

Working Paper No. 6

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April 2010



Institute of Microfinance (InM)

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1. Introduction

Microfinance is part of a strategy that aims to mitigate the moral hazard problem of lending through innovative methods such as group-based lending.¹ It is also sometimes a part of a strategy that advocates microfinance as a tool for poverty reduction by targeting the poor often excluded by traditional financial institutions. Indeed, over the years microfinance has successfully reached a large percentage of the poor, especially women. But microfinance has not reached as many ultra-poor as one would like to include among its clientele (e.g., Webb, Coates and Houser, 2002; Datta, 2004). Moreover, microfinance does not extend its services to marginal and small farmers, as evident by the small share (not more than 15 percent) of its portfolio lent to agriculture.

For example, Bangladesh's MFIs do not cover more than 20 percent of the ultra-poor among clientele (e.g., Khandker 1998; 2005). A more recent survey shows that the proportion of hard-core poor covered by MFIs is less than 40 percent of program participants (InM 2009). Bangladesh's microfinance programs provided only 10 percent of its portfolio to agriculture (Faruquee, 2009). Because MFIs do not cover much ultra-poor and crop agriculture, they have limited coverage in areas such as the North West part of Bangladesh with pronounced seasonality of agriculture and high incidence of extreme poverty (e.g., Khandker 2009).²

However, it is evident that one of the reasons for micro-credit program participation is to facilitate consumption smoothing. Households who are unable to smooth consumption are more likely to participate in micro-credit programs. Micro-credit tends to encourage income earning activities that are less vulnerable to seasonality and thus helps borrowers to smooth consumption and hence, reduce vulnerability to consumption (Pitt and Khandker 2002; Morduch 1999; Zaman 1999; 2004). Microcredit is also found to reduce extreme poverty more than moderate poverty (e.g., Khandker 2005).

The question then arises: Why do we see a small percentage of MFI portfolio lent to agriculture or why a small percentage of the ultra-poor participate in microfinance? Do income seasonality and poverty reinforce the limited coverage of microfinance in the NW region that is characterized by pronounced seasonality and high poverty? Does it mean a different type of microfinance program needed to handle seasonality and poverty than what is currently in place?

In recent years with donor assistance and government pressure, the MFIs in Bangladesh have introduced a variety of programs to deal with seasonality and hard-core poverty. Bangladesh's leading NGO program BRAC has launched a multidimensional micro-credit program targeted to the ultra-poor in 2002 (e.g., Imran and Hume, 2003; Emran et al., 2009).³ The BRAC ultra-poor program emphasizes both on human and physical capital development via

¹ Besides covariate risk, rural lending is subject to problems of asymmetric information, incentive to repay, and enforcing loan contract (e.g., Stiglitz 1990).

² Only 12 percent of villages had a Grameen Bank in the North West (NW) region of Bangladesh in 2005 as opposed to 34 percent in other regions of Bangladesh. Note that the NW region is the worst hit region in terms of negative consequences of extreme seasonality of agriculture.

³ Evaluations of such programs indicate that BRAC's ultra-poor program has desirable impacts on the poor.

transferring assets and other means such as skill-based training before the ultra-poor graduate to become members of its standard microfinance program. Similar ultra-poor programs are introduced by Grameen Bank to target the ultra-poor such as the beggars. Many MFIs have also introduced seasonal loans to address seasonality of income.

Redressing either poverty or seasonality of income is a big challenge of any institution, let alone microfinance or any financial institution. It is much more challenging when the poor encounter pronounced seasonality of income and consumption. That is, when poverty is rampant, seasonality only makes poverty worse. Therefore, tackling both seasonality and poverty with a single intervention is a major challenge to policymaking (Khandker 2009).

In 2006 a program called the Program Initiatives for *Monga* Eradication (PRIME) was introduced by the country's premier whole-sale microfinance institution (MFI) known as Palli Karma Shahayak Foundation (PKSF). The PRIME's objective is to exclusively deal with hard-core poor who are highly vulnerable to seasonal poverty, especially in the NW region of Bangladesh.⁴ PRIME is a flexible microfinance program that offers microcredit and other services at flexible terms to the ultra-poor.

Extreme poverty is caused by unfavorable agroclimates and low levels of physical and human capital. Seasonal poverty, on the other hand, is caused by seasonality when households cannot smooth consumption across seasons. But lack of consumption smoothing is pronounced much more for the poor than for the rich in a society. There is a large body of literature that shows that the observed seasonality in consumption is largely driven by the seasonal variation in income, and that lack of access to credit impedes consumption smoothing (e.g., Rosenzweig 1988, Rosenzweig and Wolpin 1993; Chaudhuri and Paxson 2001). However, if the risk is idiosyncratic (i.e., specific to certain households) then local risk pooling or insurance is feasible which becomes very limited in the event of an aggregate shock (Townsend 1995). Better access to finance is thus a useful approach for better allocation of resources (e.g., Rosenzweig and Binswanger, 1993). Pitt and Khandker (2002) find that production credit helps smooth seasonal consumption by financing new productive activities whose "income flows and time demands do not seasonally co-vary with income generated by existing activities of households."

If lack of access to credit causes households not to smooth consumption or allocate resources efficiently, then both seasonal and hard-core poverty are caused in part by lack of access to credit. An introduction of a microfinance program targeted to the hard-core poor with pronounced income seasonality is expected to make a dent on both seasonal and chronic poverty. The key research question is whether PRIME is able to meet both ends.

This paper's objective is to evaluate the PRIME program in terms of its effectiveness in reaching the ultra-poor as well impacting on seasonal and extreme poverty. The paper addresses the following issues. (i) To what extent the flexible microfinance of PRIME is effective in reaching the ultra-poor and seasonally poor? (ii) Quantify the program benefits in terms of mitigating extreme and seasonal poverty; and (iii) Assess the relative effectiveness of PRIME and regular MFIs in reducing extreme and seasonal poverty.

The paper is organized as follows. Section 2 discusses the poverty and seasonality of the NW region vis-à-vis other regions and the rationale for PRIME intervention. Section 3 presents an economic framework that lays out the role of credit in resolving both seasonality and poverty. This section also discusses an empirical framework to estimate the effects of a credit intervention. Section 4 presents a discussion of the salient features of the data and its

⁴ We will provide a description of what PRIME does and what a flexible microfinance is all about and how does it differ from the traditional microfinance in the next section.

characteristics. The data are drawn from a random survey of households carried out in program and non-program villages. Both cross-section and panel data are used to evaluate the role of PRIME in mitigating seasonality and hard-core poverty. As PRIME is a special microfinance program it becomes essential that we evaluate this program against regular microfinance. Section 5 presents the data in terms of the ultra-poor's participation in PRIME vis-à-vis regular microfinance and analyses the factors causing the ultra-poor participate in one of the programs. Section 6 reviews the methods and results on program effects on household welfare using cross-sectional data. Section 7, on the other hand, discusses and presents the results using panel data. Section 8 summarizes the paper with policy conclusions.

2. Tackling ultra-poverty and income seasonality in NW region with PRIME

The very first goal outlined in the United Nations' Millennium Development Goals (MDGs) focus on reducing poverty and hunger. The World Bank has been vigorously promoting all member countries to attain this goal. The government of Bangladesh has undertaken various steps towards achieving MDGs and made significant progress. Recent figures suggest Bangladesh's achievements. Compared to the baseline poverty of 58.8 percent in 1990, the poverty rate in 2000 was 49.6 percent - which is equivalent to roughly a 1 percent poverty reduction a year (United Nations 2005). The 2005 HIES (Household Income and Expenditure Survey) results show even more gains in poverty reduction-the overall poverty rate in 2005 was 40 percent countrywide with 28.4 percent in urban and 43.8 percent in rural areas (Table 1). Over the last five years (2000-2005) the rate of poverty reduction was around two percent per year.

Bangladesh's impressive performance in poverty reduction is, however, not uniform across the country; although overall poverty has declined, the incidence of poverty is much higher in lagging regions than in others. For example, findings from the 2005 Bangladesh HIES suggest that while the national rural headcount poverty rate was 43.8 percent, the North West region (NW)⁵ of Bangladesh, had a rural poverty rate as high as 57.4 percent (Table 1). Extreme poverty incidence was also much higher here (43 percent in 2005) than the national rural average (28.6 percent).

An analysis of HIES 2005 also suggests the following: (i) household consumption per capita is much lower in NW region than in other regions and; (ii) seasonal fluctuation in expenditures is greater in the NW than in the rest of the country (Khandker 2009). The NW region also experiences sharp shortfall in food consumption during certain months of a year that produces cyclical food insecurity locally known as *Monga* (Figure 1).⁶

Table 1: Poverty and extreme poverty incidence nationally and in the NW region

	Poverty Headcounts		Extreme Poverty Headcounts	
	2005	2000	2005	2000
National	40	48.9	25.1	34.3
Rural (nationwide)	43.8	52.3	28.6	37.9
Urban (nationwide)	28.4	35.1	14.6	19.9
Greater Rangpur	57.4	67.7	43.0	55.9

Note: Figures from 2005 and 2000 Bangladesh HIES data.

⁵ The North West (NW) region consists of five districts in greater Rangpur: Rangpur Sadar, Gaibandha, Nilphamari, Lalmonirhat, and Kurigram.

⁶ *Monga* occurs during mid-September to mid-November that corresponds to the post-planting to pre-harvesting period of Aman rice. This is the lean period for both consumption and labor demand and is most pronounced in the GRD region of Bangladesh.

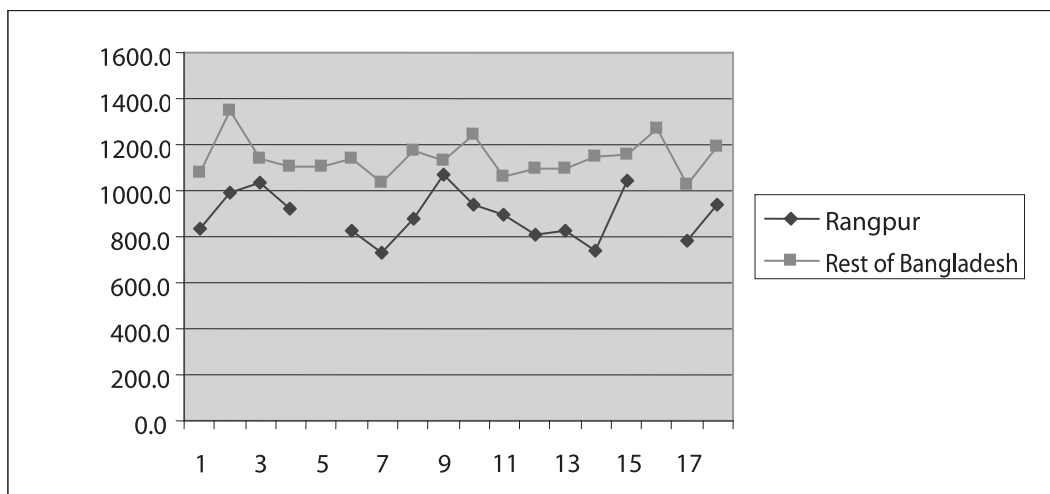


Figure 1: Distribution of mean per capita expenditure

Monga is a seasonal deprivation of food during the pre-harvest period of Aman rice when there are very few opportunities available to employ the poor in agriculture. Seasonal deprivation does not mean lack of availability of food but rather is caused by lack of access and utilization of food (WFP 2005). Lack of access to food is due to lack of income and in part by the prices for basic foods which often increase during *monga*. Lack of income is essentially due to lack of employment during the pre-harvest season. Seasonal deprivation or *monga* is thus due to the working of an economic system that limits the ability of a segment of the population in acquiring food and other basic necessities (Sen 1981).⁷

The NW region is most vulnerable to *monga* for its ecological and economic vulnerability (Rahman 1995). *Monga* affects those vulnerable rural poor, who have an undiversified income that directly or indirectly depends on agriculture (Zug 2006). *Monga* also affects women and children disproportionately due to the existence of intra-household inequity in resource allocation.

The people who suffer from seasonal deprivation are also mostly hard-core poor with a few assets and savings to smooth consumption during the lean period. Part of their inability to smooth consumption is due to a lack of access to credit markets in case they need to borrow against future income. In the absence of well-functioning credit markets, households frequently draw on an informal credit market arrangement called *dadon* to smooth consumption. *Dadon* refers to arrangements whereby laborers sell labor or farmers sell crops in advance to smooth consumption during *Monga*. The terms are often quite severe to the sellers. Households also employ traditional self-insurance methods of coping, such as use of buffer stock (livestock and the storage of grain), and mutual insurance such as inter-family transfers. However, these traditional methods are inadequate and inefficient for many households to smooth consumption.

Government institutions employ short-term measures such as cash transfers, food-for-work, food coupons, and public works to manage *Monga*. If variations in consumption are only transitory in nature and are idiosyncratic across households, these interventions may help mitigate *Monga*. But as *Monga* is widespread and a result of structural poverty caused by low

⁷ The agriculture sector of Bangladesh is characterized by three crop seasons, based on three kinds of rice - Aus, Aman and Boro. While these three crops cover the whole year, there is a period of virtual economic inactivity during the *Monga* period. During this period there is no alternate agricultural activity. The non-farm sector is also not large enough to employ the unemployed who are mostly agricultural laborers or small farmers.

income, low productivity, and lack of diversification of local economies, interventions not geared toward enhancing income and productivity are of little help to contain *Monga* on a sustainable basis.

Group-based lending as practiced by government and non-government institutions appears to have limited scope in mitigating *Monga* on a sustainable basis either for a number of reasons. First, microfinance has not reached the ultra-poor hard hit by seasonality of income and consumption. Second, the weekly repayment schedule is at odds with seasonality of income and employment, which also inhibits the ultra-poor's participation in microfinance. Third, often seasonality of income generating activities limits the ability of micro-credit agencies to support new loans during lean seasons. Finally, group-based lending works well when income variations are idiosyncratic so that group members assist/insure each other through difficult times. But when seasonality is systematic, affecting everyone in a group, the ability of mutual insurance is severely curtailed and the group as a whole has a greater incentive to collude on a strategy of default. Microfinance is not thus well suited to address either hard-core poor or seasonality of poverty. No wonder why microfinance has not reached extensively in the NW region until very recently.

In 2006 Palli Karma Shahayak Foundation (PKSF) with its partners introduced a multi-faceted program called PRIME to address seasonal deprivation as well as ultra-poverty in the NW region. PRIME offers a flexible microfinance program that lends both production and consumption loans and targets specifically the ultra-poor. Unlike traditional microfinance, PRIME's flexible microfinance has the following features: Repayment schedule is flexible; production loan can be used for consumption if needed; interest rate is not more than 10 percent compared to 20 percent for the traditional microfinance; no fixed savings and weekly meetings are stipulated. Other than flexible microfinance services, PRIME also offers the following year round services: support for income generating activities, skill-based training, remittances services, and primary health care services (InM 2009). PRIME also provides the following services during the lean or *monga* season: emergency loan for consumption smoothing, and cash for work related to local infrastructural development. PRIME, however, does not offer consumption credit without either subsequent or prior production credit.

The target beneficiaries of PRIME are hard-core poor who are identified based on a village census prior to the program intervention using the following criteria: (i) Households have strictly less than 50 decimals of land; (ii) household per capita monthly income does not exceed Tk.1500 (equivalent to US\$25) and (iii) one of household members is a daily wage worker. The pre-program intervention data collected by PKSf 2006 reveals that the eligibility conditions are strictly enforced while listing the households to be eligible for PRIME intervention. PKSf's hard-core micro-credit program intervention (i.e., PRIME) is a worthwhile intervention for a rigorous impact evaluation. It is necessary to determine whether PRIME is effective in reaching the hard-core poor as well as mitigating both seasonal and hard-core poverty.

Very important to the proper identification of policy is to understand the extent of seasonal nature of poverty vis-à-vis chronic poverty. While transient or seasonal poverty may be addressed by offering credit and bolstering other safety nets that stabilize income and consumption, the roots of chronic poverty are deeper and must be addressed through long term investments in human and physical capital (Jalan and Ravallion 2000; Khandker 2009). Therefore, the study of PRIME must examine whether the provision of credit along with other non-financial services is capable of addressing both human and physical capital needs of the ultra-poor for mitigating seasonality and hard-core poverty in a sustainable way.

3. An Analytical framework

We develop the standard inter-temporal utility maximization model of consumption smoothing and present the implications of borrowing restrictions following Deaton (1991). Each household i is to maximize the following utility function which is assumed to be increasing, strictly

concave and differentiable

$$u = E_{t=\tau} \left[\sum_{t=\tau}^T \beta^{t-\tau} u(c_{it}) \right] \quad (1)$$

Where c_i is a single aggregate consumption good and β the time discount rate. This is maximized subject to the dynamic asset constraint

$$A_{it+1} = (1+r)A_{it} + y_{it} - c_{it} \quad (2)$$

where y_{it} is labor income that is risky, A_{it} is real assets and r is that real interest rate assumed to be fixed over time. If T is large enough and with $A_{T+1} = 0$, from the Euler equations we get the standard permanent income result of the marginal utility of current consumption being equal to the discounted expected marginal utility of future consumption

$$u'(c_{it}) = \beta(1+r)Eu'(c_{it+1}) \quad (3)$$

With borrowing restrictions we need to add another constraint to the consumer's decision reflecting that assets can never be negative

$$A_{it} \geq 0 \quad (4)$$

If the credit constraint binds, then the equality of (3) will be violated and households will fail to smooth consumption.

For simplicity, if we assume the utility function to be quadratic and the rate of time preference to be equal to the interest rate, then in the absence of a binding credit constraint there would be perfect consumption smoothing, i.e., $c_{it} = c_{it+1}$. When credit constraint is binding, we get $c_{it} < c_{it+1}$.

Figure 2 illustrates the consequences of a binding credit constraint in a two period decision model. Let us assume period 1 to be the lean season and period 2 to be the harvest season. In the absence of a credit constraint a household would maximize its inter-temporal utility by consuming at e_1 . With the credit constraint binding the household would face a discontinuous budget line such as $q_2e_2c_c$. The household would then be forced to consume at e_2 with a lower lean period consumption ($c_c < c_1$) and would be at a lower welfare curve than before. Note that even if second period (harvest season) income were to rise it would have no impact on the first period (lean season) consumption.

The central hypothesis of this seasonal consumption model is that improving access to credit could enhance seasonal income and consumption level in the lean period in order to help household smooth consumption during lean period. Moreover, if the impact is large, it would have also positive impact on non-lean period. Thus, if households were credit constrained, interventions such as those of PRIME could make credit available to smooth consumption by providing alternative income and employment opportunities to enhance income both in the lean and non-lean period. The policy question is: whether credit provision of PKSF PRIME project can effectively shift the budget curve upward so that poor households smooth consumption efficiently to reach their consumption goals?

Alternatively, if consumption point represented by e in figure 2 implies the minimum bundle

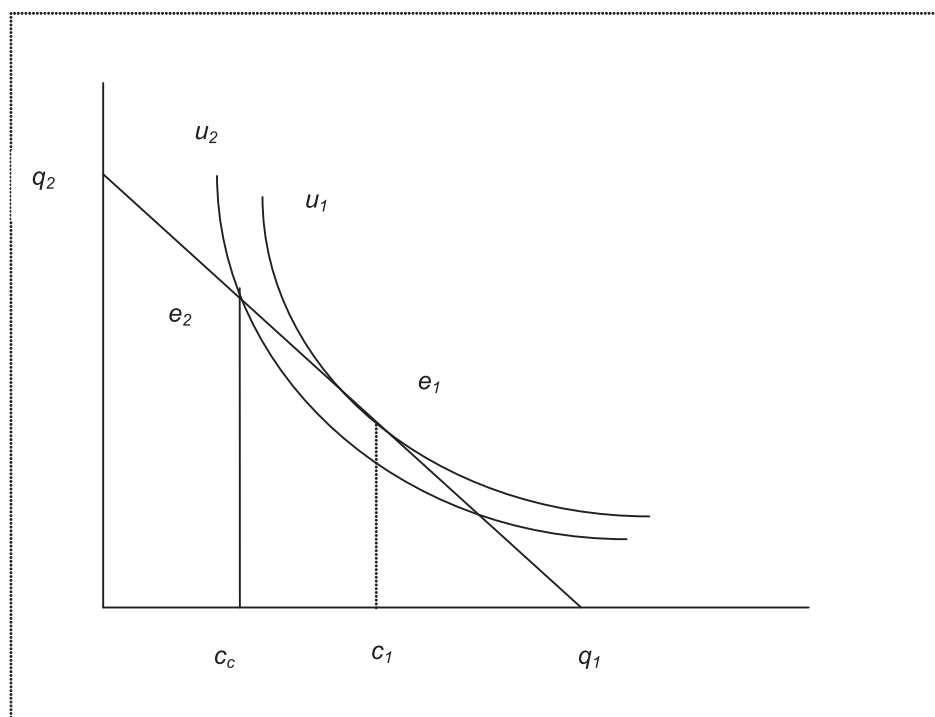


Figure 2: Lean and harvest period consumption in the presence of credit constraint

of goods households ought to consume in order to be above extreme poverty line, one can argue that having no access to smooth consumption will allow households to even consume much less than what is needed to be at the threshold point. On the other hand, even if households can manage to smooth consumption without institutional credit support, the question is whether households' better access to credit can shift the budget curve upward in order to help households move above the poverty line. If this does, one can argue that access to credit not only helps smooth consumption but also reduce poverty.

Assume that households' consumption status for a particular season (s) can be represented by the following regression:

$$y_{ijs} = \alpha + x_{ij}\beta + p_{ij}\gamma + \mu_{ij} + \eta_j + \xi_{ijs} \quad (5),$$

where y is the consumption status of households (i) living in j villages in a given season (s), x represent a vector of household and community characteristics, p is program participation status, α , β , and γ are unknown parameters to be estimated. The outcomes observed for a cross-section of households can be observed for major groups of households in a given season: Households who are not poor otherwise but have lower consumption level due to a binding credit constraint in the lean period; and households who are poor otherwise and have lower consumption level further due to a binding credit constraint in the lean season. When evaluating a program which targets a group of seasonally poor households, a number of factors are likely to affect the participation decision of a particular household. Thus, participation (p) is not exogenous but is determined by a number of factors including the variables included in equation (5).

$$p_{ij} = \alpha^p + x_{ij} \beta^p + \mu_{ij}^p + \eta_j^p + \xi_{ij}^p \quad (6),$$

The errors are likely to be correlated between equation (5) and (6). There are at least three types of errors that may affect the outcomes of interest such as consumption status in a given season as well as program participation for a cross-section of households interviewed: unobserved household characteristics (μ), unobserved village characteristics (η) and the idiosyncratic errors (ξ) randomly distributed with zero mean and unit variance.

The errors are correlated for the following reasons:

(a) Unobserved village heterogeneity (η): There may be unobserved characteristics of villages - remoteness, infrastructure, attitudes, and the like - that affect both participation (i.e. the amounts borrowed by households) and also the impact of participation on outcome variables.

(b) Unobserved household (or individual) heterogeneity (μ): There may be unmeasured characteristics of households - entrepreneurial drive, preferences, health status, and so on - that both affect participation and the impact of that participation.

(c) Endogenous Program Placement: A program such as PRIME of PKSf does not select villages randomly for program placement. Factors such as extent of seasonal famine and extent of river erosion determine the decision to place PRIME in a particular village. These attributes measured by η that influence program placement may also contribute to lower levels of household consumption.

The correlations of errors of equations (5) and (6) do not arise if program is randomly placed and households are randomly selected between participant and non-participant. In such a randomized framework, a simple comparison of post-intervention outcomes between the participants and non-participants is a measure of program effect. In contrast, when non-randomized evaluation method is adopted, it is important to take care of these correlations or endogeneity into program assessment; otherwise, the results will be biased. There are alternative non-experimental methods that may be relevant to assess the program effects. Ultimately using a particular method in program evaluation would depend on available data and its characteristics (Ravallion 2006; Khandker et al., 2009).

4. Survey data and its characteristics

The data available for an evaluation of PKSf's PRIME program comes from cross-sectional and panel surveys. PKSf followed a pre-intervention data collection strategy to identify its target group for PRIME intervention. All households in program villages were surveyed to find out who are ultra-poor and also who are vulnerable to *monga* or seasonal food deprivation. The ultra-poor vulnerable to seasonal deprivation are selected on the basis of the following: (a) Households have less than or equal to 5 decimals of land⁸; (b) Households earn livelihood through selling labor; and (c) Households have monthly income not more than Tk. 1,500 during the *monga* or lean season. After identifying the target households of PRIME using the criteria and focus group meetings, an in-depth survey was carried out by PKSf partners prior to the program intervention for all target households. This data set is considered the baseline survey data by the InM for the follow-up surveys. The baseline survey was carried out immediately after the lean

⁸ This is the overriding eligibility condition of microfinance as practiced in Bangladesh. The ultra-poor having much lower than 50 decimals of land also belong to this group; however, given the program design such as maintaining weekly repayment schedule and attending weekly meetings, the ultra-poor are found to participate less in traditional microfinance program.

season of 2006. The baseline data was analyzed for different research topics such as vulnerability, coping, and seasonal migration (e.g., Khandker et al., 2009).

The *monga*-affected households once identified are then brought under the PRIME program intervention through 235 PRIME branches in five districts of the NW region. Lalmonirhat district received intervention in 2006 while the remaining districts (i.e., Rangpur, Kurigram, Gaibandha, and Nilphamari) received in 2007. Members of PRIME are grouped into small groups of 25-30 beneficiaries, who meet weekly at their mutually agreed time and place, and follow most of the traditional micro-credit group regulations. However, the PRIME groups differ from the groups of traditional micro-credit groups. The PRIME groups may save any amount of money and are qualified for a loan against any amount of savings. The PRIME groups receive loans and other benefits for both year-round and lean seasonal activities. The year round activities include a flexible micro-credit program that allows loans for production and consumption, and the repayment schedule is flexible as per the convenience of borrowers. PRIME also offers extension services for income generating activities, training, primary health care and remittance services. The total target population of PRIME in five districts of the NW region is 482,948 households from 23 upazilas, 209 unions, and 2,531 villages (InM, 2009).

During the months of December, 2008 and January-February, 2009, a survey was conducted by InM to assess the impacts of PRIME intervention. A multi-stage cluster sampling technique was used to draw a random sample of 4,589 households from 16 upazilas, 61 unions, and 271 villages out of total area that received PRIME intervention. The sample households drawn from the PRIME catchment areas for this impact study have had baseline information collected in 2006. Interestingly, not all selected households eligible for PRIME intervention actually participated in PRIME by the time these households were surveyed after 2 years of program intervention in 2008/09. Moreover, some households selected in this random design from the PRIME catchment villages were members of traditional microfinance programs.

Besides the PRIME area sample of 4,589 households, the InM study carried out a similar survey in areas of 3 districts which did not receive any PRIME intervention by 2008/09 but are targeted to receive PRIME intervention. Out of 11 upazilas in 3 districts, 4 upazilas were selected as control upazilas. Out of 40 villages in these 4 upazilas not yet covered under PRIME, 27 villages were selected and 618 households were drawn randomly from these 27 villages based on village census. Thus, the total sample of households selected for the study is 5,207 of which 1,520 households participated in PRIME program, 1,718 participated in traditional microfinance, and 1,968 did not participate in any program.

Table 2 shows the distribution of 5,207 households by program participation status and by district. The distribution of sample is also shown by PRIME versus non-PRIME areas. There are 3 groups we have identified for the participation status of the ultra-poor households: PRIME-only, traditional program only, and program non-participants from both PRIME and non-PRIME (or control) areas. These non-participants are those who either did not participate when program was available or those eligible households from non-PRIME control villages).⁹ Thus, in all areas, 33 percent of target households were traditional micro-credit program participants, 29.2 percent were PRIME participants, and 37.8 percent were non-participants.

In PRIME areas, the distribution by program participation status is 33.2, 33.8 and 33.0, respectively. In non-PRIME villages, 26.5 percent of the ultra-poor participated in a regular microfinance program, and 73.5 percent were not-participants of any program.

Lalmonirhat district received PRIME treatment in 2006 while the remaining districts

⁹ Note that there were no non-target households sampled in this surveys.

Table 2: Household participation rate in major *monga*-intervention programs in cross-sectional sample (percent)

District	Gaibandha	Kurigram	Lalmonirhat	Nilphamari	Rangpur	All districts
PRIME area						
PRIME	28.7	39.7	31.9	36.3	29.9	33.2
Traditional microfinance	37.2	30.0	36.9	25.5	35.5	33.8
Non-participants	34.1	30.3	31.2	38.2	34.6	33.0
Observations	1,257	1,135	1,015	490	692	4,589
Non-PRIME area						
PRIME	0	-	-	0	0	0
Traditional microfinance	6.3	-	-	31.2	25.8	26.5
Non-participants	93.7	-	-	68.8	74.2	73.5
Observations	64	0	0	314	240	618
All areas						
PRIME	27.3	39.7	31.9	22.2	22.3	29.2
Traditional microfinance	35.7	30.0	36.8	27.7	33.0	33.0
Non-participants	37.0	30.3	31.3	50.1	44.7	37.8
Observations	1,321	1,135	1,015	804	932	5,207

Source: InM survey 2009.

received this treatment in 2007. Yet the percentage of PRIME participants is the highest in Kurigram followed by Lalmonirhat, Gaibandha, and other two districts. Interestingly, the percentage of traditional microfinance program participants is highest in Lalmonirhat (36.8 Percent) followed by Gaibandha (35.7 percent), Rangpur (33 percent), Kurigram (30 percent) and Nilphamari (27.7 percent).

Table 3 presents descriptive statistics of major outcomes by program participation status, while Table 4 shows those of household and community characteristics by program participation status for cross-sectional data of 5,207 households surveyed in 2008/09. Of particular importance are the poverty measures and the measures of seasonal deprivation. Three measures of poverty are calculated and presented in Table 3: Moderate poverty, food poverty, and extreme poverty. The extent of poverty of all three dimensions is similar for all 4 categories of households. For example, 86.1 percent are moderate poor among the traditional microfinance participants compared to 87.1 percent among PRIME participants, and 89.2 percent among the non-participants. In contrast, 67.6 percent are extreme poor among traditional micro-credit programs compared to 67.5 percent among PRIME participants, and 72.7 percent among the non-participants. The participants of both traditional and PRIME micro-credit programs are slightly better off than those who are not participants of any program among the target ultra-poor households.

Table 3: Summary statistics of household-level outcome indicators by program participation in cross-sectional sample

Outcomes	PRIME	MFI	Non-participants	Whole sample
Year-round outcomes				
Male employment (hours/month)	168.0 (120.8)	183.6 (127.9)	154.0 (122.9)	167.9 (124.5)
Female employment (hours/month)	41.1 (73.6)	33.8 (77.0)	30.9 (70.6)	34.9 (73.7)
Total employment (hours/month)	209.2 (134.5)	217.4 (143.4)	184.9 (133.6)	202.8 (137.9)
Per capita income (Tk./month)	963.6 (2068.1)	1,005.9 (1,483.9)	841.6 (787.2)	931.4 (1,487.7)
Current savings (Tk)	90.8 (726.1)	192.7 (2,645.1)	53.3 (657.4)	110.2 (1,620.8)
Per capita food expenditure (Tk./month)	654.7 (271.1)	656.3 (260.6)	638.5 (267.3)	649.1 (266.3)
Per capita total expenditure (Tk./month)	810.3 (371.9)	831.7 (426.3)	771.4 (360.0)	802.6 (387.2)
Moderate poverty	0.871 (0.335)	0.861 (0.346)	0.892 (0.310)	0.876 (0.330)
Food poverty	0.957 (0.204)	0.954 (0.210)	0.965 (0.184)	0.959 (0.198)
Extreme poverty	0.675 (0.469)	0.676 (0.468)	0.727 (0.446)	0.695 (0.460)
Year-round starvation	0.435 (0.496)	0.464 (0.499)	0.491 (0.500)	0.466 (0.499)
Year-round meal rationing	0.941 (0.235)	0.933 (0.250)	0.958 (0.201)	0.945 (0.228)
Seasonal outcomes				
Employment during <i>monga</i> period (days/month)	24.3 (16.0)	25.1 (16.6)	20.9 (14.8)	23.3 (15.9)
Employment during non- <i>monga</i> period (days/month)	27.1 (16.4)	27.6 (16.3)	23.5 (14.9)	25.9 (15.9)
Per capita food expenditure during <i>monga</i> (Tk./month)	510.2 (249.7)	516.1 (250.3)	498.3 (256.1)	507.6 (252.4)
Per capita food expenditure during non- <i>monga</i> (Tk./month)	702.9 (288.6)	703.1 (275.3)	685.3 (280.6)	696.3 (281.3)
Starvation during <i>monga</i>	0.428 (0.495)	0.453 (0.498)	0.483 (0.500)	0.457 (0.498)
Starvation or meal rationing during <i>monga</i>	0.938 (0.241)	0.924 (0.265)	0.954 (0.210)	0.940 (0.238)
Starvation during non- <i>monga</i>	0.022 (0.146)	0.019 (0.137)	0.022 (0.148)	0.021 (0.144)
Starvation or meal rationing during non- <i>monga</i>	0.733 (0.443)	0.739 (0.439)	0.820 (0.384)	0.768 (0.422)
Observations	1,520	1,717	1,970	5,207

Note: Figures in parentheses are standard deviations.

Source: InM survey 2009.

Two poverty measures (moderate and extreme poverty) are based on year-round consumption data in reference to the threshold poverty line. In contrast, the measure of food poverty is calculated using food consumption of the prior week of the interview period. The interview was conducted during the non-*monga* season of December-February. According to the estimates of 3 measures of poverty estimated for the ultra-poor households defined in terms of landholding, occupation, and seasonal income, more than 95 percent of the ultra-poor are food poor, more than 87 percent are moderately poor, and more than 69 percent are extreme poor. That is, the ultra-poor are likely to be food poor but need not to be extreme poor in terms of consumption-based poverty.

Three measures of poverty are objective measures of welfare based on actual consumption data with reference to the threshold consumption necessary to be above poverty line. In contrast, we have two measures of subjective measures of welfare defined in terms of the extent of occasional starvation (i.e., no meal at all in some days) or meal rationing (skipping a meal or two in some days) experienced by households. Starvation is an extreme form of food deprivation while meal rationing is an acute form of deprivation. Together they form a measure of food poverty experienced by the ultra-poor. We can compare and contrast the two measures of welfare in terms of food deprivation or food poverty.

As Table 3 shows, the year-round subjective measure of food deprivation (either starvation or meal rationing) is 94.5 percent for all households compared to 95.9 percent food poor among the same households. This suggests that the objective measure of food deprivation in terms of consuming less than 2,100 calories worth of food per day is equivalent to either skipping meal or starving in a day by the ultra-poor. This is to say households who are food poor are likely to starve or skip meal at some point of time either on a daily or weekly basis.¹⁰ That is, the ultra-poor defined in terms of landownership, occupation, or income, are also likely to be food poor in terms of subjective measure of food deprivation.

The ultra-poor are indeed similar in terms of observed characteristics (Table 4). Households have low level of education, and possess very small or negligible amount of landholding, and non-land assets. The average landholding is 15.9 decimals of land. Some 6.5 percent do have landholding exceeding 50 decimals of land, who have otherwise met the eligibility conditions by per capita income and selling labor for daily wage. We also find that participants of any type of micro-credit program are relatively more resource poor than non-participants, and that those who participated in traditional micro-credit program are relatively better off than non-participants or even PRIME participants.

Table 4: Summary statistics of household and community-level explanatory variables in cross-sectional sample

Variables	PRIME	MFI	Non-participants	Whole sample
Age of head (years)	41.6 (12.6)	41.5 (12.6)	43.3 (14.6)	42.2 (13.4)
Gender of head (1=M, 0=F)	0.88 (0.33)	0.92 (0.27)	0.86 (0.34)	0.89 (0.32)
Education of head (years)	1.33 (2.63)	1.52 (2.75)	1.33 (2.65)	1.39 (2.68)
Max. education of adult males (years)	1.84 (3.13)	2.13 (3.22)	1.70 (3.00)	1.88 (3.12)
Max. education of adult females (years)	1.57 (2.72)	1.99 (2.96)	1.64 (2.80)	1.74 (2.84)
Land (decimals)	14.6 (40.1)	14.5 (40.9)	18.0 (124.3)	15.9 (82.8)

¹⁰ Since actual consumption data is expensive to collect on a regular basis, one can adopt these subjective measures of food deprivation in surveys at low cost to monitor changes in welfare status following an intervention such as PRIME targeted to certain groups of population.

Seasonality and Hard-Core Poor with Microfinance

Variables	PRIME	MFI	Non-participants	Whole sample
Non-land asset (Tk.)	18,698.3 (19,15.9)	22,243.6 (25,713.7)	17,110.0 (26,797.6)	19,266.5 (24,559.9)
Village population	8,023 (16,785)	7,207 (13,012)	7,027 (13,005)	7,377 (14,218)
Village male wage (Tk./day)	91.9 (17.4)	93.4 (17.6)	94.0 (17.7)	93.2 (17.6)
Village female wage (Tk./day)	61.7 (73.6)	66.4 (92.7)	56.6 (52.5)	61.3 (74.0)
Village child wage (Tk./day)	43.0 (78.7)	49.3 (98.1)	37.6 (76.9)	43.0 (85.0)
Village has paved road	0.49 (0.50)	0.62 (0.49)	0.52 (0.50)	0.54 (0.50)
Village has primary schools	0.59 (0.49)	0.64 (0.48)	0.60 (0.49)	0.61 (0.49)
Village has secondary schools	0.30 (0.46)	0.35 (0.48)	0.29 (0.45)	0.31 (0.46)
Village has market	0.12 (0.32)	0.19 (0.40)	0.17 (0.38)	0.16 (0.37)
Village has electricity	0.70 (0.46)	0.76 (0.43)	0.70 (0.46)	0.72 (0.45)
Village has Grameen Bank	0.70 (0.46)	0.82 (0.38)	0.70 (0.46)	0.74 (0.44)
Village has other NGOs	0.99 (0.12)	0.99 (0.08)	0.95 (0.22)	0.97 (0.16)
Village has PRIME	1.00 (0.00)	0.83 (0.37)	0.71 (0.46)	0.83 (0.37)
Village has safety net programs	0.96 (0.19)	0.98 (0.15)	0.94 (0.24)	0.96 (0.20)
Village is in on a <i>char</i> land	0.24 (0.43)	0.18 (0.38)	0.30 (0.46)	0.24 (0.43)
Village has rivers	0.39 (0.49)	0.29 (0.45)	0.36 (0.48)	0.35 (0.48)
Proportion of highland in thana ¹	0.94 (0.08)	0.96 (0.05)	0.95 (0.07)	0.95 (0.07)
Rainfall in district (mm/year)	198.6 (6.5)	198.6 (7.1)	199.4 (8.2)	198.9 (7.4)
Observations	1,520	1,717	1,970	5,207

¹ Highland areas are either above flood-level or flooded up to 3 feet deep.

Note: Figures in parentheses are standard deviations.

Source: InM survey 2009.

Table 4 also shows the distribution of sample population by village infrastructures. It shows that PRIME serves villages that are less developed compared to villages that are served by traditional microfinance. For example, some 62 percent of traditional microfinance participants come from villages that have access to paved road compared to only 46 percent for participants of PRIME. Villages that have traditional microfinance program Grameen bank has also access to PRIME. Some 66 percent of PRIME participants come from villages that have also Grameen Bank. Some 83 percent of traditional microfinance participants come from villages that have also PRIME access. Most of the villages under study have a safety net program of one type or the other. More than 20 percent households included in this survey come from villages in *char* land. However, more than 95 percent of samples come from villages with highland, where high land is defined as the land above normal flood level.

Table 5: Household's food consumption pattern during *monga* by poverty status using cross-sectional sample (percentage)

Poverty status	Starvation	Starvation or meal rationing	Consumption of full meals
Moderate poor	48.1	95.3	4.7
Moderate non-poor	28.8	84.2	15.8
Extreme poor	51.8	96.9	3.1
Extreme non-poor	31.8	87.2	12.8
Food poor	46.6	95.5	5.5
Food non-poor	25.2	80.8	19.2
Food poor during <i>monga</i>	47.6	95.6	4.4
Food non-poor during <i>monga</i>	20.2	72.5	27.5
Food poor during non- <i>monga</i>	48.9	95.5	4.5
Food non-poor during non- <i>monga</i>	32.1	87.5	12.5

Source: InM survey 2009.

Table 5 presents the distribution of households by the subjective level of deprivation (i.e., starvation, meal rationing, and full meals) and the objective measure of deprivation (i.e., moderate, food, and extreme poverty). Some 48 percent of the moderate poor against 28.8 percent non-poor are subject to starvation, the extreme form of food deprivation. The incidence of starvation is highest among the extreme poor (51.8 percent) and lowest among the food non-poor (25.2 percent). The incidence of starvation among the food poor is not necessarily high during *monga* as compared to non-*monga* period. The extent of food deprivation (starvation or meal rationing) in both periods is much higher among the poor (moderate, extreme, or food poor) than among the non-poor. This also suggests that the subjective measure of deprivation well captures the objective measure of poverty or deprivation.

5. Does microfinance reach the ultra-poor and seasonal poor?

The ultra-poor do indeed participate in micro-credit programs. According to the InM survey of 2008/09, some 62 percent of the ultra-poor in the NW region of five districts did participate in microfinance program. Of these, 29 percent were participants of PRIME, and 33 percent were participants of regular microfinance. The growth rate of participation among the ultra-poor is, however, much lower (3.3 percent per year) for regular microfinance than for PRIME (11.2 percent per year).¹¹ This is shown in Figure 2.

The above figure also shows the participation rates of regular microfinance in areas with PRIME (MFI1 curve) and in areas without PRIME (MFI2). Participation in regular microfinance

¹¹ Some 6.1 percent of PRIME came from participants of regular microfinance (MFIs). On the other hand, among 33 percent of MFI participants, some 14 percent participated before 2006 and 19 percent participated after 2006 when PRIME was introduced.

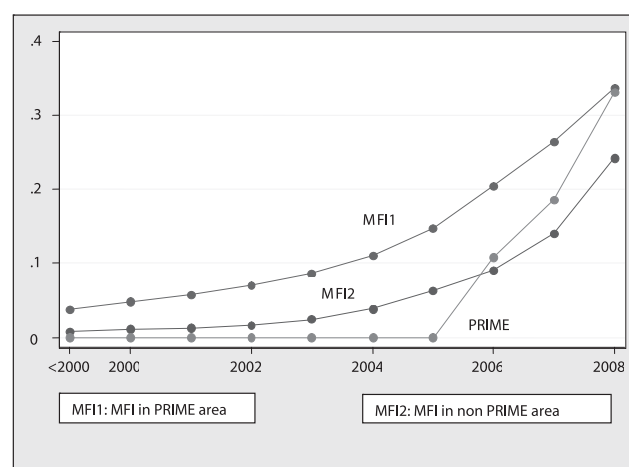


Figure 2: Cumulative program participation rate over years

gradually increases over time in both PRIME and non-PRIME areas but the participation in regular microfinance is higher in PRIME areas compared to non-PRIME areas. Figure 2 also shows that PRIME was introduced in areas with already higher rate of participation in regular microfinance among the ultra-poor. This is not surprising, given that PKSF's PRIME partner organizations (POs) are some of MFIs offering microfinance even before PRIME was introduced. As PKSF provides grants and loans at better rates for PRIME than for regular microfinance, the POs introduced PRIME first in areas of current operation. Higher participation rates of the ultra-poor with PRIME may also reflect higher demand for services of PRIME by the ultra-poor. The PRIME program is perhaps designed better to reach the ultra-poor.

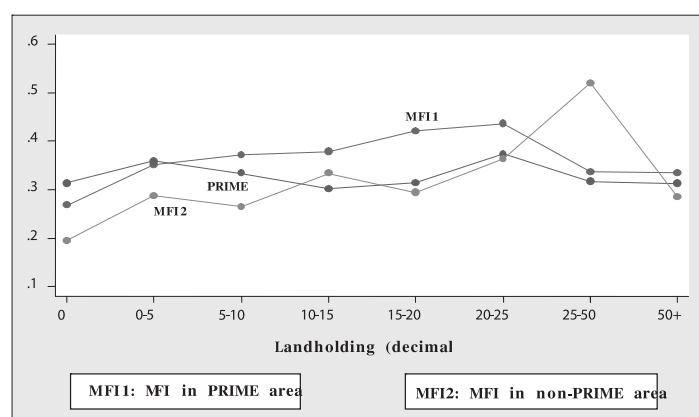


Figure 3: Program participation rate by landholding

Consider the participation of the ultra-poor by landholding in PRIME and regular microfinance (i.e., MFI) in both PRIME and non-PRIME areas. Figure 3 presents the distribution. As it is evident, the participation rate is slightly higher among the landless, holding less than 5 decimals of land, for PRIME than for MFI. Some 27 percent of the PRIME participants were completely landless (holding 0 decimals of land) as compared to 26 percent of MFI. But the participation rate among the ultra-poor, holding up to 25 decimals of land, is higher for MFIs in PRIME areas than non-PRIME areas. In both types of microfinance, only a small percentage of households from the landholding of more than 50 decimals, the official threshold for the eligibility

of most MFIs in Bangladesh, were found to participate in microfinance.¹² For PRIME, the eligibility criteria is defined not only in terms of landholding (less than 50 decimals of land) but also if any member selling labor for wage, or the household per month income less than Tk.1500 (or US \$25).

As Figure 4 shows, the bulk of microfinance participants indeed come from the landless group of having less than 50 decimals of land (over 93 percent of PRIME and MFI participants in PRIME area own less than 50 decimals of land). PRIME seems a well-targeted program that can reach the ultra-poor defined by landholding.¹³

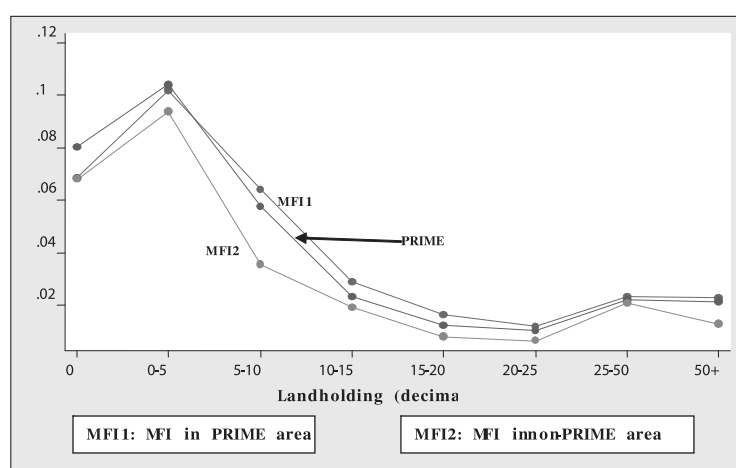


Figure 4: Distribution of total participants by landholding

Is PRIME also a well designed program to reach the seasonally poor who suffer from either occasional starvation or experience meal rationing during the lean season? Since the baseline information on seasonal food deprivation was collected before PRIME intervention was introduced, we are able to examine how households varied in their program participation by their food deprivation status. Figure 5 shows households' participation in PRIME and MFIs by meal consumption pattern during *monga* period. It is obvious from the figure that a household is twice more likely to join PRIME than MFIs regardless of its meal consumption pattern. This may have happened due to PRIME's focus on addressing households' immediate needs during the lean season.¹⁴

Given the distribution of three types of households in Table 2, we would like to determine the factors determining the choice of program participation in one of the 3 mutually exclusive categories (1= PRIME, 2=traditional microfinance, and 3=non-participants). This is done by fitting a maximum-likelihood multinomial logit (MNL) model. Formally, an MNL model expresses the

¹² Only 6 percent of the participants were from this group in both types of program.

¹³ We cannot say so for non-PRIME microfinance programs, since we have not full data on participation that may contain households not eligible based on landholding.

¹⁴ Households that were MFI members before PRIME intervention (about 15 percent of the panel households) are excluded from this figure to capture the behavior of new participants.

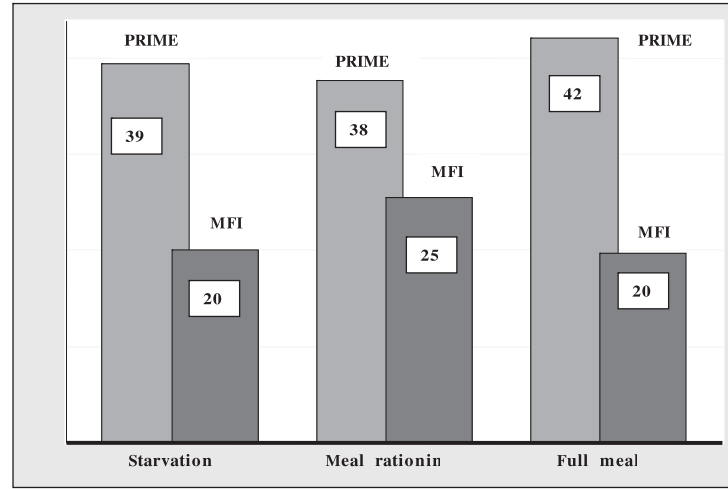


Figure 5: Program participation rate (%) by pre-intervention food consumption status

relative probability of observing a particular value k of outcome Y compared to observing a base value as:

$$\Pr(Y = k) = \frac{\exp\left(\sum_{i=0}^p x_i \beta_{ik}\right)}{\sum_{m=1}^r \exp\left(\sum_{i=0}^p x_i \beta_{im}\right)} \quad (7)$$

The objective is to find out what other factors (denoted by x) besides program availability help the ultra-poor decide to participate in one of the microfinance programs. The MNL results given in Table 6 suggest that the explanatory variables such as age and gender of household head, education, land and other asset holding do matter a lot in a household's choice in deciding to participate in one of the programs. Participants are relatively younger in both traditional and flexible microfinance. Education has in general a pronounced negative effect on the participation of traditional microfinance. However, educated males do participate more in traditional microfinance while educated females do not participate in PRIME. While land and non-land assets matter for participation in traditional micro-finance, it does not matter at all for PRIME participation. The participation rate in traditional microfinance is much lower in villages with higher population and villages with higher male wages, reflecting a negative effect of a large local economy. These factors do not matter at all for PRIME participation. This suggests that PRIME is much more pro-ultra-poor than the traditional microfinance.

Village-level infrastructure such as paved road and electrification influences positively a household's decision to participate in a microfinance program. However, better access to market reduces the probability of participation among the ultra-poor into PRIME perhaps because of availability of alternative employment opportunities. As expected, the presence of a microfinance program of any type in a village influences the decision to participate. For example, the probability of participation in traditional finance is 8.7 percent among the ultra-poor due to Grameen presence compared to 30.2 percent due to NGOs. However, some 36.0 percent of the ultra-poor do participate in PRIME due to a PRIME program intervention. Thus, PRIME does better in reaching the ultra-poor than traditional microfinance. However, Grameen bank seems to have a negative influence against PRIME participation. This is however not the case with the MFI-NGO program.

Agroclimate and location-specific factors influence returns to public and private investments. No wonder these factors do have an impact on the decision of the poor in joining a microfinance program. Better agroclimates such as higher rainfall or extent of highland reduces the probability of joining a microfinance program among the ultra-poor perhaps because of better alternatives available to ultra-poor. Similarly the probability of joining a microfinance especially traditional microfinance is much lower in villages in a *char*. Traditional microfinance programs are not thus represented well in *char* land.

6. Does microfinance tackle seasonality and hard-core poverty? Cross-sectional analysis

Microfinance in recent years incorporated features that are aimed at mitigating seasonality of income, employment, and consumption. Examples include introduction of seasonal loans in the traditional microfinance setup, or consumption loans in a flexible microfinance setting of PRIME. Given these new features of a program, we would expect that microfinance perhaps helps reduce seasonality of employment, expenditure and food consumption. By seasonality of program effects we mean the program effects on consumption, employment and income during the lean or non-lean season. On the other hand, given that the ultra-poor do participate proportionally more we would like to know if microfinance, especially PRIME, is able to reduce food and other forms of deprivation among the ultra-poor. This section uses cross-sectional methods to estimate the program impacts on household welfare.

The seasonal dimensions of poverty are measured by the seasonality of food deprivation (either starvation or meal rationing) or seasonality of food and non-food expenditure, or seasonality of employment. In contrast, the chronic or hard-core measure of welfare is measured by the year round average monthly employment days, average monthly expenditure and income, or year-round measures of food deprivation, moderate, extreme and food poverty.

With the cross-sectional data of 5,207, we have 3 types of ultra-poor households: PRIME participants, traditional microfinance participants, and non-participants. The program non-participants are divided into two categories: those who did not participate even if their villages have a program and those who did not participate because their villages did not have any (in particular PRIME). The so-called pipeline method may be used to estimate program effect which exploits the variation in timing of program implementation, using a comparison group eligible but has not yet received the treatment (e.g., Khandker et al., 2009). Thus, the control villages were the PRIME's target but did not receive any PRIME treatment by the time of the InM survey in 2008/09. We use a simple pipeline method to estimate the program effect of PRIME in the following manner:

$$ATT = [\sum_{i=1}^{N_T} (y_{ij}^T) - \sum_{i=1}^{N_C} y_{ij}^C] / \rho_T \quad (8)$$

where ATT , the average treatment effect of treated, is the differences of outcomes between program participants of treated village (T) and non-participants of control villages (C) adjusted by the program participation ratio (ρ) in treated villages. Note that equation (8) can be estimated by OLS where treatment dummy (T) is assumed exogenous as follows

$$y_{ij} = \alpha + \beta T_{ij} + \varepsilon_{ij} \quad (9)$$

This assumes that the households who participated and who did not participate are observationally equivalent (both household and village wise) except that one group is treated and the other group is not treated.

One obvious shortcoming of the pipeline method is that the timing of program placement is not necessarily exogenous but may depend on area characteristics.¹⁵ One way to resolve this non-random program placement or participation is to estimate the program effect using the propensity score matching (PSM) technique. The PSM method requires that PRIME participants match with "otherwise identical" non-participants, and quantifies any difference in outcome variables between these two groups. That is, this identification strategy relies on observable village-level and household level characteristics to match program participants with non-participants. This reduces potential bias due to the non-randomness of program placement and program participation that crop up in the pipeline method.

In essence with the PSM technique, we construct a statistical comparison group based on a model of the probability of participating in PRIME program. This helps estimate the probability score (p) of participation. Given the set of observable covariates, x , potential outcomes are independent of treatment assignment so that selection is solely based on observable characteristics and that all variables that influence treatment assignment and potential outcomes simultaneously are observed (e.g., Ravallion, 2006). We find then, for each participant, a sample of non-participants that have similar propensity scores.

The average treatment (ATT) of PRIME intervention on y can be obtained as:

$$ATT = \frac{\sum_{i=1}^{N_T} (y_{ij}^T - \sum_{j=1}^{N_C} W_{ij} y_{ij}^C) / N_T}{N_T} \quad (10)$$

where y_{ij}^T and y_{ij}^C are the outcomes for PRIME participants and non-participants, respectively, N_T is the number of PRIME participants, N_C is the number of matched control households, W_{ij} is the associated propensity score-based weight given to the control observations in matching with the participants. We will explore the robustness of these computations by using alternative weighting scheme (e.g., nearest-neighbor matching, kernel matching) to determine how many non-participant households to include in the control group and how to assign weights to each observation (For details of the procedure, see Khandker et al., 2009; Ravallion, 2006). An advantage of PSM method (4) over the OLS method (3) is that PSM reduces the number of dimensions on which to match participants and comparison units.

Alternatively, we can also use a weighted OLS method under the assumption of conditional exogeneity in the following way (Hirano et al., (2003):

$Y_{ij} = \alpha + \beta T_{ij} + \epsilon_{ij}$ with weight of $1/\sqrt{\hat{P}}$ for participants and $1/\sqrt{(1-\hat{P})}$ for the control observations, $\hat{P}$ is the estimated p-score, and, T_{ij} is the treatment indicator. This specification attempts to control for latent differences across treatment and comparison units that would affect selection into program as well as resulting outcomes.¹⁶ We call it p-score weighted regression method.

The PRIME impact estimates using these three alternative methods with cross-sectional data are presented in Table 7. The outcomes of interest are measured in two ways: year-round and seasonal. The naïve pipeline estimates using the OLS are much higher than those obtained using the two alternative methods using the PSM technique. But the estimates are similar for the two PSM

¹⁵ We have already found that PKSF's partners Introduced PRIME first in areas where they have already traditional microfinance programs. That means, PRIME placement is not randomly given.

¹⁶ Note that β estimates the average treatment effect of the treated (ATT).

methods. Note that the pipeline method compares outcomes between PRIME participants in PRIME program areas with non-participants from control areas. Hence, the sample size is much lower (1,974). In contrast, the PSM compares outcomes between participants with the matched non-participants from both PRIME and non-PRIME areas. The sample size is 3,388 for the p-score method and 3,490 for the p-score weighted regression.

Consider the p-score weighted OLS estimates of Table 7. We find that PRIME has a positive effect on almost all outcomes measured on an annual basis. PRIME increases employment hours, especially among females. It also raises per capita income, reducing seasonality of poverty as well as chronic (i.e., year-round) poverty. More specifically, PRIME participation reduces moderate poverty by 1.9 percentage points, extreme poverty by 4.8 percentage points, and year-round starvation by 3.4 percent points. It raises per capita income by 11 percent.

PRIME has also effects on seasonal outcomes. For example, during *monga* (or lean) period, PRIME increases monthly employment by 14.8 percent and reduces starvation by 3.4 percentage points. It also reduces food deprivation by 5.2 percentage points during non-*monga* period. The results clearly suggest that PRIME has contributed to reducing both seasonal and chronic poverty among the ultra-poor.

Are the PRIME effects different from those of traditional microfinance? If we believe that PRIME is a better program than the traditional microfinance, PRIME should have higher impacts than its counterpart. In order to estimate relative impacts of PRIME and MFI we extend the idea of using an outcome regression weighted by the inverse of participation probability (estimated propensity score) in the case of binary treatment to the case of ternary treatment comprising PRIME, MFI and control group. The probability of receiving PRIME or MFI treatment or neither treatment is estimated following the MNL estimates reported in Table 6. The outcome regression is then weighted as follows:

$$\begin{aligned}
 weight &= 1 / \sqrt{\hat{P}_{PRIME}} && \text{for PRIME participants,} \\
 &= 1 / \sqrt{\hat{P}_{MFI}} && \text{for MFI participants,} \\
 &= 1 / \sqrt{(1 - \hat{P}_{PRIME} - \hat{P}_{MFI})} && \text{for non-participants,}
 \end{aligned}$$

where, $\hat{P}_{PRIME}$ and $\hat{P}_{MFI}$ are estimated probability of participating in PRIME and MFIs respectively. Woolridge (1999) shows that weighting an outcome regression by the inverse of the sampling probabilities of program participation leads to appropriate estimators and efficiency gains that are better than what would have been possible by using population weights.

Table 6: Estimates of the determinants of program participation using multinomial logit model and cross-section data of 2008/09

Explanatory variables	PRIME	MFI
Age of head (years)	-0.0001 (-2.73)	-0.003 (-4.24)
Gender of head (1=M, 0=F)	-0.001 (-0.59)	0.079 (2.81)
Education of head (years)	-0.0003 (-0.88)	-0.013 (-2.39)
Max. education of adult males (years)	0.0003 (1.08)	0.011 (2.27)
Max. education of adult females (years)	-0.001 (-2.39)	0.001 (0.27)
Log land (decimals)	0.0001 (0.14)	0.012 (1.72)
Log non-land asset (Tk.)	0.001 (1.31)	0.067 (7.56)
Log village population	-0.0003 (-0.63)	-0.016 (-1.78)
Village male wage (Tk./day)	-0.00004 (-1.16)	-0.001 (-2.18)
Village female wage (Tk./day)	0.00002 (1.39)	0.0003 (1.61)
Village child wage (Tk./day)	-0.00001 (-1.38)	0.00003 (0.24)
Village has paved road	-0.0004 (-0.34)	0.072 (3.69)
Village has primary schools	-0.004 (-2.52)	0.006 (0.30)
Village has secondary schools	0.0003 (0.24)	0.020 (0.93)
Village has market	-0.006 (-3.07)	0.008 (0.31)
Village has electricity	0.004 (2.28)	0.036 (1.60)
Village has Grameen Bank	-0.005 (-2.32)	0.087 (3.76)
Village has other NGOs	0.005 (1.31)	0.302 (6.43)
Village has PRIME	0.360 (16.47)	-0.012 (-0.61)
Village has safety net programs	-0.0005 (-0.14)	0.068 (1.35)
Village is in on a <i>char</i> land	-0.002 (-1.29)	-0.128 (-5.94)
Village has rivers	0.0002 (0.16)	-0.022 (-1.01)
Proportion of highland in thana	-0.032 (-3.33)	0.225 (1.35)
Rainfall in district (mm/year)	0.0001 (0.80)	-0.004 (-3.40)
Log likelihood	-5076.11	
Observations	5,202	

Note: Excluded category is non-participation in any programs. PRIME includes micro-credit members who retained micro-credit membership even after joining micro-credit. Figures outside the parentheses are marginal impacts and those in parentheses are t-statistics.

Source: InM survey 2009.

Table 7: Estimates of PRIME impacts using alternative cross-sectional methods

Outcome variables	Pipeline estimates	Kernel matched	PSM estimates p-weighted regression estimates
Year-round outcomes			
Log male employment hours per month	0.164 (1.48)	0.156 (2.36)	0.176 (3.66)
Log female employment hours per month	1.055 (6.68)	0.554 (7.29)	0.576 (8.96)
Log total employment hours per month	0.294 (3.19)	0.203 (4.46)	0.212 (5.01)
Log per capita total income (Tk/month)	0.281 (4.59)	0.093 (3.23)	0.110 (4.04)
Log savings (Tk/month)	0.959 (7.64)	0.300 (5.57)	0.336 (6.68)
Log per capita food expenditure (Tk/month)	0.066 (2.37)	0.014 (1.10)	0.011 (0.96)
Log per capita total expenditure (Tk/month)	0.133 (4.54)	0.030 (2.18)	0.031 (2.48)
Moderate poverty	-0.060 (-2.35)	-0.018 (-1.52)	-0.019 (-1.80)
Food poverty	-0.036 (-2.37)	-0.007 (-1.02)	-0.008 (-1.39)
Extreme poverty	-0.087 (-2.41)	-0.046 (-2.81)	-0.048 (-2.95)
Year-round starvation	-0.049 (-2.81)	-0.039 (-2.17)	-0.034 (-1.88)
Year-round starvation and meal rationing	-0.064 (-2.57)	-0.005 (-0.70)	-0.006 (-1.33)
Seasonal outcomes			
Log employment days per month during <i>monga</i> period	0.189 (2.88)	0.130 (4.17)	0.148 (5.13)
Log employment days per month during non- <i>monga</i> period	0.244 (4.37)	0.137 (5.01)	0.152 (6.05)
Log per capita food expenditure during <i>monga</i> (Tk/month)	0.106 (3.14)	0.013 (0.86)	0.009 (0.65)
Per capita food expenditure during non- <i>monga</i> (Tk/month)	0.058 (2.10)	0.014 (1.12)	0.012 (1.01)
Starvation during <i>monga</i>	-0.059 (-1.81)	-0.038 (-2.12)	-0.034 (-1.85)
Starvation and meal rationing during <i>monga</i>	-0.052 (-1.87)	-0.005 (-0.60)	-0.006 (-1.20)
Starvation during non- <i>monga</i>	0.029 (0.56)	0.001 (0.25)	0.003 (0.68)
Starvation and meal rationing during non- <i>monga</i>	-0.153 (-4.43)	-0.046 (-3.06)	-0.052 (-3.75)
Observations	1,974	3,388	3,490

Note: Figures outside the parentheses are marginal impacts and those in parentheses are t-statistics.

Source: InM survey 2009.

Table 8: Estimates of alternate program effects (p-weighted regression method)

Outcome variables	PRIME	MFI	Wald test statistics for equality of PRIME and MFI coefficients
Year-round outcomes			
Log male employment hours per month	0.194 (3.92)	0.195 (4.19)	F(1,5180)=0.00, p>F=0.988
Log female employment hours per month	0.503 (7.57)	0.318 (5.10)	F(1,5180)=7.72, p>F=0.006
Log total employment hours per month	0.210 (4.94)	0.226 (5.64)	F(1,5180)=0.13, p>F=0.715
Log per capita total income (Tk/month)	0.103 (3.59)	0.085 (3.16)	F(1,5180)=0.38, p>F=0.538
Log savings (Tk/month)	0.236 (4.35)	0.142 (2.79)	F(1,5180)=2.99, p>F=0.084
Log per capita food expenditure (Tk/month)	-0.003 (-0.22)	-0.0005 (-0.04)	F(1,5180)=0.03, p>F=0.853
Log per capita total expenditure (Tk/month)	0.009 (0.66)	0.022 (1.79)	F(1,5180)=1.03, p>F=0.309
Moderate poverty	-0.009 (-0.76)	-0.011 (-0.99)	$\chi^2(1)=0.03$, p>F=0.853
Food poverty	-0.003 (-0.41)	-0.005 (-0.72)	$\chi^2(1)=0.08$, p>F=0.771
Extreme poverty	-0.031 (-1.81)	-0.023 (-1.38)	$\chi^2(1)=0.26$, p>F=0.611
Year-round starvation	-0.005 (-0.56)	0.004 (0.43)	$\chi^2(1)=1.04$, p>F=0.309
Year-round starvation or meal rationing	-0.003 (-0.26)	-0.002 (-0.18)	$\chi^2(1)=0.01$, p>F=0.924
Seasonal outcomes			
Log employment days per month during <i>monga</i> period	0.147 (5.10)	0.180 (6.64)	F(1,5180)=1.28, p>F=0.258
Log employment days per month during non- <i>monga</i> period	0.151 (6.07)	0.158 (6.77)	F(1,5180)=0.08, p>F=0.775
Log per capita food expenditure during <i>monga</i> (Tk/month)	-0.016 (-1.08)	-0.008 (-0.55)	F(1,5180)=0.32, p>F=0.572
Per capita food expenditure during non- <i>monga</i> (Tk/month)	0.0001 (0.01)	0.001 (0.10)	F(1,5180)=0.01, p>F=0.931
Starvation during <i>monga</i>	-0.007 (-0.64)	-0.0007 (-0.07)	$\chi^2(1)=0.38$, p>F=0.538
Starvation or meal rationing during <i>monga</i>	-0.005 (-0.34)	-0.010 (-0.77)	$\chi^2(1)=0.15$, p>F=0.695
Starvation during non- <i>monga</i>	-0.014 (-1.23)	-0.0001 (-0.01)	$\chi^2(1)=1.48$, p>F=0.224
Starvation or meal rationing during non- <i>monga</i>	-0.039 (-2.46)	-0.035 (-2.31)	$\chi^2(1)=0.06$, p>F=0.808
Observation	5,202		

Note: Regressions are OLS except for binomial variables (poverty and starvation variables) where a probit model is used. Figures outside the parentheses are marginal impacts and those in parentheses are t-statistics.

Source: InM survey 2009.

The relative impacts of traditional micro-credit and PRIME assessed this way are given in Table 8.¹⁷ The results tend to suggest that MFI is as good as the PRIME in mitigating both seasonal and year-round poverty and inducing other welfare indicators. For example, PRIME participation increases monthly employment hours by 21 percentage, compared to 23 percentage gain for traditional microfinance. Similarly, PRIME reduces food deprivation (either starvation or meal rationing) during non-*monga* period by 3.9 percentage points, which is slightly higher (3.5 percentage points) than the starvation reduction for traditional microfinance participants. The last column in Table 8 reports the Wald test statistics, which shows that statistically the difference between the impacts of alternate programs (i.e., PRIME versus MFI) is not significant for almost all outcomes.

7. Does microfinance tackle seasonality and hard-core poverty? Panel analysis

The cross-sectional estimates of program effects are potentially subject to bias due to violation of assumptions employed in these techniques. For example, the PSM method may not yield consistent estimates of program effects if unobserved characteristics of both villages and households also influence program participation, and consequently, outcomes. Thus, alternative methods are to be explored to check the validity of the cross-sectional findings.

One way to verify the results is with panel analysis. Panel data (i.e., repeated observations for sample households) can resolve the bias due to unobserved characteristics. Panel analysis also helps control common season-specific bias. For example, when we examine the incidence of starvation or meal rationing for a particular season, we may invariably introduce a common season effect such as seasonal preference that affects both program participation decision and consumption. It is also possible that there is a common seasonal shock that induces all households in an area to behave in a certain manner, independent of household unobserved heterogeneity that affects program participation. In other words, household consumption may be completely independent of seasonal variations and still strongly co-vary with lean season, simply because of common season-specific shocks. We need seasonal-specific household panel data for resolving both sources of bias (household/village level unobserved heterogeneity and common season effect).

InM has a pre-intervention baseline information for the target and non-target households for only the PRIME villages. Moreover, the data is limited in terms of variables of both explanatory and outcomes. Table 9 presents the summary statistics of outcomes measured seasonally between 2005 and 2008. Note that the baseline data was collected only in PRIME intervention areas in 2005 and the information collected was very limited. Also the welfare outcomes are rather qualitative than quantitative as no detailed consumption or income data was collected in the baseline. For example, we have only subjective measures of food deprivation by season. We see in Table 9 that household welfare measured in terms of food deprivation has improved over the years. For example, the rate of occasional starvation reduced from 50.1 percent in 2005 to 45.2 percent in 2008 during the lean season. The rate of occasional starvation during non-*monga* season also reduced from 9.3 percent in 2005 to 2.3 percent in 2008. Similarly, the year round starvation level declined over this period.

Fixed-effects (FE) or double difference (DD) method: As we have more than one year observation after the program intervention for the same season, we use a fixed-effects (FE)

¹⁷ The results of PRIME shown in Table 7 are slightly different from those given in Table 8. This is because Table 7 estimates are done based on simply probit regression of only participation in PRIME, while those of Table 8 are based on the MNL model of participation in either PRIME or traditional microfinance. To the extent that the participation equation errors are correlated, the estimates using MNL model and presented in Table 8 are more efficient than those of PRIME estimates as presented in Table 7.

method to estimate the program effect. With panel data available, we rewrite the outcome equation (5) as follows:

$$y_{ijst} = \alpha + x_{ijt}\beta + p_{ijt}\gamma + \mu_{ij} + \eta_j + \mu_s + \xi_{ijst} \quad (11),$$

Where t represents year and μ_s represents season-specific fixed effects. For two year period, if we take the difference of equation (11) from the 2nd to 1st period, we get rid of the unobserved time-in-varying household, village, and seasonal common fixed-effects. That is,

$$\Delta y_{ijs} = \Delta x_{ij}\beta + \Delta p_{ij}\gamma + \Delta \xi_{ijs} \quad (12),$$

We used a fixed-effects (FE) method to estimate (12) to estimate program effects on household outcomes.

However, the above model (12) assumes that the selection bias is time-invariant in which case the outcome changes for non-participants reveal the counterfactual outcome changes. So the difference between the two mean differences of participants and non-participants is the impact estimate. More formally, the simple FE or DD compares treatment and comparison groups in terms of outcome changes over time relative to the outcomes observed for a pre-intervention baseline. The FE allows for conditional dependence in the levels arising from additive time-invariant latent heterogeneity.

Double differenced PSM method: Household fixed-effects method of equation (12) may not produce consistent estimates if household-level unobservables are time-varying. For example, the initial conditions may be important enough to influence the outcomes later. So that the FE or DD estimator is a biased estimate, since the subsequent outcome changes are a function of initial conditions that also influenced the introduction of program intervention in the first place. In this case, the selection bias is not constant over time, a violation of the assumptions of the FE method. It follows that controlling for the initial heterogeneity is critical to the credibility of FE or DD method.

PSM is an obvious choice to clean this initial heterogeneity out prior to doing the differencing. If there is no observable heterogeneity in the differences (i.e., it has all been washed out by differencing) then there is no gain from matching on top of FE. Combining PSM for selecting the comparison group with FE can reduce (though probably not eliminate) the bias found in other evaluation methods, including single difference matching. Since PSM optimally balances observed covariates between the treatment and comparison groups, it is the obvious method for selecting the comparison group in panel data studies. Obviously, one requires pre-intervention baseline information for the participants and non-participants, which is fortunately available for the PKSF credit intervention program.

Under this DD-PSM technique, we apply essentially the method of difference-in-difference technique to propensity score matched (PSM) samples of treatment and control households. The sample estimate of the average impact can be written as:

$$ATT = \sum_{i=1}^{N_T} (y_{i1}^T - y_{i0}^T) - \sum_{j=1}^{N_C} W_{ij} (y_{j1}^C - y_{j0}^C) / N_T \quad (13)$$

where y_{ij}^T and y_{ij}^C are the outcomes for PRIME participants and non-participants, respectively, with before ($t=0$) and after ($t=1$) the program participation, N_T is the number of program participants, N_C is the number of control households, W_{ij} is the associated propensity score-based weight given to the control observations in matching with the participants. We will use particular weights to balance treatment and comparison units over time to reduce bias for time-varying unobserved errors that affect the changes in outcomes.

Table 9: Summary statistics of household-level outcome indicators in panel sample

Outcome variables (Meal consumption pattern)	2005	2008
Starvation during <i>monga</i>	0.501 (0.500)	0.452 (0.498)
Starvation or meal rationing during <i>monga</i>	0.962 (0.192)	0.937 (0.244)
Starvation during non- <i>monga</i>	0.093 (0.291)	0.023 (0.150)
Starvation or meal rationing during non- <i>monga</i>	0.599 (0.490)	0.755 (0.430)
Year-round starvation	0.527 (0.499)	0.462 (0.499)
Year-round starvation or meal rationing	0.963 (0.188)	0.941 (0.235)
Observations	4,517	4,517

Note: Figures in parentheses are standard deviations. Outcome variables in panel estimation consist of household's meal consumption variables only, since only those variables are available in both years.

Source: InM surveys 2006 and 2009.

Table 10: Estimates of PRIME impacts using HH FE method

Outcome variables (Meal consumption pattern)	Household Fixed-effects (FE)	Weighted FE with PSM
Starvation during <i>monga</i>	-0.055 (-2.24)	-0.054 (-2.18)
Starvation or meal rationing during <i>monga</i>	-0.017 (-1.44)	-0.014 (-1.26)
Starvation during non- <i>monga</i>	-0.030 (-2.44)	-0.028 (-2.29)
Starvation or meal rationing during non- <i>monga</i>	-0.068 (-3.07)	-0.071 (-3.20)
Year-round starvation	-0.067 (-2.75)	-0.066 (-2.68)
Year-round starvation or meal rationing	-0.016 (-1.44)	-0.013 (-1.26)
Number of households	2,991	2,991

Note: Figures in parentheses are t-statistics. Panel sample is constructed for households in program areas only because baseline survey was not conducted in non-program areas.

Source: InM surveys 2006 and 2009.

Alternatively, following Hirano, Imbens and Ridder (2003), a weighted least squares regression, by weighting the non-participants according to their propensity score, can yield a fully efficient estimator in the following regression:

$$\Delta y_{ijs} = \Delta x_{ij} \beta + \gamma T + \Delta \xi_{ijs} \quad (14),$$

where T is treatment status. The weights to be used in the above regression are 1 for treated households, $p/(1-p)$ and for control observations where is the estimated p-score using PSM method in the pre-program baseline data.

Table 11: Estimates of alternative program impacts (Weighted HH FE)

Outcome variables (Meal consumption pattern)	PRIME	MFI	Wald test statistics for equality of PRIME and MFI coefficients
Starvation during <i>monga</i>	-0.055 (-2.24)	0.039 (1.58)	$\chi^2(1)=11.19$, $p>F=0.0008$
Starvation or meal rationing during <i>monga</i>	-0.002 (-0.96)	-0.008 (-2.72)	$\chi^2(1)=2.10$, $p>F=0.147$
Starvation during non- <i>monga</i>	-0.009 (-0.81)	-0.005 (-0.47)	$\chi^2(1)=0.09$, $p>F=0.768$
Starvation or meal rationing during non- <i>monga</i>	-0.111 (-3.94)	-0.055 (-1.95)	$\chi^2(1)=3.27$, $p>F=0.071$
Year-round starvation	-0.072 (-2.92)	0.035 (1.51)	$\chi^2(1)=14.41$, $p>F=0.0001$
Year-round starvation or meal rationing	-0.002 (-1.06)	-0.004 (-2.55)	$\chi^2(1)=1.52$, $p>F=0.217$
Number of households	4,517		

Note: Figures in parentheses are t-statistics. Panel sample is constructed for households in program areas only because baseline survey was not conducted in non-program areas.

Source: InM surveys 2006 and 2009.

Does PRIME have a role in reducing food deprivation in the case of panel data analysis? Table 10 presents alternate estimates of PRIME effects, using two alternative methods: simple FE (or DD) using equation (12) and PSM-DD using equation (14). Estimates with PSM are slightly lower than that with simple FE method. That is, the estimates are slightly lower when we control for the initial conditions in the FE method. Nonetheless, the estimates clearly show that PRIME reduces food deprivation in both lean and non-lean seasons. Thus, PRIME reduces the incidence of either occasional starvation by 5.4 percentage points during the lean season and by 2.8 percentage points during the non-lean season. Consequently, PRIME reduces year-round starvation by 6.6 percentage points.

Does PRIME effect differ from that of regular microfinance? Table 11 presents the estimates of the relative impacts of PRIME and non-PRIME on a set of household welfare.¹⁸ The impact estimates measure the changes on household outcomes due to an intervention such as PRIME, given that regular microfinance is available. We find that the relative impacts of PRIME (shown in Table 8) differ slightly from those absolute effects of PRIME (shown in Table 7). Wald statistics also shows that impacts of PRIME and microfinance are significantly different for three (out of six) outcomes, unlike cross-sectional results reported in Table 8 which shows no significant difference between two impact types for most outcomes. Nonetheless, the results suggest that PRIME reduces seasonal starvation by 5.5 percentage points during the lean season, compared to 3.9 percentage points increase (statistically insignificant) by regular microfinance program. Similarly, PRIME has a larger effect (7.2 percentage points) than regular microcredit programs (3.5 percentage points increase which is again statistically insignificant) on mitigating year-round starvation. But regular microfinance has a definitely larger role in mitigating food deprivation (either starvation or meal rationing) than PRIME. Since the incidence of meal rationing is much higher than occasional starvation, we can infer that regular microfinance has a relatively larger effect in reducing meal rationing than occasional starvation.

¹⁸ This is done by implementing DD method by a p-weighted regression extending the idea demonstrated in equation (14), that is, assigning 1 as weight for participants in PRIME and MFIs, and inverse of the probability of non-participation as weight for nonparticipants.

8. Conclusions

Microfinance is criticized for not addressing adequately both seasonal and hard-core poverty in Bangladesh and elsewhere. In response to such criticism, MFIs have introduced innovations in program design to address both concerns. In Bangladesh, one such a program designed and implemented by PKSf since 2006 is the so-called PRIME initiative. The PRIME aims to target the ultra-poor of the NW region who are most vulnerable to seasonality of income, employment, and consumption. It is essentially a program that offers microfinance services at flexible terms. For example, PRIME provides consumption loans to deal with consumption seasonality, while regular MFIs offer seasonal loans for dealing with seasonality. PRIME also offers extension and training services to augment income and productivity of the ultra-poor. This paper made an attempt to evaluate PRIME relative to regular microfinance.

The results suggest that microfinance in general has reached a large percentage of the ultra-poor and seasonal poor in recent years. Some 62 percent of the ultra-poor are found to participate in microfinance. In contrast, 59 percent of the ultra-poor with occasional starvation, and 63 percent of the ultra-poor with meal rationing are beneficiaries of microfinance. The introduction of PRIME has only strengthened the ultra-poor's participation in microfinance. However, program placement and program participation are not randomly given but are determined by a host of factors including availability of a program.

Evaluating the program impact thus requires correction for the non-random placement/participation of a microfinance program. An experimental evaluation design was beyond the scope of the study. Therefore, a quasi-experimental method was adopted to estimate the program effects. The propensity score matching (PSM) method using cross-sectional data yields encouraging results for program participation. The household fixed-effects (FE) method relying on panel data yields results that either support or augment the cross-sectional results.

Both PRIME and MFI are found to reduce extreme poverty and seasonal deprivation. MFI reduces extreme poverty by 2.3 percentage points as compared to 3.1 percentage points under PRIME. PRIME reduces seasonal deprivation by 3.9 percentage points compared to 3.5 percentage points with regular microfinance. However, PRIME is found to reduce seasonal deprivation more than year-round poverty. In contrast, MFI affects chronic poverty more than seasonal poverty. Yet the impact estimates of alternative programs are not statistically significant in either cross-sectional or panel analysis.

Does it mean PRIME is just like a regular microfinance program? Note that, despite PRIME being a microfinance program, it appears to be more popular among the ultra-poor than a regular microfinance program perhaps because of its flexible design. This is evident by the fact that the program participation rate among the ultra-poor is much higher with PRIME than with MFIs in areas where both types of programs operate. As PRIME has been in operation since 2006, it is perhaps too early to say whether PRIME equals with regular microfinance in tackling poverty and seasonality. It is premature to suggest if PRIME is able to tackle both seasonality and chronic poverty simultaneously and succinctly.

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