determined by the sector generating highest income when household gets income from multiple sectors. * and **refer to statistical significance level of 10% and 5% (or less), respectively.Figures in parentheses are t-statistics based on standard errors clustered at the village level. Regressions include more control variables at household- (age, sex, household landholding) and village- level (village price of consumer goods; infrastructure such as availability of electricity, and schools; and proportion of village land irrigated).
**Source:** WB-BIDS Surveys 1991/92 and 1998/99, and WB-InM Survey 2010/11

**Table 11. Impacts of Microfinance Loans on Household Outcomes by Village Electrification Status: Propensity Score-Weighted HH FE Estimates ($N_{HH}$=1,509)**

| Microfinance Loan Variables | Log Per Capita Total Income (Tk./ month) | Log Per Capita Total Expenditure (Tk./month) | Log Male Labor Supply (hours/month) | Log Female Labor Supply (hours/month) | Log HH Non-Land Asset (Tk.) | Log HH Net-Worth (Tk.) |
|---|---|---|---|---|---|---|
| **Village Has Electricity** | | | | | | |
| Log loans of HH males (Tk.) | -0.002<br>(-0.13) | 0.007*<br>(1.96) | 0.050**<br>(3.59) | 0.054**<br>(2.24) | 0.041**<br>(4.00) | 0.026**<br>(3.05) |
| Log loans of HH females (Tk.) | 0.004<br>(0.70) | 0.002<br>(0.56) | 0.047**<br>(4.40) | 0.056**<br>(5.47) | 0.033**<br>(5.42) | 0.012**<br>(2.89) |
| **Village Does Not Have Electricity** | | | | | | |
| Log loans of HH males (Tk.) | -0.0001<br>(-0.01) | 0.004<br>(0.63) | 0.047**<br>(2.37) | 0.035*<br>(1.80) | 0.014<br>(0.85) | 0.016<br>(1.56) |
| Log loans of HH females (Tk.) | -0.012<br>(-1.47) | 0.002<br>(0.51) | 0.027**<br>(3.45) | 0.049**<br>(4.32) | 0.034**<br>(4.66) | 0.006<br>(1.00) |
| R2 | 0.137 | 0. 375 | 0.208 | 0.238 | 0.455 | 0.651 |

**Note:** * and **refer to statistical significance level of 10% and 5% (or less), respectively.Figures in parentheses are t-statistics based on standard errors clustered at the village level. Regressions include more control variables at household- (age, sex, household landholding) and village- level (village price of consumer goods; infrastructure such as schools; and proportion of village land irrigated).

**Source:** WB-BIDS surveys 1991/92 and 1998/99, and WB-InM survey 2010/11

**Table 12. Impacts of Microfinance Loans on Household Outcomes by Village Accessibility: Propensity Score-Weighted HH FE Estimates ($N_{HH}$=1,509)**

| Microfinance loan variables | Log per capita total income (Tk./ month) | Log per capita total expenditure (Tk./month) | Log male labor supply (hours/month) | Log female labor supply (hours/month) | Log HH non-land asset (Tk.) | Log HH net-worth (Tk.) |
|---|---|---|---|---|---|---|
| **Village is accessible whole year** | | | | | | |
| Log loans of HH males (Tk.) | 0.003<br>(0.19) | 0.007<br>(1.51) | 0.053**<br>(3.59) | 0.040*<br>(1.91) | 0.040**<br>(4.11) | 0.027**<br>(3.28) |
| Log loans of HH females (Tk.) | -0.004<br>(-0.77) | 0.001<br>(0.23) | 0.040**<br>(4.90) | 0.056**<br>(5.41) | 0.036**<br>(5.63) | 0.011*<br>(1.96) |
| **Village is not accessible whole year** | | | | | | |
| Log loans of HH males (Tk.) | -0.015<br>(-0.99) | 0.004<br>(0.44) | 0.041*<br>(1.63) | 0.031<br>(1.32) | 0.030*<br>(1.80) | 0.015<br>(1.18) |
| Log loans of HH females (Tk.) | 0.022**<br>(2.70) | 0.002<br>(0.84) | 0.038**<br>(2.37) | 0.051**<br>(3.05) | 0.038**<br>(4.30) | 0.013<br>(1.54) |
| R2 | 0.139 | 0.376 | 0.209 | 0.237 | 0.453 | 0.651 |

**Note:** * and **refer to statistical significance level of 10% and 5% (or less), respectively.Figures in parentheses are t-statistics based on standard errors clustered at the village level. Regressions include more control variables at household- (age, sex, household landholding) and village- level (village price of consumer goods; infrastructure such as schools; and proportion of village land irrigated).
**Source:** WB-BIDS surveys 1991/92 and 1998/99, and WB-InM survey 2010/11

# Table 13. Impacts of Microfinance Loans on Household Income and Expenditure: Quantile Regression ($N_{HH}$=1,509)

| Microfinance loan variables | Log per capita total income (Tk./month) | Log per capita total expenditure (Tk./month) |
|---|---|---|
| **15th quantile** | | |
| Log loans of HH males (Tk.) | 0.007*<br>(1.64) | 0.003**<br>(2.25) |
| Log loans of HH females (Tk.) | 0.011**<br>(2.62) | 0.004**<br>(2.44) |
| **25th quantile** | | |
| Log loans of HH males (Tk.) | 0.009**<br>(3.65) | 0.003**<br>(3.42) |
| Log loans of HH females (Tk.) | 0.011**<br>(3.99) | 0.004*<br>(1.89) |
| **50th quantile** | | |
| Log loans of HH males (Tk.) | 0.011**<br>(3.18) | 0.003**<br>(2.20) |
| Log loans of HH females (Tk.) | 0.007**<br>(2.34) | 0.002*<br>(1.64) |
| **75th quantile** | | |
| Log loans of HH males (Tk.) | 0.014**<br>(3.38) | 0.0002<br>(0.10) |
| Log loans of HH females (Tk.) | 0.003<br>(1.04) | 0.0002<br>(0.10) |
| **85th quantile** | | |
| Log loans of HH males (Tk.) | 0.018**<br>(3.13) | 0.002<br>(0.83) |
| Log loans of HH females (Tk.) | -0.0002<br>(-0.04) | -0.005*<br>(-1.70) |
| Pseudo R2 | 0.057 at 15th,<br>0.070 at 25th,<br>0.089 at 50th,<br>0.109 at 75th,<br>0.120 at 85th | 0.220 at 15th,<br>0.226 at 25th,<br>0.227 at 50th,<br>0.215 at 75th,<br>0.213 at 85th |

**Note:** * and ** refer to statistical significance level of 10% and 5% (or less), respectively. Figures in parentheses are t-statistics based on standard errors clustered at the village level. Regressions include more control variables at household- (age, sex, education of head) and village- level (village price of consumer goods; infrastructure such as availability of electricity, and schools; and proportion of village land irrigated).
**Source:** WB-BIDS surveys 1991/92 and 1998/99, and WB-InM survey 2010/11

## Table 14. Salient Features of Households by Dropout Status

| Characteristics | Households that Dropped Out (N=292) | Households That Did Not Drop Out (N=2,022) | t-statistics of the Difference |
|---|---|---|---|
| Sex of head (1=M, 0=F) | 0.90 | 0.916 | -0.92 |
| Age of head (years) | 48.0 | 44.97 | 3.18** |
| Education of head (years) | 1.99 | 2.56 | -2.27** |
| Number of adult males in HH | 1.97 | 1.70 | 3.67** |
| Number of adult females in HH | 1.53 | 1.52 | 0.16 |
| Land asset (decimals) | 101.3 | 136.6 | -1.73* |
| Share of adult male members with reading competency | 0.279 | 0.335 | -1.86* |
| Share of adult female members with reading competency | 0.169 | 0.177 | -0.35 |
| Share of adult male members with writing competency | 0.188 | 0.215 | -0.99 |
| Share of adult female members with writing competency | 0.116 | 0.095 | 1.11 |
| Share of adult male members with oral math competency | 0.514 | 0.581 | -2.09** |
| Share of adult female members with oral math competency | 0.233 | 0. 322 | -3.18** |
| Share of adult male members with written math competency | 0.212 | 0.235 | -0.84 |
| Share of adult female members with written math competency | 0.098 | 0.087 | 0.60 |
| Average microfinance loan amount by males (Tk.) | 2,337.5 | 885.3 | 4.24** |
| Average microfinance loan amount by males (Tk.) | 6,129.5 | 3,644.8 | 3.42** |

**Note:** For a given year a household is considered dropout if it is nonparticipant in that year but was participant in the preceding year. So, dropout is missing for the first survey year (1991/92).* and **refer to statistical significance level of 10% and 5% (or less), respectively. Figures show past characteristics (from preceding survey).
**Source:** WB-BIDS Surveys 1991/92 and 1998/99, and WB-InM Survey 2010/11

## Table 15. Determinants of Household Dropout from Microfinance ($N_{HH}$=1,711)

| Characteristics | Model 1 | Model 2 |
|---|---|---|
| Sex of head (1=M, 0=F) | 0.015<br>(0.28) | 0.008<br>(0.15) |
| Age of head (years) | 0.004**<br>(3.66) | 0.003**<br>(3.41) |
| Education of head (years) | -0.005<br>(-1.54) | -0.004<br>(-1.30) |
| Number of adult males in HH | 0.024**<br>(2.29) | 0.022**<br>(2.28) |
| Number of adult females in HH | -0.010<br>(-0.82) | -0.010<br>(-0.86) |
| Land asset (decimals) | 0.005<br>(0.80) | 0.007<br>(1.10) |
| Share of adult male members with reading competency | 0.005<br>(0.19) | 0.001<br>(0.05) |
| Share of adult female members with reading competency | -0.033<br>(-1.42) | -0.035<br>(-1.50) |
| Share of adult male members with writing competency | 0.009<br>(0.28) | 0.009<br>(0.32) |
| Share of adult female members with writing competency | 0.045<br>(1.14) | 0.048<br>(1.33) |
| Share of adult male members with oral math competency | -0.020*<br>(-1.83) | -0.015*<br>(-1.88) |
| Share of adult female members with oral math competency | -0.034*<br>(-1.77) | -0.038*<br>(-2.04) |
| Share of adult male members with written math competency | -0.001<br>(-0.05) | -0.007<br>(-0.29) |
| Share of adult female members with written math competency | -0.045<br>(-1.07) | -0.047<br>(-1.15) |
| Average microfinance loan amount by males (Tk.) | - | 0.014**<br>(4.24) |
| Average microfinance loan amount by males (Tk.) | - | 0.019**<br>(8.26) |
| R2 | 0.038 | 0.094 |
| Mean of dependent variable (dropout rate) | 0.054 | |

**Note:** * and **refer to statistical significance level of 10% and 5% (or less), respectively. Regressors are past characteristics (from preceding survey). Figures in parentheses are t-statistics based on standard errors clustered at the village level. Regressions include more control variables at household- (age, sex, education of head) and village- level (village price of consumer goods; infrastructure such as availability of electricity, and schools; and proportion of village land irrigated).
**Source:** WB-BIDS Surveys 1991/92 and 1998/99, and WB-InM Survey 2010/11

**Table 16. Selected Household Welfare Outcomes by Dropout status**

| Outcomes | In participation year | | | In dropout year | | |
|---|---|---|---|---|---|---|
| | **Households that Dropped Out (N=292)** | **Households That Did Not Drop Out (N=3,682)** | **t-statistics of the Difference** | **Households that Dropped Out (N=292)** | **Households That Did Not Drop Out (N=3,682)** | **t-statistics of the Difference** |
| Per capita income (Tk./month) | 571.3 | 574.8 | -0.08 | 888.9 | 947.5 | -0.40 |
| Per capita expenditure (Tk./month) | 499.3 | 435.8 | 2.59** | 556.8 | 594.4 | -1.18 |
| Moderate poverty | 0.598 | 0.640 | -1.25 | 0.363 | 0.383 | -0.58 |
| Extreme poverty | 0.417 | 0.500 | -2.28** | 0.239 | 0.243 | -0.11 |
| Non-land asset (Tk.) | 52,600.3 | 30,985.6 | 4.22** | 35,769.2 | 51,966.2 | -2.37** |
| Net worth (Tk.) | 206,067.4 | 208,987.7 | -0.04 | 254,126.5 | 380,923.8 | -1.34 |

**Source:** WB-BIDS Surveys 1991/92 and 1998/99, and WB-InM Survey 2010/11

**Table 17. Impacts of Microfinance Borrowing on Household Outcomes with Controlling for Program Dropout: Propensity Score-Weighted HH FE Estimates ($N_{HH}$=1,758)**

| Microfinance Input Variables | Log Per Capita Total Income (Tk./ month) | | Log Per Capita Total Expenditure (Tk./ month) | | Log Male Labor Supply (hours/month) | | Log Female Labor Supply (hours/month) | |
|---|---|---|---|---|---|---|---|---|
| | Not Controlling for Program Dropout | Controlling for Program Dropout | Not Controlling for Program Dropout | Controlling for Program Dropout | Not Controlling for Program Dropout | Controlling for Program Dropout | Not Controlling for Program Dropout | Controlling for Program Dropout |
| Male borrowed from microfinance | 0.020 (0.22) | 0.059 (0.63) | 0.030 (0.87) | 0.042 (1.17) | 0.347** (2.21) | 0.402** (2.45) | 0.174 (1.19) | 0.171 (1.07) |
| HH female borrowed from microfinance | 0.009 (0.23) | 0.002 (0.05) | -0.030 (-1.44) | -0.017 (-0.74) | 0.221** (2.72) | 0.250** (2.84) | 0.330** (3.48) | 0.282** (2.59) |
| R2 | 0.120 | 0.122 | 0.274 | 0.275 | 0.199 | 0.200 | 0.334 | 0.335 |

**Note:** * and **refer to statistical significance level of 10% and 5% (or less), respectively.Figures in parentheses are t-statistics based on standard errors clustered at the village level. Regressions include more control variables at household- (age, sex, education of head) and village- level (village price of consumer goods; infrastructuresuch as availability of electricity, and schools; and proportion of village land irrigated).

**Table 18. Impacts of Microfinance Borrowing and Participation on Household Outcomes: Propensity Score-Weighted HH FE Estimates (contd.) ($N_{HH}$=1,758)**

| Microfinance Input Variables | Log HH non-land asset (Tk.) | | Log HH net-worth (Tk.) | | Boys' enrollment rate (5-18) | | Girls' enrollment rate (5-18) | |
|---|---|---|---|---|---|---|---|---|
| | Not Controlling for Program Dropout | Controlling for Program Dropout | Not Controlling for Program Dropout | Controlling for Program Dropout | Not Controlling for Program Dropout | Controlling for Program Dropout | Not Controlling for Program Dropout | Controlling for Program Dropout |
| Male borrowed from microfinance | 0.260** (4.01) | 0.236** (3.44) | 0.053 (0.96) | 0.040 (0.65) | -0.026 (-0.45) | -0.047 (-0.79) | -0.004 (-0.07) | -0.025 (-0.41) |
| HH female borrowed from microfinance | 0.148** (2.66) | 0.126* (1.90) | -0.121 (-0.90) | -0.121 (-0.69) | 0.042 (0.84) | 0.010 (0.20) | 0.055 (1.39) | 0.040 (0.94) |
| R2 | 0.466 | 0.467 | 0.669 | 0.669 | 0.076 | 0.078 | 0.060 | 0.062 |

**Note:** * and **refer to statistical significance level of 10% and 5% (or less), respectively.Figures in parentheses are t-statistics based on standard errors clustered at the village level. Regressions include more control variables at household- (age, sex, education of head) and village- level (village price of consumer goods; infrastructuresuch as availability of electricity, and schools; and proportion of village land irrigated).
**Source:** WB-BIDS Surveys 1991/92 and 1998/99, and WB-InM Survey 2010/2011.

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