Seasonal Migration and the Effectiveness of Micro-credit in the Lean Period : Evidence from Bangladesh *

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Abstract

This paper investigates the relationship between access to micro-credit and temporary seasonal migration, an issue which is largely ignored in the standard rural-urban migration literature. Seasonal migration due to natural disasters or agricultural downturns is a common phenomenon in developing countries. Using primary data from a cross-sectional household survey from the northern part of Bangladesh, this study quantifies the factors that influence such migration decisions. Seasonal migration is a natural choice for individual suffering periodic hardship. However, due to strong loan repayment rules, those who have prior access to micro-credit have no such option. I find that there is no significant difference in income in lean period between those who have access to micro-credit and those who do not. Households that take the decision to migrate while having access to micro-credit earn significantly more than households who only have micro-credit in the lean period. In addition, this paper finds that network effects play a significant role influencing the migration decision, with the presence of kinsmen at the place of destination having considerable impact. The results have numerous potential policy implications, including the design of typical micro-credit schemes.
Keywords : Lean period; Seasonal migration; Micro-credit; Bangladesh; Program evaluation; Matching methods.
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1 Introduction

This paper examines the relationship between access to micro-credit and temporary seasonal migration. This is an issue which has great policy relevance, yet is largely overlooked in the literature. Hence, the aim of this paper is to better understand the causes of seasonal migration, to establish the relationship of migration with micro-credit, to evaluate the characteristics of seasonal migrants and to quantify the effects of the factors influencing seasonal migration decisions. In particular, I test the effectiveness of micro-credit programs in the lean period and the role played by networks (kinship) in the seasonal migration decision.

In the standard rural-urban migration literature, scholars primarily focus on permanent internal migration and its economic, social and demographic significance. Very few studies have discussed temporary internal migration, which is variously known as 'seasonal migration', 'circular migration', or 'oscillatory migration'. Evidence of this phenomenon exists in many regions and particularly in the developing countries of Africa (Elkan 1959, 1967; Guilmoto 1998), Asia (Hugo 1982; Stretton 1983; Deshingkar and Start 2003; Rogaly et al. 2002; Rogaly and Coppard 2003) and South America (Deutsch et al. 2003). People move from rural areas to nearby cities or towns for a short period of time during lean periods in an attempt to survive and maintain their family in such difficult times. Lean periods can occur as a result of agriculture cycles or natural disasters, such as droughts, floods, cyclones, climate change and river erosion, and temporary migration is an important livelihood strategy for a large number of poor rural people in developing countries.

In the case of seasonal downturns or shocks, a person may prefer a temporary move to a permanent one because such a decision offers an opportunity to combine village based existence with urban opportunities. Faced with highly seasonal labor demand, villagers may see temporary migration to urban areas as a relatively practical and rational strategy to cope with seasonal downturns and natural shocks. The most important factor, resulting in a temporary move rather than a permanent one, however is the reversal of the urban-rural wage differential that occurs during the peak labor demand season in the agricultural sector.

Evidence from different countries suggests that the temporary mobilization of labor from rural to urban areas has important socio-economic implications. Migration reduces the inequality in the rural area due to the flow of remittances from the migration destinations. This flow, which is quite regular, is unlikely to occur with permanent rural to urban migration, and such a flow has a large impact on rural families who through this money can afford the necessities of life. Return migrants may also diffuse ideas, information and knowledge which might play a vital role in the rural development process.

Temporary migrants, however, cause congestion and other social problems in urban areas and policy makers have insufficient information about the number of people migrating temporarily to tackle these problems. Seasonal migrants are very difficult to detect and the definition is not a clear one; hence, they are typically excluded from national surveys. As a result, it is difficult to implement effective policies to accommodate seasonal migrants.

A recent policy innovation in developing countries has been the emergence of micro-credit in poverty alleviation. It is argued that if given access to credit, small entrepreneurs from poor households will find opportunities to engage in viable income-generating activities and alleviate their own poverty. Various studies on the impact of micro-credit in developing countries have found evidence of consumption smoothing, asset building (Pitt and Khandker 1998) and the reduction of poverty (Khandker 2005). Conversely, using the same data set as Pitt and Khandker (1998), Morduch (1999) found that the average impact of micro-credit is 'non-existent'. Similarly Navajas et al. (2000) concluded that micro-credit is largely unsuccessful in reaching the poor and the vulnerable. In situations like lean period shocks, where migration is a natural response, the strict weekly loan repayment rules of Micro-credit Institutions (MFIs) can hamper this process, reducing the ability of borrowers to react to a shock. A natural extension of this study is thus to explore the effectiveness of micro-credit for the poor during the lean period, since micro-credit authorities do not address such problems when making loans. The impact of micro-credit and migration on income during the lean season hardship was estimated by using a set of 'quasi experiments' and semi-parametric matching techniques.

Primary data collected from the northern part of Bangladesh is used in this paper. A random cross-section household survey was conducted in January 2006 by Abu Shonchoy, Abu Z. Shahriar, Sakiba Zeba and Shaila Parveen as part of a project undertaken by the Economics and Social Sciences Research Group (ESSRG) of BRAC University. The study team chose the Kurigram district of northern Bangladesh because of some distinctive features. Kurigram is mainly an agri-based, severely poverty-stricken area of Bangladesh that is prone to natural disasters.[1] Due to the agricultural cycle, farmers have very little work to do on the farms after the plantation of the Aman in September-October.[2] As a result, a large number of agricultural workers become jobless every year and decide to migrate temporarily. Such migrants tend to get work in the urban informal sector and work mainly as day laborers or street vendors. AlThough the urban standard of living is typically a bare minimum for these migrants, they prefer this option to staying in the village with no income at all.

Pioneering work on seasonal migration in Bangladesh has been conducted by Shahriar et al. (2006). Unfortunately, the study did not produce efficient and consistent estimates due to the use of an incomplete dataset. However, by using an updated version of the

[1]Rural life of Bangladesh very much revolves around the agricultural cycle and our study area is no exception. As a consequence of this cycle, two major seasonal deficits occur, one in late September to early November and the other in late March to early May. With the widespread expansion of Boro cultivation, the incidence of the early summer lean period has significantly declined. However, the autumn lean season coming after the plantation of the Aman crop still affects almost all parts of the country, and especially the northern part of Bangladesh. In local terms, this lean season is called Monga or Mora Karthik (Rahman and Hossain 1991).

[2]In more than 80% of the farms in the study area, only one (Aman paddy) or two crops (Aman and Boro paddy) are produced annually.

data, the present study has improved on the model of Shahriar et al. and is able to provide efficient estimates and additional insights; hence, this study provides a significant advance in the understanding of the drivers of seasonal migration and the effectiveness of micro-credit in poverty alleviation during lean seasons.

2 Background

2.1 Seasonal Migration

The terminology of seasonal migration probably first appeared in the seminal paper by Walter Elkan in which he observed circular migration patterns of labor in East Africa and explained it 'Combined with the familiar pattern of migration, all in one direction, there is another and important movement back to the countryside' (Elkan 1967, pg. 581). However, according to Deshingkar and Start (2003), the formal definition of seasonal migration was put forward in the 1970s by Nelson (1976) who discussed such labor as 'sojourners' (page 721). This work raised interest in the causes and consequences of temporary city-ward migration in developing countries. According to Nelson, a major proportion of rural to urban migration in Africa and of Asia is temporary in nature, and Zelinsky (1971) defined seasonal migration as 'short-term, repetitive or cyclic in nature' (page 226).

The seasonal migration of labor has been studied in many disciplines other than Economics. Demography, Anthropology and Sociology have discussed such movements of labor long before it appeared in Economics. Consequently, the terminology used to describe this phenomenon varies considerably; for example, seasonal migration has also been referred to as 'return migration', 'wage-labor migration', 'transhumance' to name a few. In addition, geographers noticed this observable fact of labor movement even in the early 1920s. As mentioned in (Chapman and Prothero 1983, pg. 599):

> 'The concept of circulation as the beneficial integration of distinct places or communities dates from the 1920s mainly characterizes the work of human geographers and originated with the French led by Vidal de la Blache (1845-1918). Among French geographers, circulation refers to the reciprocal flow not only of people but also of ideas, goods, services and sociocultural influences (de la Blache, 1926: 349-445; Sorre, 1961: Part IV)'.

Chapman and Prothero (1983) provide a comprehensive study of this literature, while Nelson (1976) discusses in detail the causes and consequences of such migration.

2.2 Reasons for Seasonal Migration

Other than social issues such as family structures, social customs and religious beliefs, economic factors are the most influential reasons for migration in the lean period. Elkan (1959, pg 192) refers to these non-economic factors as 'most unlikely to be the whole story, and...it can never be the most important part of the story.' On the contrary, Elkan denoted the economic factors as 'largely a rationalization of simple economic motives'. In this section we primarily focus on the economic factors that lead to migration (rural to urban) and reverse migration (urban to rural).

2.2.1 Reasons causing rural to urban migration

Migration can be regarded as a risk diversification strategy as mentioned in Stark and Levhari (1982) and Katz and Stark (1986). During the lean period, the temporary mobility of labor provides some means of livelihood in urban areas. There are four main reasons why families take such decisions in the lean period. Firstly, it is always easier and cheaper to survive in the rural environment than in urban areas, as the prices of food grains and other household essentials are relatively cheaper. In most cases, it is the head or the most capable members of the household, who are mainly men, migrate to urban areas. Moving away from the household, a single person can cope better with urban life and typically survives on a bare minimum in order to send remittances back to the family.

Secondly, seasonal unemployment in agriculture causes an excess supply of unskilled or semi-skilled workers in rural areas. In combination with this, food grains and other necessary commodities become relatively expensive during this period as the affluent in these regions hoard a large amount of crops in good times to sell in the lean period at a high price; hence, the increase in price reduces the real wage of workers. It becomes almost impossible for an ordinary agricultural worker to maintain general living standards during the lean period in a village and thus they choose to migrate.

In recent years, much public and private investment has been concentrated in urban areas in developing countries. Little or no effort has gone into creating effective non-agricultural sectors in rural areas and there exists only a few alternative means of earning in rural areas other than agriculture and agri-based industries. This pattern of temporary labor movement is nothing but a pure response to the lack of alternatives in rural areas (Hugo 1982).

Finally, the cost of the journey to migration destinations is usually very small and unimportant for migrants. As mentioned in Hugo (1982, pg. 73) 'travel costs, time taken, and distance traversed between origin and destination generally constitute a minor element in a mover's overall calculus in deciding whether or not to migrate and where'. The recent improvement in communication in third world countries has also significantly reduced the cost of movement (Afsar 1999). Moreover, access to an informal credit market (through micro-credit schemes operated by NGOs) gives migrants the option of borrowing which can reduce their immediate relocation and travel costs. Although NGOs do not run specific programs to provide credit for migration, however, it is possible to use a loan taken by other members of the family and to repay the loan once work has been found in the migration destination.

2.2.2 Reasons causing reverse migration

There are some interesting facts which influence migrants to return to the village, causing reverse migration. Once a move to urban areas has taken place, there are some off-setting factors such as forgone skills and income in the normal season, which are quite important for the reverse migration (Mendola 2008). Poverty and resource constraints, make it extremely difficult for a migrant to devote resources to building or to invest in the skills that are required for formal urban job markets; hence, seasonal migrants end up seeking jobs in the urban informal sector where the wage is typically at a minimum and working conditions are not pleasant. The informal sector is primarily low-skilled and usually involves manual labor (such as the job of rickshaw puller, street vendor or day laborer). The wages are inadequate to support a single man, let alone a family. These people live in the slums or on the pavements of the large train stations or sometimes by the side of street; such living conditions are worse than they have in villages. Lack of job security, ineffective labor unions and illness-related insecurity also play a role in reverse migration. Seasonal migrants are generally not protected against accidents and do not have provision for retirement benefit (Elkan 1959). If a migrant becomes ill or requires money, they can seek help in the village which provides some sort of social security through the widespread network of social relations, which provides an incentive for migrants to go back (Hugo 1982).

In the lean period, large numbers of people may leave the village to seek jobs in the urban sector leading to an excess supply of labor. Employers usually exploit this by decreasing the wage rate below the standard market rate. Moreover, employers know that migrants are temporary workers, hence there is no incentive for them to provide training or invest in this short-term labor force. The lack of formal or skill-based education ensures that most migrant workers remain unskilled, making it extremely difficult for them to seek jobs in the formal urban labor market.

The most important economic factor leading to reverse migration is the reversal of the rural-urban wage difference. For a temporary migrant, the income in the rural sector during the normal time is typically more than the the urban sector. As a result, there is an obvious incentive for migrants to return to rural areas in the normal period after the shock.

2.3 Factors Influencing the Migration Decision

A number of studies have analyzed the internal migration pattern in Bangladesh; in particular Chowdhury (1978), Khan (1982), Huq-Hussain (1996), Begum (1999), Islam (2003), Hossain (2001), Barkat and Akhter (2003), Afsar (1999, 2003, 2005), Kuhn (2001, 2005), and Skinner and Siddiqui (2005). We also find some studies on circular migration such as Breman (1978), Hugo (1982), Stretton (1983), Chapman and Prothero (1983), Rogaly et al. (2002); Rogaly and Coppard (2003), Deshingkar and Start (2003), andDeutsch et al. (2003). Broadly, these studies focus on issues such as the scale and pattern of migration, the characteristics or selectivity of the migrants, causes of migration, the impacts of internal migration on urbanization and the pattern of resource transfer followed by rural-urban migration. As we could not find sufficient studies on the factors influencing the seasonal migration decision, we have used the generally used variables which are found to be significant for internal rural to urban migration studies.

Wage differential : Sir John Hicks argued in *The Theory of Wages* (1963, pg. 76) that the main cause of migration is the wage differential. Classic migration literature and theories (Harris and Todaro 1970, e.g.), whether internal or international, employ wage differentials as the core mechanism that leads to migration. Thus, following this trend, a direct relationship between the wage differential of lean and normal period income and the migration decision has been hypothesized.

Level of Asset: Interestingly, the relationship between land holding and the migration decision in empirical studies is inconclusive and ambiguous. For example, Kuhn (2005) argues that the land-holdings of households is a key determinant of rural-urban migration and the tendency to migrate will be greater for those who hold less land. Similarly, the recent work of Mendola (2008) finds a negative and significant relationship between land holding and migration decisions for temporary migrants in Bangladesh. Hossain (2001), in contrast, finds that the tendency to migrate is higher for households with some sort of land holding compared to the landless. Hence, it will be interesting to explore the role of asset holding (in the form of land) in determining the seasonal migration decision of the poor in lean period.

Micro-credit: A recent policy development in developing countries has been the emergence of micro-credit institutions in relation to poverty alleviation. It is argued that if given access to relatively small credits, entrepreneurs from poor households will find opportunities to engage in viable income-generating activities, often secondary to their primary occupation, and thus alleviate their poverty by themselves. Micro-credit is accessible in rural areas through Micro-finance Institutions (MFIs) that have expanded quite rapidly in recent years. According to the Micro-credit Summit Campaign, Micro-finance institutions had 154,825,825 clients as of December 2007, of which more than 100 million were women. In 2006, Mohammad Yunus and the Grameen Bank were awarded the Nobel Prize for Peace for their contribution to the reduction of poverty, especially in Bangladesh. However, among academics there is so far no consensus on the impact of micro-credit on income improvement and poverty reduction (Banerjee et al. 2009).

Typically, MFIs provide small loans to poor people who are deprived of access to credit offered by regular banks. Through the introduction of 'social collateral', MFIs give individual loans to villagers in groups and hold the group jointly liable for repayment. If any group member defaults, the entire group is punished by being denied future loan applications. This group mechanism creates peer pressure and solidarity, which is reported to work well in societies where social networks and bonding are of vital importance. The repayment success rate of MFIs is quite high and in Bangladesh, for example such repayment rate has never dropped below 90 percent (Develtere and Huybrechts 2005).

The major drawback of the micro-credit framework is the rigid loan repayment rule. Nearly all contracts are fixed in their repayment schedules, which entails constant equal weekly payments with a high interest rate. The members of MFIs are poor rural people who frequently have uncertain income, which makes it very difficult for them to maintain such rigid weekly loan repayments. In a lean period especially when there is no job availability in the rural agricultural sector, it is extremely difficult for the poor to generate income, let alone comply with their loan repayment scheme. Such strict repayment schedules prevent people with prior access to micro-credit from migrating, thus making it very hard for them to repay their weekly installments and survive. Hence we hypothesized a negative relationship between access to credit and seasonal migration, holding other things equal.

Ecological vulnerability: Natural disasters like floods and river erosion affect the agricultural output of rural people and dramatically decrease their income and living condition. Most developing countries are natural diaster-prone and such issues should be taken into account in considering the migration decision. Historically Bangladesh has been affected by cyclones, floods and river erosion in every alternate year. Due to the flooding of the three major rivers (Brahmaputra, Dharla and Tista), hundreds of families in the Kurigram district, the survey area used in our research, are forced to relocate every year. People affected by such natural calamities will temporarily move to other areas. As a result, such variables are important determinants of any internal migration.

Personal Characteristics: The literature shows that internal migration is most common among the younger population (Borjas 2000; Mendola 2008). Demographically, the internal migrants of Bangladesh are mostly young adults (Chowdhury 1978) and temporary migrants are even younger than permanent ones (Afsar 2002) which is perhaps not surprising since the demographic pattern of the population of Bangladesh is quite young in comparison with western countries. Household surveys at migration destinations show that three-quarters of temporary migrants and half the permanent internal migrants are 15 to 34 years of age. Based on the available literature we hypothesize that, holding other things constant, those who belong to the 20-40 age cohort are more likely to migrate in the lean period, as their moving costs are low and the probability of getting an urban job is high.

(Hugo 1982) argued that men have a significantly greater tendency for seasonal migration than women. Due to limited employment opportunities, family responsibilities and for religious reasons, female members of a family are less likely to migrate than adult male members. Studies on permanent migration reveal that those who are married have closer ties with their families and relatives, and are less likely to migrate (Lee 1984; Kuhn 2005). In contrast, Hossain (2001) argued that the propensity for migration is higher among married persons. When mere survival is critical in the agricultural lean season, the responsibility for feeding dependents (spouse and children) is expected to increase the probability of individual migration (Huq-Hussain 1996). Previous empirical works on migration suggested that household size positively influences an individual's migration decision (Deshingkar and Start 2003; Mendola 2008). Hence, a positive influence of household size on migration decision has been hypothesized.

Education: The role of education in the migration decision has been widely discussed in the literature and several studies have shown that migrants are usually more educated than non-migrants in the same locality (Chowdhury 1978; Kuhn 2005). Educated people are more likely to migrate, as job opportunities for them are higher in the urban centers than in the rural areas. Interestingly, Huq-Hussain (1996) suggests that educational attainment is not always an influential factor in the migration decision, particularly among poor female migrants in Dhaka city. Country level studies have also found a significant association of education with the on migration decision, such as like Sahota (1968) and Yap (1976) in Brazil, Herrick (1966) in Chile, Carvajal and Geithman (1974) in Costa Rica, Falaris (1979) in Peru, Lanzona (1998) in Philippines and Greenwood (1971) in India.

Role of networks and experience: Holding other things equal, an experienced worker is expected to face lower search cost in the urban job market. Thus, we hypothesize that the probability to migrate will be higher if the worker has prior migration experience. The importance of a strong support network is crucial for the immigrants (Munshi 2003; McKenzie and Rapoport 2007) as well as for the migrants (Afsar 2002). Social networks offer support in the provision of accommodation, relocation, learning new skills, better bargaining power and protection against harassment, assault and uncertainties. Afsar (2003) found that 60 percent of the internal migrants who have kinsmen at the place of destination, managed employment within a week of arrival in Dhaka city. Hence, the presence of kinship at the place of destination is expected to have a higher influence on the seasonal migration tendency.

3 Data Description

We collected the primary data of the study from Kurigram where approximately 46% of the total labor force is involved in agriculture; another 30% are agricultural day laborers (Banglapedia 2006). The study area consists of four selected thanas[3] of Kurigram district: Chilmari, Ulipur, Rajarhaat and Kurigram. The survey covered 17 villages from the four thanas: four from Chilmari, three from Rajarhat, four from Ulipur and six from the Sadar thana. Although the villages from each thana were selected randomly, the four thanas were selected to capture heterogeneity in income, communication, infrastructure facilities, catastrophic and other sociocultural factors.

The survey showed that people living in Ulipur and Chilmari were relatively poor compared to those living in Rajarhaat. We observed that Kurigram Sadar and Rajarhat had better transportation systems compared to Chilmari and Ulipur, so the ability to move is relatively higher in this area. A char[4] area was also surveyed in the Kurigram Sadar to capture the special characteristics of char livelihood in relation to the migration decision in the lean period. Among the four thanas, the history of these areas suggest that Rajarhaat suffers the least during natural disasters. In contrast, Chilmari is the worst affected by both flood and river erosion. River erosion is quite rare in Ulipur,

[3]A thana is a unit of police administration. In Bangladesh, 64 districts are divided into 496 thanas. There are ten thanas in the Kurigram district.

[4]A char is a small river island created by silt deposits and estuaries.

although annual flood ravage the area. The char area is affected by river erosion and floods quite regularly: the Kurigram town is also affected by river erosion.

According to the Banglapedia (2006) the population of Kurigram district is 1,782,277, of which 49.62% are male and 50.93% are female. The majority of the population are Muslim; as a result, only minor religious and cultural heterogeneity exists in the survey area and is negligible. The people of this region are largely illiterate, with an average literacy rate of around 22.3%. The survey area consists of 37.02% of the total population of the district.

The survey was conducted among 290 random individuals who are representative of their household. The survey questionnaire was trialed on 30 respondents in Chilmari and Ulipur before being used for the main survey. The final questionnaire consisted of 12 sections and was designed to collect individual information on the migration decision and factors influencing this decision. The survey sought general information like age, occupation, average income and the number of dependents. The questionnaire also address issues of land usage, occupation at destination if migrated, NGO membership and land ownership. The questionnaire also collected information on the nature and extent of starvation throughout the year, information on natural disasters, death of earning family members and sudden damage of crop or livestock.

Off the 290 respondents, 68 percent were identified as migrants. The variables were categorized into three groups: representing economic factors, ecological vulnerabilities and personal characteristics. The measure of income in the lean period in this study is the household earnings if the respondent stays in the village or the household earnings if the respondent migrates. We do not have the counterfactuals for this information in the dataset.

We were not confident that individuals could predict future plans for seasonal migration and we therefore asked respondents about their past migration behavior and income patterns. To capture the seasonal migration behavior of the respondents, we used a dummy variable, which has a value of one if the respondent migrated in one of the last two lean periods and zero otherwise.

The variable seasonal unemployment (i.e., unemployed during the lean period) is a binary variable. An individual reported to have remained unemployed during most of the lean season is assigned one and is otherwise assigned a value of zero. In the sample, 63 percent of the respondents reported that they were unemployed during the lean period. A simple dummy variable is used to indicate land ownership. A worker is assigned a value of one if his/her family owns any cultivable land, irrespective of the size. Otherwise, he/she is assigned a value of zero. 43 percent of the respondents reported that they were landless.

With 1200 micro-credit institutions and 19.3 million members, the micro-credit sector of Bangladesh is one of the largest in the world. According to the Credit and Development Forum Bangladesh (Credit and Development Forum 2006), approximately 37% of all households in Bangladesh have access to micro-credit. Credit does not require any collateral and is given to both individuals and groups. The major types of loans include general loans, program loans and housing loans. We measured the access to micro-credit through NGO membership by a dummy variable, which is coded as one for having access and zero otherwise.

River erosion and flood are the two major natural catastrophes which have occurred in the study area; both factors were included in the study as dummy variables (DV). For river erosion, the DV has a value of one if an individual family had ever experienced forced displacement due to river erosion. In our sample, 61% of the respondents faced such an experience at least once in their lives. One problem of this data is in locating this experience; as an individual could have been forcibly displaced by such an event in a place other than the survey area; hence, this data is noisy and care must be taken in using this information. The dummy variable for flood equals one if the respondent is a victim of a flood in the year of migration, and zero otherwise. 49 percent of the respondents reported being a flood victim in the last two years.

More males than females were interviewed (89 percent versus 11 percent). Patriarchal village societies account for such a small female response rate. 70 percent of the respondents reported to be married at the time of the survey which is quite a high number.

[Table 1 about here]

The occupation variable was divided into two broad categories including agricultural and non-agricultural, because we were interested in testing the hypothesis that agricultural workers are the group that migrates in the lean period. Consequently, farmers were assigned a value of one and zero otherwise. The occupational composition of the respondents is as follows: 47 percent of the respondents are involved in agriculture, while the reminder are non-farm workers such as fishermen, potters, petty traders, land leasers, garment workers, rickshaw-pullers or petty village musicians.

A dummy variable is also used to capture information on education. An individual having some reading ability was given a value of one and zero otherwise. In the present sample, 42 percent of the respondents have at least some education. Interestingly, 63 percent of the respondents reported having some prior migration experience, and 52 percent of the respondents had kinsmen at the urban centers at the time of survey.

The variables used in this analysis are summarized in table 14.

4 Econometric Models

4.1 Econometric Modeling of Seasonal Migration and Self-Selection

We follow Nakosteen and Zimmer (1980), and Robinson and Tomes (1982) models of migration in which switching regression models with endogenous switching are used, as characterized by Maddala and Nelson (1975). Let us assume that during the lean period, individual i elects to migrate if the percent gain in moving exceeds the associated total costs. Thus a person chooses to migrate if

$$(Y_{mi} - Y_{ni})/Y_{ni} > C_i \tag{1}$$

where C_i represents the direct and indirect costs of moving from area n to area m, by individual i as a proportion of income. Let us assume that the cost of moving is represented by economic factors, ecological vulnerabilities and personal characteristics (X) with a random disturbance term.

$$C_i = g(X_i) + e_i \tag{2}$$

Expression 1 and 2 suggest, as a general proposition, that the migrant selectivity criterion is a function of gains in earnings along with other attributes. Here, the criterion is modeled as a linear combination of these variables which explain an individual's propensity to migrate. Formally, an individual i chooses to migrate if $I_i^* > 0$ and does not migrate if $I_i^* \leqq 0$ where

$$I_i^* = \alpha_0 + \alpha_1[(Y_{mi} - Y_{ni})/Y_{ni}] - \alpha_2 X_i - e_i \tag{3}$$

Since $(Y_{mi} - Y_{ni})/Y_{ni}$ is approximated by $\log Y_{mi} - \log Y_{ni}$, then plugging this into the above equation, the decision equation becomes

$$I_i^* = \alpha_0 + \alpha_1(\log Y_{mi} - \log Y_{ni}) - \alpha_2 X_i - e_i \tag{4}$$

and

$$\log Y_{mi} = \theta_{m0} + \theta_{m1} X_i + \varepsilon_{mi} \tag{5}$$

$$\log Y_{ni} = \theta_{n0} + \theta_{n1} X_i + \varepsilon_{ni} \tag{6}$$

where

$$\begin{aligned}
X_i &= \{\text{Factors influencing the income}\}_i (\textit{observable}) \\
\varepsilon_{mi} &= \{\text{General ability, attitude towards risk and preference, specific to } m\}_i \\
&\quad (\textit{unobservable}) \\
\varepsilon_{ni} &= \{\text{General ability, attitude towards risk and preference, specific to } n\}_i \\
&\quad (\textit{unobservable}).
\end{aligned}$$

Expression 4 - 6 comprises the basic structure of the migration model. The endogenous variables are I_i^*, $\log Y_{mi}$ and $\log Y_{ni}$, but in reality we do not observe I_i^*, instead we observe $I_i = 1$ if $I_i^* > 0$ and $I_i = 0$ if $I_i^* \leqq 0$. In addition, since only part of the population moves and part of them stays, we observe $\log Y = \log Y_{mi}$ when $I_i = 1$ and $\log Y = \log Y_{ni}$ when $I_i = 0$. However, for the income equations, OLS estimations will be inappropriate due to the presence of self-selection in migration. Migration is a decision chosen by each individual i, which tends to be non-randomly distributed within the population. As a consequence, there is inherent 'selectivity bias' with the OLS estimations of income equations 5 and 6 since such estimations fail to reflect the presence of self-selection. More formally,

$$E(\varepsilon_{mi}|I_i = 1) = \sigma_{m\varepsilon^*}[-f(\psi_i)/F(\psi_i)] \tag{7}$$

$$E(\varepsilon_{ni}|I_i = 0) = \sigma_{n\varepsilon^*}[-f(\psi_i)/1 - F(\psi_i)] \tag{8}$$

where, $f(.)$ and $F(.)$ are the standard normal density and distribution functions based on the conditional formulae for the truncated normal distribution.

To correct for selectivity bias and to estimate consistent parameters, we need to follow the procedures developed by Lee (1983) described as follows. Substituting 5 and 6 into 4 provides the reduced form decision equation. If we assume the error terms of the reduced form equation is normally distributed with unit variance, then such a model could be a estimated by probit model. Hence the reduced form decision equation will become

$$\psi = \beta_0 + \beta_1 X_i' - e_i' \tag{9}$$

Probit estimations of the above model yield the fitted values of $\hat{\psi}_i$ which then will be used to construct the following variables

$$u_{mi} = [-f(\hat{\psi}_i)/F(\hat{\psi}_i)]$$

and

$$u_{ni} = [-f(\hat{\psi}_i)/1 - F(\hat{\psi}_i)].$$

In stage two, the correct income equation which could be estimated by OLS is stated below.

$$\log Y_{mi} = \theta_{m0} + \theta_{m1} X_{mi} + \theta_{m2} u_{mi} + \eta_{mi} \tag{10}$$

and

$$\log Y_{ni} = \theta_{n0} + \theta_{n1} X_{ni} + \theta_{n2} u_{ni} + \eta_{ni} \tag{11}$$

where,

$$E(\eta_{mi}|I_i = 1) = 0$$

and

$$E(\eta_{ni}|I_i = 0) = 0.$$

The estimates obtained by this procedure are known to be consistent Lee (1983). In the final stage we need to estimate the fitted values of log earnings from equation 10 and 11, which together with appropriate exogenous variables are then switched back into the structural decision equation 4. Further discussion of such estimation procedures appears in Lee (1983).

4.2 Econometric Model of Migration and access to Micro-credit

The model of the section 4.1 will produce inconsistent estimates if we assume that the access to micro-credit is endogenous in nature, which may have influence over people in the lean period and also may influence their propensity to migrate. Thus, a natural extension of the univariate probit model will be to allow two simultaneous equations;

one for the access to micro-credit and the other for the migration, with correlated disturbances, which can then be estimated with a bivariate probit model. Following Greene (2002), the general specification for a two equation model where y_{1i} is the dummy for micro-credit and y_{2i} is the dummy for migration is as follows,

$$\begin{aligned} y_1^* = {} & x_1'\beta_1 + \varepsilon_1,\ y_1 = 1\ if\ y_1^* > 0, 0\ otherwise, \\ y_2^* = {} & x_2'\beta_2 + \varepsilon_2,\ y_2 = 1\ if\ y_2^* > 0, 0\ otherwise, \\ & E[\varepsilon_1|x_1,x_2] = E[\varepsilon_2|x_1,x_2] = 0, \\ & Var[\varepsilon_1|x_1,x_2] = Var[\varepsilon_2|x_1,x_2] = 1, \\ & Cov[\varepsilon_1,\varepsilon_2|x_1,x_2] = \rho. \end{aligned} \tag{12}$$

In this case, unless we find evidence that $\rho = 0$, the probit analysis in the previous section will give inconsistent parameter estimates. Here ρ measures the unobserved heterogeneity which implies that the error term will share a common component and can be expected to be correlated with each other.

Also, we will use an endogenous treatment model where the first dependent variable (the dummy variable which is coded one to represent the access to micro-credit) appears as an independent variable in the second equation, which is a recursive, simultaneous equation model where

$$\begin{aligned} y_1^* = {} & x_1'\beta_1 + \varepsilon_1,\ y_1 = 1\ if\ y_1^* > 0, 0\ otherwise, \\ y_2^* = {} & x_2'\beta_2 + y_1\gamma + \varepsilon_2,\ y_2 = 1\ if\ y_2^* > 0, 0\ otherwise, \\ & E[\varepsilon_1|x_1,x_2] = E[\varepsilon_2|x_1,x_2] = 0, \\ & Var[\varepsilon_1|x_1,x_2] = Var[\varepsilon_2|x_1,x_2] = 1, \\ & Cov[\varepsilon_1,\varepsilon_2|x_1,x_2] = \rho. \end{aligned} \tag{13}$$

If we find that γ is significant then we can conclude that the people who choose to take micro-credit have a systematically different pattern of migration decision in the lean period.

4.3 Strategy evaluation

4.3.1 Difference-in-Difference Method

The major problem of the lean period hardship is the significant reduction of income due to joblessness in the agricultural industries; thus it is necessary to test the impact of migration and micro-credit on the lean period income.

One possible way to test the impact is by using quasi-experimental techniques, since the case explained in this study can easily be qualified as a quasi-experiment. We know that a natural experiment occurs due to some random exogenous event. Migration and access to micro-credit are the two treatments which could be ideally suited to such an experiment. A risk averse individual can choose to migrate during the lean period or can access micro-credit in the normal time to engage in income generating activities which will help him to survive during the lean period hardship. A natural experiment always consists of a control group (which is not affected by the exogenous event) and a treatment group (which is affected by the exogenous event). Under a true experimental framework, treatment and control groups are randomly chosen and arise from particular policy or event change. Thus, to control for the systematic difference between these two groups, we need two periods of data, one before and one after the policy change. In our case, we have the income information of two periods, one in the normal period and one in the lean period. We can easily convert the data to use for two period cross-sectional data sets (panel data), one before the lean period hardship and one after (which is the normal period), and can be used to determine the effect of these two treatments .

Once we have converted the data into longitudinal form with two period incomes (income in the lean period and income in the normal period), the other demographical variables (such as education, occupation, sex or marital status) will be mostly time-invariant . As a result, the data gives us the opportunity to test the impact of these two policies with the help of the difference–in–difference (DID) method. Let us use C to denote the control group and T to denote the treatment group, letting dT equal unity for those in the treatment group T and zero otherwise. Then let us call dP a dummy variable for the lean time period and variable a_i captures all unobserved, time-constant factors that affect $Y_{i,t}$. Then the equation of interest is:

$$Y_{i,t} = \beta_0 + \delta_0 dT_t + \beta_1 dP_{i,t} + Other\ Factors + a_i + u_{i,t} \tag{14}$$

where $Y_{i,t}$ is the outcome variable of interest, which is the level of income or log of income for individual i at period t for this equation. [5] To measure the effect of a strategy, without the other factors in the regression, the $\beta_1$will be the DID estimator:

$$\beta_1 = (\bar{y}_{2,T} - \bar{y}_{1,T}) - (\bar{y}_{2,C} - \bar{y}_{1,C}), \tag{15}$$

where the bar denotes the average, the first subscript denotes the period (1 for normal and 2 for the lean season) and the second subscript denotes the group. Thus the sign of the β_1 shows the effect of the treatment or policy on the average outcome of y. Moreover, differencing the mean twice eliminates almost all the observed differences for the treatment between recipients and control individuals (Johar 2009). In our case, if either the temporary internal migration or access to micro-credit have positive impact over the income during the lean season, then the expected sign of the treatment effect β_1 will be positive. The parameter β_1 is sometimes called the average treatment effect. When we add other explanatory variables to equation 14, the OLS or fixed effect estimation of β_1 will no longer be as simple as mentioned above but the interpretation will be the same.

[5]To capture the impact of micro-credit during the lean season, since people selected to have access to micro-credit before the lean season arrives, the equation will be
$Y_{i,t} = \beta_0 + \delta_0 dT_t + \beta_1 dT_t * dP_{i,t} + Other\ Factors + a_i + u_{i,t}$.
This is one special case where we need to use the interaction term to estimate the impact.

4.3.2 Propensity Score Matching Method

An important problem of causal treatment effects is to estimate treatment impact in a non-experimental comparison group. Such estimation could be biased because of problems with self-selection. In any evaluation study, problem can arise when one would like to have the outcome of the participants with and without the treatment. Obviously, the mean outcome of a non-participant could be used as a proxy but such an approximation could be problematic since participants and non-participants might systematically differ even in the absence of the treatment.

In our present study, it is possible that the people who have had prior access to micro-credit could be different from those who did not choose to have access to micro-credit during the normal time and decided to migrate in the lean period. Hence, we need to use matching techniques to correct for such sample selection bias between treatment and observable group. Propensity score matching (PSM) is currently a popular method to use for program evaluation studies, especially in labor economics (Heckman et al. 1998; Dehejia and Wahba 2002). As suggested by Rosenbaum and Rubin (1983*a*,*b*, 1985), PSM calculates the probability of participants and nonparticipants who have similar pretreatment characteristics, using any standard probability model. After that, PSM matches the participants with non-participants with similar propensity scores based on different matching techniques and finds the difference in outcomes. The underlying assumptions for such matching methods are unconfoundedness, selection on observables or conditional independence (Caliendo and Kopeinig 2008).

Matching through propensity score is basically a weighting mechanism. While computing the estimated treatment effect, different matching techniques provide different weights on comparison units. The most frequently estimated parameter for such studies are the average treatment effect (ATE) and the average treatment effect on the treated (ATT). ATE is simply the difference between the expected outcomes after participation and nonparticipation; but the most important parameter for program evaluation is the ATT which is the difference between expected outcome with and without treatment for those who have actually participated in treatment. Following Caliendo and Kopeinig (2008), let us denote N as the treatment group, $|N|$ as the number of units in the treatment group, J_i is the set of comparison units matched to treatment unit i and $|J_i|$ is the number of comparison units in J_i, then the ATT [6] will be:

$$\hat{\tau}|_{T=1} = \frac{1}{|N|} \sum_{i \in N} (Y_i - \frac{1}{|J_i|} \sum_{j \in J_i} Y_j). \tag{16}$$

Since we are interested in estimating the impact of migration and micro-credit during the lean period, we could estimate the likely impact of the aforementioned policies if we consider these policies as treatment and estimate the treatment effects using PSM. In this study we will estimate the ATT by using three different matching methods : nearest-neighbor, radius and kernel matching.

[6] For general discussion on more weighting schemes on propensity scores see Heckman et al. (1998).

Nearest Neighbor Matching Following Lluberas (2008), we define the group of matched treated individual with the matched control individual i as:

$$U(i) = \{\hat{p}(X_j) | \min_j ||\hat{p}(X_i) - \hat{p}(X_j)||\}, \tag{17}$$

where || || denotes the Euclidean distance. If we define NN as the number of matched individuals with the lowest values of the differences in propensity scores or the nearest-neighbors considered for matching purposes, the weight factor for the ATT under this method will be

$$\frac{1}{|J_i|} = \frac{1}{NN} \text{if } j\epsilon U(i), 0 \text{ otherwise.} \tag{18}$$

Radius Matching Under Radius matching, we will match all the control individuals with the propensity score of the treated individual within a predefined radius from the propensity score of the treated individual i. Hence, the group of control individuals that are matched with the treated ones is defined as:

$$U(i) = \{\hat{p}(X_j) \mid \left\|\hat{p}(X_i) - \hat{p}(X_j)\right\| < \delta \tag{19}$$

where δ being the radius assumed (for example $\delta = 0.001$). If we define R as the number of control individuals matched with the treated individual i, then ATT under this method will be

$$\frac{1}{|J_i|} = \frac{1}{R_i} \text{if } j\epsilon U(i), 0 \text{ otherwise.} \tag{20}$$

Kernel Matching (KM) Under the Kernel matching estimator, the weight we will use for ATT will be

$$\frac{1}{|J_i|} = \frac{K\left[\frac{\hat{p}(X_j) - \hat{p}(X_i)}{h}\right]}{\sum_{k=1}^{N_{u(i)}} K\left[\frac{\hat{p}(X_k) - \hat{p}(X_i)}{h}\right]} \tag{21}$$

where $K(.)$ defines the Kernel function, h the bandwidth and $N_{u(i)}$ is the number of control group members that has been matched with the treated individual i. In this study, we used Gaussian function for the Kernel matching estimations.

5 Estimation

5.1 The Determinants of the Seasonal Migration Decision

We first estimated the reduce form equation like the one stated in equation 9. Probit estimates of such equation are presented in Table 2. In the next step, fitted values of the reduced form maximum likelihood model are used to construct selectivity variables. Here we create two variables, one for the migrants and the other for the non-migrants, according to equation 7 and 8. These selectivity variables are then used for estimating the earning equations 10 and 11 by OLS (Nakosteen and Zimmer 1980). Estimates of the earning equation are not reported here but are documented separately and could be available upon request. If the combined effect of these two selectivity variables on unconditional earnings is positive then we can confirm that the process of self-selection of the migration decision serves to improve unconditional expected earnings.[7] From our results, the combined effect of self-selection on expected earnings is $\hat{\theta}_{n2} - \hat{\theta}_{m2} = 0.26$ which is positive. The final stage in the estimation entails probit estimation of the structural form equation as expressed in equation 4. The resulting maximum likelihood estimations are reported in Table 2. We have results from three sets of Probit estimations in Table 2 with coefficients and marginal effects. Here the reported marginal effects are the average values of the explanatory variables. In the first model, we have the log of migration income variable as an independent variable, which shows that as the income at the migration destination increases, people will be more inclined to seasonally migrate during the lean season. Such an estimation is highly statistically significant. In the second model, we have the log of non-migration income as the dependent variable which is also significant but shows a negative sign. This estimates reveals that as non-migration income opportunity increases in rural areas, people will be less interested in seasonally migrating during the lean season, holding all things constant. In model three, we implemented the most crucial migration determinants factor; migration and non-migration income differential. As expected, the effect of anticipated monetary gain due to migration significantly increases the probability of migration, confirming the classic Harris-Todaro theory of migration.

The probit estimates of the structural form equation show that seasonal hardship in the lean period and individual characteristics like sex, age, size of the family, farm occupation, prior experience and kinship at the place of destination and education have a significant association with the migration decision. The marginal effect of a unit change in the explanatory variables on the decision to migrate has also been calculated. It is evident that expected income difference is the most decisive among the economic factors in determining the probability of migration. Among the non-economic factors, previous migration experience has the highest magnitude in explaining the migration decision.

[Table 2 about here]

[7] Note: Unconditional expected earnings for individual i could be written as

$$E(Y_i) = E(Y_i|I_i = 1).P(I_i = 1) + E(Y_i|I_i = 0).P(I_i = 0).$$

So, if we plug all the exogenous variables in the above equation then the expression becomes

$$E(Y_i) = (\theta'_{m1}X_{m1}).F(\Psi_i) + (\theta'_{n1}X_{n1}).[1 - F(\Psi_i)] + (\theta_{n2} - \theta_{m2}).f(\Psi_i).$$

Another economic factor, land ownership; was found to be significant and negative, which shows that people who have ownership of land are not greatly affected by the lean period shocks and are less inclined to migrate. Land ownership could be used as a proxy of the wealth status of an individual showing that relatively wealthy population in lean affected areas are not particularly vulnerable as a result of seasonal shocks, because they can save sufficiently during the normal period to cover their expenditures during the lean seasons.

The present study finds that the probability of migrating is negatively associated for an individual with access to micro-credit through NGO membership, but the relationship is not significant. Usually in Bangladesh, micro-credit providers do not allow their members to migrate. However, in our study we have recorded access to credit even for those people who are not directly a member of a NGO but whose family members have taken credit. Such individuals can make the decision to migrate which might be the reason for such an insignificant but negative relationship between NGO and migration.

Prior migration experience has the strongest positive impact among all the factors influencing the migration decision. Migration experience and kinship at the place of destination reduces the cost of migration by minimizing the time for job searching. Both of these variables were found to be significant at less than the 1% level, which is a crucial finding of our study.

The results also show that migration propensity is significantly higher among males. Workers in the 20-40 age group have a significantly higher intention to move in the lean period. The size of family is found to be significant and positively influences the probability of migrating as expected. This indicates that for a large family, the chief earner is more likely to migrate as the migration income in the lean period is very important for the survival of a bigger family.

An important finding of our study is that farm occupation significantly modifies the migration decision. Since the seasonal hardship results from seasonal unemployment in agriculture, it is logical that farmers would be keen to seek an alternative livelihood strategy, preferably in the cities. The probit model suggests that the probability of migration is significantly higher among the farmers. Agricultural workers are more vulnerable to seasonal unemployment in the lean period. As a result, a large number of agricultural workers choose to migrate in the lean period and the present study has found a significant and positive impact on agricultural professionals to opt for seasonal migration. Such evidence contradicts the literature on permanent internal migration. Studying migration in Costa Rica, Carvajal and Geithman (1974), found that income elasticities of in-migration rates are higher for professionals, managers, white-collar and industrial workers. This is quite natural, as higher wages for these jobs attract migrants to cities. It provides evidence that lean period migration is basically a shock driven migration where farm laborers are the most-affected. Thus they constitute the vast majority of the population to choose temporary internal migration.

A compelling finding of the study is regarding with the river erosion. It was found that those who had experienced river erosion at least once in their lives have a lower migration propensity. This finding conforms to our hypothesis. The probit results suggest that the probability of migration falls if the worker has experienced river erosion, which is marginally significant for the first model. One possible explanation for this result might be the economic vulnerability of those people affected by the river erosion. To migrate to nearby cities, one needs at least some assets to cover the transportation and initial relocation cost, but the people who are affected by river erosion have already lost their valuable lands and houses and therefore they cannot afford to migrate in the lean period. Those who have experienced river erosion at some time in their lives fall into the trap of chronic poverty and cannot cover the minimum cost of adopting an alternative livelihood strategy such as migration. The trauma effect of forced relocation due to the river erosion could be another explanation for their diminished migration propensity.

An interesting relationship between farmers and non-farm occupants can be extrapolated from Figure 1. Here, we have created a graph of a representative individual as a base case. The individual is a male, married, with mean income, who has no migration experience, no kinship at the destination of migration, no education, no land ownership, no access to micro-credit, no social security, has been affected with river erosion, is aged 35 and is a farmer. In figure 1, the predicted probabilities of two kinds of occupation for a range of family sizes has been provided. Interestingly for the non-farm occupants, the size of family does not dramatically increase the probability of migration. As seasonal hardship results from seasonal unemployment in agriculture, agricultural workers suffer mostly from shortage of employment in the autumn lean period. The same is not true for the non-farm workers who are less likely to migrate in the lean period, and the predicted probability of migration for this cohort does not vary much with the changing size of the family. For the agricultural worker, the probability of migration is very high and has a strong upward tendency as the size of the household increases.

Another interesting relationship of education and migration probabilities is shown in Figure 2. For the same representative individual (with family size taken to be 5), education significantly affects migration probability and this impact remains almost constant even with the increase of age to the maximum. This has important policy implications as it illustrates the potential impact of education on the propensity to migrate.

Finally, we have calculated a probability table for the above-mentioned base case and calculated the predicted probability by changing units from the base case (see table 4). The predicted probability for the micro-credit is of interest. Using the base case, we have calculated that the predicted probability of migration decreases from 0.91 to 0.82 for a person who has access to micro-credit through NGO membership. This result suggests that access to micro-credit reduces the propensity to migrate in the lean period, but as we find in table 2, this effect is not significant. As a result, this interesting study finding leads us to the next section where we will investigate whether a systematic relationship exist between these two variables: migration and credit access through NGOs.

[Table 4 about here]

5.2 Seasonal Migration and Access to Micro-credit

Our probit model may encounter a problem if there exists an endogenous non-random sample selection process for the people who took NGO membership to access micro-credit and the people who migrated in the lean period. Access to micro-credit and migration in the lean period are livelihood strategies to overcome the income shock in the lean period, but access to the informal credit market through micro-credit is a long term strategy to deal with poverty, whereas temporary seasonal migration is a short term strategy to deal with seasonal hardship which largely depends on individuals' attitudes towards risk (Binswanger 1981; Quizon et al. 1984) and such strategy works as a consumption-smoothing technique for the poor rural people (Rosenzweig and Stark 1989). Selection problems may exists for individuals who took NGO membership to access micro-credit and the decision to migrate. We may also encounter the problem of unobserved heterogeneity between these two strategies.

Bi-probit estimation techniques were used with two models to investigate the aforementioned problem. In the first model (equation 12 in section 4.2), I have treated access to NGO and the migration decision as two endogenous equations. In the second equation (equation 13 in section 4.2), following Burnett (1997), I used an endogenous treatment model where the first dependent variable, NGO, appears as the independent variable in the second equation, which is a recursive, simultaneous equation model. As a result, it is possible to test the impact of treatment (in our case access to micro-credit through NGOs) on the migration decision and to test whether the allocation of treatment was random or not. We can also evaluate the covariance of the disturbance terms of these two equations by estimating ρ.

[Table 3 about here]

From the endogenous treatment model (second model), we found the treatment effect to be insignificant, and the estimate of ρ is only -0.31 with a standard error of 0.57. The Wald statistics for the test of the hypothesis that $\rho = 0$ is 0.29. For a single restriction, the chi-squared critical value is 3.84, so the hypothesis that $\rho = 0$ can not be rejected. The likelihood ratio test for the same hypothesis leads to a similar conclusion. For the simultaneous bi-variate probit model (first model in table 3), the likelihood ratio test for the hypothesis $\rho = 0$ is not significant as the χ^2 test statistics is 2.28 with an associate p -value of 0.13. However, the correlation coefficient measures the negative correlation between the disturbances of access to NGOs and the migration decision after the influence in the included factors is accounted for. However, this relationship between the errors is not significant and separate estimation of these two equations using univariate probit estimation techniques is unlikely to create inconsistency and bias in the estimations.

5.3 Testing for Effective Strategy

5.3.1 Difference-in-Difference estimates

As we have found negative relationship between access to micro-credit through NGOs and temporary internal migration, and as NGO members are most likely to stay during the lean season due to the loan bindings, a natural extension easily leads us to check which is more effective in terms of income improvement during the lean period.

Using equation 14 of section 4.3.1, the DID estimations of the policy variables are migration in the lean period (*Migdec*) and access to micro-credit through NGOs (*NGO*). Now we have two treatment groups; one is the group that chooses to migrate versus people who do not and the second is the group that chooses to have access to micro-credit through NGO membership versus the people who do not. The outcome variable for our case is the level and log of income and the parameters of interest are *Migdec* and *Lean*NGO* in the table 5 and 6. If either of the policies is effective in increasing the income in the lean period, then the variable should be positive and significant.

[Table 5 about here]

In table 5, we show two sets of estimation results for migration effectiveness. The difference between the three separate estimations for a single policy variable is that one used pooled estimation and the other used the fixed and random effect estimations with a full set of control variables. Interestingly, the coefficients of different estimations are almost identical indicating the robustness of our findings. As we can see from Table 5, the variable *Lean* is strongly significant and negative which shows the severity of the lean period shock on income. The variable is significant for all the six models. The variable *Migdec* is highly significant and positive which means migration during lean period is estimated to increase the income significantly, and highly enough to offset the lean period shock.

[Table 6 about here]

Similarly in table 6, we can see the negative and significant effect of lean period shock on income. The *NGO* variable is showing the right sign, though not significant, which is consistent with the idea that access to micro-credit is a long term policy instrument, and we do not expect the variable to have significant influence over income for the short term. Interestingly, the interaction term *Lean*NGO* is negative but not statistically different from zero, which gives us some evidence that just having access to micro-credit in short term situations like seasonal hardship is not sufficient to cover the income downfall.[8] Finally, table 7 shows the impact of migration while having access to credit in the lean period. As expected, the interaction term *Lean*Migdec* is positive and highly significant.[9] Seasonal migration is a short term solution and preferred by any

[8]We also ran several regressions by controlling for village specific effects but such inclusion did not change our result. These results can be provided upon request.

[9]For all the estimations of fixed effect and random effect in table 5, 6 and 7, the Hausman test fails to reject the null, suggesting that we can use either of the estimations.

individual who wants to alleviate short term hardship. As our estimation suggests, an individual is significantly better off with temporary migration than with micro-credit in lean periods. If we look at table 11, we can easily observe that access to micro-credit increases the mean income although the median income is the same. However, in the lean period (refer to table 13) the group of households that made the migration decision is better off than the other two groups. Households that took no credit and did not migrate are the worst affected by the seasonal shock, whereas having only credit access during lean period reduces the mean income of the household. However, individuals in the group that took both options during the lean period has more average income than any other group and is better off. The reason for such a finding is deep-rooted in the micro-credit frameworks. NGOs have a very strict policy of loan repayment; which is usually collected on a weekly basis and people are rarely allowed to migrate once they have taken a loan. For this reason, in some cases the female member of the household takes the credit but then transfers it to the male member who migrates to an urban area and sends his savings to repay the loans. In our dataset, these are the individuals who have access to micro credit but who also migrated during the lean season. The data set also confirms that all the respondents who migrated during the lean season and who had prior access to micro-credit were male. Our estimation in table 7 suggests that such technique can significantly improve income during the lean season even though the magnitude of such impact coefficient is not the highest, as it is still necessary to repay the loan during the lean season, which reduces net earnings. Those who do not exploit the credit opportunities described above are the individuals who have lost their mobility due to loan bindings and consequently can not migrate during the lean season. Therefore, it is evident that access to credit alone can not improve family income in the lean period.

5.3.2 Propensity Score Matching Estimates

Figure 3 and Figure 4 summarize the quality of matching for migration where we can see that both the treatment and control observations have considerable regions of overlap and hence will produced comparable results for different matching algorithms (Dehejia and Wahba 2002).

The propensity estimations in this study have been made using the logit model and the standard errors of the ATT estimates are given by bootstrapping with 500 replications. Lechner (2002), as well as Abadie and Imbens (2006), suggested that, while the analytical standard errors are not available, the bootstrapping technique could be used since such a method is consistent. Use of the bootstrapping method for standard error can be found in Heckman et al. (1998) for the case of Local Linear Model (LLM) estimators, Black and Smith (2004) for NN and Kernel Matching (KM) matching and Sianesi (2004) for caliper matching.

In our study, the matching choice we prefer is the Kernel weights (Gaussian) with DID (Dehejia and Wahba 2002; Smith and Todd 2005; Heckman et al. 1998) within the region of common support. DID estimation is superior in terms of not imposing linear functional form restrictions in estimating the conditional expectation of the outcome variable and re-weights the observation according to the weighting mechanism of the matching technique (Smith and Todd 2005). Since violation of common support could fuel a major source for evaluation bias (Heckman et al. 1998) we strictly implemented all the matching techniques within the common support region. Other matching estimations have also been reported in the result table for robustness check. For the purpose of discussion, we will use the result with Kernel Matching because of its advantage of lower variance by using all available observations for matching.

[Table 8 about here]

In table 8 we can see that the treatment impact of migration is strictly positive and highly significant for all of the matching methods. The ATT of kernel matching for migration is 49% which suggests that on average the treatment impact of migration on income is strictly higher than the control group during the lean season, providing stronger evidence for income improvement with migration.

By contrast, the ATT for micro-credit during the lean period is quite small in magnitude. The kernel matching estimation for micro-credit is only 2% during the lean season and not statistically different from zero, which means that the income improvement for people who only have access to micro-credit is not statistically different from people who do not have access during lean season and who stay in the village. This finding is consistent with our previous conclusion with DID estimations in section 5.3.1.

5.3.3 Quality of the Matching

A critical aspect of PSM is balancing the covariates between treated and untreated (Lluberas 2008).

[Table 10 about here]

With the SB technique, the overall bias has decreased from 25.22% to 5.16 % in the case of migration (for KM estimations). The same is true for Micro-credit where the overall bias has decreased from 21.89% to 6.24% Here the bias has been calculated as the un-weighted average of the covariates' standard bias. Though there is no direct indication of SB to infer about the success and quality of the matching, an SB of 3% or 5% after matching has been considered sufficient in most empirical literature(Caliendo and Kopeinig 2008). Hence, our KM technique has substantially reduced the overall bias and we can be assured of the quality of our result in terms of covariate balance.

As we know the estimated treatment effect with matching estimators is based on the unconfoundedness or selection of observables assumption, a 'hidden bias' may arise if there are unobserved variables which affect the assignment into treatment and outcome variable simultaneously (Rosenbaum 2002). Unfortunately, matching estimators are not roboust against such 'hidden bias' and one needs to address such problems by sensitivity analysis (Caliendo and Kopeinig 2008). We have used Rosenbaum bound because of its advantage of easily interpretable measure (Ferraro et al. 2007). Following Ferraro et al. (2007) and Johar (2009), let us consider a dichotomous outcome which is a function of observable covariates x and unobservables covariates v in case of matched pair i and j. Consider P_i and P_j as the probability of each unit receiving the treatment. The odds ratio between treatment and control is

$$\frac{P_i(1-P_j)}{P_j(1-P_i)} = \frac{\exp(\beta x_i + \gamma v_i)}{\exp(\beta x_j + \gamma v_j)} \tag{22}$$

If the matched pair has comparable covariates then the above equation can be expressed as $\exp[\gamma(v_i - v_j)]$. Under PSM, the estimates will be reliable if $\gamma = 0$ or $(v_i - v_j) = 0$. Suppose that the PSM can not satisfy the aforementioned condition, then the odds ratio for the treatment with control will be bounded by the following expression:

$$\frac{1}{\exp(\gamma)} \leq \frac{P_i(1-P_j)}{P_j(1-P_i)} \leq \exp(\gamma) \tag{23}$$

A given value of γ will limit the degree of hidden bias to which the difference between selection probabilities can be resulted. Let us define $\Lambda = e^{\gamma}$, now setting $\gamma = 0$ and $\Lambda = 1$ indicates that there exists no hidden bias in the PSM estimation. By increasing the value of Λ, we can check at what point the treatment effect is no longer statistically significant. We constructed the outcome using PSM with kernel score from table 8. The differences in outcomes between the treatment and control are calculated and then we used Wilcoxon's signed rank statistics to compare the sums of the ranks of the pairs.

[Table 12 about here]

In this table we have the result for Rosenbaum bounds analysis. Because NGO has an insignificant impact even under null of no observation bias ($e^{\gamma} = 1$), we perform robustness checks only on migration decision (Ferraro et al. 2007). Here we used the value of e^{γ} within the range of 1 to 2 as Aakvik (2001) argued that a factor of 2 (or 100 percent) should be considered as a large number since we have adjusted for many important observables (page 132-33). The result could be interpreted in the following way: given individuals with the same observables, those who would be most likely to migrate during the lean period are more able, hence there could be a positive unobserved selection effect and the estimated treatment effects will overestimate the true effect. In our result in table 12, under the assumption of no hidden bias ($e^{\gamma} = 1$), we find the evidence of significant treatment effect of migration. Hence a critical value of ($e^{\gamma} = 1.25$) states that comparing two individuals with the same co-variates differs in their odds ratio of participating in the treatment by a factor of 1.25 or 25% but it does not mean that unobserved heterogeneity exists and there is no effect of treatment on the outcome variable. Such result only states that the confidence interval for the effect would include zero if an unobserved variable caused the odds ratio of treatment assignment to differ between the treatment and comparison group by 1.25. In our study, we did not find any value of γ which is significant at the 5% level, hence providing the evidence of little or no unobserved effect that could alter our findings.

6 Concluding Remarks

Seasonal migration is not an efficient long-term sustainable solution to the seasonal downturn and natural shocks suffered in the agriculture sector vis-à-vis village level poverty. Temporary migration can provide short-time economic benefits to migrants, their families and their villages but such movements may not be possible over the years. This study has found evidence that temporary internal migration in the lean period is an efficient strategy that individuals in rural areas use to overcome income shock in the lean period. We found that economic, ecological and individual characteristics all play an important role in migration decisions. Among the economic factors, seasonal unemployment and wage difference have significant effects. Personal characteristics such as sex, age, farm occupation, the role of networks and previous migration experience, are all significant at less than the 5% level of significance.

This study has found systemic differences between seasonal migration and permanent internal migration. To the author's knowledge, existing empirical studies on permanent internal migration have found significant positive impacts of education on migration. In this study, we find a reverse relationship. Seasonal migration is temporary in nature and, as a result, individuals who have relatively better education will tend to choose permanent over temporary migration.

Micro-credit schemes have increased opportunities for rural people to have access to the informal credit market. However we found that, during seasonal shocks, individuals with access to micro-credit did not have a significantly different level of income to those that did not have access to credit. Households that took both the migration decision combined with micro-credit earn significantly more than households with only micro-credit in the lean period. MFIs have a very strict policy of loan repayments and usually collect repayment on a weekly basis. In many cases, the credit is received by the female member of the household but is used by the male member who migrates to the urban areas during the lean season and sends remittances to repay the loan. If, however, the male member of the household takes credit during the lean period, he will lose his mobility and cannot undertake migration due to the strict repayment rules. Thus MFIs should consider relaxing the loan repayment scheme during the lean period, as this would help to increase rural incomes and the ability to repay loans. Moreover, the results suggest that MFIs and governments should provide more support on adult education and the development of diverse skills (both non-agricultural and agricultural) which will help poor migrants during lean seasons and thus alleviate the social problems associated with seasonal migration.

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A Appendix

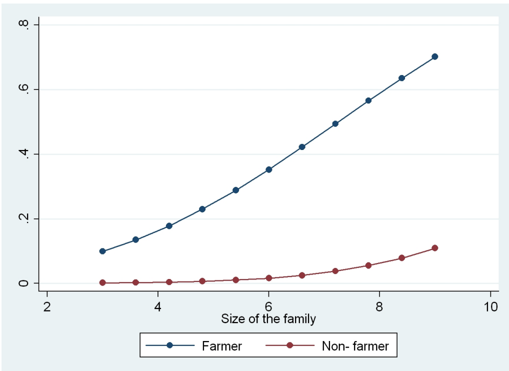

FIGURE 1: Migration propensity for farmer vs non-farmer with the change of family size

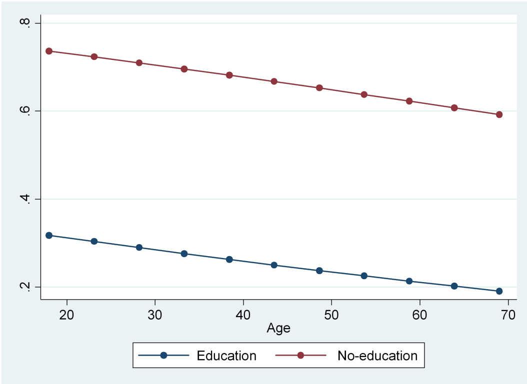

FIGURE 2: Migration propensity with education vs no-education with the change of age

TABLE 1: Descriptive statistics

Variables	Obs.	Mean	S.D.	Min	Max
Migration decision	290	0.68	0.46	0	1
Income in the normal period	290	67.13	34.46	17	270
Income in the lean period	290	58.46	42.60	0	200
Seasonal hardship	290	0.6	0.49	0	1
Seasonal unemployment	290	0.7	0.45	0	1
Previous migration experience	290	0.63	0.48	0	1
Kinship at the migration destination	290	0.52	0.50	0	1
Sex	290	0.89	0.30	0	1
Age	290	39.61	12.53	18	69
Marital status	290	0.70	0.45	0	1
Education	290	0.42	0.49	0	1
Occupation	290	0.47	0.50	0	1
NGO	290	0.19	0.39	0	1
Social security	290	0.13	0.33	0	1
River erosion	290	0.61	0.48	0	1
Flood	290	0.49	0.50	0	1
Land ownership	290	0.43	0.49	0	1
Family size	290	4.94	1.32	3	9

TABLE 2: Univariate probit model

Dependent variable	Reduced form equation		Structural form equation					
			Model 1		Model 2		Model 3	
Migration decision	Coefficients	Marginal effects	Coefficients	Marginal effects	Coefficients	Marginal effects	Coefficients	Marginal effects
Land ownership (d)	-0.591*	-0.0360	-0.605*	-0.0237	-1.970***	-0.0290	-1.129**	-0.0218
	(0.328)	(0.029)	(0.346)	(0.020)	(0.649)	(0.026)	(0.453)	(0.020)
Size of household	0.319***	0.0173*	0.361***	0.0123	0.441***	0.00190	0.379***	0.00463
	(0.112)	(0.010)	(0.136)	(0.008)	(0.128)	(0.003)	(0.145)	(0.005)
Membership of NGO (d)	-0.625	-0.0506	-0.717	-0.0412	0.632	0.00173	-0.241	-0.00362
	(0.568)	(0.062)	(0.555)	(0.046)	(0.533)	(0.003)	(0.561)	(0.010)
Social security (d)	1.054*	0.0297*	1.260**	0.0195	2.693***	0.00396	1.936***	0.00849
	(0.588)	(0.016)	(0.587)	(0.014)	(0.700)	(0.005)	(0.625)	(0.009)
River erosion (d)	-0.569	-0.0283	-0.935***	-0.0289	-0.750*	-0.00301	-1.093**	-0.0128
	(0.348)	(0.022)	(0.353)	(0.023)	(0.422)	(0.005)	(0.428)	(0.014)
Seasonal hardship (d)	1.181***	0.0919**	1.293***	0.0713**	3.019***	0.116	2.085***	0.0821*
	(0.428)	(0.042)	(0.474)	(0.035)	(0.731)	(0.071)	(0.555)	(0.046)
Age dummy (d)	0.743**	0.0607	1.117***	0.0781	0.829**	0.00795	1.267***	0.0445
	(0.363)	(0.042)	(0.408)	(0.052)	(0.401)	(0.010)	(0.461)	(0.038)
Sex (d)	1.758***	0.322*	1.799***	0.264	4.737***	0.892***	2.778***	0.439*
	(0.478)	(0.168)	(0.556)	(0.167)	(1.254)	(0.167)	(0.852)	(0.245)
Farm occupation (d)	1.342***	0.0829**	1.677***	0.0758*	1.984***	0.0191	1.946***	0.0425
	(0.386)	(0.039)	(0.414)	(0.042)	(0.446)	(0.020)	(0.446)	(0.035)
Marital status (d)	0.323	0.0201	0.258	0.00992	0.125	0.000587	0.165	0.00222
	(0.414)	(0.030)	(0.435)	(0.018)	(0.453)	(0.002)	(0.465)	(0.007)
Education (d)	-0.981***	-0.0677*	-1.005***	-0.0460	-1.009***	-0.00724	-0.965***	-0.0173
	(0.302)	(0.040)	(0.313)	(0.030)	(0.337)	(0.010)	(0.352)	(0.017)
Migration experience (d)	3.719***	0.641***	4.262***	0.686***	5.208***	0.616***	4.890***	0.678
	(0.499)	(0.082)	(0.571)	(0.083)	(0.827)	(0.109)	(0.737)	.
Kinsmen (d)	2.334***	0.216***	2.540***	0.184***	3.615***	0.130	3.088***	0.151**
	(0.412)	(0.057)	(0.431)	(0.062)	(0.649)	.	(0.564)	(0.069)
$\log(Y_m)$			2.520***	0.0856				
			(0.697)	(0.056)				
$\log(Y_n)$					-7.861***	-0.0340		
					(2.105)	(0.047)		
$\Delta \log \hat{Y}$							3.177***	0.0388
							(0.910)	(0.039)
No. of Observations	290	290	290	290	290	290	290	290
Pseudo R2	0.7967		0.8246		0.8484		0.8505	
Log likelihood	-36.52		-31.50		-27.22		-26.85	
AIC	101.0	101.0	93.01	93.01	84.45	84.45	83.72	83.72
BIC	152.4	152.4	148.1	148.1	139.5	139.5	138.8	138.8

Note: Values in the parentheses are the reported standard errors of the estimates. (d) stands for discrete change of dummy variable from 0 to 1. Marginal effects have been calculated at the mean. Significance code: ***1%, ** 5%, * 10%.

TABLE 3: Bivariate probit estimations

	Bivariate Probit		Endogenous treatment model	
NGO Equation	Coefficients	Standard errors	Coefficients	Standard errors
Land ownership	0.194	(0.19)	0.194	(0.19)
Size of the household	-0.075	(0.077)	-0.075	(0.077)
Social security	1.289***	(0.236)	1.286***	(0.24)
River erosion	0.185	(0.192)	0.189	(0.204)
Seasonal hardship	-0.135	(0.208)	-0.133	(0.21)
Age	-0.113**	(0.045)	-0.114**	(0.047)
Age squared	0.001**	(0.000)	0.001**	(0.000)
Sex	0.59*	(0.315)	0.59*	(0.314)
Farm occupation	-0.321*	(0.188)	-0.324*	(0.194)
Marriage	0.317	(0.222)	0.321	(0.231)
Education	0.08	(0.19)	0.076	(0.200)
Constant	0.82	(1.013)	0.802	(1.108)
Migration equation				
log (Y_m)	2.437***	(0.69)	2.46**	(0.661)
Land ownership	-0.69*	(0.34)	-0.616*	(0.339)
Size of the household	0.353**	(0.128)	-0.357**	(0.136)
Membership of NGO			-0.149	(1.343)
Social security	0.94	(0.505)	1.013	(0.801)
River erosion	-0.933**	(0.349)	-0.936**	(0.345)
Seasonal hardship	1.275**	(0.428)	1.287**	(0.483)
Age dummy	1.064**	(0.385)	1.083**	(0.403)
Sex	1.674**	(0.527)	1.712**	(0.591)
Farm occupation	1.679***	(0.394)	1.686***	(0.405)
Marriage	0.184	(0.407)	0.203	(0.457)
Education	-0.967**	(0.305)	-0.982**	(0.313)
Prior experience	4.13***	(0.523)	4.177***	(0.651)
Kinship at destination	2.475***	(0.407)	2.5***	(0.511)
Constant	-9.44***	(1.64)	-9.55***	(1.88)
N	290		290	
Rho	-0.368	(0.221)	-0.31	(0.57)
Log likelihood	-148.73		-148.73	

Values in the parentheses are the reported standard errors of the estimates.
***,**,* represents significant at 1, 5 and 10 percent level.

TABLE 4: Probability score table

Individual Characteristics	Migration	Not-Migration
Base case	0.908	0.091
Change from the base		
No seasonal unemployment	0.614	0.389
With land ownership	0.831	0.169
Size of the household =6, not 5	0.949	0.051
Membership of NGO=1, not 0	0.819	0.181
Social security =1, not 0	0.979	0.021
River erosion =1, not 0	0.725	0.273
Seasonal hardship =0, not 1	0.662	0.338
Age is 36, not 35	0.907	0.093
Female not male	0.398	0.602
Occupation = 0, not 1	0.333	0.667
Married = 0, not 1	0.873	0.127
Education = 1, not 0	0.583	0.417
Prior experience of migration = 1, not 0	1.00	0.000
Kinsmen at destination =1, not 0	0.999	0.000

The base case is with sex=1, marital=1, occupation=1,
seasonal hardship=1, mounemp=1, age=35 and family=5.

TABLE 5: Quasi experiment estimations for migration

	Dependent Variable: Level of income			Dependent Variable: Log of income		
Variables	Pool	Fixed	Random	Pool	Fixed	Random
Constant	64.3***	66.5***	64.3***	4.23***	4.1***	4.23***
	(17.0)	(1.57)	(17.0)	(0.27)	(0.02)	(0.27)
Lean =1 if lean	-52.3***	-68.4***	-52.3***	-1.04***	-1.33***	-1.04***
period, zero otherwise	(7.55)	(9.64)	(7.55)	(0.12)	(0.14)	(0.11)
Migdec	60.9***	61.8***	60.9***	1.12***	1.21***	1.12***
	(5.44)	(4.95)	(5.44)	(0.09)	(0.08)	(0.09)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	468	468	468	447	447	447
Adjusted R squared	0.27	0.23		0.32	0.33	

Values in the parentheses are the reported standard errors of the estimates.
***,**,* represents significant at 1, 5 and 10 percent level.

TABLE 6: Quasi-experiment estimations for NGO

	Dependent Variable: Level of income			Dependent Variable: Log of income		
Variables	Pool	Fixed	Random	Pool	Fixed	Random
Constant	50.7***	65.8***	47.5**	3.93***	4.11***	3.95***
	(14.8)	(0.49)	(19.5)	(0.2)	(0.008)	(0.23)
NGO	1.33		1.6	0.008		0.01
	(5.46)		(5.96)	(0.05)		(0.06)
Lean =1 if lean	-51.8***	-43.5***	-45.0***	-1.04***	-0.99***	-1.01***
period, zero otherwise	(3.3)	(2.28)	(1.86)	(0.06)	(0.05)	(0.05)
Lean*NGO	-1.22	-1.77	-1.29	-0.04	-0.05	-0.04
	(6.01)	(5.19)	(3.87)	(0.1)	(0.09)	(0.08)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	380	380	380	358	358	358
Adjusted R squared	0.39	0.83		0.53	0.87	

Values in the parentheses are the reported standard errors of the estimates.
***,**,* represents significant at 1, 5 and 10 percent level.

TABLE 7: Quasi-experiment estimations for migration who have prior access to Micro-credit

	Dependent Variable: Level of income			Dependent Variable: Log of income		
Variables	Pool	Fixed	Random	Pool	Fixed	Random
Constant	48.8**	69.6***	48.8**	3.65***	4.16***	3.65***
	(24.6)	(3.12)	(24.6)	(0.39)	(0.04)	(0.39)
Lean =1 if lean	-47.0***	-38.0***	-47.0***	-1.05***	-0.95***	-1.05***
period, zero otherwise	(8.92)	(10.1)	(8.92)	(0.15)	(0.17)	(0.15)
Lean*Migdec	59.1***	45.8***	59.1***	1.13***	1.00***	1.33***
	(9.38)	(9.32)	(9.38)	(0.15)	(0.17)	(0.15)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	112	112	112	111	111	111
Adjusted R squared	0.28	0.26		0.47	0.49	

Values in the parentheses are the reported standard errors of the estimates.
***,**,* represents significant at 1, 5 and 10 percent level.

TABLE 8: Difference in mean lean period income for migration using Propensity Score Matching

Method[1]	No. of Treat[6]	No. of Sup[7]	ATT[3]	ATU[4]	ATE[5]
Without replacement					
Nearest neighbor (nn=1)	166	101	0.39***(0.11[2])	0.25	0.32
Radius matching (δ = 0.01)	166	74	0.38***(0.11)	0.34	0.36
With replacement					
Nearest neighbor (NN=1)	166	101	0.4***(0.1)	0.35	0.36
Nearest neighbor (NN=5)	166	101	0.47***(0.12)	0.29	0.34
Radius matching (δ = 1.0)	166	92	0.4***(0.11)	0.35	0.36
NN=5 with Radius (δ = 1.0)	166	92	0.39***(0.11)	0.31	0.33
Kernel Matching (Gaussian)	166	101	0.49***(0.1)	0.27	0.33

Note 1:Propensity scores are estimated using treatment status on family size, age, age squared, sex, occupation, marital, socsecurity, rivererosion, edu, seasonhrd, mounemp, landownerd with logit estimation technique under common support. 2: Values in the parentheses are the standard errors estimated through bootstrapped technique (500 repetitions). 3: Means average treatment effect on treated. 4: Means average treatment effect. 5: Average treatment effect on the untreated. 6: Treatment. 7: Support. *** Represents significant at 1 percent level.

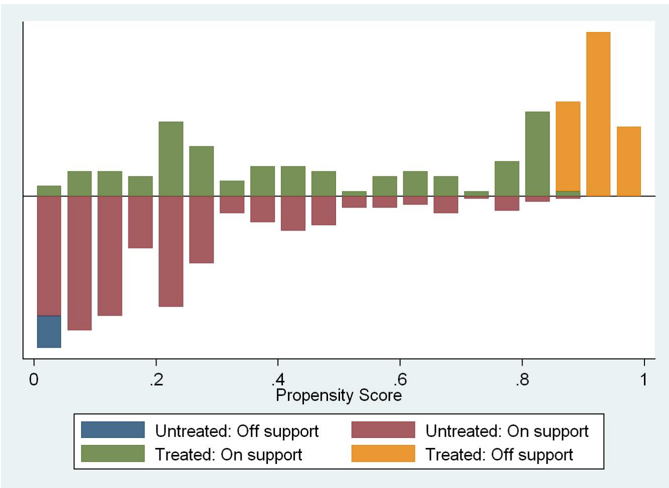

FIGURE 3: Propensity score distribution for migration (Kernel Matching)

TABLE 9: Difference in mean normal period income for Micro-credit using Propensity Score Matching

Method[1]	No. of Treat[6]	No. of Sup[7]	ATT[3]	ATU[4]	ATE[5]
Without replacement					
Nearest neighbor (NN=1)	77	76	0.06(0.1[2])	-0.07	-0.005
Radius matching (δ = 0.01)	77	53	0.05(0.1)	0.07	0.06
With replacement					
Nearest neighbor (NN=1)	77	76	0.02(0.1)	-0.02	-0.007
Nearest neighbor (NN=5)	77	76	0.02(0.1)	-0.16	-0.12
Radius matching (δ = 0.01)	77	58	0.02(0.11)	-0.01	-0.004
NN=5 with Radius (δ = 0.01)	77	58	-0.02(0.01)	-0.01	-0.01
Kernel Matching (Gaussian)	77	76	0.02(0.09)	-0.02	-0.008

Note 1: Propensity scores are estimated using treatment status on family size, age, age squared, sex, occupation, marital, socsecurity, rivererosion, edu, seasonhrd, mounemp, landownerd with logit estimation technique under common support. 2: Values in the parentheses are the standard errors estimated through bootstrapped technique (500 repetitions). 3: Means average treatment effect on treated. 4: Means average treatment effect. 5: Average treatment effect on the untreated. 6: Treatment. 7: Support.

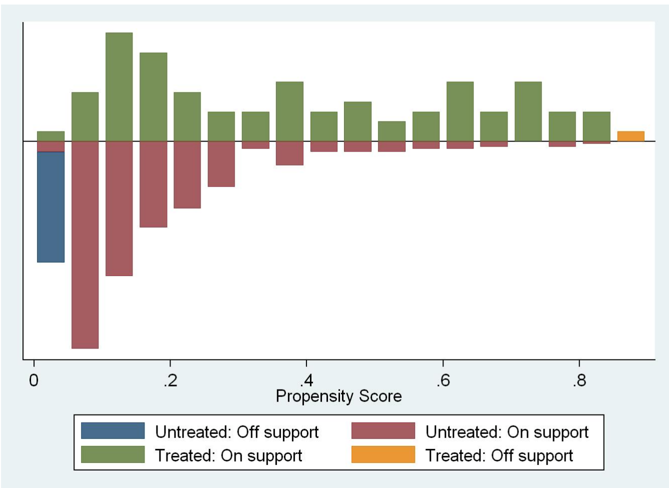

FIGURE 4: Propensity score distribution for micro-credit in lean period (Kernel Matching)

TABLE 10: Standardized bias(SB) before and after matching for different matching algorithms

	Migration		Micro-credit	
Matching algorithms	biased[1] before	biased after	biased before	biased after
Without replacement				
Nearest neighbor (NN=1)	25.22	41.66	21.89	61.81
Radius matching (δ = 0.01)	25.22	12.3	21.89	17.64
With replacement				
Nearest neighbor (NN=1)	25.22	11.65	21.89	6.72
Nearest neighbor (NN=5)	25.22	7.65	21.89	7.47
Radius matching (δ = 0.01)	25.22	11.18	21.89	9.92
NN=5 with Radius (δ = 0.01)	25.22	11.07	21.89	13.2
Kernel Matching (Gaussian)	25.22	5.16	21.89	6.24

Note 1: Following Rosenbaum and Rubin (1985) and Caliendo et al. (2005), for each covariates X it is defined as the difference of sample means in the treated and matched control sub-samples as a percentage of the square root of the average of sample variances in both groups. The SB before the matching is given by $SB_{before} = 100(\frac{\bar{X}_T - \bar{X}_C}{\sqrt{0.5(V_T(X)+V_C(X))}})$; $SB_{after} = 100(\frac{\bar{X}_{T|M} - \bar{X}_{C|M}}{\sqrt{0.5(V_{T|M}(X)+V_{C|M}(X))}})$; where $\bar{X}_T(V_T(X))$ is the mean (variance) in the treatment group before matching and $\bar{X}_C(V_C(X))$ is the same for control group. $\bar{X}_{T|M}(V_{T|M}(X))$ and $\bar{X}_{C|M}(V_{C|M}(X))$ are the corresponding values for the matched samples.

TABLE 11: Some summary statistics of income in normal period

	Normal Period	
	without NGO support	with NGO support
Mean	59.63	67.95
Median	60	60
SD	19.64	23.28
Min	20	50
Max	120	150

TABLE 12: Sensitivity analysis of unobserved heterogeneity for migration

			Hodges-Lehman point estimates		
e^{γ}	p-value[1]+	p-value−	t-hat+	t-hat−	CI[2]
1	0.00000	0.00000	0.45814	0.45814	0.30-0.60
1.1	0.00000	0.00000	0.42364	0.48785	0.29-0.62
1.2	0.00000	0.00000	0.39992	0.51082	0.23-0.64
1.3	0.00002	0.00000	0.36698	0.53941	0.21-0.68
1.4	0.00008	0.00000	0.34657	0.56793	0.18-0.69
1.5	0.00024	0.00000	0.33533	0.58156	0.16-0.71
1.6	0.00061	0.00000	0.30306	0.60198	0.14-0.74
1.7	0.00134	0.00000	0.28768	0.60617	0.12-0.75
1.8	0.00267	0.00000	0.25541	0.63425	0.10-0.78
1.9	0.00491	0.00000	0.23500	0.64046	0.74-0.80
2.0	0.00841	0.00000	0.23500	0.66087	0.05-0.81

Note 1: Reported P-values are the Wilcoxon sign-rank test of significance under hidden bias. Results based on stata ado routine "rbounds". Calculation is done based on Rosenbaum bounds for ATT; nearest neighbor (1) matching with common support. The outcome variable is the log of income. "+"("−") reports the results for positive (negative) selection on unobservables. 2: Confidence Interval.

TABLE 13: Some Summary statistics of Income in lean period

	Lean Period	
	NGO=0,Migdec=0	NGO=0,Migdec=1
Mean	16.17	77.16
Median	20	75
SD	13.16	38.80
Min	0	5
Max	50	200
	NGO=1,Migdec=1	NGO=1,Migdec=0
Mean	74.85	22.72
Median	80	25
SD	37.18	9.47
Min	10	0
Max	200	50

TABLE 14: Variable description

Name	Description	Variable
Migration decision	A dummy variable that equals one if the individual migrated in one of the last two lean seasons and zero otherwise.	migdec
Income in the lean period	Earnings of the household if the chief earner stayed in the village in the lean period or the earnings of the household if the chief bread-earner migrates in the lean period (per day in Local Currency Units, LCU).	mincomelean
Seasonal unemployment	A dummy variable that equals one if the worker remains unemployed during most of the lean season, zero otherwise.	mounemp
Seasonal hardship	A dummy variable that equals one if the individual has one meal or less on a typical day in the lean period, zero otherwise.	season_hrd
Land ownership	A dummy variable that equals one if the respondent's family owns any land irrespective of the size of land, zero otherwise.	landownerd
Access to Micro-credit	A dummy variable, which is coded as one for having access to Micro-credit through any NGOs, zero otherwise.	ngo
River erosion	A dummy variable, such that an individual has a value of one if his/her family ever experienced forced displacement by river erosion, zero otherwise.	rivererosion
Flood	A dummy variable that equals one if the respondent faced flood in the year of migration, and zero otherwise.	flood
Age	Actual age of the respondent.	age
Sex	Sex is coded as one if the respondent is male and zero if she is female.	sex
Marital status	A dummy variable, coded as one for those who are married and zero otherwise.	marital
Education	A dummy variable, coded as one for those who have any education, zero otherwise.	edu
Household size	Number of family members	family
Farm occupation	A dummy variable, coded as one for the farmers, zero otherwise.	occupationdum

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Table 14 – continued from previous page

Name	Description	Variable
Kinship at the place of destination	A dummy variable, coded as one for those who have kinsmen at the potential place of destination, zero otherwise.	knship
Migration experience	A dummy variable, coded as one for those who have prior migration experience (any previous experience), zero otherwise.	migexp
Social security	A dummy variable, equals one for those who reported to receiving any transfer payment from the government, zero otherwise.	sossecurity