WPS5331

Policy Research Working Paper 5331

Seasonal and Extreme Poverty in Bangladesh

Evaluating an Ultra-Poor Microfinance Project

Shahidur R. Khandker
M. A. Baqui Khalily
Hussain A. Samad

The World Bank
Development Research Group
Agriculture and Rural Development Team
June 2010

Abstract

Microfinance is often criticized for not adequately addressing seasonality and hard-core poverty. In Bangladesh, a program known as PRIME was introduced in 2006 to address both concerns. Unlike regular microfinance, PRIME introduces a microfinance scheme that offers a flexible repayment schedule and consumption smoothing, as well as production, loans. It targets the ultra-poor, many of whom are also seasonally poor, with a severe inability to smooth consumption during certain months of the year. Besides providing loans, PRIME offers extension and training services. This paper uses a quasi-experimental survey design to evaluate PRIME against regular microfinance programs. The results show that PRIME is more effective than regular microfinance in reaching the ultra-poor, as well as the seasonal poor. PRIME also helps reduce seasonal deprivation and extreme poverty. Although the program has demonstrated its promise, it is too early to conclude whether the accrued benefits are large enough to contain both seasonal and chronic poverty on a sustained basis.

This paper—a product of the Agriculture and Rural Development Team, Development Research Group—is part of a larger effort in the department to understand the role of micro-finance in agriculture growth and poverty reduction. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at skhandker@worldbank.org.

Seasonal and Extreme Poverty in Bangladesh: Evaluating an Ultra-Poor Microfinance Project[1]

Shahidur R. Khandker

M. A. Baqui Khalily

Hussain A. Samad

[1] The paper is based on a collaborative research project funded by the Institute of Microfinance (InM) and World Bank. We would like to thank Jashimuddin, Abdul Latif, Wahid Mahmud, Will Martin and Umar Serajuddin for helpful comments on an earlier draft of this paper. We also thank Norma Adams for editorial assistance. Views expressed in this paper are those of authors and do not reflect views of the World Bank or InM.

Seasonal and Extreme Poverty in Bangladesh: Evaluating an Ultra-Poor Microfinance Project

1. Introduction

Microfinance is part of a strategy to mitigate the moral hazard problems of lending by adopting innovative methods such as group-based lending.[2] It is also a strategy to reduce poverty by targeting the poor, who are often excluded by regular financial institutions because of a lack of sufficient physical collateral. In recent decades, microfinance has successfully reached a large percentage of the poor, especially women. Yet it has not reached as many ultra-poor as one would like to include among its clientele (Webb, Coates, and Houser 2002; Datta 2004).[3]

Bangladesh is a good example. Despite the country's overwhelmingly large proportion of ultra-poor, microfinance reaches not more than 20 percent (Khandker 1998, 2005). While a recent survey found coverage as high as 40 percent in certain areas of the country (InM 2009), service coverage of marginal and small farmers is small, with agriculture representing only about 10–15 percent of the microfinance lending portfolio. Also microfinance institutions (MFIs) have limited coverage in such areas as the northwest region

[2] Besides covariate risk, rural lending is subject to problems of asymmetric information, incentive to repay, and enforcing loan contracts (Stiglitz 1990).

[3] Although the terms *ultra-poor*, *extreme poor*, and *hard-core poor* are often used interchangeably, for targeting purposes, MFIs specifically designate the ultra-poor based on landholdings, income, and employment as defined in section 2 of this paper.

of Bangladesh, which is characterized by pronounced seasonality of agriculture and higher incidence of extreme poverty compared to other areas of the country (Khandker 2009).[4,5]

Microfinance does not usually provide agricultural lending in Bangladesh. Rather, the poor access microcredit to initiate income-earning activities in rural non-farm sectors. A major reason for microcredit program participation is to help facilitate consumption smoothing. Households unable to smooth consumption due to income seasonality are more likely to participate in microcredit programs, which promote income-earning activities in rural non-farm sectors that are less vulnerable to seasonality; in this way, borrowers are helped to smooth consumption and thus reduce vulnerability to consumption (Pitt and Khandker 2002; Zaman 1999, 2004). Moreover, if gains from microfinance are not large, it is shown that microcredit can reduce extreme poverty more than moderate poverty (Khandker 2005).

The question then arises: Why do we see a small share of the microfinance portfolio in such areas as the northwest region, which features pronounced income seasonality? Why does a small percentage of the ultra-poor participate in microfinance? Does income seasonality reinforce extreme poverty and, as a result, the limited coverage of microfinance in the northwest region? Does it mean a microfinance program different from what is currently available is needed to handle both income seasonality and hard-core poverty?

In recent years, with donor assistance and under government pressure, some MFIs in Bangladesh have introduced a variety of programs to better handle seasonality and hard-core poverty. In 2002, BRAC, Bangladesh's leading nongovernmental organization (NGO),

---

[4] The northwest region of Bangladesh consists of five districts in greater Rangpur: Rangpur Sadar, Gaibandha, Nilphamari, Lalmonirhat, and Kurigarm. The terms *northwest region* and *greater Rangpur region* are used interchangeably throughout this paper.

[5] In 2005, only 12 percent of villages in the northwest region of Bangladesh had a Grameen Bank, compared to 34 percent in other regions of the country. It should be noted that the northwest region is the worst hit in terms of the negative consequences of extreme seasonality of agriculture.

launched a multidimensional microcredit program targeting the ultra-poor (Matin and Hulme 2003; Emran, Robano, and Smith 2009).[6] The BRAC ultra-poor program emphasizes both human and physical capital development via transferring assets and other means, such as skills-based training before the ultra-poor graduate to become members of its regular microfinance program. Similar ultra-poor programs introduced by Grameen Bank target the ultra-poor, such as beggars. Many MFIs, including Grameen Bank, have introduced seasonal loans as part of their regular microfinance programs to address seasonality of income.

Addressing hard-core poverty or pronounced seasonality of income is a formidable task for any institution, let alone a microfinance or financial institution. When poverty is already rampant, pronounced seasonality of income and consumption only makes it worse. Therefore, tackling both seasonality and poverty with a single intervention, such as microfinance, is a major challenge for policy makers (Khandker 2009).

In 2006, the Program Initiatives for *Monga* Eradication (PRIME) was introduced by the Palli Karma Shahayak Foundation (PKSF), the country's premier wholesale MFI.[7] PRIME's objective is to deal exclusively with the hard-core poor, who are highly vulnerable to seasonal poverty, especially in the northwest region. PRIME offers the ultra-poor microcredit and other services on flexible terms.

Extreme poverty is caused by unfavorable agroclimatic conditions and low levels of physical and human capital. Seasonal poverty is caused when households cannot smooth consumption across seasons because regular income is received only in certain seasons. Lack of consumption smoothing is more pronounced for the poor than for the rich. A large body of literature shows that the observed seasonality in consumption is driven mainly by the seasonal variation in income and lack of access to credit impedes consumption

[6] Evaluations of such programs indicate that BRAC's ultra-poor program has desirable impacts on the poor.
[7] The term *monga* means seasonal food deprivation.

smoothing, often among the poor (Rosenzweig 1988; Rosenzweig and Wolpin 1993; Chaudhuri and Paxson 2002; Paxson 1993). However, if the risk is idiosyncratic (i.e., specific to certain households), then local risk pooling or insurance is feasible, which becomes limited in the event of an aggregate shock (Townsend 1995). Better access to finance is a useful approach for better allocation of resources (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 a lack of access to credit. Introducing a microfinance program targeted to the hard-core poor with a program designed to tackle pronounced income seasonality is thus expected to make a dent in reducing seasonal and chronic poverty. The key research question is whether such a program as PRIME can achieve both aims.

The objective of this paper is to evaluate PRIME in terms of its effectiveness in reaching the ultra-poor and reducing seasonal and extreme poverty. Specifically, the paper (i) evaluates the extent to which PRIME's flexible microfinance program has been effective in reaching the ultra-poor and seasonally poor, (ii) quantifies program benefits in terms of mitigating extreme and seasonal poverty, and (iii) assesses the relative effectiveness of PRIME and regular microfinance in reducing extreme and seasonal poverty.

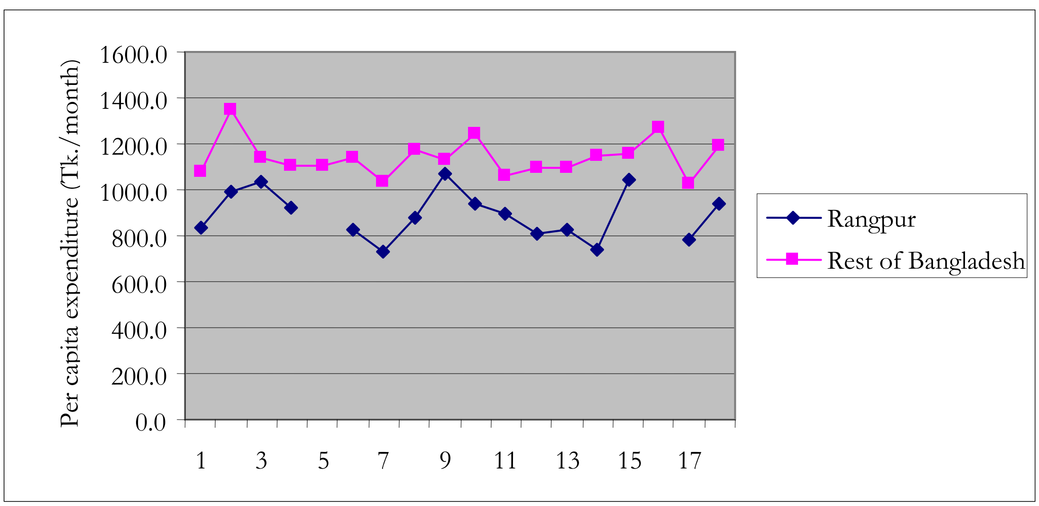
Section 2 discusses the poverty and seasonality of the northwest region vis-à-vis other regions and the rationale for the PRIME intervention. Section 3 presents an economic framework that lays out the role of credit in resolving income seasonality and extreme poverty. This section also discusses an empirical framework to estimate the effects of a credit intervention. Section 4 discusses the data, which are drawn from a random household survey carried out in program and non-program villages. Both cross-sectional 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 is essential to evaluate it against regular microfinance. Section 5 presents the data in terms of the ultra-poor's participation in PRIME vis-à-vis regular microfinance and analyzes the factors responsible for the participation of the ultra-poor in one of the programs. Section 6 reviews the methods and results and program effects on household welfare using cross-sectional data. Section 7 then discusses the methods and results using panel data. Section 8 provides a summary and policy conclusion.

2. Tackling Seasonal and Extreme Poverty in the Northwest with PRIME

The first goal outlined in the United Nations Millennium Development Goals (MDGs) focuses on reducing poverty and hunger. The World Bank has vigorously promoted all member countries to attain this goal. The Government of Bangladesh has undertaken various steps toward achieving the MDGs and had 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, roughly equivalent to a 1-percent poverty reduction per year (United Nations 2005). Results of the 2005 Household Income and Expenditure Survey (HIES) 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 2000–05 periods, the rate of poverty reduction was about 2 percent per year.

Bangladesh's impressive performance in poverty reduction, however, is not uniform across the country; although overall poverty has declined, the incidence of poverty is much higher in lagging regions (greater Rangpur). For example, HIES findings suggest that, while the rural poverty-headcount rate nationwide was 43.8 percent in 2005, the greater Rangpur (northwest) region had a rural poverty rate of 57.4 percent (Table 1). Incidence of extreme poverty was also much higher in the northwest (43 percent) than the nationwide rural average (28.6 percent).

Figure 1, which shows per capita monthly consumption at 18 points during the year (spaced at 20-day intervals), suggests that (i) household consumption per capita is much lower in the northwest than in other regions year round and (ii) seasonal fluctuation in expenditures is greater in the northwest than in the rest of the country (Khandker 2009). The northwest region also experiences a sharp shortfall in food consumption during certain months of the year, which produces cyclical food insecurity.



Source: HIES survey, 2005.

Figure 1: Distribution of per capita expenditure

Seasonal deprivation of food, locally known as *monga*, occurs from mid-September to mid-November, corresponding to the post-planting to pre-harvesting period of *Aman* rice. This is the lean period for both consumption and labor demand, with few opportunities to employ the poor in agriculture. *Monga* does not imply a lack of availability of food but rather the lack of access and utilization of food (WFP 2005). Lack of access to food is due to a lack of income, along with higher prices for basic foods, which often occurs during *monga*. Lack of income is essentially due to lack of employment during the pre-harvest season. Seasonal deprivation 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).[8]

Monga is most pronounced in greater Rangpur, owing to this northwest region's ecological and economic vulnerability (Rahman 1995). *Monga* affects those rural poor who have an undiversified income that directly or indirectly depends on agriculture (Zug 2006). Women and children are affected disproportionately due to intra-household inequity in resource allocation.

Those who suffer from seasonal deprivation are mostly the hard-core poor, who have few assets and scarce savings with which to smooth consumption during the lean period. Because they lack access to credit markets, they are unable to borrow against future income. Without well-functioning credit markets, households frequently attempt to smooth consumption during *monga* by drawing on informal credit-market arrangements, known locally as *dadan*. Under these arrangements, laborers sell labor or farmers sell crops in advance on terms that are often severe. Households also employ traditional self-insurance methods of coping, such as use of buffer stock (livestock and grain storage), and mutual

[8] Bangladesh's agriculture sector is characterized by three crop seasons (based on three types of rice): *Aus*, *Aman*, and *Boro*. While these three crops cover the entire year, there is virtually no economic activity during the *monga* period, with no alternate agricultural activity. The non-farm sector is not large enough to hire the unemployed, who are mostly agricultural laborers and small farmers.

insurance, such as inter-family transfers. But for many households these traditional methods of smoothing consumption are inadequate and inefficient.

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 and idiosyncratic across households, these interventions may help mitigate *monga*. However, *monga* is widespread and results from structural poverty caused by low income, low productivity, and lack of diversification of local economies. Thus, interventions not geared toward enhancing income and productivity are of little help in containing *monga* on a sustainable basis.

Group-based lending as practiced by government and nongovernmental institutions appears to have limited scope in mitigating *monga* on a sustainable basis for various reasons. First, microfinance has not reached the ultra-poor, who are 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, activities generating seasonality of income often limit the ability of microcredit 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. Thus, microfinance is not well suited to address either hard-core poverty or seasonality of poverty. It is little wonder that microfinance has only recently extended its reach in the northwest region.

In 2006, the PKSF and its partners introduced PRIME to address seasonal deprivation and ultra-poverty in the northwest region. As mentioned above, PRIME offers a flexible microfinance program that includes both production and consumption loans and specifically targets the ultra-poor. Unlike regular microfinance, PRIME has a flexible repayment schedule, a production loan can be used for consumption if needed, the interest rate is not more than 10 percent (compared to 20 percent for regular microfinance), and no fixed savings or weekly meetings are stipulated. In addition to flexible microfinance, PRIME offers year-round services to support income-generating activities, skills-based training, remittances, and primary health care (InM 2009). During the *monga* season, PRIME also provides emergency loans for consumption smoothing and cash for work related to local infrastructure development. However, PRIME does not offer consumption credit without either subsequent or prior production credit.

The target beneficiaries of PRIME are the ultra-poor, 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 Tk1,500 (equivalent to US$25) and (iii) one household member is a daily wage worker. The pre-program intervention data collected by the PKSF in 2006 reveals that, in listing the households for PRIME intervention, eligibility conditions are strictly enforced. PRIME is worthy of a rigorous impact evaluation, which must determine whether the intervention is effective in reaching the hard-core poor, as well as mitigating both seasonal and hard-core poverty.

Important to the identification of appropriate policies is an understanding of the extent of the 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 evaluation of PRIME must examine whether the provision of credit, along with other non-financial services, is capable of addressing both the human and physical capital needs of the ultra-poor for mitigating seasonal and hard-core poverty in a sustainable way.

3. Role of Credit in Seasonal and Hard-core Poverty: An Analytical Framework

<u>Theory</u>

We follow a 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.

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

where

c_i = a single aggregate consumption good and

β = the time discount rate.

This is maximized subject to the following dynamic asset constraint:

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

where

y_{it} = labor income that is risky,

A_{it} = real assets, and

r = real interest rate (assumed fixed over time).

If t is large enough and $A_{it+1} = 0$, from the Euler equations, the standard permanent income result of the marginal utility of current consumption is then equal to the discounted expected marginal utility of future consumption; that is,

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

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

$$A_{it} \geq 0 \tag{4}$$

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 that the utility function is quadratic and the rate of time preference equal to the interest rate, then, in the absence of a binding credit constraint, there would be perfect consumption smoothing; that is, $c_{it} = c_{it+1}$. When the credit constraint is binding, $c_{it} < c_{it+1}$.

Figure 2 illustrates the consequences of a binding credit constraint in a two-period decision model, with period 0 representing the lean season and period 1 the harvest season. In the absence of a credit constraint, a household would maximize its inter-temporal utility by consuming at e_0. With the binding credit constraint, the household would face a discontinuous budget line, such as $q_0e_1c_1$; it would then be forced to consume at e_1, with a lower lean-period consumption ($c_1 < c_0$) and would be at a lower welfare curve than before. Even if the period 1 (harvest season) income were to rise, it would have no impact on period 0 (lean season) consumption.

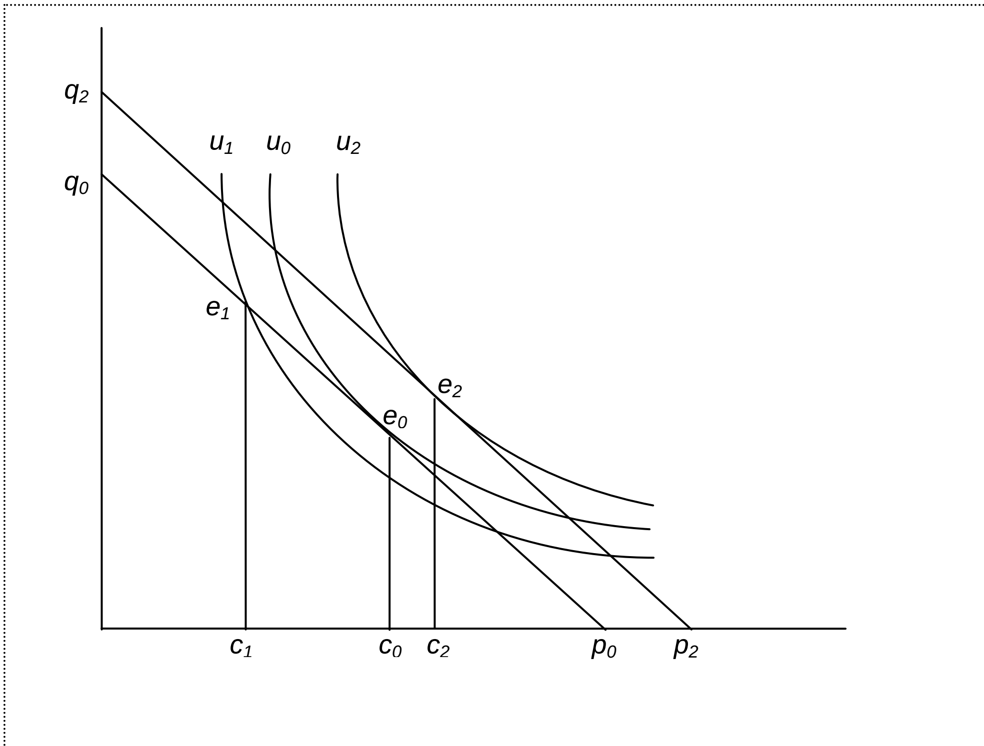


Figure 2: Lean- and harvest-period consumption with a credit constraint

Moreover, if the consumption point represented by e_0 implies the minimum bundle of goods households ought to consume to stay above the extreme poverty line, one can argue that having no access to credit to smooth consumption would force households to consume much less than what is needed to maintain the threshold point. Therefore, without access to credit, households would likely fall into both seasonal and extreme poverty. Conversely, improved access to credit helps households to both smooth consumption and approach or move above the extreme poverty line. More importantly, improved access to credit can shift the budget curve upward, thus helping households move above the poverty line (i.e., above consumption point e_1). If this happens, one can argue that access to credit helps not only to smooth consumption but also reduce poverty. For example, a shift of the budget curve to q_2p_2 yields a consumption level denoted by e_2, meaning a higher level of welfare that lifts households out of extreme, as well as seasonal, poverty.

The central hypothesis of this seasonal consumption model is that improving access to credit enhances seasonal income and the lean-period consumption level to help a household smooth consumption during lean period. Moreover, if the credit impact is large, it would have also a positive effect on the non-lean period. Thus, if households were credit constrained, such interventions as 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 periods. The policy question is whether the credit provision of a project such as PRIME—in contrast to a regular microfinance program, which also aims to enhance the income and consumption of poor borrowers—can effectively shift the budget curve upward so that ultra-poor households smooth consumption and allocate their resources more efficiently to reach higher consumption goals.

<u>Model specification and estimation strategy</u>

We assume that the status of household consumption for a particular season (*s*) can be represented by the following regression:

$$y_{ijs} = \alpha + x_{ij}\beta + p_{ij}\gamma + \mu_{ij} + \eta_j + \xi_{ijs} \tag{5}$$

where

y_{ijs} = consumption status of household i living in village j in season s,

x = a vector of household and community characteristics,

p = status of credit program participation, and

a, β, and γ = unknown parameters to be estimated.

The outcomes observed for a cross-section of households can be observed for two major groups in a given season: (i) otherwise non-poor households that have a lower consumption level due to a binding credit constraint in the lean period and (ii) otherwise poor households that have an even lower consumption level due to a binding credit constraint in the lean period. When evaluating a program that 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, as equation (6) shows, is determined by a number of factors, including the variables in equation (5):

$$p_{ij} = \alpha^{p} + x_{ij}\beta^{p} + \mu_{ij}^{p} + \eta_{j}^{p} + \xi_{ij}^{p} \qquad (6)$$

The errors between equations (5) and (6) are likely to be correlated. At least three types of errors may affect the outcomes of interest (e.g., consumption status in a given season or program participation for a cross-section of households interviewed): (i) unobserved household characteristics (μ), (ii) unobserved village characteristics (η), and (iii) idiosyncratic errors (ξ) randomly distributed with zero mean and unit variance.

The errors are correlated for several reasons. First, there may be unobserved village hetereogeneity (η)—such characteristics as remoteness, infrastructure, and attitudes—which affects both participation (i.e., the amounts borrowed by households) and its effect on outcome variables. Second, there may be unobserved household or individual heterogeneity (μ))—such unmeasured characteristics as entrepreneurial drive, preferences, and health status—which also affects participation and its effect. Third, there may be endogenous program placement. That is, a program such as PRIME does not select villages randomly for program placement; rather, such factors as extent of seasonal famine or river erosion determine the decision to place PRIME in a particular village. These attributes that influence program placement, measured by η, may also contribute to lower levels of household consumption.

The correlated errors of equations (5) and (6) do not arise if a 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 participants and non-participants is a measure of program effect.[9] In contrast, when a non-randomized evaluation method is adopted, it is important to account for these correlations or endogeneity in program assessment; otherwise, the results will be biased. There are alternative non-experimental methods that may be relevant to assess program effects. Using a particular method in a program evaluation would ultimately depend on available data and its characteristics (e.g., whether the data is drawn from a cross-sectional or panel survey (Ravallion 2006; Khandker, Koolwal, and Samad 2009). Although randomization is beyond the scope of this study, we use non-experimental design based on both cross-sectional and panel surveys to estimate the effects of PRIME vis-à-vis regular microfinance on seasonality of income and consumption, as well as hunger and poverty.

4. Survey Data and Its Characteristics

The available data to evaluate PRIME comes from a survey conducted by the Institute of Microfinance (InM). PKSF carried out a pre-intervention data-collection survey to identify its target group for PRIME. Along with its partner organizations (POs), PKSF conducted a village census that listed households to determine which were ultra-poor and which were also vulnerable to seasonal food deprivation. The ultra-poor were then selected based on the previously mentioned criteria.[10] After identifying the ultra-poor target households of PRIME using these criteria and focus group meetings, a small survey questionnaire was administered by the PKSF and its POs with the help of the InM (who designed the survey

[9] The PKSF has not allowed the InM to do a random design of PRIME program evaluation.

[10] This is the overriding eligibility condition of regular microfinance as practiced in Bangladesh. The ultra-poor, who have much less than 50 decimals of land, also belong to this target group; however, given the program design, which includes maintaining a weekly repayment schedule and attending weekly meetings, the ultra-poor often find it difficult to participate in regular microfinance programs.

and trained PO staff in how to collect information) prior to program intervention. The data set may be considered as a baseline for any evaluation of PRIME intervention. This baseline survey was conducted in December 2006 immediately following the lean season. The baseline data was analyzed for various research topics, such as vulnerability, coping, and seasonal migration (Khandker, Khalily, and Samad 2009).

The *monga*-vulnerable, ultra-poor households were offered the PRIME program through 235 PRIME branches in 5 districts of the northwest region.[11] The intervention was first implemented in Lalmonirhat district in 2006 and in the other 4 districts (Rangpur, Kurigram, Gaibandha, and Nilphamari) the following year. PRIME beneficiaries meet in small groups of 25–30 each at a mutually agreed time and place. However, unlike regular microfinance, PRIME groups may save any amount of money and are qualified for a loan against any amount of savings. PRIME groups receive loans and other benefits for both year-round and specific lean-period activities, such as consumption-smoothing loans. Year-round activities include a flexible microcredit program that allows loans for production and consumption, with a repayment schedule convenient for borrowers. PRIME also offers extension services for income-generating activities, training, primary health care, and remittance services.

Between December 2008 and February 2009 a detailed survey was administered by InM that sampled target households to assess the impact of PRIME. 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 from the total area that received the intervention. Interestingly, not all selected households eligible for the PRIME intervention were

---

[11] Greater Rangpur's 5 districts include 34 upazilas (subdistricts). In its first phase, the PRIME intervention targets 23 upazilas (covering 482,948 households), 209 unions, and 2,531 villages (InM 2009). A second phase, beginning in early 2010, covers the remaining 11 upazilas.

participating at the time of the second interview (two years after program intervention began). Moreover, some randomly sampled households from PRIME catchment villages participated in regular microfinance.

In addition to this sample survey of households, the InM carried out a similar survey in areas of 3 districts that were targeted for the PRIME intervention by 2010, but had not received it by 2008–09. Out of 11 upazilas in 3 districts, 4 were selected as control upazilas. Out of 40 villages in these 4 upazilas not yet covered under PRIME, 27 were selected from which 618 PRIME-eligible households were randomly drawn based on the village census. Thus, the total sample of households selected for the study was 5,207, of which 1,520 participated in PRIME, 1,718 participated in regular 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 in the greater Rangpur region. The sample distribution was further disaggregated by PRIME and non-PRIME areas. Three groups were identified by program participation status: PRIME-only, regular microfinance only and non-participants (in PRIME, non-PRIME, or control villages).[12] In all areas, 33 percent of target households were regular microcredit program participants, 29.2 percent PRIME participants, and 37.8 percent non-participants.

In PRIME areas, the shares of PRIME participants, regular microfinance participants, and non-participants were 33.2, 33.8 and 33.0 respectively. In non-PRIME villages, 26.5 percent of the ultra-poor participated in regular microfinance programs while 73.5 percent were non-participants.

[12] Although non-participants may include non-eligible households from PRIME or control villages, they were not sampled in these surveys.

Although Lalmonirhat district received PRIME treatment the earliest, Kurigram district had the highest percentage of PRIME participants, followed by Nilphamari, Lalmonirhat, Rangpur, and Gaibandha (Table 2). Interestingly, Lalmonirhat has high participation in regular microfinance programs (36.9 percent), second only to Gaibandha.

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 the 2008–09 survey of 5,207 households. Of particular importance are the poverty and seasonal deprivation measures. Three measures of poverty are calculated and presented in Table 3: moderate poverty, food poverty, and extreme poverty.[13] The two poverty measures (moderate and extreme poverty) are calculated using the year-round consumption data. In contrast, the measure of food poverty is calculated using food consumption during the week preceding the interview, which occurred during the non-*monga* season (December–February). The extent of poverty of all three dimensions is about the same for all three household categories. For example, the share of moderate poverty is 86.1 percent among the regular microfinance participants, compared to 87.1 percent among PRIME participants and 89.2 percent among non-participants. By contrast, among regular microcredit programs, 67.6 percent are extremely poor, compared to 67.5 percent among PRIME participants and 72.7 percent among non-participants; that is, among the targeted

[13] Poverty measures indicate the proportion (or percentage) of households in a sample or population that cannot meet certain predefined welfare requirements called poverty lines. The food poverty line is based on a food basket needed to maintain the per-capita daily caloric requirement (2,120 calories) recommended by the UN Food and Agriculture Organization (FAO) and the World Health Organization (WHO) (FAO and WHO 1973). For rural Bangladesh, the food basket includes mostly rice and other food items including pulses, milk, meat, fish, fruits, and vegetables in specific quantities. The cost of such a food basket (food poverty line) is calculated using local food prices. The non-food poverty line is estimated as 30 percent of the food poverty line. Together, these two poverty lines constitute the moderate poverty line. Thus, moderate poverty and food poverty are defined by the proportions of households whose total and food expenditures cannot meet the respective poverty lines, while extreme poverty is the dire situation that results when a household's total expenditure cannot even meet the food poverty line.

ultra-poor, participants in both regular and PRIME microcredit programs are slightly better off than non-participants.

Among the ultra-poor households, about 85 percent are food poor, 88 percent are moderately poor, and 70 percent are extremely poor. This means that some ultra-poor households have food poverty, but are not extremely poor.

The three measures of poverty just discussed are objective measures of welfare based on actual consumption data. We have also constructed two subjective measures of welfare based on the extent of reported occasional starvation (i.e., no meal in some days) or meal rationing (skipping a meal or two some days) by households. Starvation is an extreme form of food deprivation, while meal rationing is a more moderate type of deprivation

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 85.4 percent food poverty among the same households. Although the objective measure of food deprivation indicates less hardship than the subjective measure, it is not inconsistent as the objective measure has been constructed using food intake during the post-*monga* harvest period while the subjective measure refers to food consumption during both the *monga* and non-*monga* periods. But the high correlation between the two measures suggests that most households who are food poor are likely to starve or skip meals at certain times, either on a daily or weekly basis.[14] That is, the majority of the ultra-poor are likely to be food poor any time of the year.

The ultra-poor are also similar in terms of observed characteristics (Table 4). Households have a low level of education and have small or negligible amounts of

[14] Since actual consumption data is expensive to collect on a regular basis, one can collect these subjective measures of food deprivation at low cost to monitor changes in welfare status following an intervention, such as PRIME.

landholdings and non-land assets. Their average landholding is 15.9 decimals. Only 6.5 percent who meet the eligibility conditions by income or wage employment have landholdings exceeding 50 decimals. We also find that PRIME participants are more resource poor than non-participants and those who participate in regular microcredit programs are better off than PRIME participants and non-participants.

Table 4 also shows the sample population distribution by village infrastructure. It shows that PRIME programs serve villages that are less developed, compared to those served by the regular microfinance programs. For example, some 62 percent of participants in regular microfinance programs come from villages that have access to paved roads, compared to only 46 percent of PRIME participants, who are from similar villages. Seventy percent of PRIME participants come from villages that have the Grameen Bank. On the other hand, 83 percent of regular microfinance participants come from villages that also have PRIME access. Most of the villages under study have some type of safety net program. More than 20 percent of households included in the survey come from villages located on tiny island fragments, known as *chars*.[15] However, 95 percent of the sampled households come from villages in the highlands.[16]

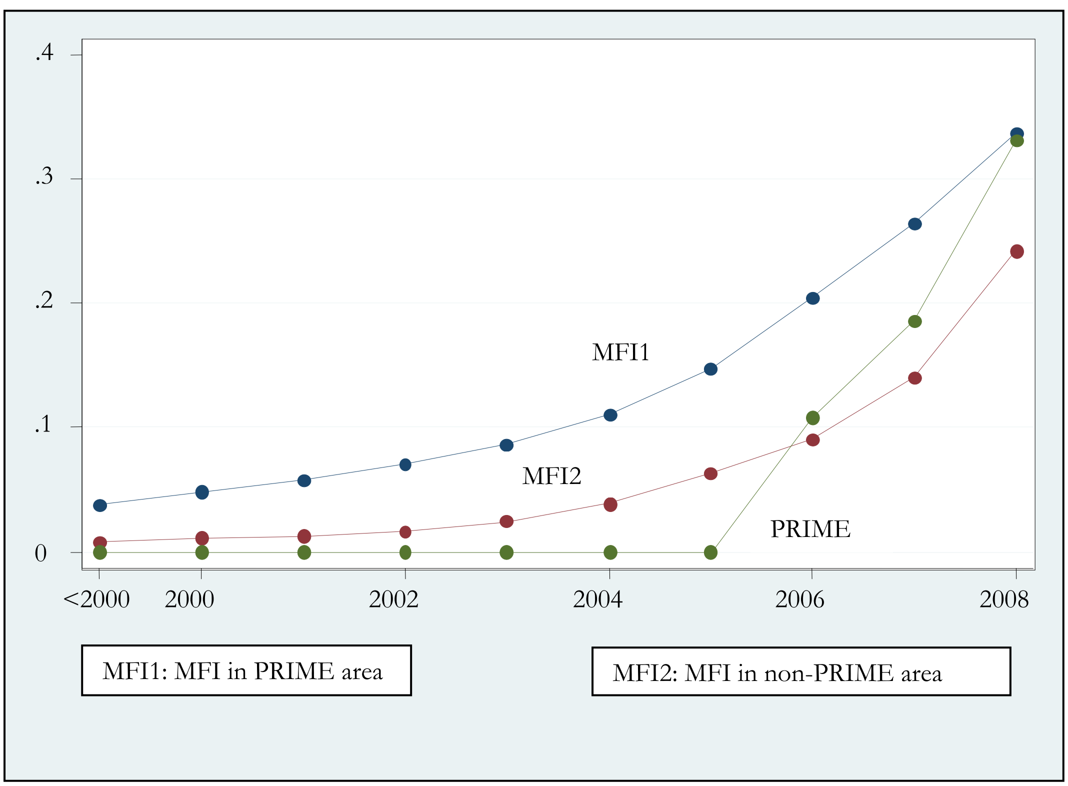
Table 5 presents the household distribution by the subjective level of deprivation (i.e., starvation, meal rationing, and full meals) and the objective measure of deprivation (i.e., moderate, food, and extreme poverty). Some 48 percent of the moderate poor and 28.8 percent of the moderate non-poor are subject to starvation during the *monga* period. The incidence of starvation is highest among the extreme poor (51.8 percent) and lowest among the food non-poor during the *monga* period (20.2 percent). Overall, the extent of food

[15] Created by silt in riverbeds, chars serve as shelters for many destitute people who have almost nothing.
[16] Highlands are defined as land areas either above flood level or flooded up to a 3-ft. depth.

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 food poverty or deprivation.

5. Does PRIME Reach the Seasonal and Hard-core Poor?

According to the 2008–09 InM survey, some 62 percent of the ultra-poor in the northwest region's 5 districts participate in some form of microfinance. Of these, 29 percent are PRIME participants, while 33 percent participate in regular microfinance. However, the annual growth rate of participation among the ultra-poor is much lower for regular microfinance (3.3 percent) than for PRIME (11.2 percent) (Figure 3).[17]



[17] About 6.1 percent of PRIME participation came from those who had participated in regular microfinance. Of the 33 percent who participated in regular microfinance, some 14 percent participated before 2006 (the year PRIME was introduced); after 2006, the participation rate fell to 19 percent.

Figure 3: Cumulative rate of program participation

Figure 3 also shows the participation rates of regular microfinance in areas with PRIME (MFI1 curve) and without PRIME (MFI2). Participation in regular microfinance gradually increases over time in both PRIME and non-PRIME areas, but participation in regular microfinance is much higher in PRIME areas compared to non-PRIME areas. PRIME was introduced in areas that already had a higher rate of regular-microfinance participation among the ultra-poor. This is not surprising, given that PKSF's POs, who introduced PRIME, were providers of regular microfinance before PRIME was introduced by PKSF. As PKSF provides grants and loans on better, more flexible terms for PRIME than for regular microfinance, the POs understandably introduced PRIME initially in areas of their current operation. Higher participation rates of the ultra-poor with PRIME may also reflect greater demand for PRIME services by the ultra-poor. The PRIME program is perhaps better designed than regular microfinance to reach the ultra-poor.

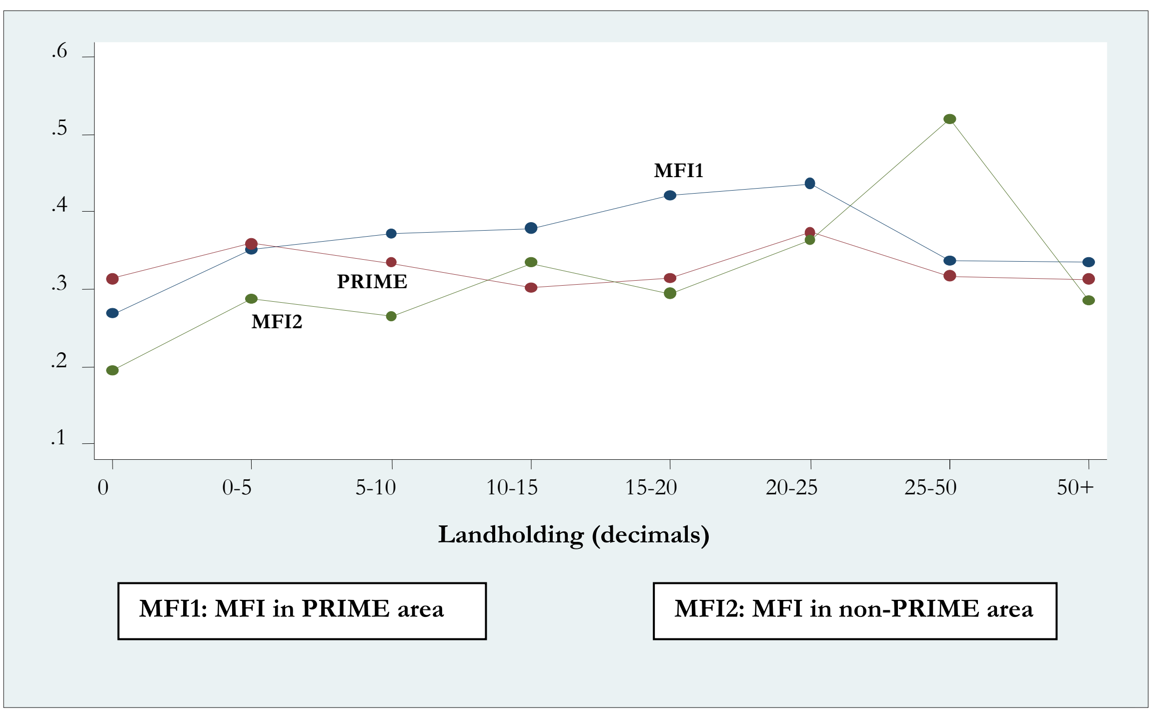


Figure 4: Program participation rate by landholding

If we consider the distribution of ultra-poor participation by landholding, we find that the participation rate among the landless (less than 5 decimals in landholdings) is slightly higher for PRIME versus regular microfinance (Figure 4). Some 27 percent of PRIME participants are completely landless (0 decimals of landholdings), compared to 26 percent of MFI participants. But the participation rate among the ultra-poor holding up to 25 decimals of land is higher in PRIME than non-PRIME areas. In both types of microfinance, only a small percentage of households with more than 50 decimals in landholdings, the official threshold for eligibility in most MFIs in Bangladesh, were found to participate in microfinance.[18] For PRIME, the eligibility criteria is defined not only by landholdings (less than 50 decimals) but also by household members selling labor for wage or household monthly incomes of less than Tk1,500 (US$25).

The landless group with less than 50 decimals in landholdings represents the bulk of microfinance participants (more than 93 percent of PRIME and regular microfinance in PRIME areas) (Figure 5). It appears that PRIME is a well-targeted program that effectively reaches the ultra-poor defined by landholdings.[19]

[18] Only 6 percent of the participants were from this group in both types of programs.

[19] We cannot say so for regular microfinance programs, since we have not full data on participation that may contain households not eligible based on landholding.

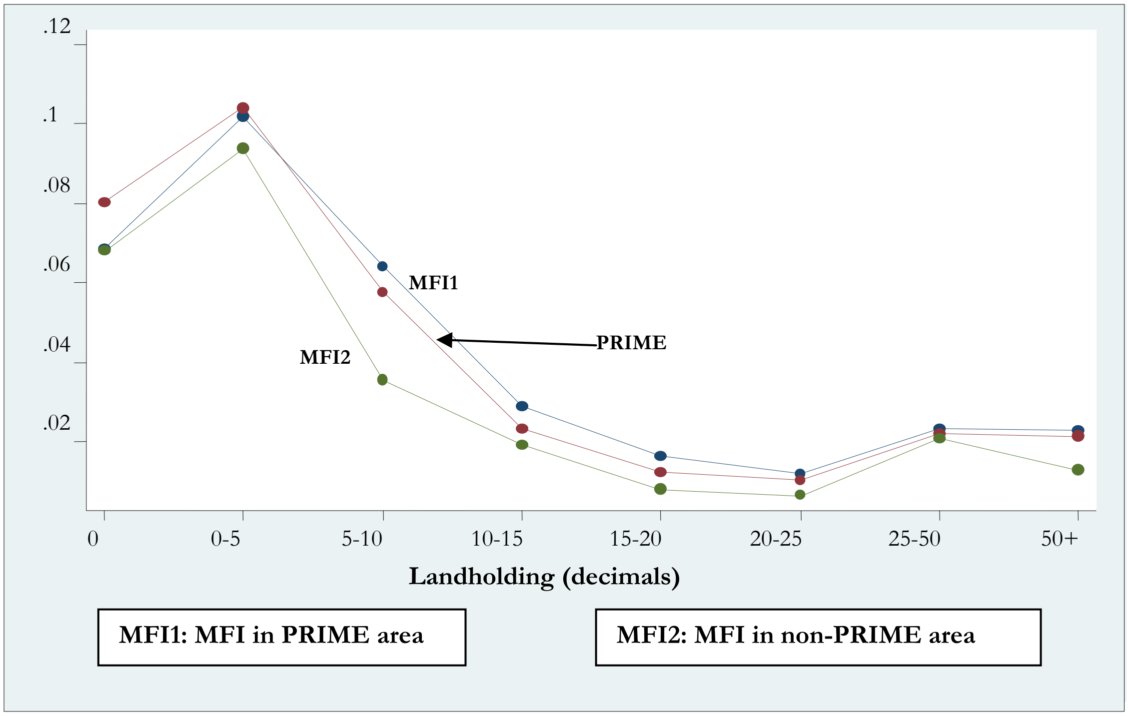


Figure 5: Distribution of total participants by landholdings

Is PRIME also a well-designed program to reach the seasonally poor who suffer from occasional starvation or experience meal rationing during the lean season? Since the baseline information on seasonal food deprivation was collected before PRIME was introduced, we can examine how households varied in program participation by their prior-program participation status of food deprivation. Observation of household participation in PRIME and MFIs by meal consumption patterns during *monga* period shows that, regardless of its meal-consumption pattern, a household is twice as likely to join PRIME than a regular microfinance program, which may be attributable to PRIME's focus on addressing immediate household needs during the lean season (Figure 6).[20]

[20] Households that were MFI members before the PRIME intervention (about 15 percent of panel households) were excluded from this figure in order to capture the behavior of new participants.

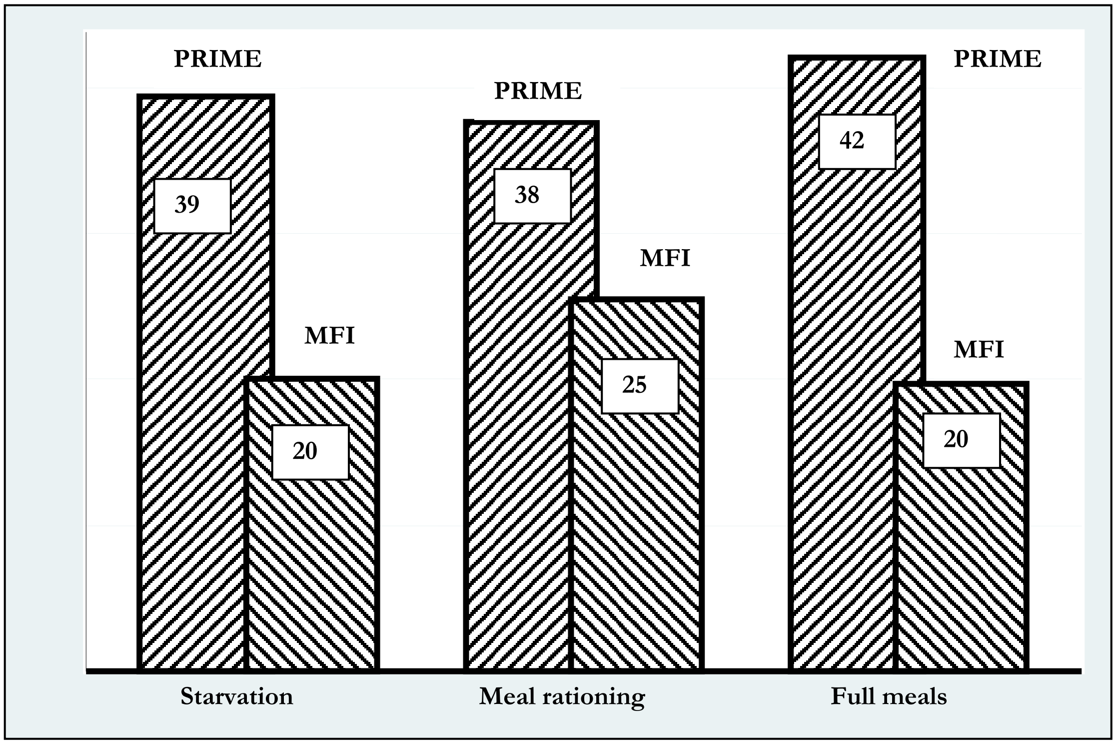


Figure 6: Program participation rate (percent) by pre-intervention, food-consumption status

Given the distribution of 3 household types presented in Table 2 (PRIME, regular microfinance, and non-participants), we would like to identify the factors that determine the choice of participation in each of these mutually exclusive categories (1 = PRIME, 2 = regular microfinance, and 3 = non-participants). This is done by fitting a maximum-likelihood multinomial logit (MNL) model.[21]

The objective is to discover what factors (denoted by *x*) besides program availability help the ultra-poor decide to participate in one of the microfinance programs. The MNL results suggest that the explanatory variables (e.g., age and gender of household head,

[21] Formally, an MNL model expresses the relative probability of observing a particular value *k* of outcome *Y* compared to observing a base value as: $\Pr(Y = k) = \exp\left(\sum_{i=0}^{p} x_i \beta_{ik}\right) \Big/ \sum_{m=1}^{r} \exp\left(\sum_{i=0}^{p} x_i \beta_{im}\right)$

education, landholdings, and other assets) are important in a household's decision to participate in one of the programs (Table 6). Participants in both PRIME and regular microfinance are relatively young. Education generally has a pronounced negative effect on participation in regular microfinance. However, educated males participate more in regular microfinance, while educated females do not participate in PRIME. While land and non-land assets matter for participation in regular microfinance, they are irrelevant to PRIME participation. The participation rate in regular microfinance is much lower in villages with higher populations and villages with higher male wages, reflecting a negative effect of a large local economy. These factors do not matter for PRIME participation, suggesting that PRIME is more pro ultra-poor than is regular microfinance.

Village-level infrastructure, such as paved roads and electrification, positively influences a household's decision to participate in a microfinance program. However, better access to markets reduces the probability of PRIME participation among the ultra-poor, perhaps because of the availability of alternative employment opportunities. As expected, the presence of any type of microfinance program in a village influences the decision to participate. For example, the probability of participating in regular microfinance is 8.7 percent among the ultra-poor owing to the Grameen Bank's presence, compared to 30.2 percent due to the presence of NGOs. However, some 36.0 percent of the ultra-poor participate in PRIME because of a PRIME intervention. Thus, PRIME does better than regular microfinance in reaching the ultra-poor. Although the Grameen Bank discourages participation in PRIME, this is not the case with NGO programs.

Agroclimatic and location-specific factors influence returns to public and private investments. It is little wonder that these factors affect the decision of the ultra-poor to join a microfinance program. Better agroclimatic conditions, such as more rainfall or greater extent of highlands, reduces the probability that the ultra-poor will join a microfinance program, perhaps because of the better alternatives available. Similarly, the probability of microfinance participation, especially regular microfinance, is much lower in char villages. Thus, regular microfinance programs are not well represented in such areas.

6. Estimating the Impact of Microfinance Using Cross-sectional Methods

In recent years, microfinance has incorporated features aimed at mitigating seasonality of income, employment, and consumption. Examples include introducing seasonal loans in the regular microfinance setup or consumption loans in a flexible PRIME microfinance setting. Given these new program features, we would perhaps expect that microfinance helps to reduce seasonality of employment, expenditure, and food consumption, especially during the lean season. Given the proportionally greater participation of the ultra-poor, does microfinance, especially PRIME, reduce food deprivation (and other indicators of seasonal welfare) among the ultra-poor? This section uses cross-sectional methods to estimate the impacts of microfinance programs on household welfare.

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

As mentioned previously, the cross-sectional data include three types of ultra-poor households based on program participation: (i) PRIME, (ii) regular microfinance, and (iii) non-participants. Non-participants can be further divided into those from villages with or without any type of microfinance program. This breakdown is used in the so-called pipeline method, which estimates program effect by exploiting the variation in timing of program implementation, using an eligible comparison group that has not yet received the treatment. Thus, the control villages were PRIME target villages where no intervention had occurred by the time the InM survey was conducted in 2008–09. We use a simple pipeline method to estimate the program effect of PRIME, as follows:

$$ATT = [\sum_{i=1}^{N_T}(y_{ij}^T) - \sum_{i=}^{Nc} y_{ij}^C)] / \rho_T \tag{7}$$

where

ATT (average treatment effect of treated) = 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 (7) can be estimated by OLS where treatment dummy (*T*) is assumed exogenous, as follows:

$$y_{ij} = \alpha + \gamma T_{ij} + \varepsilon_{ij} \tag{8}$$

This equation assumes the observational equivalence (both household and village-wise) of households that participated and those who did not, except that one group is treated and the other is not. In equation (8), γ estimates the average treatment effect of the treated (ATT).

An obvious shortcoming of the pipeline method is that the timing of program placement is not necessarily exogenous but may depend on area characteristics.[22] One way to resolve this non-random program placement or participation is to estimate the program effect using the propensity score matching (PSM) technique. PSM requires that PRIME participants match with "otherwise identical" non-participants, and quantifies any difference

[22] Since PKSF's POs introduced PRIME initially in areas where they already had regular microfinance programs, PRIME placement is not randomly given.

in outcome variables between these two groups. That is, this identification strategy relies on observable village- 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.

Using the PSM technique, we essentially construct a statistical comparison group based on a model of the probability of PRIME participation. This helps to 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 based solely on observable characteristics and all variables that influence treatment assignment and potential outcomes are simultaneously observed (Ravallion 2006). We then find, for each participant, a sample of non-participants that have similar propensity scores.

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

$$ATT = \sum_{i=1}^{N_T} (y_{ij}^T - \sum_{j=1}^{N_C} W_{ij} y_{ij}^C) / N_T \qquad (9)$$

where

y_{ij}^T = outcome for PRIME participants,

y_{ij}^C = outcome for non-participants,

N_T = number of PRIME participants,

N_C = number of matched control households, and

W_{ij} = associated propensity score-based weight given to control observations in matching with the participants.

We explore the robustness of these computations using alternative weighting schemes (e.g., nearest-neighbor matching or kernel matching) to determine how many non-participant households to include in the control group and how to assign weights to each observation (Khandker, Koolwal, and Samad 2009; Ravallion 2006). An advantage of the PSM over the OLS method is that PSM reduces the number of dimensions on which to match participants and comparison units.

Alternatively, we can use a weighted OLS method under the assumption of conditional exogeneity (Hirano, Imbens, and Ridder 2003):

$$Y_{ij} = \alpha + \gamma T_{ij} + \varepsilon_{ij} \tag{10}$$

with a weight of $1/\sqrt{\hat{P}}$ for participants and $1/\sqrt{(1-\hat{P})}$ for control observations, where $\hat{P}$ is the estimated p-score and T_{ij} is the treatment indicator. This specification, which attempts to control for latent differences across treatment and comparison units that would affect selection in program and resulting outcomes, is called the p-weighted regression method.

PRIME impacts are estimated using three alternative methods (Table 7). The outcomes of interest are measured as year-round and seasonal. Pipeline estimates using the OLS method are much higher than those obtained using the two PSM methods, whose estimates are similar. It should be noted that the pipeline method compares outcomes between PRIME participants in PRIME areas with non-participants from control areas (hence a smaller sample of 1,974). In contrast, the PSM compares outcomes between participants matched with 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-weighted regression).

If we consider the p-weighted OLS estimates shown Table 7, we find that PRIME has a positive effect on nearly all annual outcomes. PRIME increases employment hours, especially among females. It also raises per capita income and reduces seasonal and 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. PRIME also affects seasonal outcomes. For example, during the lean (*monga*) 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.

Do the effects of PRIME differ from those of regular microfinance? If we believe that PRIME is a better program than regular microfinance for the ultra-poor, then its impacts should be greater. We have just estimated the outcome regression weighted by the inverse of participation probability (estimated propensity score) in the case of binary treatment. We can extend this concept to participants of PRIME, regular microfinance, and the control group to estimate the relative impacts of PRIME and regular microfinance. The probability of receiving PRIME, regular microfinance, or neither treatment is estimated following the MNL estimates shown in Table 6.

The outcome regression is then weighted as follows:

$$weight = 1/\sqrt{\hat{P}_{PRIME}} \quad \text{for PRIME participants,}$$

$$= 1/\sqrt{\hat{P}_{MFI}} \quad \text{for regular microfinance participants, and}$$

$$= 1/\sqrt{(1 - \hat{P}_{PRIME} - \hat{P}_{MFI})} \quad \text{for non-participants,}$$

where

$\hat{P}_{PRIME}$ = estimated probability of PRIME participation and

$\hat{P}_{MFI}$ = estimated probability of regular microfinance participation.

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 using population weights.

The results suggest that regular microfinance is as good as PRIME in mitigating both seasonal and year-round poverty, as well as in affecting other welfare indicators (Table 8). For example, PRIME participation increases monthly employment hours by 21 percentage points, compared to a 23 percentage-point gain for regular microfinance. Similarly, PRIME reduces food deprivation (either starvation or meal rationing) during the non-*monga* period by 3.9 percentage points, which is slightly higher than the reduction with regular microfinance (3.5 percentage points). The last column in Table 8 presents the Wald test statistics, which show that the differences between the impacts of alternate programs (i.e., PRIME versus regular microfinance) are not statistically significant for nearly all outcomes.

7. Do the Findings Differ with Panel Estimation Methods?

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

One way to verify the results is to use panel analysis. Panel data at the household level can resolve the bias due to unobserved characteristics. Panel analysis also helps control for 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 seasonal effect, such as seasonal preference that affects both the participation decision and consumption. It is also possible that a common seasonal shock could induce all households in an area to behave in a certain way, independent of unobserved household heterogeneity, which would affect program participation. That is, household consumption may be completely independent of seasonal variations and still co-vary strongly with the lean season, simply because of common season-specific shocks. Resolving both sources of bias—unobserved household- and village-level heterogeneity and common seasonal effects—requires season-specific household panel data.

InM has pre-intervention baseline information for the target and non-target households from the PRIME villages only. However, the data has limited information in terms of both explanatory variables and outcomes. Table 9 presents the summary statistics of seasonal outcomes in 2005 and 2008 with the pre- and post-intervention data. In the baseline data, we have only subjective measures of food deprivation by season as outcomes.[23] In Table 9, we see that household welfare measured in terms of food deprivation improves between 2005 and 2008. For example, the rate of occasional starvation during the lean (*monga*) season declined from 50.1 percent in 2005 to 45.2 percent in 2008, while the rate of occasional starvation during the non-*monga* season also decreased from 9.3 percent in 2005 to 2.3 percent in 2008. Year-round starvation similarly declined over this period.

<u>Fixed-effects or double difference method</u>

As we have more than one year of observation after the program intervention for the same season, we use a fixed-effects (FE) method to estimate the program effect. With panel data available, we rewrite the outcome equation (5), as follows:

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

where

t = year and

[23] However, we earlier found that the qualitative measures of deprivation are good approximations of quantitative measures of deprivation.

μ_s = season-specific FEs.

For the two-year period, if we take the difference of equation (11) from the 2nd to 1st period, we eliminate the unobserved time-in-varying household, village, and seasonal common FEs; that is,

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

where an FE method is used to estimate program effects on household outcomes. However, the above model (12) assumes that the selection bias is time-invariant, in which case the changes in outcome for non-participants reveal the counterfactual outcome changes. Thus, the difference between the mean differences of participants and non-participants is the impact estimate. More formally, the simple FE or double difference (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.

DD PSM method

The household fixed-effects method in 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 such that the FE or DD estimator is a biased estimate, since subsequent outcome changes are a function of initial conditions that also influenced program participation in the first place. In this case, the selection bias is not constant over time, introducing a violation of the assumptions of the FE method. It follows that controlling for the initial heterogeneity is critical to the creditability of the FE or DD method.

PSM is an obvious choice for cleaning out this initial heterogeneity prior to doing the differencing. If there is no observable heterogeneity in the differences (i.e., it has been cleaned 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 a method of choice for selecting the comparison group in panel data studies. Obviously, one requires pre-intervention baseline information for the participants and non-participants, which fortunately is available for the PKSF credit intervention program.

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

$$\Delta y_{ijs} = \Delta x_{ij}\beta + \gamma T + \Delta\xi_{ijs}, \qquad (13)$$

where

T = treatment status.

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

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 p-weighted FE using equation (13). Estimates with p-weighted FE are slightly lower than that with the simple FE method. That is, the estimates are slightly lower when we control for the initial conditions in the FE method, which is expected. Nonetheless, the estimates clearly show that PRIME reduces food deprivation in both lean and non-lean seasons. For example, PRIME reduces the incidence of occasional starvation during the lean season by 5.4 percentage points and during the non-lean season by 2.8 percentage points. Consequently, PRIME reduces year-round starvation by 6.6 percentage points.

Does the effect of PRIME differ from that of regular microfinance? Table 11 presents the estimates of the relative impacts of PRIME and regular microfinance on a household welfare set.[24] The impact estimates measure changes in household outcomes due to an intervention such as PRIME, given the availability of regular microfinance. We find that the relative impacts of PRIME differ slightly from its absolute effects, shown in Table 10. Wald test statistics also show that the impacts of PRIME and regular microfinance differ significantly different for three out of six outcomes, unlike the cross-sectional results, which show no significant differences between the two impact estimates for most outcomes (Table 8).

The results suggest that PRIME reduces seasonal starvation by 5.5 percentage points during the lean season, compared to a 3.9 percentage point increase (statistically insignificant) due to regular microfinance programs. Similarly, PRIME has a larger effect (7.2 percentage points) than regular microfinance programs (positive 3.5 percentage points, but statistically insignificant) on mitigating year-round starvation. But regular microfinance has a larger role than PRIME in mitigating food deprivation generally (i.e., when starvation and meal rationing are combined). Since the incidence of meal rationing is much higher than that of occasional starvation, we infer that regular microfinance has a relatively larger effect on reducing meal rationing than reducing the incidence of occasional starvation.[25]

---

[24] This is done by implementing the DD method by a p-weighted regression after extending the concept demonstrated in equation (13); that is, assigning a weight of 1 for participants in PRIME and MFIs and an inverse of the probability of non-participation for nonparticipants.

[25] It is possible that regular microfinance programs, because of their longer-term operation, are more suited to handling the general hardship associated with meal rationing than PRIME which helps alleviate more acute form of hardship (i.e., starvation). We re-ran the same regression with two types of microfinance memberships - those started before PRIME and those after PRIME (that is, after 2006). We find that longer exposure to

8. Summary and Conclusion

Microfinance is often criticized for not adequately addressing 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 program, designed and implemented by PKSF is the so-called PRIME initiative. Begun in 2006, PRIME targets the northwest region's ultra-poor, who are most vulnerable to seasonality of income, employment, and consumption. The program essentially offers microfinance services on flexible terms. For example, PRIME provides consumption loans to address consumption seasonality, while regular MFIs offer seasonal production loans to deal with seasonality.

This study evaluated the effectiveness of PRIME, relative to regular microfinance, in tackling seasonal and hard-core poverty in Bangladesh's northwest region. The results suggest that microfinance generally has reached a large percentage of the ultra-poor and seasonal poor in recent years. It was found that about 62 percent of the ultra-poor participate in microfinance. In contrast, 59 percent of the ultra-poor who experience occasional starvation and 63 percent of the ultra-poor with meal rationing are beneficiaries of microfinance. The introduction of PRIME has only enhanced the ultra-poor's participation in microfinance. However, PRIME program placement and participation are not randomly given but are determined by a host of factors, including prior availability of a regular microfinance program.

Evaluating the program impact thus requires correction for the non-random placement/participation of a microfinance program. An experimental evaluation design was

regular microfinance have higher impact on meal rationing than the shorter ones, thus confirming our assumption.

beyond the scope of the study. Therefore, a quasi-experimental method was adopted to estimate the program effects. The PSM method using cross-sectional data yields encouraging results for program participation. The household FE method relying on panel data yields results that either support or augment the cross-sectional results.

Both PRIME and MFIs are found to reduce extreme poverty and seasonal deprivation. MFI reduces extreme poverty by 2.3 percentage points, compared to 3.1 percentage points under PRIME; while 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, MFIs affect chronic poverty more than seasonal poverty. Yet the relative impact estimates of alternative programs (PRIME versus MFI) are not statistically significant with either cross-sectional or panel analysis.

Do the results suggest that PRIME is just like a regular microfinance program? It should be noted that, despite PRIME being a microfinance program, it is more popular than regular microfinance among the ultra-poor, perhaps because of its flexible design. This is evidenced by the higher PRIME participation rate among the ultra-poor in areas where both types of programs operate. As PRIME has been in operation only since 2006, it is perhaps too early to say whether PRIME equals or surpasses regular microfinance in tackling poverty and seasonality. It is also not possible to confirm whether PRIME or microfinance more broadly can simultaneously tackle seasonality and chronic poverty in an efficient way.

References

Chaudhuri, Shubham, and Christina Paxson. 2002. "Smoothing Consumption under Income Seasonality: Buffer Stocks vs. Credit Markets." Discussion Paper 0102-54, Department of Economics. New York: Columbia University.

Datta, Dipankar. 2004. "Microcredit in Rural Bangladesh: Is It Reaching the Poor?" *Journal of Microfinance* 6(1): 55–81.

Deaton, Angus. 1991. "Savings and Liquidity Constraints." *Econometrica* 59(4): 1221–48.

Emran, Shahe, Virginia Robano, and Stephen C. Smith. 2009. "Assessing the Frontiers of Ultra-Poverty Reduction: Evidence from CFPR/TUP, an Innovative Program in Bangladesh" (mimeo).

FAO and WHO (UN Food and Agriculture Organization and World Health Organization). 1973. "Energy and Protein Requirements." FAO Nutrition Meetings Report Series, No. 52 and WHO Technical Report Series, No. 522, Report of a Joint FAO/WHO ad hoc Expert Committee, Geneva.

Hirano, Keisuke, Guido Imbens, and Geert Ridder. 2003. "Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score." *Econometrica* 71(4): 1161–89.

InM (Institute of Microfinance). 2009. "Impact of PRIME Interventions on *Monga* Mitigation in Greater Rangpur Region in Bangladesh." Report submitted to the Palli Karma Shahayak Foundation (PKSF) and the UK Department for International Development (DFID), Institute of Microfinance, Dhaka.

Jalan, Jyotsna, and Martin Ravallion. 2000. "Is Transient Poverty Different?: Evidence for Rural China." *Journal of Development Studies* 36(6): 82–99.

Khandker, Shahidur R. 1998. *Fighting Poverty with Microcredit: Experience in Bangladesh*. New York: Oxford University Press.

———. 2005. "Microfinance and Poverty: Evidence Using Panel Data from Bangladesh." *World Bank Economic Review* 19(2): 263–86.

———. 2009. "Poverty and Income Seasonality in Bangladesh." Policy Research Working Paper No. 4923. Washington, DC: World Bank.

Khandker, Shahidur R., M. A. Baqui Khalily, and Hussain Samad. 2009. "Seasonal Hunger and Its Mitigation in Northwest Bangladesh" (mimeo).

Khandker, Shahidur R., Gayatri Koolwal, and Hussain Samad. 2009. *Handbook on Impact Evaluation: Quantitative Methods and Practices*. Washington, DC: World Bank.

Matin, Imran, and David Hulme. 2003. "Programs for the Poorest: Learning from the IGVGD Program in Bangladesh." *World Development* 31(3): 647–65.

Paxson, Christina. 1993. "Consumption and Income Seasonality in Thailand." *Journal of Political Economy* 101(1): 39–72.

Pitt, Mark, and Shahidur R. Khandker. 1998. "The Impact of Group-based Credit Programs on Poor Households in Bangladesh: Does the Gender of Participants Matter?" *Journal of Political Economy* 106(5): 958–96.

———. 2002. "Credit Programmes for the Poor and Seasonality in Rural Bangladesh." *Journal of Development Studies* 39(2): 1–24.

Rahman, Hossain Zillur. 1995. "Mora Kartik: Seasonal Deficits and the Vulnerability of the Rural Poor." In *Rethinking Rural Poverty: Bangladesh as a Case Study*, eds. Hossain Zillur Rahman and Mahabub Hossain. New Delhi: Sage Publications.

Ravallion, Martin. 2006. "Evaluating Anti-poverty Programs." *Handbook of Development Economics,* vol. 4, eds. Robert E. Evenson and T. Paul Schultz. Amsterdam: North-Holland.

Rosenzweig, Mark. 1988. "Risk, Implicit Contracts and the Family in Rural Areas of Low-income Countries." *The Economic Journal* 98: 1148–70.

Rosenzweig, Mark, and Hans Binswanger. 1993. "Wealth, Weather Risk, and the Composition and Profitability of Agricultural Investments." *Economic Journal* 103(416): 56–78.

Rosenzweig, Mark, and Kenneth Wolpin. 1993. "Credit Market Constraints, Consumption Smoothing and the Accumulation of Durable Production Assets in Low-income Countries: Investments in Bullocks in India." *Journal of Political Economy* 101(2): 223–44.

Sen, Amartya. 1981. *Poverty and Famines: An Essay on Entitlement and Deprivation.* New York: Oxford University Press.

Stiglitz, Joseph. 1990. "Peer Monitoring and Credit Markets." *World Bank Economic Review* 4(3): 351–66.

Townsend, Robert. 1995. "Consumption Insurance: An Evaluation of Risk-bearing Systems in Low-income Economies." *Journal of Economic Perspectives* 9(3): 83–102.

United Nations. 2005. "Millennium Development Goals: Bangladesh Progress Report." A joint publication of the Government of Bangladesh and the United Nations Country Team in Bangladesh, Dhaka.

Webb, Patrick, Jennifer Coates, and Robert Houser. 2002. "Does Microcredit Meet the Needs of all Poor Women?: Constraints to Participation among Destitute Women in Bangladesh." Tufts Nutrition Discussion Paper, No. 3. Boston: Tufts University. Available at http://nutrition.tufts.edu

WFP (World Food Programme). 2005. "Bangladesh Food Security Brief." August. Available at www.wfp.org

Woolridge, J. 1999. "Asymptotic Properties of Weighted M-Estimators for Variable Probability Samples." *Econometrica* 67(6): 1385–406.

Zaman, Hassan. 1999. "Assessing the Impact of Micro-credit on Poverty and Vulnerability in Bangladesh." Policy Research Working Paper No. 2145. Washington, DC: World Bank.

———. 2004. "The Scaling Up of Microfinance in Bangladesh: Determinants, Impacts, and Lessons." Policy Research Working Paper No. 3398. Washington, DC: World Bank.

Zug, Sebastian. 2006. *Monga*: Seasonal Food Insecurity in Bangladesh—Understanding the Problems and Strategies To Combat It (mimeo).

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

Area	Poverty Headcount (%)		Extreme Poverty Headcount (%)	
	2000	2005	2000	2005
Country	48.9	40	34.3	25.1
Rural	52.3	43.8	37.9	28.6
Urban	35.1	28.4	19.9	14.6
Northwest (greater Rangpur) region	67.7	57.4	55.9	43.0

Source: HIES surveys, 2000 and 2005.

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

Program type	Gaibandha	Kurigram	Lalmonirhat	Nilphamari	Rangpur	All districts
PRIME area						
PRIME	28.7	39.7	31.9	36.3	29.9	33.2
Regular 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 (no.)	1,257	1,135	1,015	490	692	4,589
Non-PRIME area						
PRIME	0	-	-	0	0	0
Regular microfinance	6.3	-	-	31.2	25.8	26.5
Non-participants	93.7	-	-	68.8	74.2	73.5
Observations (no.)	64	0	0	314	240	618
All areas						
PRIME	27.3	39.7	31.9	22.2	22.3	29.2
Regular 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 (no.)	1,321	1,135	1,015	804	932	5,207

Source: InM survey, 2009.

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

Outcome indicator	PRIME	Regular MFIs	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 headcount	0.871 (0.335)	0.861 (0.346)	0.892 (0.310)	0.876 (0.330)
Food poverty headcount	0.854 (0.353)	0.845 (0.362)	0.862 (0.345)	0.854 (0.353)
Extreme poverty headcount	0.675 (0.469)	0.676 (0.468)	0.727 (0.446)	0.695 (0.460)
Household with year-round starvation	0.435 (0.496)	0.464 (0.499)	0.491 (0.500)	0.466 (0.499)
Household with year-round starvation or meal rationing	0.941 (0.235)	0.933 (0.250)	0.958 (0.201)	0.945 (0.228)
Seasonal outcomes				
Employment during *monga* period (days/month)	24.3 (16.0)	25.1 (16.6)	20.9 (14.8)	23.3 (15.9)
Employment during non-*monga* period (days/month)	27.1 (16.4)	27.6 (16.3)	23.5 (14.9)	25.9 (15.9)
Per capita food expenditure during *monga* (Tk/month)	510.2 (249.7)	516.1 (250.3)	498.3 (256.1)	507.6 (252.4)
Per capita food expenditure during non-*monga* (Tk/month)	702.9 (288.6)	703.1 (275.3)	685.3 (280.6)	696.3 (281.3)
Household had starvation during *monga*	0.428 (0.495)	0.453 (0.498)	0.483 (0.500)	0.457 (0.498)
Household had starvation or meal rationing during *monga*	0.938 (0.241)	0.924 (0.265)	0.954 (0.210)	0.940 (0.238)
Household had starvation during non-*monga*	0.022 (0.146)	0.019 (0.137)	0.022 (0.148)	0.021 (0.144)
Household had starvation or meal rationing during non-*monga*	0.733 (0.443)	0.739 (0.439)	0.820 (0.384)	0.768 (0.422)
Observations (no.)	1,520	1,717	1,970	5,207

Source: InM survey, 2009.

Note: Figures in parentheses are standard deviations.

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

Explanatory variable	PRIME	Regular MFIs	Non-participants	Whole sample
Age of household head (years)	41.6 (12.6)	41.5 (12.6)	43.3 (14.6)	42.2 (13.4)
Gender of household head (1 = M, 0 = F)	0.88 (0.33)	0.92 (0.27)	0.86 (0.34)	0.89 (0.32)
Education of household head (years)	1.33 (2.63)	1.52 (2.75)	1.33 (2.65)	1.39 (2.68)
Maximum education of adult males (years)	1.84 (3.13)	2.13 (3.22)	1.70 (3.00)	1.88 (3.12)
Maximum 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)
Non-land assets (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 (no.)	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 char 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 areas in administrative subdivision (*thana*)	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 (no.)	1,520	1,717	1,970	5,207

Source: InM survey, 2009.
Note: Figures in parentheses are standard deviations.

Table 5: Household food-consumption pattern during *monga* by poverty status using cross-sectional sample

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	48.7	95.5	4.5
Food non-poor	28.5	84.6	15.4
Food poor during *monga*	47.6	95.6	4.4
Food non-poor during *monga*	20.2	72.5	27.5
Food poor during non-*monga*	48.9	95.5	4.5
Food non-poor during non-*monga*	32.1	87.5	12.5

Source: InM survey, 2009.

Table 6: Estimates of the determinants of program participation using MNL model and cross-sectional data of 2008–09

Explanatory variable	PRIME	Regular microfinance
Age of household head (years)	-0.0001 (-2.73)	-0.003 (-4.24)
Gender of household head (1 = M, 0 = F)	-0.001 (-0.59)	0.079 (2.81)
Education of household head (years)	-0.0003 (-0.88)	-0.013 (-2.39)
Maximum education of adult males (years)	0.0003 (1.08)	0.011 (2.27)
Maximum 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 assets (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 char land	-0.002 (-1.29)	-0.128 (-5.94)
Village has rivers	0.0002 (0.16)	-0.022 (-1.01)
Proportion of highlands 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 (no.)	5,202	

Source: InM survey, 2009. T-statistics are in parentheses. Coefficients are marginal impacts.

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

Outcome variable	Pipeline estimates	Kernel-matched PSM estimate	p-weighted regression estimates
Year-round outcomes			
Log male employment (hours/month)	0.164 (1.48)	0.156 (2.36)	0.176 (3.66)
Log female employment (hours/month)	1.055 (6.68)	0.554 (7.29)	0.576 (8.96)
Log total employment (hours/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 headcount	-0.060 (-2.35)	-0.018 (-1.52)	-0.019 (-1.80)
Food poverty headcount	-0.010 (-0.37)	-0.014 (-1.10)	-0.008 (-0.69)
Extreme poverty headcount	-0.087 (-2.41)	-0.046 (-2.81)	-0.048 (-2.95)
Household had year-round starvation	-0.049 (-2.81)	-0.039 (-2.17)	-0.034 (-1.88)
Household had year-round starvation or meal rationing	-0.064 (-2.57)	-0.005 (-0.70)	-0.006 (-1.33)
Seasonal outcomes			
Log employment in *monga* period (days/month)	0.189 (2.88)	0.130 (4.17)	0.148 (5.13)
Log employment in non-*monga* period (days/month)	0.244 (4.37)	0.137 (5.01)	0.152 (6.05)
Log per capita food expenditure in *monga* period (Tk/month)	0.106 (3.14)	0.013 (0.86)	0.009 (0.65)
Per capita food expenditure in non-*monga* period (Tk/month)	0.058 (2.10)	0.014 (1.12)	0.012 (1.01)
Household had starvation during *monga* period	-0.059 (-1.81)	-0.038 (-2.12)	-0.034 (-1.85)
Household had starvation or meal rationing during *monga* period	-0.052 (-1.87)	-0.005 (-0.60)	-0.006 (-1.20)
Household had starvation during non-*monga* period	0.029 (0.56)	0.001 (0.25)	0.003 (0.68)
Household had starvation or meal rationing during non-*monga* period	-0.153 (-4.43)	-0.046 (-3.06)	-0.052 (-3.75)
Observations (no.)	1,974	3,388	3,490

Source: InM survey, 2009.
Note: Figures outside parentheses are marginal impacts and those in parentheses are t-statistics.

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

Outcome variable	PRIME	Regular microfinance	Wald test statistics for equality of PRIME and MFI coefficients
Year-round outcomes			
Log male employment (hours/month)	0.194 (3.92)	0.195 (4.19)	F(1,5180) = 0.00, p>F = 0.988
Log female employment (hours/month)	0.503 (7.57)	0.318 (5.10)	F(1,5180) = 7.72, p>F = 0.006
Log total employment (hours/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 headcount	-0.009 (-0.76)	-0.011 (-0.99)	$\chi^2(1)$ = 0.03, p>F = 0.853
Food poverty headcount	0.002 (0.12)	-0.006 (-0.49)	$\chi^2(1)$ = 0.35, p>F = 0.554
Extreme poverty headcount	-0.031 (-1.81)	-0.023 (-1.38)	$\chi^2(1)$ = 0.26, p>F = 0.611
Household had year-round starvation	-0.005 (-0.56)	0.004 (0.43)	$\chi^2(1)$ = 1.04, p>F = 0.309
Household had 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 in *monga* period (days/month)	0.147 (5.10)	0.180 (6.64)	F(1,5180) = 1.28, p>F = 0.258
Log employment in non-*monga* period (days/month)	0.151 (6.07)	0.158 (6.77)	F(1,5180) = 0.08, p>F = 0.775
Log per capita food expenditure in *monga* period (Tk/month)	-0.016 (-1.08)	-0.008 (-0.55)	F(1,5180) = 0.32, p>F = 0.572
Per capita food expenditure in non-*monga* period (Tk/month)	0.0001 (0.01)	0.001 (0.10)	F(1,5180) = 0.01, p>F = 0.931
Household had starvation during *monga* period	-0.007 (-0.64)	-0.0007 (-0.07)	$\chi^2(1)$ = 0.38, p>F = 0.538
Household had starvation or meal rationing during *monga* period	-0.005 (-0.34)	-0.010 (-0.77)	$\chi^2(1)$ = 0.15, p>F = 0.695
Household had starvation during non-*monga* period	-0.014 (-1.23)	-0.0001 (-0.01)	$\chi^2(1)$ = 1.48, p>F = 0.224
Household had starvation or meal rationing during non-*monga* period	-0.039 (-2.46)	-0.035 (-2.31)	$\chi^2(1)$ = 0.06, p>F = 0.808
Observations (no.)	5,202		

Source: InM survey, 2009.

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

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

Outcome variable (meal consumption pattern)	2005	2008
Household had starvation during *monga* period	0.501 (0.500)	0.452 (0.498)
Household had starvation or meal rationing during *monga* period	0.962 (0.192)	0.937 (0.244)
Household had starvation during non-*monga* period	0.093 (0.291)	0.023 (0.150)
Household had starvation or meal rationing during non-*monga* period	0.599 (0.490)	0.755 (0.430)
Household had year-round starvation	0.527 (0.499)	0.462 (0.499)
Household had year-round starvation or meal rationing	0.963 (0.188)	0.941 (0.235)
Observations (no.)	4,517	4,517

Sources: InM surveys, 2006 and 2009.
Note: Figures in parentheses are standard deviations. Outcome variables in panel estimation consist of household meal-consumption variables only, since only those variables are available in both years.

Table 10: Estimates of PRIME impacts using household fixed-effects (FE) method

Outcome variable (meal consumption pattern)	FE	p-weighted FE
Household had starvation during *monga* period	-0.055 (-2.24)	-0.054 (-2.18)
Household had starvation or meal rationing during *monga* period	-0.017 (-1.44)	-0.014 (-1.26)
Household had starvation during non-*monga* period	-0.030 (-2.44)	-0.028 (-2.29)
Household had starvation or meal rationing during non-*monga* period	-0.068 (-3.07)	-0.071 (-3.20)
Household had year-round starvation	-0.067 (-2.75)	-0.066 (-2.68)
Household had year-round starvation or meal rationing	-0.016 (-1.44)	-0.013 (-1.26)
Households (no.)	2,991	2,991

Sources: InM surveys, 2006 and 2009.
Note: Figures in parentheses are t-statistics. A panel sample is constructed for households in program areas since a baseline survey was not conducted in non-program areas.

Table 11: Estimates of alternative program impacts (p-weighted FE)

Outcome variable (meal consumption pattern)	**PRIME**	**Regular microfinance**	**Wald test statistics for equality of PRIME and MFI coefficients**
Household had starvation during *monga* period	-0.055 (-2.24)	0.039 (1.58)	$\chi^2(1) = 11.19$, $p>F = 0.0008$
Household had starvation or meal rationing during *monga* period	-0.002 (-0.96)	-0.008 (-2.72)	$\chi^2(1) = 2.10$, $p>F = 0.147$
Household had starvation during non-*monga* period	-0.009 (-0.81)	-0.005 (-0.47)	$\chi^2(1) = 0.09$, $p>F = 0.768$
Household had starvation or meal rationing during non-*monga* period	-0.111 (-3.94)	-0.055 (-1.95)	$\chi^2(1) = 3.27$, $p>F = 0.071$
Household had year-round starvation	-0.072 (-2.92)	0.035 (1.51)	$\chi^2(1) = 14.41$, $p>F = 0.0001$
Household had year-round starvation or meal rationing	-0.002 (-1.06)	-0.004 (-2.55)	$\chi^2(1) = 1.52$, $p>F = 0.217$
Households (no.)	4,517		

Sources: InM surveys, 2006 and 2009.
Note: Figures outside parentheses are marginal impacts and those in parentheses are t-statistics.