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

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Abstract

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, we quantify the factors that influence the seasonal migration decision. Controlling for other characteristics, we find that individuals with access to micro-credit did not have a significantly different level of income to those who did not have access to credit. Households that took the decision to migrate combined with micro-credit earn significantly more than households with only micro-credit in the lean period. In addition, we find a significant role for network effects in influencing the migration decision, with the presence of kinsmen at the place of destination having a significant impact. The results have numerous potential policy implications, including for the design of micro-credit schemes.

Keywords : Lean period; Seasonal migration; Micro-credit; Bangladesh; Program evaluation; Matching methods.
JEL Classification : J62, J64, J65, O15, O18, R23.

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1 Introduction

The aim of this paper is to better understand the causes of seasonal migration, evaluate the characteristics of seasonal migrants and to quantify the effects of the factors influencing seasonal migration decisions. Of particular interest, we test the effectiveness of micro-credit programs in the lean period and the role of networks (kinship) on the seasonal migration decision.

In the standard rural-urban migration literature, researchers primarily focus on permanent internal migration and its economic, social and demographic significance. Only a 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), Elkan (1967), Guilmoto (1998)), Asia (Hugo (1982), Stretton (1983), Deshingkar and Start (2003), Rogaly et al. (2002) and Ben Rogaly (2003)) and South America (Deutsch et al. (2003)). People move from rural areas during lean periods to nearby cities or towns for a short period of time in an attempt to maintain their living standards. Lean periods can occur due to agriculture cycles or natural disasters, such as draught, flood, cyclone, climate change and river erosion. Thus 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 over a permanent move because such a decision offers an opportunity to combine the village based existence with the urban opportunities. In the face of village-based highly seasonal labor demand, villagers may see the temporary migration to the urban areas as relatively practical and rational strategy to cope with seasonal downturn and natural shocks. But the most important factor, which leads to a temporary move rather than a permanent one, 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 temporary mobility of labor from rural to urban areas has important socio-economic implications. Migration reduces the inequality in the rural area with a flow of remittances back to the migration destinations. This flow is quite regular which is unlikely to occur with permanent rural to urban migration. Such a flow plays a large role for rural families who through this income can afford the necessities of life. Also the return migrants may diffuse ideas, information and knowledge which could play a vital role in rural development process.

However, temporary migrants cause congestion and other social problems in urban areas. Policy makers do not have enough information about the number of people migrating temporarily to tackle these problems. Seasonal migrants are very hard 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.

One of the recent policy developments 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 thus, get rid of the poverty by their own. Various studies on the impact of micro-credit in developing countries have found evidence of consumption smoothing, asset building (Pitt and Khandker (1998))and 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-finance is "non-existent". Similarly Navajas et al. (2000) concluded that micro-credit is largely unsuccessful in reaching the poor and the vulnerable. Hence a natural extension of this study is to explore the effectiveness of micro-credit on the poor people especially during the lean period and how micro-credit authorities address such problems while giving loans. This paper uses a set of "quasi experiments" and semi-parametric matching techniques to estimate the impact of micro-credit and migration on income during the lean season hardship.

We use primary data collected from the Northern part of Bangladesh. The random cross-section household survey was conducted in January 2006 by Abu Shonchoy, Abu Z. Shahriar, Sakiba Zeba and Shaila Parveen as part of the project undertaken by the Economics and Social Sciences Research Group (ESSRG) of BRAC University. We choose the Kurigram district of Northern Bangladesh because of some distinct features. Kurigram is mainly an agri-based, natural disaster prone and severely poverty-striken area of Bangladesh.[1] Due to the agricultural cycle, after the plantation of the Aman in September-October, farmers have very little work to do on the farms.[2] As a result, every year a large number of agricultural workers become jobless and decide to migrate temporarily. Such migrants tend to get work in the urban informal sector and work mainly as day laborers. Though the urban standard of living is typically a bare minimum for these migrants, they prefer this option than to stay 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 incomplete data. However, by using an updated version of the data, the present study has improved on the model of Shahriar *et. al.* and is able to provide efficient estimates and additional insights on this research.

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.

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[1] Rural life of Bangladesh very much evolves around the agricultural cycle and our study area is not an exception. As a consequence of this cycle, two major seasonal deficits occur, one in late September to early November and the other is 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 nearly all parts of the country, specially 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.

2 Background

2.1 What is Seasonal Migration

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

The seasonal migration of labor has been studied in many disciplines other than Economics. Disciplines like Demography, Anthropology, Sociology have discussed such movements of labor long before it appeared in Economics. Consequently, the terminology used to describe this phenomenon varies a lot. For example, seasonal migration has also been referred to as return migration, wage-labor migration, transhumance, etc. to name a few. In addition, geographers have noticed this observable fact of labor movement even in the early 1920s. As mentioned in Chapman and Prothero (1983), *"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 on this literature. Also, Nelson (1976) has a detail discussion on the causes and consequences of such migration.

2.2 Reasons for Seasonal Migration

Other than social issues like family structures, social customs and religious beliefs, economic factors are the most influential reasons to migrate in the lean period. In his seminal work, Elkan (1959, page 192) refers to these non-economic factors as the *"...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 the urban areas. There are mainly four reasons why families take such decision in the lean period. Firstly, it is always easier and cheaper to survive in the rural than in the urban area as the prices of food grains and other household essentials are relatively cheaper. Hence, in the most cases the head or the most capable member of the household, who are mainly men, migrates to urban area. Being the lone mover from the household, a person can cope up with the urban life and typically survives on a bare minimum in order to send remittances back to the families.

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

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

Finally, there is typically significant journey exists between the migration destination and origin, but interestingly, the cost of the journey is usually very small and unimportant for migrants. As mentioned in Hugo (1982, page 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 reduced the cost of a movement significantly (Afsar (1999)). Moreover, access to formal 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 NGO's do not run any specific programs to provide credit for the migration, it is possible to use a loan taken by the other members of the family and repay the loan once they have found work in the migration destination.

2.2.2 Reasons causing reverse migration

There are some interesting facts which influence the migrants to come back to the village hence cause reverse migration. Once moved to the urban areas, there are some off-setting factors like forgone income in the normal season and skills which are quite important for the reverse migration (Mendola (2008)). Moreover, due to poverty and resource constraints, it is extremely difficult for a migrant to devote resources to building or investing in skills that are required for the 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 requires manual labor (like Rickshaw pulling, construction works or day laborer). The wages are very poor 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 streets. Such conditions of living are worse than what they had in the villages. Moreover, lack of job security, ineffective labor unions and illness related insecurity also play roles towards reverse migration. Seasonal migrants are generally not protected against accident and do not have provision for retirement benefit (Elkan (1959)). If a migrant becomes ill or requires money, the migrant can seek help in the village which provides some sort of social security by the widespread network of social relations thus provides incentives for the 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 which leads 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 mean that most of the migrant workers remain unskilled making it extremely difficult for them to seek jobs in the formal urban labor market.

But the most important economic factor that leads 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 that of the the urban sector. As a result, there is a obvious incentive for migrants to come back to the rural areas in normal period after the shock.

2.3 Factors Influencing Migration Decision

A number of studies have analyzed the internal migration pattern in Bangladesh; 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), to name a few. We also find some studies on circular migration like Breman (1978), Hugo (1982), Stretton (1983), Chapman and Prothero (1983), Rogaly et al. (2002); Ben Rogaly (2003), Deshingkar and Start (2003), Deutsch et al. (2003) etc. Broadly, these studies generally 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 seasonal migration decision, we use the generally used variables which are found significant for the internal rural to urban migration studies.

Wage differential : Sir John Hicks Hicks (1932) argued that the main cause of migration is the wage differential as mentioned in his book "The Theory of Wages" (1932, page 76). Classic migration literatures and theories (like Harris and Todaro (1970)), whether internal or international, employs wage differentials as the core mechanism that leads to migration. Thus, following the trend, a direct relationship between wage differential of lean and normal period income and migration decision has been hypothesized.

Assets and access to credit : Interestingly the relationship between land holding and migration decision in empirical studies are 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. Hossain (2001), in contrast, finds that the tendency to migration is higher for the households with some sort of land holding as compared to the landless. Following the recent work of Mendola (2008) who finds negative and significant relationship between land holding and migration decisions for temporary migrants in Bangladesh. Thus we hypothesized a positive relationship between landless individual and seasonal migration, holding other things equal.

Though the existing evidence suggests that researchers do not have a unanimous stand on whether or not micro-credit increases the income of the participants significantly and but they do, more or less, agree that access to micro-credit reduces the vulnerability of the participants. Therefore, NGO members expected earnings from staying in the village are higher than the non-members and hence the probability to migrate is likely to be lower.

Ecological vulnerability: Natural disasters like floods and river erosion affect the agricultural output of the rural people and decrease the income and living condition dramatically. Most of the developing countries are natural diaster prone, hence we should take account of such issues on 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 each year of Kurigram, the survey area used in our research, are forced to relocate. 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), to name a few). Demographically, the internal migrants of Bangladesh are mostly concentrated in young adult ages (Chowdhury (1978)) and temporary migrants are even younger than permanent ones(Afsar (2002)). Household surveys at migration destinations show that three fourth of temporary and half of the permanent internal migrants were 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 costs of moving are low and the probability of getting an urban job is high.

Hugo (1982) argued that men have significantly more tendency for seasonal migration than women. Due to limited employment opportunities, family responsibilities and religious reasons female members of a family are less likely to migrate than the adult male members. Studies on permanent migration reveal that those who are married have closer ties with their families and relatives hence less likely to migrate (Lee (1984), Kuhn (2005)). On the contrary, Hossain (2001), argued that migration propensity is higher among married persons. When mere survival is crucial in the agricultural lean season, the responsibility to feed dependents (spouse and children) is expected to increase the probability of individual migration (Huq-Hussain (1996)). Previous empirical works on migration suggested that size of household positively influence individual's migration decision (Deshingkar and Start (2003), Mendola (2008), etc.). 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 the non-migrants in the same locality (Chowdhury (1978) and Kuhn (2005), for example). Educated people are more likely to migrate as job opportunities are higher for them in the urban centers than in the rural areas. Interestingly, Huq-Hussain (1996) suggests that educational attainments are not always an influential factor in the migration decision, particularly among poor female migrants in Dhaka city. Country level studies have also find significant association of education on migration decision 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 provide support for 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 are 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 about 46% of the total labor force is involved in agriculture; another 30% are agricultural day laborers (Banglapedia (2006)). The study area consisted of four selected thanas[3] of Kurigram district which are 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. Though 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

[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.

had better transportation systems compared with 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 regarding 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. On the contrary, Chilmari is the worst affected by both flood and river erosion. River erosion is quite rare in Ulipur, though flood every year ravage the area. The char area is affected by river erosion and flood quite regularly. The Kurigram town was 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. Majority of the population are Muslim. As a result, there is only a minor religious and cultural heterogeneity exists in the survey area which is negligible. The people of this region are largely illiterate, with an average literacy rate of around 22.3%. The sample area consists of 37.02% of the total population of the district.

The survey consisted of 290 random individuals who are representative of their household. The survey questionnaire was trialed on 30 respondents in Chilmari and Ulipur before using for the main survey. The final questionnaire consisted of 12 sections. It 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 went on to ask about land usage, occupation at destination if migrated, NGO membership and landownership. 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.

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

We were not confident that individuals could predict future plans for seasonal migration. Hence, we asked respondents about their past behavior of migration 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 the one of the last two lean periods and zero otherwise.

The variable seasonal unemployment (unemployed during lean period) is a binary variable. An individual reported to have remained unemployed during most of the lean season is assigned one and 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 the 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

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

reported that they are 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 Credit and Development Forum Bangladesh (Credit and Development Forum (2006)), about 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 of these factors were included in the study as dummy variables (DV). For river erosion, the DV has a value of one if an individual family 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 such data is identifying the place of such experience as one could have been forcefully displaced by such an event which is different than the survey area. Hence, such data is noisy and one has be careful 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 flood victim in the last two years.

More males than females were interviewed (89 percent versus 11 percent). Patriarchal village societies are the reasons 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. This is because we are interested in testing the hypothesis that agricultural workers are the group who migrate 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 and the rest are non-farm workers like fishermen, potters, petty traders, land leasers, garment workers, rickshaw-pullers to 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 whereas 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

In order to translate the seasonal migration context into an econometric model, we take the approach of the random utility model framework. Let us assume that, the utility from the choice of migration$(j) = 1$ or 0 at the lean period for the individual $i = 1, 2..., N$ can be specified in the flowing form

$$U_{ij} = V_{ij} + \varepsilon_{ij}$$

where V_{ij} is the systematic component of utility and the ε_{ij} is the random component. The model is completed by specifying V_{ij}, say $V_{ij} = x'_{ij}\beta$. Here the x_{ij} are the vectors of economic factors, ecological vulnerabilities and personal characteristics. As a result, the utility of migration of an individual i at the time of the lean period will be

$$U^{migration}|Lean\ Period = x'\beta_a + \varepsilon_a, \tag{1}$$

and the utility of staying of individual i at the time of lean period will be

$$U^{stay}|Lean\ Period = x'\beta_b + \varepsilon_b. \tag{2}$$

Now if we denote $Y_{ij} = 1$ if $U^{migration} - U^{stay} = Y^*_{ij} > 0$, and $Y_{ij} = 0$ otherwise, then the respondent's choice of migration in the lean period will be

$$\begin{aligned}
\Pr[Y = 1|x] &= \Pr[U^{mig} > U^{stay}] \\
&= \Pr[x'\beta_a + \varepsilon_a - x'\beta_b + \varepsilon_b > 0|x] \\
&= \Pr[x'(\beta_a - \beta_b) + \varepsilon_a - \varepsilon_b > 0|x] \\
&= \Pr[x'\beta + \varepsilon > 0|x],
\end{aligned}$$

where the distribution of ε is $N(0, 1)$. In this study we will estimate such a model with univariate probit estimation techniques.

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 and may have influence over the people in the lean period and also may influence there 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^*_1 is the dummy for

Micro-credit and y_2^* is the dummy for migration is as follows,

$$\begin{aligned} y_1^* = &\ x_1'\beta_1 + \varepsilon_1,\ y_1 = 1\ if\ y_1 > 0, 0\ otherwise, \\ y_2^* = &\ x_2'\beta_2 + \varepsilon_2,\ y_2 = 1\ if\ y_2 > 0, 0\ otherwise, \\ & E[\varepsilon_1|x_1,x_2] = E[\varepsilon_2|x_1,x_2] = 0, \\ & Var[\varepsilon_1|x_1,x_2] = Var[\varepsilon_2|x_1,x_2] = 1, \\ & Cov[\varepsilon_1,\varepsilon_2|x_1,x_2] = \rho. \end{aligned} \tag{3}$$

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 represents the access to micro-credit) appears as an independent variable in the second equation, which is a recursive, simultaneous equation model where

$$\begin{aligned} y_1^* = &\ x_1'\beta_1 + \varepsilon_1,\ y_1 = 1\ if\ y_1 > 0, 0\ otherwise, \\ y_2^* = &\ x_2'\beta_2 + y_1\gamma + \varepsilon_2,\ y_2 = 1\ if\ y_2 > 0, 0\ otherwise, \\ & E[\varepsilon_1|x_1,x_2] = E[\varepsilon_2|x_1,x_2] = 0, \\ & Var[\varepsilon_1|x_1,x_2] = Var[\varepsilon_2|x_1,x_2] = 1, \\ & Cov[\varepsilon_1,\varepsilon_2|x_1,x_2] = \rho. \end{aligned} \tag{4}$$

If we find that γ is significant then we can conclude that the people who choose to take micro-credit has 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 the joblessness in the agricultural industries, thus it would be better if we could test the impact of migration and micro-credit on the lean period income.

One possible way to test the impact is by using quasi-experiment 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, in our case, the two strategies described in this study can ideally be suitable for such experiment. An risk averse individual can choose to migrate or access micro-credit as strategies. A natural experiment always consists of a control group (which is not affected by the exogenous event) and a treatment group (which is effected by the exogenous event). Under a true experiment 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. Thus we can easily convert the data to use it for two period cross-sectional data sets (panel data), one before the lean period hardship and after the lean period hardship (normal period) and can be used to determine the effect of the two strategies.

Once we have converted the data into longitudinal form with two period incomes (income in lean period and income in normal period) the other demographical variables will be mostly time-invariant (like education, occupation, sex, marital status etc.). As a result, the data gives us the opportunity to test the impact of these two policies with the help of difference–in–difference (DID) method. Let us use C to donate the control group and T to donate 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:

$$Y_{i,t} = \beta_0 + \delta_0 dT_t + \beta_1 dP_{i,t} + Other\ Factors + a_i + u_{i,t} \tag{5}$$

where $Y_{i,t}$ is the outcome variable of interest, which is the level 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:

$$\beta_1 = (\bar{y}_{2,T} - \bar{y}_{1,T}) - (\bar{y}_{2,C} - \bar{y}_{1,C}), \tag{6}$$

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 treatment or policy on 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 5, 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.

4.3.2 Propensity Score Matching Method

An important problem of causal treatment effects is to estimate treatment impact in non-experimental comparison group. Such estimation could be biased because of problems with self-selection. In any evaluation study, problem could arise when one would like to have the outcome of the participants with and without the treatment. Obviously,

[5]To capture the impact of micorcredit during lean season, since people choose 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.

the mean outcome of 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 might be possible that the people who have prior access to micro-credit could be different from the people who did not choose to have access to micro-credit during normal time and opt for migration in the lean period. Hence, we need to use matching technique to correct for such sample selection bias between treatment and observable group. Propensity score matching (PSM) is now a days a popular method to use for program evaluation studies especially in labor economics (e.g. Heckman et al. (1998) and Dehejia and Wahba (2002)). As suggested by Rosenbaum and Rubin (1983*a*,*b*, 1985), PSM calculates the probability of participants and nonparticipants those 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 average treatment effect (ATE) and 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:

$$\hat{\tau}|_{T=1} = \frac{1}{|N|} \sum_{i \in N} (Y_i - \frac{1}{|J_i|} \sum_{j \in J_i} Y_j). \tag{7}$$

Since, we are interested to estimate the impact of migration and micro-credit during lean period, we could estimate the likely impact of 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.

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

$$U(i) = \{\hat{p}(X_j) | \min_j ||\hat{p}(X_i) - \hat{p}(X_j)||\}, \tag{8}$$

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

where || || denotes the Euclidean distance. If we define NN as the number of matched individual 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

$$\frac{1}{|J_i|} = \frac{1}{NN} \text{if } j \epsilon U(i), 0 \text{ otherwise.} \tag{9}$$

Radius Matching Under Radius matching, we will match all the control individual 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:

$$U(i) = \{\hat{p}(X_j) \mid \left\|\hat{p}(X_i) - \hat{p}(X_j)\right\| < \delta \tag{10}$$

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

$$\frac{1}{|J_i|} = \frac{1}{R_i} \text{if } j \epsilon U(i), 0 \text{ otherwise.} \tag{11}$$

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

$$\frac{1}{|J_i|} = \frac{K\left[\frac{\hat{p}(X_j)-\hat{p}(X_i)}{h}\right]}{\sum_{k=1}^{N_{u(i)}} K\left[\frac{\hat{p}(X_k)-\hat{p}(X_i)}{h}\right]} \tag{12}$$

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 have results from two sets of Probit estimations in the Table 2. In the second Model, we have log of difference of income between normal and lean period as the dependent variable. But this variable can be endogenous as one can argue that income difference between the two period could be influenced by the prior migration decision. As a result we used seasonal unemployment as a proxy for the endogenous variable mentioned before. Our proposed proxy variable for the lean period income suits the model very well as both of the models have the almost same significant variables (exceptions are social security, river erosion and age variable) and hardly any coefficients changed the sign (except for marriage). Due to the use of log of difference in the second model, we lost some degrees of freedom which may lead to those aforementioned exceptions in the model. Hence the model is well estimated and robust.

The probit estimates show that seasonal unemployment and 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 seasonal unemployment in the autumn lean period is the most decisive among the economic factors in determining the probability of migration, increases the probability by 10% for a typical worker. The results, however, do show significant effects of wage differential (in second model) on migration decision.

[Table 2 about here]

Another economic factor, land ownership was also found to be insignificant. It was observed during the survey that there are at least three types of landowners in the Kurigram district: a) absentee landlords who live in urban areas and are engaged in other occupations, b) small land owners who work on their own lands and c) landless or effectively landless workers who work in other people's farm. It was very hard from our survey to distinguish among these types land ownership as respondents of the survey were either very reluctant or unaware of this information, which could eventually increase the explanatory power of this factor as well as of the model.

The present study finds that the probability to migrate is negative for an individual with access to micro-credit through NGO membership with typical characteristics, but the relationship is not significant. 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 reduce 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 of age group 20-40 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 to migrate 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.

One 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 quite logical that the farmers would be keener 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 chose to migrate in the lean period and the present study has found a significant and positive impact of agricultural professionals to opt for seasonal migration. Such evidence contradicts the literature on permanent internal migration. Studying the 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. So, it provides evidence that lean period migration is basically a shock driven migration where farm laborers are mostly affected. Thus they are the vast majority of the population who choose temporary internal migration.

A compelling finding of the study is that regarding river erosions. It was found that those who experienced river erosion at least once in their lives have a lower migration propensity. This result conforms to our hypothesis. The probit results suggest that the probability to migrate falls if the worker experienced river erosion, which is marginally significant for the first model. One possible explanation of this result might be due the economic vulnerability of the river erosion affected peoples. To migrate to nearby cities, one needs at least some assets to cover the transportation and initial relocation cost. Hence, the people who are affected by river erosion have already lost their valuable lands and houses, therefore they can not afford to migrate in the lean period. Those who ever experienced river erosion in their lives fall into the trap of chronic poverty and they cannot cover the minimum cost of adopting an alternative livelihood strategy like migration. Another explanation could be the trauma effect of forced relocation due to the river erosion which may have diminished their 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, aged 35 and 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 increase the probability of migration dramatically. As seasonal hardship results from seasonal unemployment in agriculture, in the autumn lean period, agricultural workers suffer mostly from shortage of employment. The same is not true for the non-farm workers. As a result, non-farm workers 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 has been shown in figure 2. For the same representative individual (with family size taken to be 5) education significantly affects migration probabilities 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 the mentioned base case and calculated the predicted probability by changing units from base case; see table 4. The predicted probability for the micro-credit is of the interest. Using the base case, we calculated that predicted probability of migration decreases from 0.91 to 0.82 for a person who has access to micro-credit through NGO membership . Thus this result suggests that access to micro-credit reduces the propensity to migration in the lean period but as we find in table 2 this effect is not significant. As a result, this interesting finding of the study leads us to the next section where we will investigate if there exists a systematic relationship between these two variables, migration and credit access through NGOs.

[Table 4 about here]

5.2 Seasonal Migration and Access to Micro-credit

A problem our probit model may encounter is, 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 formal credit market is a long term strategy to deal with seasonal hardship. Whereas temporary seasonal migration is a short term strategy which largely depends on individuals' attitudes towards risk (Binswanger (1981), Quizon et al. (1984)) and such strategy works as consumption smoothing technique for the poor rural people (Rosenzweig and Stark (1989)). Hence, there may exist selection problems with the individuals who took NGO membership to access micro-credit and the decision to migrate. Also, we may encounter the problem of unobserved heterogeneity between these two strategies.

I used bi-probit estimation techniques with two models to investigate the aforementioned problem . In the first model (equation 3 in section 4.2), I have treated access to NGO and the migration decision as two endogenous equations. In the second equation (equation 4 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, we can also test the impact of treatment (in our case access to NGOs) on the migration decision and can test if the allocation of treatment was random or not. Also we can evaluate the covariance of the disturbance terms of these two equations by estimating the 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 -0.41 with a standard error of 0.67. The Wald statistics for the test of the hypothesis that $\rho = 0$ is 0.38. 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 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 2.83 with an associate p -value of 0.21. 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. But, 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 biasedness in the estimations and the allocation of treatment is most likely random.

5.3 Testing for the Effective Strategy

5.3.1 Difference-in-Difference estimates

As we have found evidence in the previous section that access to micro-credit through NGOs and temporary internal migration in the lean period are the two alternative livelihood strategies to overcome the income shock in the lean period, a natural extension easily leads us to test these two strategies to check which one is more effective in terms of income improvement.

Here, using equation 5 of section 4.3.1, the DID estimations of the policy variables are migration in the lean period (*Migdec*) and access to micro-finance through NGOs (*NGO*). Now we have two treatment groups; one is the people who choose to migrate versus people who do not and the second is the people who choose 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 full set of control variables. Interestingly, the coefficients of different estimations are almost similar indicating robustness of our findings. As we can see from Table 5, the variable *Lean* is strongly significant and negative which shows the severeness 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. Also 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 of micro-credit's ineffectiveness in improving income in short term situations like temporary or seasonal hardship[7]. 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.[8] Seasonal migration is a short term solution and preferred by any individual who wants to alleviate short term hardship. In contrast, access to micro-credit is a long term policy and the impact of such a policy can not be observed within a short time span. Hence, a myopic individual will always opt for temporary migration over the micro-credit option. Interestingly, if we look at table 11, we can easily observe that access to micro-credit increases the mean income of the people though the median income is the same. However, in the lean period (refer to table 13) household that took migration decision is better off than other two groups. Household that took no credit and did not migrate are the worst affected with the seasonal shock. Whereas, during lean period, by having only credit access does not improve the income of the household significantly. So the individual that took both the option during lean period has more average income than any other group and is better off. The reason for such finding is deep rooted in the micro-credit frameworks. NGO's have very strict policy of loan repayment, usually collected on weekly basis and mostly not allow persons to migrate once having the loan . Hence, in some cases the female member of the household takes the credit but than transfer it to the male member who migrates in the urban areas and send the savings to repay the loans. In our data-set, these are the individuals who have access to micro credit but migrated during lean season. Also our data set confirms that all the respondent who migrated during lean season but had prior access to micro-credit are male. Our estimation in table 7 suggest that such technique can significantly improve income during lean season though the magnitude of such impact coefficient is not the highest one as one has to still repay the loan during lean season which reduces the net earning. Hence individuals that do not exploit the credit opportunities described above, are the individuals who has lost their mobility due to loan bindings hence can not migrate during the lean season. Consequently, access to credit alone can not improve the family income in the lean period.

5.3.2 Propensity Score Matching Estimates

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

[7]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.

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

The propensity estimations in this study have been done 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, we could use the bootstrapping technique since such method is consistent. Use of 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 (Gaussain) with DID (Dehejia and Wahba (2002); A. Smith and E. Todd (2005); Heckman et al. (1998)) within the region of common support. DID estimation is superior in term 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 (A. Smith and E. 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 common support region. Other matching estimations have also been reported in the result table for roboustness 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 observation 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 lean season, providing stronger evidence for income improvement with migration.

On the contrary, the ATT for micro-credit during lean period is quite small in magnitude. The kernel matching estimation for micro-credit is only 2% during lean season and not statistically different from zero, which means that the income improvement for the people who only have access to micro-credit is not statistically different from the people who do not have the access during lean season. 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 the 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). Same is true for the 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, in most empirical literatures an SB of 3% or 5% after matching has been considered as sufficient (Caliendo and Kopeinig (2008)). Hence, our KM technique has substantially reduced the overall bias and we can be assured about the quality of our result in term 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 rise 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 problem 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 Johar (2009) and Ferraro et al. (2007), 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 odd ratio between treatment and control is

$$\frac{P_i(1-P_j)}{P_j(1-P_i)} = \frac{\exp(\beta x_i + \gamma v_i)}{\exp(\beta x_j + \gamma v_j)} \tag{13}$$

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:

$$\frac{1}{\exp(\gamma)} \leq \frac{P_i(1-P_j)}{P_j(1-P_i)} \leq \exp(\gamma) \tag{14}$$

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 roboustness 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 as the following way: given individuals with same observables, those who would most likely to migrate during the lean period are more able, hence there could be 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 individual with 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 heterogeniety 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 assignmenr 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 provides 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 to their villages but such movements may not be possible over the years. This study has found evidence that access to micro-credit through NGOs and temporary internal migration in a lean period are two strategies that individuals in the rural areas use to overcome the income shock in the lean period. We found that economic, ecological and individual characteristics, all play an important factors in migration decision. 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 the rural people to have access to the informal credit market. However we found that, during seasonal shocks, individual with access to micro-credit did not have a significantly different level of income to those that did not have access to credit. We found that, households that took both the migration decision combined with micro-credit earn significantly more than households with only micro-credit in the lean period. NGO's have a very strict policy of loan repayment 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 in the urban areas during lean season and send remittances to replay the loans. If, however, the male member of the household take credit during the lean period, he will lose his mobility and cannot undertake migration due to the strict repayment rules. Thus NGOs should consider addressing such problem by relaxing the loan repayment scheme during the lean period. Moreover, the results suggest that NGOs and governments should provide more support on adult education and building capacities on 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

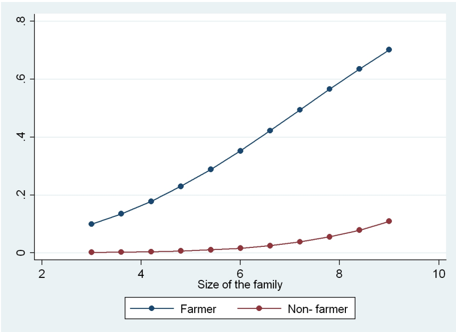

FIGURE 1: Migration propensity for farmer vs non-farmer with the change of family size

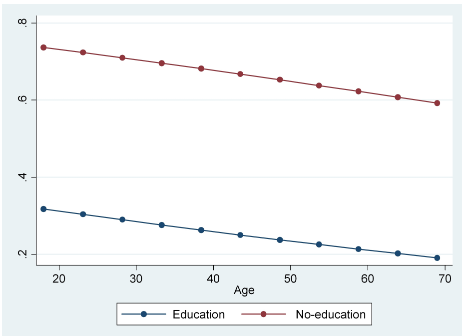

FIGURE 2: Migration propensity with education vs no-education with the change of age

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

	Model with seasonal unemployment		Model with income difference	
Variables	Coefficients	Marginal effects	Coefficients	Marginal effects
Seasonal Unemployment	1.274(0.479[1])**[2]	0.097		
Log of Income difference between normal and lean period			0.925(0.376)**	0.022
Land Ownership	-0.485(0.402)	-0.021	-0.671(0.422)	-0.02
Size of the Household	0.399(0.17)**	0.015	0.403(0.171)**	-0.009
Membership of NGO	-0.713(0.512)	-0.046	-0.587(0.521)	-0.022
Social Security	1.187(0.657)*	0.022	0.884(0.633)	0.012
River Erosion	-0.885(0.471)*	-0.031	-0.696(0.473)	-0.015
Seasonal Hardship	1.052(0.469)**	0.058	0.867(0.474)*	0.029
Age dummy	1.066(0.488)**	0.08	0.694(0.464)	0.027
Sex	1.76(0.671)*	0.27	1.39(0.688)**	0.131
Farm Occupation	1.66(0.56)**	0.083	1.603(0.559)**	0.053
Marriage	0.287(0.45)	0.013	-0.144(0.511)	-0.003
Education	-1.02(0.472)**	-0.052	-1.009(0.465)**	-0.034
Prior experience of Migration	4.104(0.694)***	0.672	3.943(0.659)***	0.596
Kinsmen at Destination	2.472(0.567)***	0.191	2.279(0.56)***	0.128
Constant	-7.422(1.86)***		-8.565(1.965)***	
No. of Observation	290		266	
Pseudo-R-Squared	0.82		0.80	
Log Likelihood	-32.29		-30.88	

Note 1: Values in the parenthesis are the reported standard error of the estimation. 2: Values in the parenthesis are the reported standard error of the estimation.

TABLE 3: Bivariate Probit estimations

	Bivariate Probit		Endogenous treatment model	
NGO Equation	Coefficients	Standard errors	Coefficients	Standard errors
Land Ownership	0.215	(0.201)	0.213	(0.202)
Size of the household	-0.081	(0.092)	-0.081	(0.092)
Social Security	1.272***	(0.239)	1.273***	(0.24)
River Erosion	0.173	(0.212)	0.169	(0.214)
Seasonal Hardship	-0.032	(0.208)	-0.033	(0.208)
Age	-0.113**	(0.046)	-0.115**	(0.047)
Age Squared	0.001**	(0.000)	0.001**	(0.00)
Sex	0.518	(0.421)	0.521	(0.421)
Farm Occupation	-0.417*	(0.217)	-0.413	(0.219)
Marriage	0.386	(0.243)	0.384	(0.243)
Education	0.108	(0.199)	0.113	(0.202)
Constant	0.901	(1.106)	0.909	(1.125)
Migration equation				
Log of income difference	0.904**	(0.373)	0.892**	(0.382)
Land ownership	-0.69*	(0.413)	-0.687*	(0.407)
Size of the household	0.398**	(0.165)	-0.391**	(0.173)
Membership of NGO			0.19	(1.441)
Social security	0.631	(0.568)	0.542	(0.874)
River erosion	-0.701	(0.466)	-0.698	(0.46)
Seasonal hardship	0.853*	(0.46)	0.835*	(0.478)
Age Dummy	0.667	(0.438)	0.644	(0.469)
Sex	1.32**	(0.668)	1.283*	(0.727)
Farm occupation	1.63**	(0.547)	1.624**	(0.543)
Marriage	-0.202	(0.492)	0.223	(0.515)
Education	-0.997	(0.449)	-0.978**	(0.466)
Prior Experience	3.85***	(0.653)	3.786***	(0.839)
Kinship at destination	2.241***	(0.562)	2.212***	(0.612)
Constant	-8.391***	(1.916)	-8.249***	(2.24)
N	266		266	
Rho	-0.328	(0.245)	-0.414	(0.674)
Log Likelihood	-140.87		-140.86	

Values in the parenthesis are the reported standard error of the estimation.
***,**,* 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 landownership	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 parenthesis are the reported standard error of the estimation.
***,**,* 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 parenthesis are the reported standard error of the estimation.
***,**,* 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 parenthesis are the reported standard error of the estimation.
***,**,* 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 parenthesis are the standard error 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.

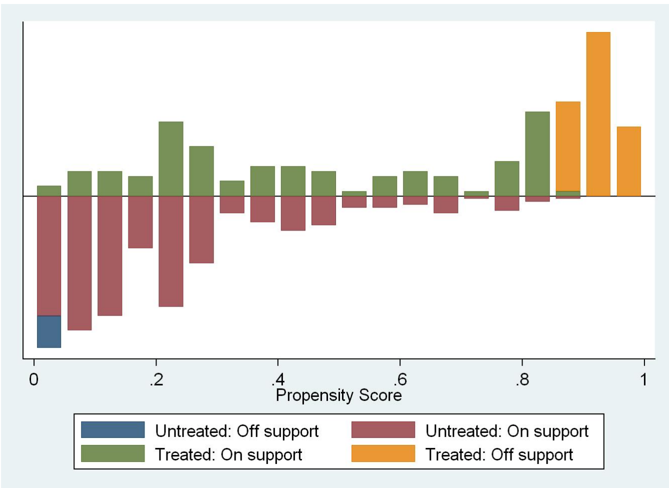

FIGURE 3: Propensity score distribution for migration (Kernel Matching)

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
Karnel 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 parenthesis are the standard error 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.

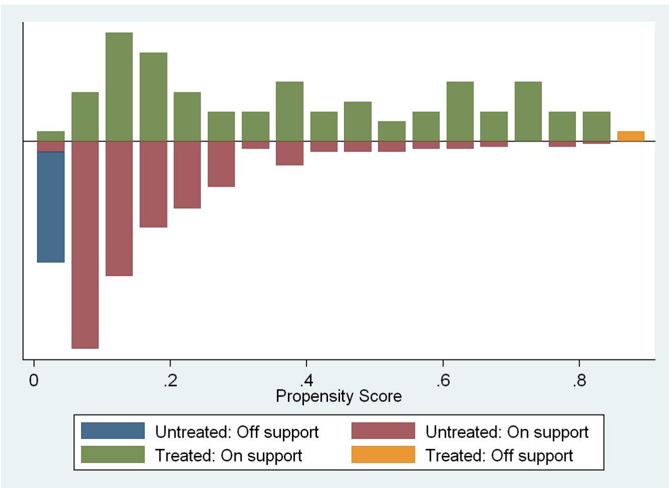

FIGURE 4: Propensity score distribution for micro-credit in Lean period (Kernel Matching)

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 neighbour (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
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