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THE IMPACT OF MIGRATION ON MULTIDIMENSIONAL POVERTY IN GURAGE ZONE, SNNPR, ETHIOPIA.

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Abstract

This study examined the impact of migration on multidimensional poverty in the Gurage zone of Southern National Regional State in Ethiopia. The key objectives of the study were to analyze the prevalence of multidimensional poverty, identifying the determinants of MPI, and estimating the impact of migration on multidimensional poverty of rural households in the study area. Data were collected from a total of randomly selected 384 sample households. The data were analyzed using a multidimensional poverty index, probit regression model and propensity score matching. From multidimensional poverty index, the adjusted headcount ratio in non-migrant households, migrant sending households, and overall population was 19.8%, 10.5%, and 15.7%, respectively. The incidence of poverty in non-migrant and migrant sending households was 43.5% and 25.6%, in that order. The average deprivation share of poor people in migrant sending and non-migrant households in the weighted indicators was 41% and 43.5%, correspondingly. The contribution of non-migrant and migrant sending households to the adjusted headcount ratio was 70.5% and 29.5%, respectively. The result of an econometric model indicated that; household size, number of migrants, education of household head, and livestock holding have a significant effect on rural household multidimensional poverty in the study area. The average effect of migration on multidimensional poverty reduction was 4.3% and 1.6% in migrant sending households and the entire population, respectively. This study showed that the scale and the prevalence of multidimensional poverty is well controlled by migration. Therefore, this study recommended for development planners to mainstream migration and all stakeholders are requested to participate in awareness creation on top of effective migration management and efficient use of its remunerations.

Keywords: MPI, its determinants, impact of migration, Gurage zone, SNNPR, Ethiopia.

I. INTRODUCTION

The strategies for poverty reduction and improvement in basic household amenities have often been emphasized in national and international development agenda. The two issues are vital developmental concerns of the contemporary world. Poverty symbolizes the deprivation of the basic necessities of life and vital services, and a lack of prospects or means for development (Zhang, 2003; Alkire & Santos, 2014; Alkire S. , et al., 2015). Multidimensional measures of poverty realized poverty along a range of deprivations encircling diverse features of welfare such as economic, social and material (Alkire & Foster, 2011; Alkire & Santos, 2014; Santos & Alkire, 2015; Alkire, et al., 2015). On the other hand, migration is the movement of people from one geographical location to another for a strategy against poverty (Ekong, 2003; Zhang, 2003).

Theoretically, the two phenomena are interconnected either positively or negatively through declaring subjective evidence on the probable effects of one on the other. Migration as a livelihood strategy has either a cheerful or downbeat effect in the life of migrant-sending households due to the variation occurring in migration management capability. From the optimistic point of view, the

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benefits obtained from labor migration are multiple and have merry effects in escalating rural household incomes and tumbling rural households' poverty (De Haas, 2006; McCarthy, Carletto, Davis, & Maltsoglou, 2006; Adams R. , 2006; Hull, 2007; John.O, Linda A., & Vollan, 2014; Yousra & Julie, 2016). On the other hand, pessimists perceive migration as a win-lose situation and do not take into consideration its role in poverty reduction. Pessimistic study results signified that, labor migration leads to poverty by reducing agricultural income due to the loss of productive agricultural labor (Todaro, 1969; Mazambani, 1990; Gunjan & B.V Chinnappa, 2015) and through detaching child's attachment to school (Kelemework, Zenawi, Tsehaye, Awet, & Kelil, 2017) in the departure area.

Rural-urban migration and household poverty are prolonged existence and they are two sides of a coin in the Gurage zone where those two phenomena have an important magnitude. Gurage zone is the most outstanding net out-migration area in the country's rural-urban migration (Worku, 1995). In the study area, long term rural-urban migration as a livelihood strategy has been common and well cultured with a significant contribution on household poverty reduction and development of the community through remittances (Feleke, n.d; Worku, 1995; Feleke, Alula, Philippa, & Tom, 2006; Ferework, 2007).

Household migration and poverty in the view of development and the interconnection between the two has attracted considerable research in Ethiopia. Even though there are significant empirical research works in the area of migration and household poverty as a separate investigation, very few studies (Yousra & Julie, 2016; Katie, Lisa, & Melissa, 2018) explored the link by measuring the effect of migration on household wellbeing at country level. Even so, these studies did not provide a comprehensive picture of multidimensional poverty for strategizing and decision making processes of reducing overlapping deprivations of rural households as they are delimited on wellbeing outcomes. Further, measuring household poverty following a unidimensional approach (money as a proxy for poverty either income or expenditure means) is comparatively well-researched in Ethiopia. However, except for a few studies (Adams, 2010; Adams & Cuecuecha, 2013; Santos & Alkire, 2015) executing a multidimensional approach to measure poverty is not ordinary. Examining the bond between migration and non-economic aspects (such as education, health and living standards) and quantifying the fruits of migration on rural household multidimensional poverty is vital and needs to be understood in Ethiopia in general and in the study area in particular.

Thus, this study seeks to provide some analytical evidence on the picture of multiple deprivations, determinants of multidimensional poverty, and effect of migration on multidimensional poverty in the study area. The investigation conveyed information on the overlapping deprivations that members of a household experienced and joint distribution of the deprivations related to the SDGs among rural households by decomposing them into subgroups based on migration status. This is very useful to clarify how migration impacts on the poverty of migrant sending households in the study area. It also provides a comprehensive picture of multidimensional poverty to the study area in strategizing and decision making processes of reducing overlapping deprivations of rural households. The study also donates to the few existing studies in Ethiopia that gives insight to researchers and can be used as a springboard for further similar research. With the aim of achieving the above proposed objectives, a broad research question emerges: is rural-urban migration a solution to poverty alleviation in the Gurage zone?

II. RESEARCH METHODOLOGY

2.1 Description of the study area

The study was conducted to examine the prevalence of multidimensional poverty, identify the determinants of multidimensional poverty, and estimating the impact of migration on multidimensional poverty in the Gurage zone of Southern National Regional state in Ethiopia. The topographic character of the Gurage zone is demonstrated into three categories. These are the mountainous high land (indicated by the Guraghe mountain sequence and separating the zone east to west by an elevation of 3600 m), the plateau lands and the small extending area (the western border of the rift valley and the Wabe-Gibe gorge having an altitude of 1000 m) (Wondwossen, Zewde, Tesfaye, & Habtamnesh, 2018). Based on CSA (2007), the zone has a total population of 1,280483 with an average 4.5 persons per household. Of the total population of the zone, 48.6% are male and 51.4 % are female, and also 57.55 and 42.45% are residents of rural and urban areas, respectively.

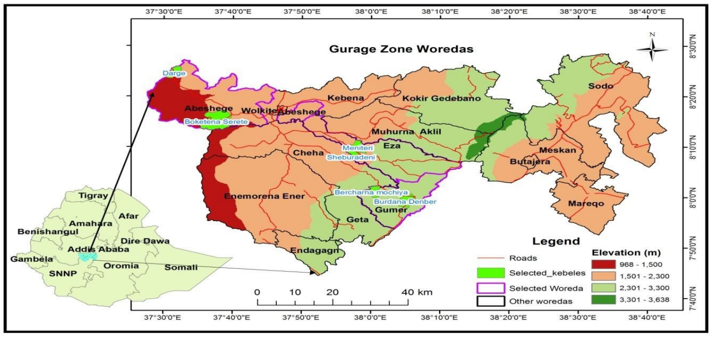

Figure 1: location map of the study area
Source: Generated using Google Earth

2.2 Population and Sample

Based on the multistage sampling technique and probability proportional to size random sampling technique, a sample of 384 rural households was used for the study. The sample size was determined using the Cochran (1963) formula as we desired to estimate the effect of migration on household multidimensional poverty. Assume there are many households, but that we do not know the variability in the proportion in adopting migration as a livelihood strategy. For that reason, we assumed 0.5 value of proportion for p (maximum variability), and assigned a 95% confidence level, ±5% precision and 1.96 for Z- value found in statistical tables. The resulting sample size is confirmed as:

$$n = \frac{(z^2 * p * q)}{e^2} = \frac{1.96^2 * 0.5 * 0.5}{0.05^2} = 384 \text{ Households} \ldots\ldots\ldots\ldots\ldots (1)$$

Where n is a sample household, Z is the abscissa of the standard curve that passes an area α at the tails (1 - α equals the 95% confidence level), p is proportion of variability present in the population, q is 1-p and e is the desired level of precision.

2.3 Indicators and measurements

The study examined the poverty of rural households based on internationally agreed deprivation cutoffs through customizing into Ethiopian context. Among the ten globally listed dimensions in the HDI, the study adopted three of the major ones and widely used in the various research works. These are education, health and living standard dimensions. As the methodology of multidimensional poverty analysis demonstrated, for the identified dimensions suitable indicators with their normative threshold or cutoffs were developed based on the Ethiopian situation and the available empirical evidence. Dual cutoff method was used to identify the poor (Alkire & Foster, 2011; Alkire, et al., 2015). First, normative dimension cutoff (33%) was created by dividing 1 to the chosen number of dimensions (1/3), so as to differentiate the multidimensional poor households. Second, indicators' weight or indicator cutoffs (poverty line) were developed by dividing 1/3 via the number of indicators in each dimension in an attempt to scrutinize the deprivation score of the poor.

Thus, the deprivation score of each household was analyzed by engaging a weighted sum of the number of deprivations with the intention that the total deprivation score for each household was laid between 0 and 1 (Alkire & Foster, 2011; Alkire, et al., 2015; Santos & Alkire, 2015). The score was enlarged as the amount of the deprivations of the household boost and reached a maximum of 1 when the household is deprived in all component indicators (Santos & Alkire, 2015). A household who is not deprived in any indicator received a score equal to 0.

The households were deemed as deprived in a specified indicator as the poverty line set for the given indicator is not met. Hence, MPI is constructed from ten indicators and the weighting vector received the value of 1.67 for the indicators of health and education and 0.56 for the living standard indicators (Table 1). Finally, the achievement of each household was equally applied to all household members in computing the MPI for the entire population in the study area.

Table 1: Indicators and measurement

Dimensions	Indicators	The household is not deprived if…	Related to…	Weight of Indicators
Education	Literacy	No illiterate person (> 15 years)	SDG4	0.167
	Schooling	No child (7-16 age) out of school	SDG4	0.167
Health	Good health	No person with chronic illness	SDG3	0.167
	Medical	Able to meet medical needs	SDG3	0.167
Living Standard	Room	More than one room	SDG11	0.056
	Electricity	Access to electricity (at least solar)	SDG7	0.056
	Water	Access to improved water	SDG6	0.056
	Sanitation	Access to private toilet	SDG6	0.056
	Fuel	Energy source for cooking other than charcoal	SDG7	0.056
	Broadcasting	Access to more than one broadcasting assets	SDG9	0.056

Note: SDG3 is Good Health and wellbeing, SDG4 is Quality Education, SDG6 is Clean Water and Sanitation, SDG7 is Affordable and Clean Energy, SDG9 is Industry, Innovation and Infrastructure, and SDG11 is Sustainable Cities and Communities. In all cases a cutoff of being deprived in 33% of the weighted indicators was used.

2.4 Methods of data analysis

Descriptive statistics were used to illustrate, compare and contrast a range of data collected from rural households. Multidimensional poverty index, probit regression model and propensity score matching were employed to analyze the prevalence of rural household poverty, determinants of multidimensional poverty, and the impact of migration on multidimensional poverty of migrant sending households and entire population in the study area, correspondingly. Thus, the specification of each model provided below in a few words.

2.4.1 Specification of multidimensional poverty index

The multidimensional poverty index provides a holistic approach for understanding poverty by going beyond monetary components to include factors such as education, health, and social inclusion (Alkire S. , 2002; 2005; Alkire & Santos, 2010; Santos & Alkire, 2015). The index uncovered deprivations in which the poor are experienced and the connections among those deprivations. Thus, the generalized version of Alkire and Foster (2011) index was employed with the support of DASP software in the estimation process. According to Alkire *et al.* (2015), the index is specified as:

$P(X, Z) =$ …………………………………………………………………………… (2)

Where $p(X, Z)$ is household poverty level (with vector of indicators $X_i = (X_{i,1} \ldots X_{i,j})$ and vector of poverty lines $Z = (Z_1 \ldots\ldots Z_j)$, determining indicators' contribution to total poverty p (X, Z). Moreover, the relative contribution of population subgroups and indicators to the multidimensional poverty indices is also computed by using formula 1 and 2, respectively.

$$C_t^o = S^p \frac{M_O(X^t)}{M_o(X)} \qquad (3)$$

Where, C_t^0 is the poverty contribution of subgroup, S^P is the sample population share of subgroup, $M_o(X^t)$ is MPI of the subgroup, and $M_O(X)$ is the MPI of the whole population.

Besides, the contribution of indicators' to the overall poverty (M_O) was calculated as:

$$\phi_i^0(k) = w_i \frac{h_i(k)}{M_O} \qquad (4)$$

Where; $\phi_i^o(k)$ is the contribution of an indicator at a dimension cutoff point k, W_i is the weight of the indicator I, $h_i(k)$ is Censored headcount ratio of an indicator I at a cutoff point k, and M_O is adjusted headcount poverty ratio of the population.

2.4.2 Specification of probit model for identifying the determinants of MPI

The binary choice model was employed to identify the major determinants of multidimensional poverty in the study area by categorizing the households as poor and non-poor based on their censored deprivation score *Ci*. Households who achieved a censored deprivation score (*Ci)* above the poverty cutoff (33%) were identified as multidimensional poor. Thus, the outcome variable is considered as dummy and gets a value of 1 and 0 for multidimensional poor and non-poor households respectively and represented as follows:

$$Y_i = \{1 \ if \ \complement i \geq k \ 0 \ otherwise \qquad (5)$$

Afterwards, the probit regression model was fitted to estimate the probability of a household to be multidimensional poor (y=1) using the maximum likelihood estimator (Pindyck & Rubinfeld, 1981; Hosmer & Lemeshow, 1989; Liao, 1994; Gujarati, 2004) and the results are interpreted in terms of marginal effect (Eric, Luke, David, Julia, & Brendan, 2018). Thus, the model is specified as follows:

$$y_i = \{0 \ if \ \leq 0 \ 1 \ if \geq 0 \qquad (6)$$

Where, y_i is the dependent variable with a binary form which takes 1 for multidimensional poor households and 0 for non-poor households as a base category, and y^* is a latent variable with $y^* = X\beta + \varepsilon$, ϵ~ N (0, δ^2). Where X and β are vectors of explanatory variables and unknown parameters estimated by maximum likelihood estimation methods, respectively. While, ϵ represents a random disturbance term.

The explanatory variables incorporated in this illustration were non-indicator measurement variables. Which includes: migration, defined as number of migrants; household size, defined as number of current household members; education of household head, defined as the number of years of education; gender of household head, represented by a dummy variable taking a value of one if the household head is a male and zero if female; livestock holding, defined as the quantity of livestock in TLU and soil infertility, represented by a dummy variable taking a value of one if the household faced soil infertility problem and zero otherwise.

2.4.3 Specification of PSM as an impact measurement

Alternatively, the propensity score matching model was used to estimate the effect of migration on multidimensional poverty. The basic idea of the model is to search in a large number of control groups, those who are comparable with the treated groups in all important pretreatment characters (Caliendo and Kopeinig, 2005). Thus, the usual framework in the analysis is the potential outcome approach with the main pillars individuals, treatment, covariates and potential outcomes (Rubin, 1974, Caliendo and Kopeinig, 2005) by employing an appropriate propensity score model.

Numerous iterations of steps were engaged in creating and estimating propensity scores. First, relevant covariates were selected based on available literature and then probit regression model was employed for estimating the probability of taking treatment in the way migration as a treatment variable, deprivation score as an outcome variable, and the potential covariates as explanatory variables. Propensity scores, overlaps, weight of matched controls, and value of the outcome of matches has been calculated for each observation following the nearest neighbor matching algorithm. A weighted combination of control observations was used to create a match for each treated individual, where control individuals were weighted by their distance in propensity score from treated individuals within a range of the propensity score (Mingxiang, 2012). High level common support (similar propensity score distribution across groups in each block) was achieved and that the propensity score is properly specified (Imbens, 2004). Thus, observations outside the range of common support (off support) were discarded in treatment effect analysis. To ensure the quality of matches, covariate balance diagnosis has been made across treatment and control groups. Afterwards, the potential outcome of the two groups within a range of common support has been computed for calculating the average effect of migration on the multidimensional poverty of migrant sending households and the entire sample population in the study area. Finally, sensitivity analysis has been performed to check whether the estimated average treatment effects are truly predicted.

To specify the model, in the case of a binary outcome, let us assume that $T=1$ if the household is in the treated group (migrant sending household) and $T = 0$ control groups (non-migrant households). The potential outcomes were defined as Yi (Ti) for each individual i, in which the potential outcomes of the treated groups denoted as Y (1) and the potential outcome of control groups as Y (0). So, the treatment effect is captured by estimating the average treatment effect on the population (ATE) and average treatment effect on the treated groups (ATT). Then the effect of treatment on the population was calculated as the difference of the two outcomes and has been specified as;

$$T_i = \text{ATE} = \text{E}(\Delta Y) = Y_i(1) - Y_i(0)$$

$$= \frac{1}{N}\sum_{i=1}^{N}(Y_i(1) - Y_j(0)) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (8)$$

Where Y_i (1) is the average outcome for all treated groups (migrant sending households) matched with the average outcome of control groups (non-migrant households) Y_i (0) and N is the number of treated cases (migrant and non-migrant households). Average treatment effect on the treated groups (ATET) was estimated as:

$$ATET = E[Y(1) \mid T=1] - E[Y(0) \mid T=1]$$

$$= \Delta Y = \text{E}(Y(1) - \text{Y}(0) \mid \text{T=1}) = \text{E}(\text{Y}(1) \mid \text{T=1}) - \text{E}(\text{Y}(0) \mid \text{T=1}) \ldots\ldots\ldots \quad (9)$$

The counterfactual treatment effect was estimated by subtracting average treatment effect on treatment groups (ATET) from the average effect on population (ATE) and has been represented as:

$$\text{Counterfactual effect} = \text{ATE} - \text{ATET} = (Y_i(1) - Y_i(0)) - ((Y(1) - \text{Y}(0) \mid \text{T=1}))$$

$$= (\text{Y}(1) \mid \text{T=0}) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \ (10)$$

Sensitivity analysis has been carried out, whether the unmeasured covariate would have changed the estimated treatment effects as sensitivity analysis takes a range of possible values attributed to hidden bias. When the hidden bias is null or very small, there is no mean effective selection bias in the estimated average treatment effects (Joo & LaLonde, 2014). Let assume that there are two groups, *m* and *n,* and that the two groups have the similar observed covariates **x** but perhaps varied probability of receiving treatment; that is, **x** [m] = **x** [*n*], but T[*m*] ≠ T[n]. Thus, the two groups are harmonized to form a matched pair in the same subclass in an attempt to control evident bias due to **x (**Shenyang & Mark, 2015)**.** The likelihood that group m and *n* receive the treatment is T [m] / (1 − T [*m*]) and T [*n*] / (1 − T[*n*]), correspondingly. Thus, the probability is calculated as:

$$\frac{T(m)/(1-T[m])}{T(n)/(1-T[n])} = \frac{T[m](1-T[n])}{T[n](1-T[m])} \quad \ldots\ldots (11)$$

The sensitivity analysis assumed that, the odds ratio for groups with the similar **x** was at most some number of λ ≥ 1; that is:

$$\frac{1}{\lambda} \leq \frac{T[m](1-T[n])}{T[n](1-T[m])} \leq \lambda$$ For all m and n with **x** [m] = **x** [*n*]……………………… (12)

By the earlier explanations, if hidden bias (λ) was 1, then T[*m*] = T [*n*] whenever **x**[*m*] = **x** [*n*], thus the study would be free of hidden bias. Lastly, bootstrap r (att), reps (1000): psmatch2 treatment, pscore (myscore) out (deprivation) has been carried on the estimated samples to make sure whether the average treatment effects are accurately estimated.

III. RESULTS AND DISCUSSION

This section gives a detail on the study results attained from household survey data analysis of descriptive statistics and econometric models. In the preliminary part, the various measures of multidimensional poverty have been presented by decomposed into household subgroups based on migration status. The subsequent sections explained the determinants of multidimensional poverty and the impact of migration on MPI in the study area using econometric model results.

3.1 Raw headcount deprivations practiced by rural households in the study area

Contingency Table 2 demonstrates the measure of raw headcount deprivations in each indicator for the two household groups without considering the size of peoples in the household. The table gives a picture of the proportion of households that are either well-off or deprived for each indicator including the deprivations of non-poor. The deprivation of all sample households in child schooling and adult literacy was 11.5 and 49%, respectively. Migrant sending households were experiencing the higher portion of the deprivations in education dimensions. Of the deprivations of all households in education, 86.36% of deprivation in children's schooling and 58% in adult literacy were shared by migrant sending households. The remaining 13.64% of the deprivation in children's schooling and 42% in adult literacy were linked with non-migrant households.

In the study area, the deprivation of rural households in the health dimension was relatively lower when compared with the other two dimensions. Only 5.73 and 16.67% of the sample households were deprived in good health and medical needs, respectively. As we compare the deprivation achievements of the two household groups in health dimension, migrant sending households were 63.6 and 53.1% lesser deprived in good health and medical needs than the counterpart as non-migrant households were shared 81.8% of chronic sickness and 76.56% of the deprivation in medical needs.

The table also revealed that the average deprivation of sample households in all indicators of living standard was much less than 50 %, except for indicators such as access to electricity (46.1%) and energy source for cooking other than solid fuel (76.56%). Comparing migrant sending households across non-migrant households showed that households with migrant members were considerably more likely to be better-off in all indicators of living standards except access to an energy source for cooking. In which, 55.8% of the deprivation associated with cooking fuel were experienced by migrant sending households. The largest difference across migrant sending households with non-migrant households was found in the number of rooms, access to more than one broadcasting asset and access to a private toilet. Wherein, the deprivation share of non-migrant households was much greater than 50% in the described living standard indicators. Generally, the raw headcount deprivation was examined without considering the size of people in the household, but the deprivation of non-poor households was included in the analysis.

Table 2: The extent of multidimensional deprivations experienced by household groups

Dimensions	Indicators	Deprivation status	Household subgroups		
			Migrant sending (214)	Non migrant (170)	Total (384)
Education	Child schooling	Non-deprived = 0	176	164	340
		Deprived =1	38	6	44
	Adult literacy	Non-deprived = 0	105	91	196
		Deprived =1	109	79	188
Health	Chronic sickness	Non-deprived = 0	210	152	362
		Deprived =1	4	18	22
	Meeting medical needs	Non-deprived = 0	199	121	320
		Deprived =1	15	49	64
Living standards	Access to above one room	Non-deprived = 0	208	129	337
		Deprived =1	6	41	47
	Access to electricity	Non-deprived = 0	125	82	207
		Deprived =1	89	88	177
	Access to drinking water	Non-deprived = 0	170	116	286
		Deprived =1	44	54	98
	Access to private toilet	Non-deprived = 0	203	139	342
		Deprived =1	11	31	42
	Access to cooking fuel	Non-deprived = 0	50	40	90
		Deprived =1	164	130	294
	Broadcasting asset	Non-deprived = 0	193	105	298
		Deprived =1	21	65	86

3.2 Relationships among the indicators

The key intention for research on multiple dimensions is that any single indicator does not entirely confine all determinants of multidimensional poverty (Anand S. , 1977; Callan, Nolan, & Whelan, 1993; Ringen, 1995; Alkire S. , et al., 2015; Alkire & Santos, 2014). Meaning that any single indicator is not an ideal predictor of poverty and as a result not perfectly correlated with the other indicators under consideration. Hence, we took a closer look at the relationship between the ten indicators before implementing multidimensional poverty measures under the consideration of household migration status. Such analysis is helpful to drop or reweight an indicator, to join some set of indicators into a sub index, or to correct the classification of indicators into dimensions (Alkire & Santos, 2010; Alkire, et al., 2015). It can also notify the choice of indicators and their robustness tests, the situation of deprivation values, and the explanation of outcomes (Alkire & Foster, 2011; Alkire, et al., 2015). For this, Spearman (1904) pairwise correlation was used to check the associations across indicators and to view their joint sharing that may exist. The result from Table 3 showed that most correlation coefficients, except the relationship between electricity and fuel (r = 0.5), are much smaller than a half. Therefore, it is rational to take a multidimensional approach since all the indicators are poorly correlated with each other and contributing to multidimensional poverty.

Table 3: Spearman pairwise correlation matrix between indicators (observation = 384)

	Mig.	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Mig	1.00										
(1)	-0.2***	1.00									
(2)	-0.044	-0.06	1.00								
(3)	0.19***	-0.02	-0.02	1.00							
(4)	0.29***	-0.05	-0.1*	0.07	1.00						
(5)	0.32***	-0.09*	0.016	0.15**	0.2***	1.00					
(6)	0.10*	0.061	-0.1*	0.11*	0.12*	0.021	1.00				
(7)	0.13**	0.033	0.002	0.2***	-0.04	0.02	0.3***	1.00			
(8)	0.21***	-0.074	0.024	-0.05	0.13**	0.12*	0.11	0.005	1.00		
(9)	-0.002	0.006	-0.07	0.057	0.049	0.04	0.5***	0.11*	0.095	1.00	
(10)	0.34***	-0.09*	-0.03	0.11*	0.25**	0.2**	0.2***	0.07	0.2***	0.1*	1.00

Note: Mig is migration status, (1), (2), (3), (4), (5), (6), (7), (8), (9) and (10) are indicators which denote child schooling, adult literacy, good health, medical needs, room, electricity, water, sanitation, cooking fuel and broadcasting asset, respectively. Where ***, ** and * are levels of significance at 1%, 5% and 10%, respectively.

3.3 The scope of multidimensional poverty in the study area

Table 4 presents estimates of multidimensional poverty coverage by migrant sending and non-migrant rural households at a poverty threshold *k*=33%. The sample population share of people in the analysis of MPI in this paper was 44.1% and 55.9 % in migrant sending and non- migrant households, correspondingly. MPI is deeper than raw headcount deprivation as it provides information on the share of weighted deprivations experienced by the poor and the proportion of the population who has been identified as poor. Thus, the examination of multidimensional poverty index was focused on the data of the poor and considered the size of people in the household. The MPI of the two subgroups was estimated by censoring the deprivations of the non-poor and calculated the proportion of people who have been recognized as multidimensionally poor in the population. The value of MPI was broken-down into the incidence and intensity of poverty since it is a linear product of the two indices.

The multidimensional poverty index of subgroups is obtained by adding the censored deprivation scores weighted by the population share of each household group or by multiplying poverty headcount ratio by intensity of poverty. Following poverty decomposability property, the entire multidimensional poverty index of the study area was obtained by adding the poverty of subgroups after multiplied by each sample population shares', which is estimated as 0.55.9 * 0.198 + 0.441 * 0.105 = 0.157. As the values indicated in Table 4, the study satisfied dimensional monotonicity property (Alkire & Santos, 2010; Alkire, et al., 2015) as a poor person became deprived in extra indicators, then the intensity of poverty and MPI values were climbing together.

When we are comparing the two subgroups based on a multidimensional poverty index, a big gap between migrant sending and non-migrant sending households has been occurring in the study area. A higher value of MPI was observed in non-migrant sending households than migrant sending households as the associated value of headcount and intensity are higher for them. The average number of multidimensional poor people in non-migrant households is almost twofold of the multidimensional poor people in migrant sending households with a variety of 9.3 percentage units. This is due to unequal distributions of poverty incidence and intensity of deprivations among the two household groups. The incidence of poverty (proportion of the population who has been identified as poor) in migrant sending and non-migrant households was varied by 19.9 percentage units with an upper share of non-migrant households. The average deprivation share (the breadth of poverty) of poor people in migrant sending and non- migrant households in the weighted indicators was accounted for 41 and 43.5%, correspondingly.

Furthermore, the study result showed that, non-migrant households have higher contribution in the overall multidimensional poverty of the study area. The contributions of non-migrant and migrant sending households to the overall multidimensional poverty were 70.5 and 29.5 %, respectively, with the contribution sum of the two groups equal to 100%. As indicated in Table 4, the contribution of non-migrant sending households to the overall multidimensional poverty (70.5%) considerably exceeded its sample population share (55.9%). This suggested that there is a seriously unequal distribution of multidimensional poverty (Alkire S. , et al., 2015; Katie, Lisa, & Melissa, 2018) among non-migrant households by bearing a top-heavy share in the study area. This study result signified, non-migrant households have a higher share than migrant sending households in the overall MPI, poverty headcount and intensity of deprivation by 41, 38.6 and 13.6 percentage points, respectively. Generally, migrant sending households were better off in any of multidimensional poverty indicators and have lesser contribution to the overall multidimensional poverty in the study area.

Table 4: Multidimensional poverty indices of the respondents (observation 384)

Population subgroups	Pop. Share	MPI value	Poverty headcount	Intensity of deprivation	Contributions to…		
					MPI	Headcount	Intensity
Non-migrant sending HHs	0.559	0.198	0.455	0.435	0.705	0.693	0.568
Migrant sending HHs	0.441	0.105	0.256	0.410	0.295	0.307	0.432
Whole sample	1.000	0.157	0.367	0.428	1.000	1.000	1.000
Difference	-0.118	-0.093	-0.199	-0.025	-0.41	-0.386	-0.136

Note: The difference is calculated between the migrant sending and non-migrant households

3.4 The relative contributions of indicators to the overall multidimensional poverty

Table 5 illustrates a multidimensional poverty index consisting of ten indicators grouped into three dimensions. The weights were computed such that, each dimension receives an equal weight of 1/3 and the weight is equally divided by the number of indicators in each dimension. As a result, each education and health indicator received larger weights (0.167) than the standard of living indicators (0.056). The table also displays the relative contribution of indicators to the aggregate deprivations of poor (censored headcount). The contribution of an indicator to poverty has a key message to the proportion of the population who are deprived in that indicator. Using the value of headcount ratio and the weight of each indicator, the contribution of each indicator is computed. Even though, the headcount ratio of an indicator can be computed from uncensored (raw) deprivation matrix (aggregate deprivation of poor and non-poor) and censored deprivation matrix (deprivation of poor only) (Alkire S. , et al., 2015), only the censored headcount ratio is used in the estimation process.

Table 5 shows the proportion of multidimensional poor people who are destitute in each indicator. We clarify that these are 'multidimensional' poor people because people who are deprived in 33% and above of dimensions. However, the rest were considered as non-poor since they have fewer deprivations. As presented in the table, the computation of the relative contributions of all indicators is 100%. Looking at the censored headcount rations, we can see that the poor in the study area exhibit the highest deprivation levels in access to an energy source for cooking other than solid fuel and literacy level, followed by the ability to meet medical needs, and access to electricity. An indicator in which its percentage contribution to the aggregate poverty has exceeded its weight, comparatively high censored headcount ratio of the indicator is observed. Indicators such as; adult literacy level, medical needs, access to electricity, access to drink water, and access to energy sources for cooking other than solid fuel have higher percentage contributions than their weight. The poor are more likely to be deprived in these indicators and they are policy relevant variables to deal with the composition of multidimensional poverty in the study area.

It was noticed that fuel and electricity have lower contribution to the overall multidimensional poverty, even though their censored headcount ratio is greater than any other indicators. This is because the weights assigned to these indicators are lower than those assigned to literacy and medical needs. In migrant sending households; adult literacy, child schooling, access to energy source for cooking other than solid fuel, the ability to meet medical needs were the top four indicators as they cumulatively contribute 49.63% of the deprivations. However, for peoples in non-migrant household adult illiteracy, ability to meet medical needs, access to energy source for cooking other than solid fuel, and access to electricity were the top four deprivations with 84.5% contribution to the overall multidimensional poverty.

When we compared the two subgroups, except in child schooling, people in migrant sending households were better off in all indicators which is consistent with the study result of Katie *et al.,* (2018). Generally, in the study area the contribution of education, health and living standard dimensions to the overall multidimensional poverty index is 34.8%, 24.3% and 40.9%, correspondingly.

Table 5: The proportion of people who are poor and experiencing deprivations in each indicator

Indicators	Weight	Censored *headcount ratio of indicators*			*Percent Contribution of indicators to MPI (Wi*HR/M0) = 0.157*		
		Non-migrant HHs	Migrant HHs	All HHs	Non-mig HHs	Migrant HHs	All HHs (0.157)
Schooling	0.167	0.043	0.101	0.0683	4.63	10.74	7.2
Literacy	0.167	0.2996	0.2104	0.2603	31.87	22.38	27.62
Good health	0.167	0.101	0.0193	0.0649	10.74	2.05	6.90
Medical	0.167	0.2385	0.0701	0.1638	25.37	7.46	17.43
Room	0.056	0.1574	0.0363	0.1031	5.61	1.30	3.70
Electricity	0.056	0.3378	0.1898	0.2739	12.91	6.77	9.77
Water	0.056	0.2328	0.1125	0.1791	8.30	3.98	6.39
Sanitation	0.056	0.1116	0.0302	0.0754	3.98	1.10	2.69
Fuel	0.056	0.4169	0.2455	0.3403	14.87	9.05	12.14
Broadcast	0.056	0.2538	0.0677	0.1713	9.06	2.40	6.11
Total	1	2.1924	1.0828	1.7004			100

Where, NMHHs and MSHHs are referring to non-migrant and migrant sending households, respectively.

3.5 The determinants of multidimensional poverty in the study area

Rural household multidimensional poverty is associated with various demographic and socioeconomic characteristics in the study area. For simplicity of quantifying the relevant determinants, the households were categorized as poor (1) and non-poor (0) based on the deprivation score *(Ci)* value. As illustrated in the methodological part of this paper, a poverty cutoff (33%) was used and then households with a censored deprivation score of 33% and above were poor and below are categorized as non-poor. Thus, the study employed a probit regression model as a tool to compute the determinants of household multidimensional poverty. As it is shown in Table 6, eleven explanatory (6 continuous and 5 discrete) variables were selected and tested their significant association with household multidimensional poverty status before entering into the model. Of which six explanatory variables (such as household size, number of migrants, age and education of household head, livestock holding, and soil infertility) were significantly associated with household multidimensional poverty status and chosen for the model as a major determinant in the study area.

Table 7 confirms the coefficients, marginal effect, and associated p-values of the coefficients. The log likelihood -210.70697 with a p-value of 0.000 indicated that, the model as a whole is statistically significant and better fits than a model with no predictors. This means all the explanatory variables included in the model have an effect on the dependent variable. The probit model coefficients provide the change in the z-score or probate index for a unit change in the forecaster. As the probit regression model output exposed, the coefficients of the number of migrants and livestock holding in TLU were negative and have an inverse effect on the household multidimensional poverty status. Whereas, the explanatory variables such as gender and education of the household head, household size and soil infertility problem have a positive relationship with household multidimensional poverty status. Except for the gender of the household head and soil infertility problem, all the other explanatory variables were statistically significant and determined the poverty of rural households either positively or negatively.

Probit regression was carried out to examine the relationship between migration and multidimensional poverty in the study area. The model result confirmed that there was a negative association between migration and overall MPI of rural households. As the econometric model revealed, having a migrant household member decrease the possibility of rural household multidimensional poverty and the effect is statistically significant at 10%. The marginal effect of the number of migrants in the household indicated that; additional number of migrants decrease the likelihoods of being multidimensional poor by 2.8 percentage points, holding other variables constant. The study result is in line with various *migration* optimistic studies which argued remittance receiving households are better off and having more migrants in the household seems to reduce multidimensional poverty through smoothening household income and increasing access to capital (Adams R. , 1998; Adams R. , 2006; Katie, Lisa, & Melissa, 2018). Besides, the neoclassical (optimistic) migration theory highlights migration as an investment where the benefits gained from migration have to exceed the costs associated for migration to take place. The gains obtained from migration are a flow of remittances, skills, knowledge, experience, and other household amenities that migrants acquired and are expected to be used in migrant sending households (Borjas, 1989; Worku, 1995; De Haas, 2006).

This finding is in contradiction with the structural migration theory (migration pessimist studies) that argued the multidimensional poverty of rural households increased due to the effect of migration. Migration pessimistic studies signified that, the remittance obtained from migrants creates remittance dependent society and cannot cover all the costs incurred by migrant sending households as spent on conspicuous consumption and unproductive investments (Russell, 1992; Lipton, 1980).

The size of the household was also another responsible factor for determining the level of multidimensional poverty in the study area. In this research a strong positive relationship between household size and multidimensional poverty was found. While a household size is increased, all the measures of multidimensional poverty were also increased at 1% significance level. The result of the study showed that, for each additional household member would increase the likelihood of rural household multidimensional poverty by 5.42%, *ceteris paribus.* This is because in a large household, the dependent population would be higher and household per capita income would be decreased and then the household unable to meet all the necessary requirements for life. It is obvious that larger household size has acutely rooted in the poverty circle since larger households are required with higher levels of income and other household amenities to live (Lekha, 2014; Alkire S. , et al., 2015).

The education of household heads is significantly related to the multidimensional poverty of households at a level of 1% and shows unexpected signs. The study signified that, for a given household a unit raise in the year of education of the household head, would enlarge the probability of rural household multidimensional poverty by 1.67 percentage units, holding other variables constant. The possible reason for this may be household heads with higher years of education are in dilemma to engage in petty works and thus gain lower income. Consequently, they are more likely to be poor. In the study area, there are many jobs that are not suitable for the educated person, maybe for their risk or for the societal norms and values. As such households with highly educated heads have higher possibilities of being poorer than their counterparts. The study result is inconsistent with the study result of Alkire, *et al.,* (2015) which revealed that the log of the odds of being multidimensional poor decreases with the education of the household head by 49 percentage points. Furthermore, Muhammad, *et al.,* (2015) revealed that an increase in the year of education is a signal for the household to engage in different livelihood activities and it creates higher access to information that will help households to improve their way of life.

Similarly, the correlation between livestock holding and multidimensional poverty of rural households is indirect and statistically significant at 5%. The marginal effect for TLU of the household shows that a unit increase in TLU decreases the probability of a household to be multidimensional poor by 3.3%, holding other variables constant. This is because, households with greater TLU have provided with a wide spectrum of benefits, such as cash income, food, manure, draft power and transportation services, savings and insurance, and social status and social capital (Bebe, Udo, Rowlands, & Thorpe, 2003; Moll, 2005; Upton M, 2004) which are basic for reducing household poverty. Empirical studies such as Birthal and Singh (1995), Thornton, *et al.,* (2002), Birthal and Ali (2005) and

Minot, *et al.,* (2006) have revealed similar results in the study that livestock rearing has a significant affirmative effect on poverty reduction in rural areas.

Table 6: The association between explanatory variables and household multidimensional poverty

Explanatory Variables	The variable handled as	Statistical tests		
		T-test	Chi-square	K-Smirnov test
Agro-ecology	Categorical (HL, ML, LL)	0.1367	0.002***	
Household size	Continuous	0.0000***		0.000***
No̲ of migrants	Continuous	0.0000***		0.000***
Year of education	Continuous	0.0003***		0.004**
Ethnicity of head	Dummy, 1 if Gurage	0.1746	0.174	
Age of HHs head	Continuous	0.5685		0.535
Gender of HHs head	Dummy,1 if male	0.0102 **	0.010**	
Landholding size	Continuous	0.45		0.979
Livestock holding	Continuous	0.0787*		0.055*
Soil infertility	Dummy, 1 if a problem	0.0798*	0. 079*	
Non- farm work	Dummy, 1 if participated	0.7347	0.734	

Where ***, ** and * are significant levels at 1%, 5% and 10%, respectively.

Table 7: Probit model result for the determinants of multidimensional poverty (n =384).

Explanatory variable	Coefficients	Std. Err	Z-value	P-value	Marginal effect
Household size	.1738669	.08683	3.43	0.001 ***	.0541605
Number of migrants	-.0900571	.0841488	-1.84	0.065 *	-.0280533
Education of HH head	. 0534579	.0301489	2.98	0.003***	.0166524
Gender of HH head	.2911225	.357467	1.40	0.160	.0906862
Livestock holding	-.1064683	.0748192	-2.63	0.009**	-.0331654
Soil infertility	.0252202	.2538265	0.17	0.867	.0078562
Constant	-1.414831	.651115	-3.65	0.000***	
Number of Obs = 384; LR chi2 (6) = 58.69; Prob > chi2 = 0.0000; Pseudo R^2 = 0.1222					

Where ***, ** and * are significant levels at 1%, 5% and 10%, respectively.

3.6 The effects of migration on multidimensional poverty

3.6.1 Covariates association and propensity score estimation

The major effort made in this section was measuring the effect of migration on migrant sending rural households' multidimensional poverty. For this, propensity score matching model was utilized by seeking observed mean deprivation differences between treated and control groups. Deprivation score as an outcome variable was estimated based on the assigned weights of covariates and the size of people within the household. The covariates chosen for the estimation of propensity scores were child schooling, adult literacy, good health, medical, access to more than one room, access to electricity, access to drinking water, access to private toilet, access to more than solid fuel for cooking, and access to more than one broadcasting asset. The study result showed that, among the covariates; child schooling, adult literacy and cooking fuel were negatively associated with treatment variables and would increase the level of deprivation in migrant sending households. The other covariates were positively associated with the treatment variable and trimmed down the poverty of migrant sending households. Except adult literacy and access to cooking fuel, all other covariates were significantly associated with treatment.

Table 8: The association between treatment variable and covariates

Migration	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Schooling	-1.079205	0.2970223	-3.63	0.000***	-1.6614	-0.49705
Adult literacy	-0.151715	0.1462409	-1.04	0.300	-0.4383	0.13491
Good health	0.75940	0.3527909	2.15	0.031**	0 .0679	1.450858
Medical need	0.747982	0.21009	3.56	0.000***	0.3362	1.15975
More room	1.1688	0.2683968	4.35	0.000***	0.64275	1.69484
Electricity	0.064463	0.1829597	0.35	0.725	-0.29413	0.423057
Drinking water	0.4145292	0.1783421	2.32	0.020**	0.06498	0.764073
Sanitation	0.614142	0.2420465	2.54	0.011**	0.13974	1.088545
Cooking fuel	-0.333718	0.2015612	-1.66	0.098*	-0.72877	0.061335
Broadcasting	0.7984262	0.1852986	4.31	0.000***	0.43525	1.16160
Cons	-2.621009	0.560728	-4.67	0.000***	-3.720	-1.5220

Number of Obs = 384; LR chi2(10) = 131.32; Prob > chi2 = 0.0000; Pseudo R^2 = 0.2491

Where ***, ** and * are significant levels at 1%, 5% and 10%, respectively.

Besides, a T-test was performed to measure the mean difference between migration and household deprivation score. From the analysis, a significant outcome difference was observed between the two groups at 1% level with higher deprivation score in non-migrant households before matching. With an unmatched sample, the deprivation score of migrant sending households was less than non-migrant households by 6.7%. After the match the effect of treatment on the treated group was insignificant as the mean outcome of the two groups was almost the same (Table, 9).

Table 9: Value of ATET from propensity score estimation model

Variable	Sample	Treated	Control	Difference	S.E.	T-stat
Deprivation	Unmatched	0.217206	0.284047	-0.0668415	0 .014491	-4.61***
	ATET	0.199829	0.200442	-0.0006133	0.045366	-0.01

Where: ATET is the average treatment effect on treated groups & *** is a 1% significance level.

3.6.2 Examination of match quality

We have carried out further analysis in order to identify the true effect of treatment by ensuring sufficient overlap between the two groups and making a covariate balance diagnosis before trusting on the estimated value of ATET from the previous propensity score estimation model. From the estimated propensity score, we make sure adequate overlap in the range of propensity scores across treatment and comparison groups. We found a high level of overlap (91.4%) between the two groups which is greater than the minimum satisfactory level of overlap (75%) to conduct PSM (Greg & Heath, 2018). Only 33 treatment observations (from 214 observations) were outside the range of common support and they are discarded in treatment effect analysis. Thus, the overlap distribution of the propensity scores across treatment and comparison groups was ample and displayed in Figure 2

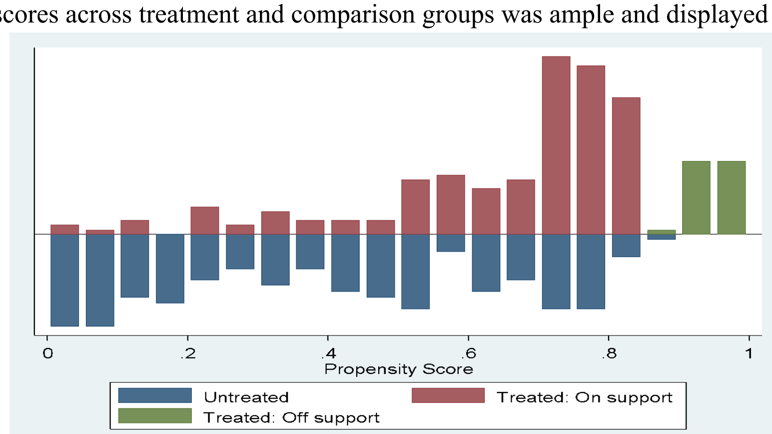

Figure 2: distribution of propensity score across treatment and comparison groups

After the propensity score is balanced within common support, a covariate balance diagnosis test was performed across treatment and comparison groups. A starting test of covariate balance was to ensure that the mean propensity score is equivalent in the treatment and comparison groups within each of the quintiles. From the analysis, we see that matching significantly decreased unbalance in the samples (See table 10 and 11). The ratio of variances in the propensity score between the treated and control groups changed from 0.54 in the unmatched sample to 2.00 in the matched sample. The two groups were balanced because the ratio of variances of the propensity score and covariates found between "1/2 and 2 extreme values" (Rubin, 2001; Imbens, 2004). All the covariates were likely balanced as there is no significance difference between propensity scores and any of the covariates (Leonardo & Carla, 2011; Greg & Heath, 2018) after matching. Generally, the matching reduced unbalancing and it is satisfactory as the mean absolute bias less (2.2) than 5 and the standardized difference (20.2) is less than 25 (Grill & Rampichini, 2011) after matching.

Table 10: Balanced sample tests within blocks of the propensity score

Variable	Sample	Mean		% bias	% reduced	t-test	
		Treated	Control		|bias|	t	p>|t|
Schooling	Unmatched	0.82243	0.96471	-47.3		4.45	0.000***
	Matched	0.97238	0.98895	-5.5	88.4	-1.14	0.253
Literacy	Unmatched	0.49065	0.53529	-8.9		0.87	0.386
	Matched	0.47514	0.44751	5.5	38.1	0.53	0.599
Good health	Unmatched	0.98131	0.89412	36.6		3.71	0.000***
	Matched	0.9779	0.97238	2.3	93.7	0.34	0.737
Medical	Unmatched	0.92991	0.71176	59.2		5.94	0.000***
	Matched	0.91713	0.92818	-3.0	94.9	-0.39	0.695
More than 1 room	Unmatched	0.97196	0.75882	65.5		6.67	0.000***
	Matched	0.96685	0.96685	0.0	100.0	-0.00	1.000
Electricity	Unmatched	0.58411	0.48235	20.4		1.99	0.047*
	Matched	0.58564	0.58564	0.0	100.0	-0.00	1.000
Water	Unmatched	0.79439	0.68235	25.6		2.52	0.012**
	Matched	0 .79006	0.77901	2.5	90.1	0.25	0.799
Sanitation	Unmatched	0.9486	0 .81765	41.5		4.16	0.000***
	Matched	0.94475	0.95028	-1.8	95.8	-0.24	0.814
Cooking fuel	Unmatched	0.23364	0.23529	-0.4		-0.04	0.970
	Matched	0.22099	0.22099	0.0	100.0	-0.00	1.000
Broadcast	Unmatched	0.90187	0.61765	70.3		7.03	0.000***
	Matched	0.88398	0.89503	-2.7	96.1	-0.33	0.738

Note: (***), (**), and (*) are levels of significances at 1, 5, and 10%, respectively.

Table 11: Summary of covariates balance diagnosis result

Sample	Pseudo R2	LR chi2	P>chi2	Mean Bias	Median Bias	B	R
Unmatched	0.249	131.32	0.000	38.4	41.5	125.8*	0.54
Matched	0.004	2.05	0.996	2.2	2.3	14.8	2.00

Where: B denotes standardized differences and R stands for variance ratio

3.6.3 Estimated treatment effects on multidimensional poverty

The goal of impact assessment is to figure out the effect of treatment on the outcomes of treated groups and the population after ensuring quality of matches between the two groups. The analysis depicted the potential poverty gains from migration in multidimensional poverty by estimating the average treatment effect on the entire sample and average treatment effect on the treated groups. The ATET is the estimated effect of the intervention among treated individuals and received the most attention in impact evaluation. The ATE combines the ATET with the estimated treatment effect for untreated individuals. The estimated value of ATE answered the question "What would be the expected effect of the treatment if individuals in the population are randomly assigned to treatment?" But estimating the individual treatment effect *is* not possible.

Standard errors were calculated with Abadie-Imbens (AI) Robust method for the interpretation of ATEs and ATETs as AI standard error provides a reliable estimate in match data (Abadie & Imbens, 2008; Austin, 2009; Abadie & Imbens, 2012; Melissa, et al., 2014). As our ATET and ATE estimated value showed, migration has played a crucial role in reducing poverty in the study area by a move out of people from multiple deprivations. In the area, the average gain from the current labor migration is estimated at 4.3% and 1.6 % overlapping deprivation reduction in migrant sending households and the entire population, respectively. The counterfactual outcome (the outcome of treatment groups if they were not treated) was estimated by subtracting the average treatment effect of treatment groups from the average treatment effect on the entire population. The resulting value was positive and indicated that, the overlapping deprivations of migrant sending households would be increased by 2.7% if they were not participating in the migration, another thing remained constant.

Thus, the study result is in line with the neoclassical migration theory which always noticed the migration as it has a positive effect on the socioeconomic conditions of households in the community of origin. In this perspective, the gains obtained from migration are a flow of remittances, skills, knowledge and experience that migrants acquired and which can be used as an intermediate tool in multidimensional poverty reduction strategy. Furthermore, the positive impact of migration is recognized in terms of price balancing in a condition wage differential (Todaro, 1969; Katie, Lisa, & Melissa, 2018). This means, where there is free migration, labor scarcity would be created in the community of origin, which would then result in a higher wage rate and reduce multidimensional poverty.

Table 12: The effect of migration on rural household poverty (Obs=384)

Treatment effect	Coefficients	AI Std. Err	P-value	(95% conf. Interval)	
ATE Migration (1 vs.0)	-0.015935	0.015664	0.309NS	0.04664	0.01477
ATET Migration (1 vs.0)	-0.043215	0.025828	0.094*	-0.0938	0.00741
Estimator = PSM; Outcome model= Matching; Treatment Model= Probit regression					

Note: (*) is the level of significance at 10%.

Qualitative information obtained from the focused group discussions and key informant interviews also exposed similar ideas regarding the effect of migration on multidimensional poverty. Many of the voices conveyed a concrete message on the power of migration in the reduction of rural households' poverty and its positive reward in every aspect of household needs. During focused group discussion an old woman in the study area stated the effect of migration as: “Harvesting adequate crops and owning lots of milking cows are not sufficient conditions for rural household life unless there is a migrant household member in the town and transferring remittance either in cash or kind form.” Another key informant in the study area said: “Everyone can easily differentiate migrants sending households from other households by their appearance. Households with migrant members are privileged; they look as if urban dwellers in every aspect of their life condition, and they are not dismayed at what to eat and where to live. However, households without migrants are almost deprived and they are always troubled to fulfill the minimum amount of life necessities.”

IV. CONCLUSIONS AND RECOMMENDATIONS

In this paper an effort has been made to estimate the effect of migration on multidimensional poverty in the Gurage zone of Southern National Regional State, Ethiopia, using survey data. The result of the study confirmed that, one in six people is multidimensional poor and the state of poverty varies across household groups due to migration. In the study area, migration has a substantial effect in reducing the multidimensional poverty of migrant sending households and the entire population by 4.3% and 1.6 %, respectively. Migrant sending households have a lower proportion of multidimensional poor compared to non-migrant households. The contribution of non-migrant households to the overall multidimensional poverty is much greater than the contribution of migrant sending households. Except in child schooling, migrant sending households were better off in all the chosen indicators. So, a practical action of the governing body is highly needed in mainstreaming migration and maximizing its benefits. Encouraging potential migrants to generate attractive livelihood opportunities in rural areas and suggesting them to invest in overlapping deprivations is very essential in the area of poverty reduction strategy at all levels of governments.

Indicators in living standard dimension have a higher cumulative contribution in the overall multidimensional poverty compared to indicators in education and health dimensions. This indicated that working on improving living standard indicators could help to reduce the prevalence of multidimensional poverty and thus needs high priority in policy initiatives in the study area. A policy maker who is concerned with reducing overall poverty might perform so in various mechanisms. First, the adjusted headcount ratio can be decreased by centering on the poor who have a lesser intensity of poverty and afterward there will be a big decline in headcount. However, there may not be a huge diminution in the average intensity. Second, an overall reduction in the adjusted headcount ratio can be achieved by centering on the higher intensity of deprivation rather than headcount (giving extraordinary consideration to the poorest of the poor). Thus, while monitoring poverty reduction, it is strongly recommended to see how overall poverty has been reduced.

The study has recognized that multidimensional poverty is determined by migration, household size, education of household head and livestock holding. Households with migrant members would like to reduce multidimensional poverty as they obtain migration reward in the form of cash and other material endowments. The result of the study also confirms that large household size enhances a household's multidimensional poverty. Households with more household size would like to increase their multidimensional poverty situation because larger households’ per capita income would be decreased and they are required with higher levels of income and other household amenities to live.

The study also predicted that, in the study area, households with higher years of head's education have higher deprivations than their counterparts. As this prophecy is unusual in ordinary research studies, the study has been made a profound attempt to investigate the possible reasons. In the study area, people with higher years of education normally do not engage in petty works (for instance, working as an agricultural laborer and the like) for their risk or for the societal norms and values. In this perspective, households with higher years of heads' education cut off one source of income for satisfying household amenities. As a result, they are more likely to be poor. So, encouraging people with higher years of education to engage in any alternative sources of income generating activities is a useful solution to amplify the earning potential of the households. On the other hand, households with more livestock holding are less multidimensional poor than others as higher livestock holding is a signal for acquiring cash and non-cash benefits, which are ways for poverty reduction.

Therefore, development planners are supposed to mainstream migration and should be focused on intensity rather than headcount ratio in order to achieve a larger reduction in MPI in the study area. Besides, this study calls for stakeholders to actively participate in societal training and awareness creation in the area of managing migration effectively and make use of its benefits efficiently to reduce multidimensional poverty.

V. LIST OF ABBREVIATIONS

ATE	Average Treatment Effect on population
ATET	Average Treatment Effect on Treated groups
CSA	Central Statistical Authority
DASP	Distributive Analysis Stata Package
HDI	Human Development Index
MPI	Multidimensional Poverty Index
SDG	Sustainable Development Goals
TLU	Tropical Livestock Unit

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VIII. Appendix tables

Appendix table 1: DASP output of the estimated value of MPI

Alkire and Foster (2007) MDP indices
Household size : hhsize
Group variable : migstatus

Group	Pop. share	H0	M0	M1	M2
0: Group_0	0.559	0.455	0.198	0.198	0.198
	0.027	0.039	0.018	0.018	0.018
1: Group_1	0.441	0.256	0.105	0.105	0.105
	0.027	0.034	0.014	0.014	0.014
Population	1.000	0.367	0.157	0.157	0.157
	0.000	0.027	0.012	0.012	0.012

The relative contribution to the Alkire and Foster (2007) MDP indices

Group	H0	M0	M1	M2
0: Group_0	0.692	0.705	0.705	0.705
	0.042	0.042	0.042	0.042
1: Group_1	0.308	0.295	0.295	0.295
	0.042	0.042	0.042	0.042

The relative contribution of dimensions to the Alkire and Foster (2007)
MDP indices estimated at population level (results in %).

Dimensions	M0	M1	M2
Scholing	7.24	7.24	7.24
	1.33	1.33	1.33
Literacy	27.61	27.61	27.61
	1.74	1.74	1.74
Goodhealth	6.90	6.90	6.90
	1.41	1.41	1.41
Medical	17.43	17.43	17.43
	1.77	1.77	1.77
Room	3.70	3.70	3.70
	0.58	0.58	0.58
Electricity	9.77	9.77	9.77
	0.57	0.57	0.57
Water	6.39	6.39	6.39
	0.63	0.63	0.63
Sanitation	2.69	2.69	2.69
	0.50	0.50	0.50
Fuel	12.14	12.14	12.14
	0.40	0.40	0.40
Broadcasting	6.11	6.11	6.11
	0.63	0.63	0.63

Appendix table 2: Probit model output and estimated marginal effects for determinants of MPI

```
. probit Poverty Migrants hhsize Edulevel Gender TLU Soilinfer2

Iteration 0:   log likelihood = -240.04991
Iteration 1:   log likelihood = -210.85647
Iteration 2:   log likelihood = -210.70701
Iteration 3:   log likelihood = -210.70697
Iteration 4:   log likelihood = -210.70697

Probit regression                               Number of obs     =        384
                                                LR chi2(6)        =      58.69
                                                Prob > chi2       =     0.0000
Log likelihood = -210.70697                     Pseudo R2         =     0.1222
```

Poverty	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Migrants	-.0900571	.0488855	-1.84	0.065	-.1858709	.0057566
hhsize	.1738669	.0507218	3.43	0.001	.0744541	.2732798
Edulevel	.0534579	.0179184	2.98	0.003	.0183384	.0885774
Gender	.2911225	.2073578	1.40	0.160	-.1152912	.6975363
TLU	-.1064683	.0405467	-2.63	0.009	-.1859384	-.0269981
Soilinfer2	.0252202	.1509285	0.17	0.867	-.2705942	.3210345
_cons	-1.414831	.3710208	-3.81	0.000	-2.142018	-.6876431

```
. margins, dydx( Migrants hhsize Edulevel Gender TLU Soilinfer2)

Average marginal effects                        Number of obs     =        384
Model VCE    : OIM

Expression   : Pr(Poverty), predict()
dy/dx w.r.t. : Migrants hhsize Edulevel Gender TLU Soilinfer2
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
Migrants	-.0280533	.0150228	-1.87	0.062	-.0574975	.0013909
hhsize	.0541605	.0151703	3.57	0.000	.0244273	.0838937
Edulevel	.0166524	.0053941	3.09	0.002	.0060802	.0272247
Gender	.0906862	.0641047	1.41	0.157	-.0349567	.2163291
TLU	-.0331654	.0123881	-2.68	0.007	-.0574456	-.0088853
Soilinfer2	.0078562	.0470176	0.17	0.867	-.0842967	.1000091

Appendix table 3: Probit model output for treatment assignment and Pscore estimation

```
Probit regression                               Number of obs   =        384
                                                LR chi2(10)     =     131.32
                                                Prob > chi2     =     0.0000
Log likelihood = -197.98089                     Pseudo R2       =     0.2491
```

migstatus	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
Scholing	-1.079205	.2970223	-3.63	0.000	-1.661358	-.4970522
Literacy	-.1517148	.1462409	-1.04	0.300	-.4383417	.1349121
Goodhealth	.7594003	.3527909	2.15	0.031	.0679429	1.450858
Medical	.7479824	.21009	3.56	0.000	.3362135	1.159751
Room	1.1688	.2683968	4.35	0.000	.6427525	1.694848
Electricity	.064463	.1829597	0.35	0.725	-.2941315	.4230575
Water	.4145292	.1783421	2.32	0.020	.064985	.7640734
Sanitation	.6141424	.2420465	2.54	0.011	.1397401	1.088545
Fuel	-.3337179	.2015612	-1.66	0.098	-.7287706	.0613347
Broadcasting	.7984262	.1852986	4.31	0.000	.4352476	1.161605
_cons	-2.621009	.560728	-4.67	0.000	-3.720015	-1.522002

Variable	Sample	Treated	Controls	Difference	S.E.	T-stat
Deprivation	Unmatched	.217205609	.284047063	-.066841454	.014491027	-4.61
	ATT	.199828732	.200441991	-.00061326	.045365966	-0.01

Note: S.E. does not take into account that the propensity score is estimated.

psmatch2: Treatment assignment	psmatch2: Common support		
	Off suppo	On suppor	Total
Untreated	0	170	170
Treated	33	181	214
Total	33	351	384

Appendix table 4: Propensity score matching model output for treatment effect estimation

```
. teffects psmatch ( Deprivation )( migstatus Scholing Literacy Goodhealth Medical Room Electricity Water Sanitation Fuel Broa
> dcasting ), nn(1) atet

Treatment-effects estimation                   Number of obs      =        384
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: logit                                        max =         28

------------------------------------------------------------------------------
             |              AI Robust
 Deprivation |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATET         |
   migstatus |
   (1 vs 0)  |   -.043215    .025828    -1.67   0.094    -.0938368    .0074069
------------------------------------------------------------------------------

. teffects psmatch ( Deprivation )( migstatus Scholing Literacy Goodhealth Medical Room Electricity Water Sanitation Fuel Broa
> dcasting ), nn(1)

Treatment-effects estimation                   Number of obs      =        384
Estimator      : propensity-score matching     Matches: requested =          1
Outcome model  : matching                                     min =          1
Treatment model: logit                                        max =         28

------------------------------------------------------------------------------
             |              AI Robust
 Deprivation |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
ATE          |
   migstatus |
   (1 vs 0)  |  -.0159349   .0156642    -1.02   0.309    -.0466362    .0147664
------------------------------------------------------------------------------
```