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Who Benefits Most from Microfinance in Bangladesh?

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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 programme effects may arise due to household (such as landholding, head's education, employment or skills in oral math) and community (electrification and accessibility) characteristics. Benefits do vary by such characteristics. For example, large and medium holders benefit more than marginal or small holders from microfinance in non-land asset, net worth and labour 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, programme dropouts are not large enough to affect the overall benefits of microfinance.

Keywords: Microfinance, Heterogenous Programme Effects, Household Physical Resource Endowments, Entrepreneurial Skills, Community Resources, Panel Data

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I. INTRODUCTION

Literature on microfinance benefits focuses mostly on the average effects of programme participation, which do not reveal whether and to what extent programme benefits vary across participants. Since the productive use of

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microfinance loans depends on the entrepreneurial ability of a borrower, and such skills vary among borrowers, programme benefits are expected to vary too.

This is why policymakers and researchers often find it important to consider how gains from a programme 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). So even if the average or marginal effect is not statistically significant, it is important to consider the distributional gains of a programme for various reasons. For example, many recent studies using randomised control trial (RCT) argued that microfinance does not reduce poverty as often claimed (Banerjee, Karlan and Zinman 2015). While RCT models are not applicable in a country such as Bangladesh, where microfinance has been saturated, such findings, if at all relevant, may imply that microfinance participants who have been with the programmes once they join as there is hope for them to graduate from the programme. That is, they keep on borrowing, and hence, become dependent on MFIs. If this were indeed the case with Bangladeshi microfinance participants, does it mean that the programme is not benefiting any group at all so that the operations of microfinance programmes cannot be justified? On the other hand, even if there is a positive effect of participation, does it mean everybody benefits equally? If not, who are the beneficiaries among programme participants?

Therefore, a study that examines only average effects such as those reported in Banerjee *et al.* (2015) and finds negative or small effects of microfinance does not necessarily refute the role of microfinance (e.g., Wydick 2016). It is possible that there are certain groups that benefit from such a programme, although their benefits may not be large enough to outweigh the negative effect of others, implying an overall negative or insignificant effect of programme participation. There are studies which question the development performance of a targeted programme 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 programme in the short run may not benefit in the long run or vice versa (King and Behrman 2009, van de Walle 2009). This means, studying the distributional or heterogeneous effects of microfinance is indeed important. After all, microfinance is not a charity; benefits accrued from microfinance depend 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 characteristics. Therefore, when such ability or such endowment is not uniformly 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 locations. This paper addresses this critical policy issue.

II. HETEROGENEOUS EFFECTS OF MICROFINANCE: WHAT DO WE KNOW?

There is a large body of literature on the varying impacts of microfinance, which are worth a review. A recent study of over 3,000 rural households in Bangladesh finds a varying effect of microfinance borrowing on household per capita expenditure based on household landholding (Islam 2015). Using both village level fixed-effects and instrumental variables estimates, this study finds that poor households (with landholding less than once acre) benefits the most, and women benefit more than men. Another study, using two rounds of surveys (2006 and 2010) conducted for 400 households from the Tigray region in Northern Ethiopia, examines microfinance effect on children's malnutrition (stunting measure by height-for-age z-score) (Ewunetu 2011). This study finds that the programme lowers stunting more among the poorest of the poor than among the moderately poor. An RCT-based study on the microfinance programme of the First Macro Bank of Philippines finds a statistically significant profit increase for male business owners but not for female owners (Karlan and Zinman 2010). The same study finds that business profits are higher for borrowing households who already have high income. A non-experimental study of the Ethiopian microfinance programme Dedebit Credit and Savings Institution using household panel data of 2000, 2003 and 2006 finds that households continued to benefit after they left the programme (Berhane 2009). This study also finds that early participants do better than late entrants.

III. DATA

The data used to address the heterogeneity of the effects of microfinance programme is the long panel data set collected by the World Bank with the help of Bangladesh Institute of Development Studies (BIDS) and Institute of Microfinance (InM). The World Bank and the 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 were new.[1]

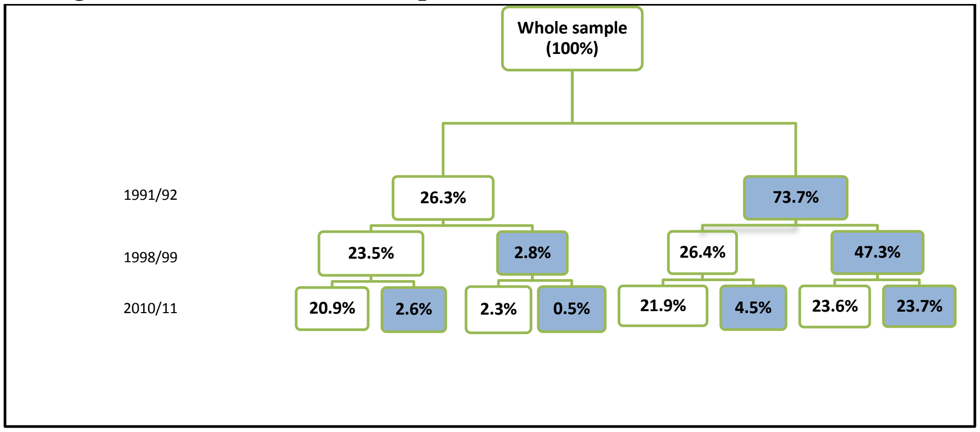
The households were resurveyed again in 2010/11, this time jointly with the InM. The resurvey tried to revisit all the households (2,599) surveyed in 1998/99. However, due to attrition, 2,342 households were located, which spawned to 3,082 households due to split off. The analysis of this study is based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

How does microfinance participation vary over time among the sample households? Figure 1 presents the breakdown of the 1,509 households (that are common in all three panel years) from 1991/92 to 2010/11 by programme participation status.

In 1991/92, 26.3 per cent of the 1,509 households were microfinance programme participants and 73.7 per cent were non-participants. By 1998/99, 10.6 per cent of the participants had quit the programme (this corresponds to 2.8 per cent of the whole sample), while 35.8 per cent of non-participants had joined the programme (this corresponds to 26.4 per cent of the whole sample). Similar transitions continued between 1998/99 and 2010/11. These movements show that the majority of programme participants remained with the programme for a number of years, while a good proportion of non-participants switched to microfinance programmes over a period of time, resulting in a continuous growth in membership.

[1]The survey areas for the panel sample cover the whole of rural Bangladesh except for the southeast region which was affected by the 1991 cyclone. The households represent mostly low-income households in Bangladesh (households mostly targeted by microfinance programmes); so, they cannot be considered fully representative of the national rural population. These households roughly compare to the lower 60 per cent of the households covered in Bangladesh Household Income and Expenditure Survey (HIES) – comparison is based on income, matching with 1998/99 and 2010/11 households with the 2000 and 2010 samples, respectively, from HIES.

Figure 1: **Transition of Participation Status Over Time: 1991/92-2010/11**



Source: World Bank-BIDS surveys 1991/92 and 1998/99; and World Bank-InM survey 2011.

Note: Boxes at each level (survey year) show the breakdown of participants or non-participants from the previous year (represented by the parent box year). Clear boxes represent participants and shaded boxes non-participants.

IV. DISTRIBUTION OF PROGRAMME BENEFITS: DO CHARACTERISTICS 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 2010/11.

We are interested in seeing how the outcomes of interest such as income, expenditure, asset and net worth vary by characteristics 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 I-VI show descriptive statistics of such outcomes by household and community characteristics.

As Table I shows, 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 per cent higher than that of marginal holders, and large holders have 47 per cent higher per capita expenditure than medium holders. Marginal holders, however, have the highest labour supply in all three survey years for both males and females, which is not surprising given that they are mostly wage-employed.

TABLE I

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.)
1991/92						
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.

We also observe somewhat similar pattern in household outcomes by head's education and oral math skills.[2] Households that are least endowed in education and skill characteristics have again the lowest welfare in outcomes, except for labour supply (Tables II and III). 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 per cent higher than that of those without adults with math competency in 1991/92 and 27 per cent 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 IV).[3] That said, households dependent on self-employed non-farm 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.

[2]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 the most important to entrepreneurship, even though findings do not vary much for other skills.

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

TABLE II
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 labour supply (hours/ month)	Female labour supply (hours/month)	Non-land asset (Tk.)	Net-worth (Tk.)
1991/92						
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 III
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 labour supply (hours/ month)	Female labour supply (hours/ month)	Non-land asset (Tk.)	Net-worth (Tk.)
1991/92						
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 IV
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 labour supply (hours/month)	Female labour 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 non-farm sector	792.42	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 non-farm 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	579.11	553.1	198.7	59.2	44,623.6	287,685.3
Self-employment in farm sector	573.44	647.7	79.3	39.8	97,769.8	1,001,881.0
Self-employment in non-farm 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.

How do the household outcomes vary by village characteristics? To investigate this, we consider two important village-level infrastructures: electricity and roads. Villages are grouped based on whether they have electricity and they are accessible throughout the year. As Table V 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 VI). Whatever the trends in outcomes are, these descriptive analyses clearly show that the outcomes do vary by household or community characteristics. Now the question is to what extent such variation can be attributed to microfinance borrowing?

TABLE V
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 labour supply (hours/ month)	Female labour 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 VI

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 labour supply (hours/ month)	Female labour supply (hours/ month)	Non-land asset (Tk.)	Net-worth (Tk.)
1991/92						
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.

V. DISTRIBUTION OF PROGRAMME BENEFITS: ESTIMATION USING A NON-LINEAR REGRESSION APPROACH

The underlying assumption is that the source of heterogeneity in programme 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 programme works better for households with better resource characteristics. We can answer this question by estimating the outcome equation with programme participation interacted with characteristics of households and communities. The estimating equation can help us understand if household and community characteristics constrain benefits accrued to households. We would then formally test if treatment effects vary 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 programmes and of the outcomes they affect (consumption, non-land assets, labour 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 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 – do the worst-off households get the greatest benefit from these programmes?

The basic model for estimating the common effect of microfinance participation (captured by cumulative borrowing), (P_{ij}), of *i*-th household of *j*-th village on household level welfare outcomes (Y_{ij}), such as consumption, female and male labour supply, asset holding, and net worth, is given below:.

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

where X_{ij} is set of household and village level exogenous variables such as age and gender of the household head, and village-level prices and wage; E is a set of characteristics 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 programme participants. Also $\gamma_f, \gamma_m, \beta, \delta$ are parameters to be estimated. Equation suffers from two sources of unobserved heterogeneity (both at household and at village level); one source is time-invariant heterogeneity (μ) and the other source is time-varying heterogeneity (η). 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 (μ) cancels out because of differencing over time. The time varying heterogeneity (η) persists, for which a simple fixed-effect (FE) method cannot resolve sample selection bias and hence, special treatment is needed to resolve this matter. One good example of unobserved factors is individual entrepreneurial ability or business intelligence. Such ability cannot usually be captured by survey questions but it can affect both programme participation and the outcomes. If such ability does not change over time (denoted by μ) then its effects are cancelled when we use equation (2) to estimated programme impacts. However, if such ability varies over time (denoted by η) then equation (2) will give biased estimates of the impacts. This is possible if the experience gained in initial years augment business intelligence in an unobserved way over time, and such variation in business intelligence will have a varying effect over time.

There are alternative methods to control for the time varying heterogeneity while using fixed effects (FE) method on panel data (see a discussion of such methods in Khandker, Koolwal and 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 score based on a participation equation where the probability of participating in a microfinance programme 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 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 non-participating households in any year where P is the predicted probability of participation by the household.[4]

In order to estimate how the common effects of participation by gender vary by resource characteristics, 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 characteristics (expressed as binary variables) to see if microfinance participation effects vary with changes in characteristics either at the household or community level. With such interactions the differenced outcome equation (2) can be expressed as follows:

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

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[4]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.

where λ_m and λ_f are parameters for the interaction terms of characteristics with male and female credits, respectively. The characteristics (*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 characteristics (that is, using the example, head has no primary education, and E_{it} =0), equation (3) reduces to the basic differenced equation of (2):

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

and γ_m and γ_f give the estimates of credit effects for households without the characteristics (those with heads with no primary education). On the other hand, for households with characteristics (that is, head has primary education, and E_{it} =1), equation (3) becomes:

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

and $(\gamma_m + \lambda_m)$ and $(\gamma_f + \lambda_f)$ give the estimates of credit effects for households with characteristics (those with heads who have primary education).[5]

Table VII 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 labour supply, non-land assets, and net worth for all three categories of farmers. It also increases female labour supply for small and medium farmers. Female credit also increases labour supply of male and female family workers, non-land asset, and net worth for marginal, and small to medium farmers. For example, a 10 per cent increase in female borrowing, while does not increase net worth for marginal farmers, increases net worth by one per cent for small and medium farmers and 1.5 per cent for large farmers.

[5]In practice, we measure the credit effects for households with characteristics 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).

TABLE VII

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 male labour supply (hours/month)	Log female labour 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	0.007*	0.047**	0.031	0.036**	0.024*
	(-0.41)	(1.73)	(2.97)	(1.40)	(2.88)	(1.71)
Log loans of HH females (Tk.)	0.013*	0.001	0.045**	0.052**	0.032**	-0.002
	(1.70)	(0.43)	(4.85)	(4.62)	(4.71)	(-0.21)
Small and medium holders (land size 0.5-2.5 acres)						
Log loans of HH males (Tk.)	0.008	0.007	0.052**	0.068**	0.065**	0.072**
	(0.59)	(0.99)	(3.13)	(3.07)	(5.32)	(5.87)
Log loans of HH females (Tk.)	0.002	0.003*	0.027**	0.068**	0.063**	0.095**
	(0.38)	(1.80)	(2.18)	(4.29)	(7.22)	(9.34)
Large holders (land size>2.5 acres)						
Log loans of HH males (Tk.)	0.015	0.007	0.100**	0.004	0.054**	0.077**
	(0.53)	(1.31)	(3.30)	(0.11)	(2.06)	(2.98)
Log loans of HH females (Tk.)	0.042**	0.003	-0.009	0.112**	0.099**	0.151**
	(2.34)	(1.06)	(-0.24)	(4.01)	(5.41)	(6.29)
R^2	0.135	0.372	0.210	0.237	0.376	0.377

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

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; infrastructures such as availability of electricity, and schools; and proportion of village land irrigated).

Table VIII 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 per cent increase in male credit increases household net worth by 0.17 per cent for households headed by individuals with no primary schooling, compared to 0.37 per cent and 0.27 per cent increase for households with heads completing primary education and secondary education, respectively.

TABLE VIII

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 male labour supply (hours/ month)	Log female labour supply (hours/ month)	Log HH non-land asset (Tk.)	Log HH net-worth (Tk.)
Did not complete primary level						
Log loans of HH males (Tk.)	-0.001 (-0.08)	0.002 (0.42)	0.054** (3.79)	0.014 (0.63)	0.033** (3.27)	0.017* (1.79)
Log loans of HH females (Tk.)	-0.0004 (-0.08)	-0.0001 (-0.04)	0.041** (4.63)	0.059** (5.40)	0.034** (5.18)	0.009* (1.63)
Completed primary level						
Log loans of HH males (Tk.)	0.002 (0.15)	0.014** (2.23)	0.052** (3.83)	0.046** (2.80)	0.057** (4.46)	0.037** (4.44)
Log loans of HH females (Tk.)	0.001 (0.19)	0.005* (1.68)	0.040** (4.70)	0.037** (3.35)	0.036** (4.23)	0.016* (1.98)
Completed secondary level or above						
Log loans of HH males (Tk.)	-0.007 (-0.38)	0.012 (1.22)	0.052** (3.69)	0.039 (0.80)	0.010 (0.68)	0.027** (2.10)
Log loans of HH females (Tk.)	-0.016 (-1.35)	0.017** (3.07)	0.040** (4.87)	0.031 (0.98)	0.061** (3.75)	0.016 (1.10)
R^2	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 IX 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 labour 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 IX

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 (1.55)	0.003 (0.36)	0.034 (1.16)	0.044 (0.91)	0.008 (0.46)	0.038** (2.15)
Log loans of HH females (Tk.)	-0.001 (-0.16)	-0.001 (-0.32)	0.012* (1.83)	0.036* (1.95)	0.041** (4.10)	-0.012 (-1.05)
Household has no adults with oral math competency						
Log loans of HH males (Tk.)	0.035 (1.50)	-0.004 (-0.36)	0.019 (0.50)	0.043 (0.75)	-0.014 (-0.65)	0.025* (1.79)
Log loans of HH females (Tk.)	-0.006 (-0.81)	-0.002 (-0.36)	-0.005 (-0.27)	0.015** (3.51)	0.039** (5.86)	-0.004 (-0.36)
R^2	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 X shows how the benefits accrued to households 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 per cent gain in female credit increases labour supply by 0.6 percentage point for both men and women. On the other hand, male borrowing increases only men's labour 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 per cent increase in male credit increases non-land asset and net worth by 0.4 per cent and 0.2 per cent, respectively, for self-employed farmers. The corresponding figures for female credit are 0.5 per cent and 0.3 per cent, respectively. Female labour supply also decreases male labour supply.

TABLE X

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 labour supply (hours/month)	Log female labour supply (hours/month)	Log HH non-land asset (Tk.)	Log HH net-worth (Tk.)
Wage employment						
Log loans of HH males (Tk.)	-0.015 (-1.35)	0.002 (0.52)	0.062** (3.08)	0.038 (1.41)	0.021* (1.75)	0.018** (1.99)
Log loans of HH females (Tk.)	-0.008 (-1.30)	-0.002 (-0.68)	0.055** (5.40)	0.055** (4.32)	0.025** (3.61)	0.007 (1.12)
Self-employment in farm sector						
Log loans of HH males (Tk.)	0.044** (2.26)	0.011* (1.68)	0.044** (2.06)	0.052** (2.35)	0.043** (3.97)	0.023** (2.36)
Log loans of HH females (Tk.)	0.061** (6.06)	0.003 (0.75)	-0.031** (-2.11)	0.052** (2.85)	0.050** (5.09)	0.029** (3.61)
Self-employment in non-farm sector						
Log loans of HH males (Tk.)	0.031** (3.34)	0.008 (1.44)	0.050** (3.12)	0.029 (1.35)	0.041** (4.03)	0.026** (2.57)
Log loans of HH females (Tk.)	0.029** (4.80)	0.004 (1.49)	0.067** (7.13)	0.058** (5.41)	0.042** (5.59)	0.008 (1.31)
Mostly from non-earned activities						
Log loans of HH males (Tk.)	0.032 (1.59)	0.003 (0.30)	0.058** (2.34)	0.039 (1.39)	0.030** (2.01)	0.019 (1.46)
Log loans of HH females (Tk.)	0.007 (0.77)	0.013** (2.53)	-0.120 (-1.16)	0.046** (2.34)	0.057** (5.50)	0.018** (2.15)
R^2	0.240		0.269	0.238	0.459	0.652

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

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).

The benefits of microfinance also vary by village attributes. Table XI shows the heterogeneous effects of credit by whether the village is electrified or not. For both male and female credit, the effects are at least equal or higher on non-land assets and net worth in villages with electricity than in non-electrified villages. The same is true for labour 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 XII).

TABLE XI

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 labour supply (hours/month)	Log female labour 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	0.007*	0.050**	0.054**	0.041**	0.026**
	(-0.13)	(1.96)	(3.59)	(2.24)	(4.00)	(3.05)
Log loans of HH females (Tk.)	0.004	0.002	0.047**	0.056**	0.033**	0.012**
	(0.70)	(0.56)	(4.40)	(5.47)	(5.42)	(2.89)
Village does not have electricity						
Log loans of HH males (Tk.)	-0.0001	0.004	0.047**	0.035*	0.014	0.016
	(-0.01)	(0.63)	(2.37)	(1.80)	(0.85)	(1.56)
Log loans of HH females (Tk.)	-0.012	0.002	0.027**	0.049**	0.034**	0.006
	(-1.47)	(0.51)	(3.45)	(4.32)	(4.66)	(1.00)
R^2	0.137	0. 375	0.208	0.238	0.455	0.651

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

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).

TABLE XII

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 labour supply (hours/month)	Log female labour 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	0.007	0.053**	0.040*	0.040**	0.027**
	(0.19)	(1.51)	(3.59)	(1.91)	(4.11)	(3.28)
Log loans of HH females (Tk.)	-0.004	0.001	0.040**	0.056**	0.036**	0.011*
	(-0.77)	(0.23)	(4.90)	(5.41)	(5.63)	(1.96)
Village is not accessible whole year						
Log loans of HH males (Tk.)	-0.015	0.004	0.041*	0.031	0.030*	0.015
	(-0.99)	(0.44)	(1.63)	(1.32)	(1.80)	(1.18)
Log loans of HH females (Tk.)	0.022**	0.002	0.038**	0.051**	0.038**	0.013
	(2.70)	(0.84)	(2.37)	(3.05)	(4.30)	(1.54)
R^2	0.139	0.376	0.209	0.237	0.453	0.651

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

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).

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.

VI. DISTRIBUTION OF PROGRAMME BENEFITS: A QUANTILE REGRESSION APPROACH

Does borrowing from a microfinance programme, besides yes-no participation, also work better for households with better existing characteristics? 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 characteristics constrain benefits accrued to households. We can also formally test whether the effect of credit programme 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 the 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 generalised 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 minimises the sum of absolute residuals corresponding to the quantile value in question as opposed to minimising the sum of squares of the residuals achieved by ordinary regression. Microfinance programmes, by design, try to reach the poorest groups, especially women, and so, it is expected that the poorer households may benefit more from these programmes than the better-off households. A quantile regression enables us to investigate this issue.

A detailed theoretical exploration of quintile regression is beyond the scope of this paper (for a technical explanation, please see Koenker and Basset 1978, Buchinsky 1998). To estimate quantile regression for panel data, we use a semi-parametric approach to examine the distributional effects of non-random treatment.[6] 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:

$$Q_\tau(Y_{ijt}|Z_{ijt}, E_{ijt}, \eta_{ijt}) = \psi_\tau Z_{ijt} + \delta_\tau E_{ijt} + \eta_{ijt}, \tau \in (0,1) \quad (6)$$

where $Q_\tau(Y_{ijt}|Z_{ijt}, E_{ijt}, \eta_{ijt})$ denotes the quantile τ 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 η subsumes unobserved commune and household heterogeneity. One problem in applying the quantile regression model to panel data is that differencing variables are 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 η non-parametrically as an unknown function $\phi(\cdot)$ of the covariates *X*, as follows:[7]

$$\eta = \varphi(Z_{ij1}, Z_{ij2,} ..., Z_{ijt}) \quad (7)$$

Substituting equation (7) in each conditional quantile in equation (6) allows us to estimate the distributional impact of income on outcomes *Y*.[8] In practice, we

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

[7]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*.

[8]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 $\hat{Q}_\tau(Y_{ijt}|Z_{ijt}, E_{ijt}, \eta_{ijt}) - \hat{Q}_\tau(Y_{ijt-1}|Z_{ijt-1}, E_{ijt-1}, \eta_{ijt-1})$ from the estimations can be regressed on the differenced regressors since the proxies for the fixed effects fall out of the estimation.

transform equation (6), and take the quantile over the difference of the outcome and its mean as shown below:

$$Q_{\tau}(\Delta Y_{ijt}) = \psi_{\tau}\Delta Z_{ijt} + \delta_{\tau}\Delta E_{ijt} + \theta_{1\tau}Z_{ij1} + \theta_{2\tau}Z_{ij2} + \theta_{3\tau}Z_{ij3} + \Delta\varepsilon_{ijt} \quad (8)$$

Table XIII 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 per cent increase male borrowing increases per capita expenditure by 0.03 per cent 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 per cent increase in female borrowing increases per capita income by 0.11 per cent for the 15th quantile and 25th quantile, and 0.07 per cent for the 50th 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 per cent increase in male borrowing increases per capita income by 0.18 per cent for the 85th quantile, 0.14 per cent for the 75th quantile, 0.11 per cent for the 50th quantile, 0.09 per cent for the 25th quantile and only 0.07 per cent for the lowest 15th quantile.

TABLE XIII
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*	0.003**
	(1.64)	(2.25)
Log loans of HH females (Tk.)	0.011**	0.004**
	(2.62)	(2.44)
25th quantile		
Log loans of HH males (Tk.)	0.009**	0.003**
	(3.65)	(3.42)
Log loans of HH females (Tk.)	0.011**	0.004*
	(3.99)	(1.89)
50th quantile		
Log loans of HH males (Tk.)	0.011**	0.003**
	(3.18)	(2.20)
Log loans of HH females (Tk.)	0.007**	0.002*
	(2.34)	(1.64)

(Contd. Table XIII)

Microfinance loan variables	Log per capita total income (Tk./month)	Log per capita total expenditure (Tk./month)
75th quantile		
Log loans of HH males (Tk.)	0.014**	0.0002
	(3.38)	(0.10)
Log loans of HH females (Tk.)	0.003	0.0002
	(1.04)	(0.10)
85th quantile		
Log loans of HH males (Tk.)	0.018**	0.002
	(3.13)	(0.83)
Log loans of HH females (Tk.)	-0.0002	-0.005*
	(-0.04)	(-1.70)
Pseudo R^2	0.057 at 15th, 0.070 at 25th, 0.089 at 50th, 0.109 at 75th, 0.120 at 85th	0.220 at 15th, 0.226 at 25th, 0.227 at 50th, 0.215 at 75th, 0.213 at 85th

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

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).

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.

VII. 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 XIV shows the characteristics of two groups of participating households, one group that drops out and the other group who did not. The average dropout rate is 13.8 per cent between the surveys, with 11.8 per cent in 1998/99 and 13.8 per cent in 2010/11. One key difference between these two groups is that the average loan 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 programme are less able in terms of possessing skill in both reading and oral mathematics compared to those who continued.

TABLE XIV
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**

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

What determines the dropout rate? Table XV 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 programme, higher the probability of dropout from the programme. 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 programme. Hence, programme dropout is not random; both own and household characteristics matter for a member's dropout from a programme.

TABLE XV

DETERMINANTS OF HOUSEHOLD DROPOUT FROM MICROFINANCE

(N_{HH}=1,711)

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

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

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).

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 XVI, those who dropped out from a microfinance programme 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.

TABLE XVI

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.

Since dropout is not random (as it is determined by human characteristics) 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:

$$Y_{it} = \beta T_t + \lambda_r M_{it}^r + \lambda_d M_{it}^d + \gamma_1 T_t M_{it}^r + \gamma_2 T_t M_{it}^d + \gamma_3 M_{it}^r M_{it}^d + \gamma_4 T_t M_{it}^r M_{it}^d + \varepsilon_{it} \qquad (9)$$

where, T_t is the time control, M_{it}^r is the intervention variable for continuing members, M_{it}^r is the intervention variable for dropout members, and ε_{it} is the random error, and β, λ and γ are parameters to be estimated. The parameter of interest here is γ_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 XVII shows the participation effects on household outcomes for two scenarios: when member dropout is controlled for and when it is not.[9]

TABLE XVII

IMPACTS OF MICROFINANCE BORROWING ON HOUSEHOLD OUTCOMES WITH CONTROLLING FOR PROGRAMME 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 labour supply (hours/ month)		Log female labour supply (hours/ month)	
	Not controlling for programme dropout	Controlling for programme dropout	Not controlling for programme dropout	Controlling for programme dropout	Not controlling for programme dropout	Controlling for programme dropout	Not controlling for programme dropout	Controlling for programme 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)
R^2	0.120	0.122	0.274	0.275	0.199	0.200	0.334	0.335

Source: WB-BIDS surveys 1991/92 and 1998/99.

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).

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 labour supply, and overestimates the credit effects for female labour supply and non-land asset. There is no difference

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

in the effects for household net worth and children's schooling.[10] So, we can summarise by saying that change in credit impacts is very little when member dropout is controlled for.

VIII. CONCLUSION

This paper examines the heterogeneous impacts of microfinance intervention in rural Bangladesh. Heterogeneity in programme effects may arise due to household and community characteristics. For household characteristics, we consider household landholding, head's education, competency in oral math (as proxy for entrepreneurial ability) and employment types, and for village characteristics we consider village electrification and accessibility. We find that while large holders experience income gain from microfinance, marginal and small-to-medium holders do not. For other outcomes (labour 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 labour 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 utilise 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 characteristics, 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 lower welfare brackets (in terms of income or expenditure) benefit more than those in the higher welfare brackets. This means that microfinance programmes are perhaps well-targeted. This is very critical as alleviating poverty is a stated objective of microfinance interventions.

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

This paper also tries to identify who the programme 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 programmes. Perhaps the dropout members, having borrowed more than they could handle and 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 programme dropouts are not large enough to affect the overall impacts of microfinance.

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