Comparison of Multidimensional Measurements of Poverty Analysis: Cross Sectional Data Evidence from Tigray

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Abstract
This paper examines the extent of poverty using the data from Tigray rural and urban baseline socio economic survey of 2200 households collected in 2011 by comparing and contrasting Alkire and Foster dual cut off approach, with Cluster analysis multidimensional poverty approaches. In addition for comparison purposes, a unidimensional poverty using per capita income approach was used. The study measure multidimensional deprivation in ten dimensions: education, health condition, housing quality, electrification, and access to safe drinking water, sanitation, energy for cooking, per capita income, house congestion and child health. The results indicate that the multidimensional deprivation far exceeds the unidimensional poverty. It has been estimated that about 69 percent, 56.45 percent and 41.6 percent of the households are poor in Alkire and Foster counting approach, in cluster analysis approach and unidimensionally poor respectively. In addition, the results also show that the decomposition of multidimensional and unidimensional poverty by location, indicates that in both methods of analysis, poverty is more prevalent in rural than urban areas. In comparing Dual cutoff and cluster analysis we find that at k=4, as cut off point 69 percent and 54.6 percent of the households are multidimensional poor in Alkire and Foster counting approach and in cluster analysis approach respectively. This shows that, Alkire and Foster dual cut off approach is the best estimation to measure the magnitude of multidimensional poverty and the level of deprivation in many dimensions. Using the intersection method at k=1, 99.6 percent of the total households are deprived in one or more dimensions. Among dimensions, above 88 percent of household head deprivation was due to lack of source of energy for cooking, i.e. the highest contributor to overall multidimensional poverty. Finally, the comparison results of the dual cutoff and counting approach with the cluster analysis of multidimensional poverty approach shows that the former one is the best suitable approach in estimation of multidimensional poverty analysis using different methods of poverty estimation.
Keywords: Multidimensional, Unidimensional, Dual cut off, Cluster, Tigray

1. Introduction

Poverty is a complex Phenomena. Consequently, a holistic approach is needed to develop poverty reduction strategies and programs. The development of effective policies and programs to deal with various dimensions of poverty, especially given the limited resources available has a challenging task for Developing country.

The trend in the expansion of poverty in terms of the number of poor and depth or severity of poverty is high in the sub-Saharan African countries. The evidence (WDR, 2000/2001) shows that the Share of population living on less than $1 a day in Sub-Saharan Africa was highest with 49.7 percent and lowest with 46.3 percent in the year 1993 and 1998, respectively. In the same period number of poor people increased from an already high 217 million in 1987 to 291 million in 1998 leaving almost half the residents of that continent poor. This shows over this period, the number of poor people who live below $1 a day has increased by 74 million people (WDR, 2000/2001).

According to UNDP's 2011 Human Development Index Ethiopia is one of the poorest countries in the world, ranking 174 out of 187 countries. About 39 percent of Ethiopia's populations were living in absolute poverty in 2005. Furthermore, 83 percent of the rural population has no access to safe drinking water, compared to 8 percent of the urban population. The Ethiopian government has expanded its health-care services in the last five years. Therefore, targeting of poverty alleviation remains an important issue in many countries.

Poverty remains widespread in Ethiopia. Using a unidimensional measure of poverty, 38.7 percent of Ethiopians were poor in 2004/05, implying that 27.5 million people were living below the poverty line. Poverty is slightly higher in rural areas (39.3 percent) than urban areas (35.1 percent). The headcount poverty rate fell in rural areas from 0.475 in 1995/96 to 0.393 in 2004/05. Over the same period, in urban areas it rose slightly, from 0.332 to 0.351 (MoFED, 2008).

Most empirical studies of poverty are usually based on unidimensional indicators of individual welfare, such as income (or total expenditure) per capita or per equivalent adult. When more than a single dimension of welfare is considered outside of the axiomatic approach, poverty comparisons are either based on a combination of a series of indicators that have been previously aggregated across individuals or on individual data that allow the retained welfare indicators to be aggregated at the individual level first, and then across individuals.

A simple way of dealing with the multidimensional aspect of poverty consists of assuming that individuals' various attributes can be aggregated into a single indicator of welfare. Poverty can then be defined with respect to this indicator. In other words, individuals will be considered poor if their global welfare index falls below a certain poverty line, the specification of which accounts for the multidimensional aspects of poverty.

According to Smeeding *et al*. (1993), individuals' welfare depends not only on monetary income, but also on their access to certain social services, such as education and health care. Furthermore, when they own their homes, individuals benefit from the services their residences provide. Consequently, imputing the same level of welfare to two individuals with the same income, one of whom owns his own home while the other rents, has the net effect of underestimating the welfare level of the homeowner. To incorporate this element, impute a value to the service homeownership confers, using either the market value of a rental, when available or the yield on the capital market of an equivalent investment when the market value of an equivalent residence is unknown.

As per the same author, education and healthcare services, the imputed global values are assumed equal to the amount the government spends on them. The distribution across households of education services is obtained by estimating the per capita cost of primary, secondary, and university education. Expenditures on education are thus allocated according to the number of individuals in each household having completed a certain level of education. Finally, as to the distribution of healthcare spending, Smeeding *et al.* (1993) treat healthcare spending as an insurance benefit received by all individuals, regardless of their actual use of these services. These benefits vary by age and sex. The value of the benefits imputed to households is thus estimated as a function of healthcare expenditures by age and sex for each group in the population.

Fighting extreme poverty on a multidimensional base like improving Wealth, education, Sanitation, Source of watering condition, Sources of energy for cooking and housing condition are among the main Millennium Development Goals (MDGs) agreed by 189 heads of state in 2000. Hence, this study compare and contrast among the different multidimensional poverty measurement and identify the better estimation results of the analysis and to show the situation of poverty in having development interventions and strategies designed to address the welfare need of the society at large in Tigray region.

2. Data Sources and Methodology

The data used in this study is a cross sectional data of Tigray rural and urban baseline socio economic survey collected in 2011 jointly by Mekelle University and Tigray Bureau of Planning and Finance. The total number of households covered in the study after the entire data clearing task is 2200. These households are properly measured for ten of the Multidimensional measurements of poverty analysis, i.e. education, health condition, housing quality, electrification, and access to safe drinking water, sanitation, energy for cooking, per capita income, house congestion and child health.

2.1. Sampling Method

The study was conducted in both urban and rural areas of the region. The survey is designed to provide statistically representative information about household socio-economic conditions at regional level. A two stage selection process was followed, first tibias from each werda were selected and households were selected from each of the selected kebeles. To collect the necessary data from all weredas and administrative towns, interviews with selected 2500 households from rural areas and 1000 households from urban areas were conducted.

Tabia/kebele selection method: A list of all tabias in all rural weredas and kebeles in the 12 urban administrations was obtained. First tabias were classified according to their agro-ecological conditions (highland, midland and low land). Most of the tabias in the werdas are stratified either as highland and midland; or midland and lowlands. Based on this classification two tabias were selected randomly from each stratum.

In urban areas all kebeles were selected but in towns like Mekelle, Axum and Adigrat all kebeles were not covered. Sample kebeles were selected because the numbers of kebeles were greater than three and the area is large to cover fully.

Household selections: Number of households for each wereda and urban area were allocated proportionally according to the population of the wereda or urban area obtained from the National Housing and Population Census conducted by the CSA in 2007. After allocating the number of sampled population for each wereda, number of households for each tabia is also allocated proportionally based on the number of population of the tabia. In each selected tabia/kebele, a list of all household within the tabia as a sampling frame to select households for the survey. The list of household is used as a sampling frame to select household for the survey. Systematic sampling is employed to select household from each tabia.

2.2. Method of Data Analysis

This study used both statistical and econometric analyses. The nature and actual situation of multidimensional poverty have been examined on the descriptive part of analysis the percentage and summary statistics of frequency tables used to make analysis in the form of tables. In econometric analysis, three sets of models have been utilized: the dual cutoff approach developed by Alkire and Foster (2007), Cluster analysis, and FGT poverty measure models are used.

i. Unidimensional Poverty Measurements

In order to explore the extent of *u*nidimensional poverty measurements, the FGT poverty measure that was introduced by Foster, Greer, and Thorbecke, (1984) is used.

$$P_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)^\alpha,$$

Pα is simply the mean over the whole population of an individual poverty measure which takes the value (1 - Yi/z) α for the poor and zero for the non-poor. The head-count index has α = 0, while α = l for Poverty Gaps and α = 2 is for poverty severity. For both the poverty-gap index and P2 the individual poverty measure is strictly decreasing in the living standard of the poor (the lower the standard of living the poorer you are deemed to be). Furthermore, P2 has the property that the increase in your measured poverty due to a fall in standard of living will be deemed greater the poorer you are. The higher the value of α the more sensitive the measure is to the wellbeing of the poorest person; as α approaches infinity the measure collapses to one which only reflects the poverty of the poorest person. In other words, the larger the value of α is, the greater the weight given to the severity of poverty. It is noted that all the three measures are additively decomposable. This enables us to examine the relative contributions of different subgroups to overall poverty.

ii. Multidimensional Approaches of Poverty Measurements

a. Principal Components Analysis

The idea to describe poverty in a multidimensional way is based on the assumption that it various components translate into several variables, on which individuals accumulates deprivation. Each component therefore constitutes a given set of 'capabilities', be it financial conditions, housing conditions, sanitation, health or any other state that may hinder human development. An important step is the determination of the weights that each component carries. Different multivariate statistical techniques can be used to solve the weighting problem.

Principal Components Analysis is a method that reduces data dimensionality by performing a covariance analysis between factors. As such, it is suitable when you have obtained measures on a number of observed variables and wish to develop a smaller number of artificial variables (called principal components) that will account for most of the variance in the observed variables. The principal components may then be used as predictor or criterion variables in subsequent analyses.

The applicability of classical factorial techniques is generally limited by the kind of data availability. Specifically, standard PCA can in principle be applied only if all the variables are numeric (the variables are either quantitative or continuous) and the relationships between variables are assumed to be linear. But most of the variables available in our dataset are categorical, measured at nominal and ordinal level. Accordingly, linear or classical PCA would not be the most appropriate method. The discrete data violate distributional assumptions in methods where continuous variables are assumed or expected. Also, even despite the finite range, the discrete data tend to have high skewness and kurtosis, especially if the majority of the data points are concentrated in a single category (Kolenikov and Angeles, 2009). Thus the standard PCA model is no longer appropriate.

Therefore, to avoid limitations of standard PCA, we propose to adopt an alternative approach, allowing us to treat ordinal and binary variables. Kolenikov and Angeles (2004) have described a technique, called polychoric PCA, which improves on the regular PCA. The polychoric PCA technique is especially appropriate for discrete data (binary and ordinal).

To specify the polychoric PCA model, we follow Kolenikov and Angeles (2004). If x is a random variable of dimension p with finite p x p variance-covariance matrix $V(x) = \Sigma,$ principal components analysis solves the problem of finding directions of the greatest variance of the linear combinations of x's. In other words, the principal components (Y_j) of the variables $X_1,\dots X_p$ are linear combinations $a_1x,\dots a_px$ such that

$Y_j = a_j x \quad j = 1, \dots, K$ …………………………………………………………………… (1)

The motivation behind this problem is that the directions of greatest variability give most information about the configuration of the data in a multidimensional space. The first PC will have the greatest variance and extract the largest amount of information from the data, the second component will be orthogonal to the first one, and extract the greatest information in that sub-space; and so on. Also, the PCs minimize the sum of squared deviations of the residuals from the projections onto linear sub-spaces. The first PC gives a line such that the projections of the data onto this line have the smallest sum of squared deviations among all possible lines.

The solution to equation (1) is found by solving the eigen problem for the correlation matrix Σ. This consists of finding and a such that:

$\sum a = \lambda a$ ……………………………………………………………………(2)

The solution to the eigenproblem (2) for the correlation matrix gives the set of principal components weights a (also called factor loadings), the linear combinations a'x (referred to as factor scores) and eigenvalues $\lambda_1 \geq \lambda_2 \geq \cdots\cdots \geq \lambda_p$. Total variance $= \lambda_1 + \lambda_2 + \dots\dots + \lambda_p$ and consequently the proportion of total variance explained by the

$$k-th\ PC = \frac{\lambda k}{\lambda 1+\lambda 2+\cdots+\lambda p}$$

Note that since the variables in our model are binary and ordinal, the matrix on which the PCA is based is the polychoric correlation matrix, and not the standard Pearson correlation matrix. Polychoric correlations are those correlations between ordinal variables and the latent continuous variables underlying each of the ordinal variables. They can be interpreted just as the standard Pearson correlation coefficients.

Determining poverty threshold

We next want to proceed by identifying groups in the population which are more or less homogenous when using these measures of multidimensional poverty. To this end, we rely on cluster analysis. Clustering is a common technique used to partition a set of data points into groups (clusters), so that the points in each group share some common characteristics-typically proximity according to some distance or similarity measure. The goal is thus to bring together individuals having relatively similar characteristics, while individuals belonging to different groups are as disparate as possible (Fredu *et al*, 2010).

Clustering algorithms fall into two broad categories: hierarchical, which partition the data by successively applying the same process to clusters discovered in previous iterations, and partitional, which determine the clusters in a single step. Hierarchical methods can be agglomerative (bottom-up) or divisive (top-down). The agglomerative methods begin with each observation being considered as separate clusters and then proceeds to combine them until all observations belong to one cluster, whereas the divisive methods start with all of the observations in one cluster and then proceeds to split (partition) them into smaller clusters.

With the agglomerative hierarchical clustering method we will use, the main steps of the groups 'identification procedure are as follows. Let there be n individuals with m characteristics (in our case the various scores of poverty). At the beginning, every individual is considered as a separate group. A similar index, namely the Euclidean distance between the scores, is computed for all n.(n-1)/2 potential pairs of individuals and the two closest are grouped. In the next step, the same procedure is applied to the (n-1) remaining clusters, which implies (n-1).(n-2)/2 distances. When comparing groups of individuals, the average distance between the individuals of the groups is used as criterion (average-linkage method). This process goes on until all observations belong to the same group, and hence creates a hierarchy of clusters.

The agglomerative hierarchical clustering methods leave open the choice of the final number of clusters. Many stopping rules can help this decision and we will make use of the best two – the Calinski and Harabasz (1974) pseudo-F index and the Duda and Hart (1973) Je(2)/Je(1) index. For both rules, larger values indicate more distinct clustering. Presented with the Duda-Hart Je(2)/Je(1) values are pseudo-T-squared values. Smaller pseudo-T-squared values indicate more distinct clustering. If possible, the number of clusters will be chosen such that the information loss is limited (the number of clusters is set as the number where the Pseudo-t2 is maximal plus one) while the difference between the clusters (the pseudo-F) is maximized.

b. Alkire and Foster dual cutoff approach

This part presents poverty dimensions and indicators used in Alkire and Foster (2007) dual cutoff and counting approach to multidimensional poverty measures. In this study we computed 10 dimensions of poverty based on public consensus, data availability and theoretical ground. These include education, health, housing congestion, electrification, access to safe drinking water, sanitation, Per capita income, Housing quality, energy used for cooking, and Child health.

Alkire and Foster (2007) suggest a counting approach which follows the method of aggregation proposed by Foster, Greer, and Thorbecke (1984) in the sense that it is built on the same family of measures. This family satisfies a certain number of axioms such as symmetry, replication invariance, decomposability, etc.

Consider a population of n individuals. Let d >=2 be the number of dimensions and $x = [x_{ij}]$ the $n * d$ matrix of achievements, where x_{ij} is the achievement of individual $i(i = 1; ..., n)$ in dimension j (j =1, ……, d) x is of the following form:

$$X = \begin{bmatrix} X_{11} & \cdot & X_{1j} & \cdot & X_{1d} \\ \cdot & & \cdot & & \cdot \\ X_{i1} & \cdot & X_{ij} & \cdot & X_{id} \\ \cdot & & \cdot & & \cdot \\ X_{n1} & \cdot & X_{nj} & \cdot & X_{nd} \end{bmatrix}$$

Let z be a row vector of dimension-specific thresholds z_j, xi the row vector of individual i's achievements in each dimension, and xj a column vector of dimension j achievements across the set of individuals.

Identification

To identify the poor we assume that all dimensions are equally weighted. Suppose that a matrix of deprivations $X^0 = [X_{ij}^0]$ is derived from x as follows;

$$For\ all\ i\ and\ j, Xij = \begin{cases} 1\ if\ xij < zj \\ 0\ other\ wise \end{cases}$$

For example $X^0_{ij} = 1$ means that individual i is deprived in dimension j and $X^0_{ij} = 0$ that individual i is not deprived. By summing each row of X^0_{ij}, we can obtain a column vector c of deprivation counts containing c_i the number of deprivations suffered by individual i.

For identifying, consider the identification function ρ (xi; z) such that

$$\rho(xi;\ z) = \begin{cases} 1\ \text{if individual}\ i\ \text{is multidimensionally poor} \\ 0\ if\ not \end{cases} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Let k be the cutoff. An individual i will be considered as poor or $\rho\ (xi;\ z) = 1$ if $ci \geq k$. $\rho(xi;\ z)$ is the identification function relating to the cutoff k. The equation (1) could be rewritten:

$$\rho(xi;\ z) = I\ (ci\ \geq\ k)\ = \begin{cases} 1\ if\ ci\ \geq\ k) \\ 0\ if\ not \end{cases} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

I ($ci \geq k$) is the standard indicator function taking the value 1 if the expression in brackets holds and the value 0 if not.

The most commonly used identification criteria of multidimensional poverty is the union method of identification. In this approach a person i is said to be multidimensionally poor if there is at least one dimension in which the person is deprived ($(xi;\ z)$ = 1 if and only if ci≥1) (Alkire, 2008). In this case, the cutoff k = 1. This definition seems to strong and could overestimate the poverty, especially when the number of dimensions d is high enough with possible substitutability among some dimensions (Batana, 2008).

A second identification approach is the intersection approach, which identifies person i as being poor only if the person is deprived in all dimensions ($\rho(xi;\ z)$ = 1 if and only if ci=d) (Alkire,et,al. 2008).This could on the other hand underestimate the poverty by not considering, for example, a healthy homeless as poor when health and housing are two of the dimensions (Batana, 2008).

A natural alternative is to use an intermediate cutoff level for c_i that lies somewhere between the two extremes 1 and d that is 1<k<d. In this case ρ_k identifies person i as poor when the number of dimensions in which i is deprived is at least k; otherwise if the number of deprived dimension fall below the cutoff k, then i is not poor according to ρ_k. Since ρ_k is dependent on both the within dimension cutoffs Z_j and across dimension cutoff k it is referred to as dual cutoff method of identification (Alkire *et al*. 2008).

Multidimensional poverty measure

In general M0, $M1$, and $M2$ to a class $M\alpha(x;z)$ of multidimensional poverty measures associated with the unidimensional FGT class.

The *adjusted* FGT *class* of multidimensional poverty measures are given by $M\alpha=\mu(g^{\alpha}(k))$ for α>0. In other words, $M\alpha$ is the sum of the α powers of the normalized gaps of the poor, or $|g^{\alpha}(k)|$, divided by the highest possible value for this sum, or nd. The methodology employing the dual cutoff function ρk and an associated FGT measure $M\alpha$ will be denoted by $Mk\alpha - (\rho k, M\alpha)$.

Suppose that $M(x;\ z)$ is the class of multidimensional poverty measures proposed by Alkire and Foster (2007). The first measure is given by headcount ratio. Let qk be the number of poor identified according to the thresholds vector z and the cutoff k, the headcount ratio H, the percentage of the population that is poor given by:

$$H = \frac{qk}{n}$$

Where, $qk\ = \sum_1^n \rho(xi;\ z)\ = \sum_1^n I\ (ci\ \geq\ k)$

The headcount ratio has its own weakness in the sense that if a poor person becomes deprived in a new dimension, H remains unchanged. This violates one important axiom of 'dimensional monotonicity', which says that if poor person i become newly deprived in an additional dimension, then overall poverty should increase. Also, H cannot be broken down to show how much each dimension contributes to poverty. To encompass these concerns, there is a need to have extra information on the breadth of deprivation experienced by the poor.

The *share of possible deprivations* suffered by a poor individual i is given by $ci(k) = \frac{1}{d}[ci\ \rho(xi;\ z)]$ and the *average deprivation share* across the poor by; $A = \frac{1}{qkd}\sum_i^n ci\ \rho(xi;\ z)$. The second measure proposed by Alkire and Foster (2007) combines H and A to obtain an expression satisfying the dimensional Monotonicity. The new measure M_0 called *adjusted headcount ratio* is given by: $M0\ = HA = \ \mu\,(g^0\ (k))$

$$M0 = HA = \frac{1}{nd}\sum_i^n ci\, \rho(xi;\, z)$$

As a simple product of H and A, the measure M_0 is sensitive to the frequency and the breadth of multidimensional poverty. In particular, the methodology (ρk, M_0) clearly satisfies dimensional monotonicity, since if a poor person becomes deprived in an additional dimension, then A rises and so does M_0.

The methodology (ρk, M_0) is based on a dichotomization of data into deprived and non-deprived states, and so it does not make use of any dimension-specific information on the depth of deprivation. Consequently it will not satisfy the traditional Monotonicity requirement that poverty should increase as a poor person becomes more deprived in any given dimension.

To develop a methodology that is sensitive to the depth of deprivation (when data are cardinal), we return to the censored matrix of normalized gaps g^1 (k). Let G be the *average poverty gap* across all instances in which poor persons are deprived, given by $G=|g^1(k)|/|g^0(k)$.

The adjusted poverty gap is given by M1=HAG=μ(g1(k)).It is thus the product of the adjusted headcount ratio M_0 and the average poverty gap G. The equivalent definition $M_1=\mu(g^1(k))$ says that the adjusted poverty gap is the sum of the normalized gaps of the poor, or $|g^1(k)|$ divided by the highest possible sum of normalized gaps, or nd. Under methodology (ρk, M^1) if the deprivation of a poor person deepens in any dimension, then the respective g^1_{ij} (k) will rise and hence so will M_1. Consequently, (ρk, M1) satisfies the monotonicity axiom .However, it is also true that the increase in a deprivation has the same impact no matter whether the person is very slightly deprived or acutely deprived in that dimension. One might argue that the impact should be larger in the latter case.

Consider the censored matrix g^2 (k) of squared normalized shortfalls which provides information on the severity of deprivations of the poor (as measured by the square of their normalized shortfalls). The *average severity* of deprivations, across all instances in which poor persons are deprived, is given by $S=|g^2(k)|/|g^0(k)|$. The following multidimensional poverty measure $M_2(x;z)$ combines information on the prevalence of poverty , the range and severity of deprivations.

The *adjusted* FGT *measure* is given by $M2 = HAS.$

M_2 is thus the product of the adjusted headcount ratio M_0 and the average severity index S. Its alternative definition $M_2= \mu(g^2(k))$ indicates that M_2 is the sum of the squared normalized gaps of the poor, or $|g^2(k)|$, divided by the highest possible sum of the squared normalized gaps, or *nd*. Under (ρk, M_2), a given-sized increase in a deprivation of a poor person will have a greater impact the larger the initial level of deprivation. Consequently, the methodology satisfies the transfer property and is sensitive to the inequality with which deprivations are distributed among the poor, and not just their average level.

In general M0, *M*1, and *M*2 to a class $M\alpha(x;z)$ of multidimensional poverty measures associated with the unidimensional FGT class. The *adjusted* FGT *class* of multidimensional poverty measures are given by $M\alpha=\mu(g^\alpha(k))$ for α>0.

In other words, $M\alpha$ is the sum of the α powers of the normalized gaps of the poor, or $|g^\alpha(k)|$, divided by the highest possible value for this sum, or *nd*. The methodology employing the dual cutoff function ρk and an associated FGT measure $M\alpha$ will be denoted by $Mk_\alpha = (\rho k, M\alpha)$

3. Data Analysis and Interpretation

Both descriptive and econometric analyses were used to present the result. The descriptive analysis includes percentage, mean, standard deviation and summary statistics of frequency tables and in the econometric analysis, three sets of models were used - Alkire and Foster dual cutoff (2007) approach, cluster analysis, and FGT measure of poverty.

3.1. Descriptive Analysis-

Table 1: below shows the distribution of the sample size in the rural and urban areas.

Location of the Household Head	Total number of the Household Head	
	Frequency	Percentage
Rural	1,342	61.00
Urban	858	39.00
Total	2,200	100

Source: own computation based on Tigray baseline socioeconomic survey (2011).

According to table 1, out of the total respondents (2200), 61 percent are rural areas household and the rest 39 percent are from urban areas.

Table 2: Total number of respondents' in rural and urban areas by gender

Sex of the household head	Rural		Urban	
	Frequency	Percentage	Frequency	Percentage
Male	1052	78.39	482	58.18
Female	290	21.61	376	43.82
Total	1342	100	858	100

Source: own computation based on Tigray baseline socioeconomic survey (2011).

Table 2: indicates that from the total rural area respondents, 78.39 percent were male headed household and the rest 21.61 percent were female headed household. And out of the total respondents in urban areas 58.18 percent were male headed and the rest 43.82 percent were female headed household.

Table 3: Total number of respondents' by Zone

	Zone of the Household							
	Central	East	Mekelle	North West	South	South East	West	Total
Frequency	445	404	254	396	394	251	56	2,200
Percent	20.23	18.36	11.55	18.00	17.91	11.41	2.55	100

Source: own computation based on Tigray baseline socioeconomic survey (2011).

The study reveals that the distribution of respondents by zone indicated that 20.23 percent from Central, 18.36 percent from East, 11.55 percent from Mekelle, 18 percent from North West, 17.91 percent from South, 11.41 percent from South East, and 2.55 percent are from West.

Table 4: Descriptive statistics of each dimensions used in multidimensional analysis

Dimensions	Rural areas		Urban areas		Total	
	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Education	0.5991058	0.4902623	0.9755245	0.1546103	0.7459091	0.4354479
Electrification	0.0804769	0.2721315	0.9312354	0.253201	0.4122727	0.4923557
Energy for cooking	0.0230999	0.1502767	0.2692308	0.4438188	0.1190909	0.3239691
water	0.7026826	0.4572478	0.988345	0.10739	0.8140909	0.3891217
Sanitation	0.5469449	0.4979769	0.6911422	0.4622918	0.6031818	0.893489
House quality	0.0506706	0.219406	0.9452214	0.2276802	0.3995455	0.4899163
Health	0.8643815	0.3425106	0.8717949	0.3345131	0.8672727	0.3393569
House congestion	0.5275708	0.4994254	0.7424242	0.4375541	0.6113636	0.4875512
Per capita income	268.9311	209.3372	322.4707	298.732	289.81150	249.36940
Child Health	0.8092399	0.3930468	0.9289044	0.2571343	0.8559091	0.3512617

Source: own computation based on Tigray baseline socioeconomic survey (2011).

Table 4 presents the descriptive summary statistics of each dimensions used in the cluster multidimensional poverty analysis their mean, standard deviation for each dimensions. In a headcount perspective, the mean deprivation levels vary quite substantially across binary variables.

3.2. Econometric Analysis

3.2.1. Estimation of Total Poverty in Tigray Region

In analyzing the Headcount, Poverty gap and the Squared poverty gab 2508 birr poverty line was used in this study, i.e. developed in the report of Baseline socioeconomic survey of Tigray Region in 2011. Table 5 indicated that about 41.6 percent of the households in the region are below the poverty line, these are the households who could not consume enough to the minimum kilo calorie requirement of 2200 Kcal per day adjusted to basic non-food consumption. The depth of poverty and the intensity of poverty are indicated by the poverty gap and the squared poverty gap respectively. So that, the poverty gap in the region is 12.8 percent. The severity of poverty as indicated in the squared poverty gap is only 5.7 percent.

Table 5: Estimation of Total poverty in the region by per capita income

FGT	Poverty index	SE
Headcount ratio	0.416	0.010
Poverty gap ratio	0.128	0.004
Squared poverty gap ratio	0.057	0.002

Source: own computation based on Tigray baseline socioeconomic survey (2011).

3.2.2. Estimation of Poverty by Rural and Urban Areas of Tigray

Table 6 indicates that the magnitude of poverty separately for urban and rural areas. Poverty in the rural area is 48.5 percent while poverty in the urban areas is 31 percent as measured by the headcount ratio. The poverty gap in rural areas is 14.1 percent and 10.8 percent in urban areas. While the squared poverty gap in rural areas is 5.6

percent and 5.9 percent in urban areas. The result shows poverty is more of a rural phenomenon.

Table 6: Estimation of poverty by rural and urban areas

FGT	Rural		Urban	
	Poverty index	**SE**	**Poverty index**	**SE**
Headcount ratio	0.485	0.013	0.310	0.015
Poverty gap ratio	0.141	0.005	0.108	0.007
Squared poverty gap ratio	0.056	0.002	0.059	0.005

Source: own computation based on Tigray baseline socioeconomic survey (2011).

3.3. Dimensions and Poverty thresholds

The selection of dimensions of deprivation is an important aspect of the multidimensional poverty measurement. The choice of indicators describing deprivation is country specific and depends on the level of development, the nature of poverty, type of social exclusion and availability of data. This study analyzed household poverty in multidimensional perspective. The identification of the dimensions and variables to include in a multidimensional analysis of poverty is a crucial step.

In an extensive review of literature on the selection of dimensions and indicators, Alkire finds researchers justifying their selection of indicators on the basis of up to five criteria (Alkire 2007). These criteria are: 1) data availability and adequacy; 2) based upon theoretical frameworks; 3) public discussions; 4) deliberative participation; and 5) empirical analysis. In this analysis by adopting the criteria to derive multidimensional poverty based on theoretical assumptions, empirical analysis and availability of appropriate data, a list of 10 dimensions are selected for this study.

1. **Education**: Education is a central capability that has intrinsic as well as instrumental importance in enhancing individual wellbeing. It has a potential to enable individuals to participate in the social, economic and political spheres of their lives. Access to universal primary education is Goal2 of the MDGs that Ethiopia is committed to achieving by 2015.
   ***Poverty** cut-off point*: A household is declared poor if any member of the household in the age group of 7 to 18 is not able to go to school.
2. **Health**: Like education, health has instrumental as well as intrinsic value in determining the wellbeing of individuals. Achievement of several valuable capabilities critically depends upon the health status of individuals (Ariana and Naveed 2009).
   Poverty cut-off point: A household is declared poor in the health dimension if there was at least one member of the household who was sick and unable to do his/her normal activities in the last four weeks.
3. **Housing Congestion**: housing Congestion in this case represents the number of people per room of the household.
   Poverty cut-off points: A household is said to be poor in this dimension if three or more people live in one room
4. **Electrification**: Access to electricity is an important aspect of everyday life of the household and it is part of the MDGs.
   Poverty cut-off points: A household is declared poor in electrification if it does not have access to electricity.
5. **Access to safe drinking water**: Access to safe drinking water is an important dimension of wellbeing. Diarrhea, several communicable diseases, such as Hepatitis is spread through unsafe drinking water. Moreover, increased access to safe drinking water is part of the MDG's Goal 7 (ensure environment sustainability).
   Poverty cut-off point: A household is declared poor in this dimension if it has no access to covered sources of drinking water.
6. **Sanitation**: Like access to safe drinking water, access to sanitation is also an important dimension of the wellbeing of households. Various aspects of public health are closely associated with sanitation. Access to improved sanitation is also part of MDG's Goal 7 (ensure environment sustainability).
   Poverty cut-off point: A household is declared poor if it has shared dry pit toilet or none.
7. **Per capita income**: Power to purchase goods and services that one values and has reason to value, is an important capability (Naveed and Islam, 2010). While the capability approach has strongly contested the exclusive reliance upon income or consumption as the only indicator of wellbeing and poverty. As poverty is officially measured in terms of consumption level, this dimension corresponds to MDG's Goal 1 (Eradicating poverty and hunger).
   Poverty Cut-off point: Using the poverty line for the year 2011, households with adult equivalent per capita consumption below 2508 birr are considered poor in this dimension.
8. ***Housing quality*:** Housing is an important indicator of living standards. We focus on the quality of house that is assessed by quality of the material –wall material, roof material and floor material a house is constructed. This is related to MDG goal 7 (ensure environmental sustainability).
   Poverty cut-off points: A household is declared poor in the housing dimension if it lives in a mud floor and

straw roof house.

9. ***Fuel used for cooking:*** The type of fuel used for cooking is consequential for the health of a household. If solid waste material such as cow dung, wood or coal is used for cooking, the health of household members who breathe in such an environment for long periods can be adversely affected (Dufflo, et al. cited in Seth and Alkire 2009). Moreover, cooking fuel also impacts the environment. This dimension indirectly corresponds to MDG's Goal 7 (ensure environment sustainability).
   Poverty cut-off point: A household is declared poor if it uses wood, cow dung or coal for cooking.
10. ***Child health*:** three child health indicators namely standardized height for age; standardized weight for age and standardized weight for height of children below the age of five are used. The poverty threshold for standardized health indicators are based on the usual -2 z-score. Household without a child below five years of the age are considered non-poor. Three out of eight MDGs pertain to various aspects of health (Goal 4: Reduce child mortality. Malnutrition is yet another of the MDGs (Goal 1: Eradicate extreme poverty and hunger).

Poverty cut-off point: A household is said to be poor in this dimension if it has at least one child below the poverty threshold for any one of the three child health indicators.

The selection of dimensions to be included is not the only controversial task when measuring multidimensional poverty. Defining the weights to give to each dimension is another difficult issue since it implicitly entails value judgments. The main methods of weighting proposed in literature includes equal weights, frequency based weights, most favorable weights, multivariate statistical weights, regression based weights and normative weights (Decanq and Lugo, 2008).None of these methods has been proved to be the best, and most approaches to poverty measurement don't provide suitable methods to address the weighting issues (Wambugu, 2010). Instead, they give the latitude to assign weights to each dimension in the normative way. Thus, the most commonly used approach to weighting is equal weighting (Alkire and Foster, 2007).

3.2.3. Aggregate Deprivation by dimensions

This section presents the extent of multidimensional poverty in Tigray Region. Table 7 presents the estimated Headcount in each dimension and also shows the percentage contribution of deprivations in each of the ten dimensions by rural and urban locations.

Table 7: proportion of deprived rural-urban household in each dimension

No.	Dimensions	Total number of deprived HH's	Rural Headcount Index (%)	Urban Headcount Index (%)	Total Headcount Index (%)
1	Energy for Cooking poor	1,938	97.69	73.07	88.09
2	House quality poor	1,321	94.93	5.47	60.05
3	Electrification poor	1,293	91.95	6.87	58.77
4	Per capita income poor	917	48.5	31.00	41.68
5	Sanitation poor	873	45.30	30.88	39.68
6	House congestion poor	855	47.24	25.75	38.86
7	Education poor	559	40.16	2.44	25.41
8	Drinking water poor	409	29.73	1.16	18.59
9	Child health poor	317	19.07	7.11	14.41
10	Health poor	292	13.56	12.82	13.27

Source: own computation based on Tigray baseline socioeconomic survey (2011).

Table 7, indicates that the proportion of people who are poor and deprived in each dimensions. From this table, it can be seen that the highest deprivation is access to source of energy for cooking and it is more than 88 percent of the household are deprived in access to energy from electricity and gas. Following access to energy source, the next highest deprivation is access to quality house. Above 60 percent of the household live in poor quality houses defined in terms of construction materials of the wall, roof and floor. That is households live in houses whose walls were constructed from stone/wood with mud, the floor is earth/mud, and the roof material is wood/stone/thatch with mud.

Above 58 percent of the population don't have access to electrification and almost 39 percent of the population of Tigray regional state lives in a household with three or more people per room, and 41.68 percent of the respondents live below a poverty line set at ETB 2508 per year per person and more than 25 percent of the populations are illiterate that means any member of the household in the age group of 7 to 18 is not able to go to school. Less than 19 percent of the sample households don't have access to drinking water (i.e., water from tap as well as protected well or spring water). Around 13 percent of the sample households were unable to carry on their usual activities due to illness or injury during the four weeks before the survey period.

Based on the poverty cutoff for each dimension all the deprived population in access to safe drinking water, education, electricity and house quality lives more in rural than urban areas. Most of the population deprived in child health, room, energy, consumption and health also live in rural areas. A significant portion (i.e. 73.07 percent) of all the deprived in energy source in urban areas suggesting that improvement is needed in this dimension in urban areas as well.

3.2.4. Magnitude of Multidimensional Poverty

3.2.4.1. Distribution of deprivation counts

In common understanding, it is clear that it is not the same to suffer from only one deprivation as it is to suffer from multiple deprivations simultaneously. As the number of derivation increase the proportion of multidimensional poor reduce (Alkire, 2007). This part presents the proportion of multidimensional poverty in number of deprivation. The evidence in table 8 shows that the percentage and number of household who would be identified as poor for each value of k = 1, 2, 3… 10. in rural and urban areas of Tigray.

Table 8: Multidimensional Headcount Ratio (H) and Adjusted Headcount Ratio (M_0) in Tigray Regional State-different K-values equal weight, ten dimensions.

Equal Weights			
Poverty Cut-off (K)	**Headcount Ratio (H_0)**	**Adjusted Headcount Ratio (M_0)**	**Average deprivation (A)**
1	0.996	0.470	4.72
2	0.943	0.465	4.93
3	0.835	0.443	5.31
4	0.690	0.399	5.78
5	0.549	0.343	6.25
6	0.390	0.264	6.77
7	0.206	0.153	7.43
8	0.079	0.064	8.10
9	0.011	0.010	9.09
10	0	0	-

Source: own computation based on Tigray baseline socioeconomic survey (2011)

According to Alkire (2007), multidimensional poverty decreases as k increase. With equal weights, estimates indicate that 99.6 percent of the population of the Tigray regional state is deprived in one or more of any of the ten dimensions, and on average they are deprived in 4.72 dimensions, so that the adjusted Headcount Ratio is 0.47. This is a very high level of multidimensional poverty, and the average intensity of deprivation indicates that, even when the union approach is used, those identified as multidimensional poor do experiences on average more than four deprivations.

As the table 8 indicates that more than 94 percent of the population in the rural and urban area is deprived in two or more of the ten deprivations, and on average they are deprived in 4.93 dimensions, so that the adjusted Headcount Ratio is 0.465. The percentage of people deprived in three or more of the ten dimensions is 83.5 percent, with M_0 being 0.443 and people being deprived on average in 5.31 dimensions. The result at k=4 seems more reasonable and is in accordance with the previous result of the World Bank findings that, in average ,about 50% of individuals are poor in Sub-Saharan Africa (Batana,2008). Then, the cutoff=4 may be considered as suitable enough for doing some analysis of poverty in our case. So that, in four or more of the ten dimensions, 69 percent of the population is multidimensionally poor with M_0 being 0.399 and the average intensity of deprivation being 5.78 dimensions. The multidimensional poverty level continues to decline with a rise in the k-values. Only 1.1 percent of the people are deprived in 9 dimensions, and out of the 2200 household 25 household are deprived in all the 9 dimensions and no household is deprived in total of the ten dimensions.

Table 9: Multidimensional Poverty Headcount Ratio for different k-values Rural and Urban contributions.

Multidimensional Headcount Ratio (H_0)			
Poverty Cut-off (K)	**Rural**	**Urban**	**Total**
1	0.610	0.386	0.996
2	0.610	0.333	0.943
3	0.608	0.227	0.835
4	0.588	0.102	0.690
5	0.511	0.038	0.549
6	0.380	0.010	0.390
7	0.202	0.004	0.206
8	0.079	0	0.079
9	0.011	0	0.011
10	0	0	0

Source: own computation based on Tigray baseline socioeconomic survey (2011)

Table 9 presents the multidimensional poverty Headcount Ratio for different k-values rural and urban contiributions. This indicates that at k=1, 61 perecnt of the deprived 99.6 percent of the population of Tigray regional state are living in rural areas, where as 38.6 percent of them who are living in urban areas are deprived in one or more of any of the ten dimensions. At k=2, 61 percent out of the 94.3 percent are living in rural areas on the other hand 33.3 percent of them are living in urban areas are deprived in two or more of the ten dimensions. The result shows multidimensional poverty in rural areas is significantly higher than in urban areas.

Table 10: Multidimensional Adjusted Headcount Ratio for different k-values Rural and Urban contributions.

Poverty Cut-off (K)	Multidimensional Adjusted Headcount ratio (M_0)		
	Rural	Urban	Total
1	0.360	0.110	0.470
2	0.360	0.105	0.465
3	0.359	0.084	0.443
4	0.353	0.046	0.399
5	0.323	0.020	0.343
6	0.257	0.007	0.264
7	0.151	0.002	0.153
8	0.064	0.0004	0.0644
9	0.010	0	0.010
10	0	0	0

Source: own computation based on Tigray baseline socioeconomic survey (2011).

Table 10 compares rural and urban poverty for the adjusted multidimensional headcout ratio. It indicates that there is high difference in poverty between urban and rural locations for different k-values. Like table 9 this table also shows that multidimensional poverty is a rural phenomenon. So that, the relative contribution of the urban area to the total multidimensional poverty is small and continuously declines with a rise in k-value and becomes negligible after k=3 in comparing the rural areas. This is not surprising since such outcomes were ready observed in the pervious studies. Using various welfare indicators (asset poverty, enrollement, infant mortality rate, adult mulinitrtiion, etc.) Sahn and Stifel (2003b) show that standards of living in rural areas are lower than those in urban areas in African countries.

3.2.5. Rural and Urban Multidimensional poverty estimates

Table 11 shows multidimensional poverty is estimated separately for rural and urban areas with 10 dimensions. Multidimensional poverty is dominant in the rural than urban areas for all values of k. almost all of the rural households were deprived in at least one of the ten dimensions considered for a k=1 with 100 percent with an average deprivation of 5.89 But the urban area was 99.1 percent with an average deprivation of 2.85. For two or more dimensions, the headcount ratio shows a decline for urban areas to 85.5 percent but the result for rural areas shows only a marginal decline. It decreases only by 0.1 percent.

Table 11: Multidimensional Headcount Ratio (H) and Adjusted Headcount Ratio (M_0) and Average deprivation for rural and urban areas separately different K-values equal weights, ten dimensions.

Poverty Cut-off (K)	Rural			Urban		
	H_0	M_0	average	H_0	M_0	Average
1	1.000	0.589	5.89	0.991	0.282	2.85
2	0.999	0.589	5.89	0.855	0.268	3.13
3	0.996	0.589	5.91	0.583	0.214	3.67
4	0.963	0.579	6.01	0.261	0.117	4.48
5	0.838	0.529	6.31	0.097	0.052	5.38
6	0.623	0.421	6.76	0.027	0.017	6.34
7	0.332	0.246	7.42	0.009	0.006	6.44
8	0.129	0.105	8.15	0.001	0.0009	7.72
9	0.019	0.016	8.59	0.000	0	-
10	0.000	0	-	0.000	0	-

Source: own computation based on Tigray baseline socioeconomic survey (2011).

The multidimensional poverty Headcount Ratio (H) for different k-values rural and urban contiributions can be related to the rural and urban unidimensional income/expenditure poverty Headcount Ratio reported on the tabel 5 which is 48.4 percent for rural areas and 31.9 percent for urban areas. The estimated multidimensional poverty level is much higher than income/expenditure poverty for k-values of 5 or less for rural areas. So that the income/expenditure poverty is comparable to the multidmensional poverty olny at k = 6 in rural areas. However, the multidimensional poverty at urban areas are less than the unidimensional income/expenditure poverty at less than k=4.

3.2.6. Cardinal and Mixed dimensions

The data available for multidimensional poverty assessment may be ordinal for some dimensions and cardinal for others. Ordinal dimensions justify only Mo while cardinal dimensions incorporates all Mα for α=0, 1 and 2 measures. Applying Mα measures for ordinal dimensions lose some information in M1 and M2 since it is difficult to measure adjusted gap and severity for dichotomized dimensions (Alkire, 2008).

Table 12: Multidimensional poverty measures: Mixed case and equal weights for all k-values

Cutoffs (K)	H_0	M_0 (AH)	M1 (HAG)	M2 (HAS)	A	G	S
1	0.996	0.470	0.222	0.105	0.472	0.312	0.223
2	0.943	0.465	0.229	0.113	0.492	0.333	0.243
3	0.835	0.443	0.235	0.136	0.530	0.401	0.307
4	0.690	0.399	0.231	0.141	0.579	0.459	0.353
5	0.549	0.343	0.214	0.138	0.625	0.525	0.402
6	0.390	0.264	0.178	0.122	0.676	0.576	0.464
7	0.206	0.153	0.114	0.085	0.744	0.644	0.557
8	0.079	0.064	0.052	0.043	0.814	0.714	0.664
9	0.011	0.010	0.009	0.008	0.900	0.800	0.842
10	0	0	0.000	0.000	-	0.000	0.000

Source: own computation based on Tigray baseline socioeconomic survey (2011).

When we use cardinal and ordinal dimensions simultaneously it creates hybrid (mixed dimensions) as presented in the above table 12. The third column in table 12 report the value of Mo for cutoff k=1 with adjacent cutoffs. In this case when k=1 the incidence of poverty would be 47 percent while at k=2 it would be reduced to 0.5 percent, which implies as the dimension cutoff increases the incidence of poverty will be reduced. The fourth and the fifth columns present the values of M1 and M2 with normalized gaps for cardinal data and dichotomized values otherwise. The value of Mα changes very high from α=0 to α=2.This would be due to high effect of dichotomized values on the depth and severity of multidimensional poverty. For dichotomized dimensions Mo, M1 and M2 achieve almost the same values where as for continuous variables the value of Mα is strictly decreasing in α (Alkire, 2008).

3.3. Estimation of latent poverty factors and clusters of poor

Table 13 indicates that estimation of the principal component analysis model. The polychoric principal component analyses are used 10 dimensions like the Alkire and Foster multidimensional poverty. In the analysis of the polychoric correlation matrix, we ensured that it be positive semi-definite, and so be proper co-variance matrix. Estimation of the polychoric correlation matrix shows that the first PC has an eigenvalue of 4.017 and explains 40.17% of the total variance and the second PC has an eigenvalue of 1.199 and explains 11.99 % of the total variance while the third PC has an eigenvalue of 1.069 and explains 10.69 % of the total variance.

Table 133**: Principal Components / Eigenvalues**

Factor analysis/correlation Number of obs = 2200
Method: principal factors Retained factors = 4
Rotation: (unrotated) Number of params = 34

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	4.017721	3.16538	0.401772	0.401772
Factor2	1.199849	0.22542	0.119985	0.521757
Factor3	1.069461	0.09032	0.106946	0.628703
Factor4	1.004244	0.08582	0.100424	0.729128
Factor5	0.829731	0.09415	0.082973	0.812101
Factor6	0.683892	0.09531	0.068389	0.880490
Factor7	0.530082	0.01524	0.053008	0.933498
Factor8	0.413011	0.07757	0.041301	0.974799
Factor9	0.199912	0.09758	0.019991	0.994790
Factor10	0.052096	-	0.005210	1.000000

Source: own computation based on Tigray baseline socioeconomic survey (2011).

The next step involves choosing the appropriate number of latent factors. To this end, the study rely on some standard visual and statistical tools, commonly used in factor analysis, although one should be aware that most of these rules are somehow *ad hoc* and cannot avoid value judgments. The test we use consists of an examination of the plot of the eigenvalues against the corresponding factor numbers, the so-called scree diagram (Cattell, 1966). The rate of decline is sharp for the first few factors but then levels off. The elbow or the point, at which the curve bends, is considered to indicate the maximum number of factors to extract. One factor less than the number at the elbow might also be appropriate (Luzzi et al. 2008).

Annex 2 in the appendix represents the scree diagram. In this case, the plot seems to indicate the presence of a general factor, as suggested by a large first eigenvalue, but a secondary elbow occurs at the forth eigenvalue implying three-factor solution, which is the one selected by the researcher.

In the next step, the researcher tries to identify the correlation between the variables. The simple correlation between the original and the new variables, also called loadings, gives an indication of the extent to which the original variables are influential or important in forming new variables. Therefore, each latent factor is formed based on the loadings of the variables used to define multidimensional poverty. The higher the loadings of a variable, the more influence in the formation a given latent factor and vice versa, and hence the loadings are used to determine which variables are influential in the formulation of a given latent factor and to give a meaning or label the factor.

In order to provide a more meaningful and easily interpretable solution for the loading matrix I have applied a rotation of the factors as it was stated by Everitt and Dunn, 2001. It makes sense to hypothesize that the common factors of deprivation are correlated, since one can assume that deprivation in one is positively correlated with deprivation in another. For example, a household's deprivation in public service can be associated with income or poor sanitation. Therefore, we perform an oblique (promax) rotation that allows the factors to be correlated (Hendrickson and White, 1964). The resulting loadings are presented in table 14 below.

Table 144: Factor loadings

Variable	Factor1	Factor2	Factor3	Uniqueness
Sanitation	0.0937	0.0320	0.2825	0.8818
Water	0.7117	0.0609	-0.1255	0.3579
Energy	0.5902	0.1109	0.1486	0.4718
Light	0.9680	-0.0629	0.0348	0.1038
School	0.6799	0.0857	-0.0994	0.3731
Per capita income	-0.0899	0.6054	-0.0825	0.7042
House quality	1.0062	-0.0804	0.0593	0.0294
Health	0.0267	0.0544	-0.0193	0.9900
Child Health	0.1210	0.0851	0.3822	0.7722
House congestion	-0.0382	0.6152	0.1454	0.5778

Source: own computation based on Tigray baseline socioeconomic survey (2011).

A glance at table 14 shows some clearly distinctive patterns. The three factors are labeled by observing which variables are having higher loading on each component and then trying to find a general name on the basis of the variables that had high loadings to a single component. Out of the total, five dimensions have positive and high loadings in the first factor. All these dimensions pertain to deprivation in basic goods and services that are due to the lack of public services, like poor education, poor housing quality, poor electricity, and poor access to safe drinking water, and poor fuel used for cooking.

The second factor has positive and high loadings on the three dimensions. These dimensions are mainly related to the lack of having proper house congestion, health condition of the household and per capita income. This can be termed as poor income and health. Due to this effect more than three people live in one room and the household member who was sick is unable to do his/her normal activities in the last four weeks.

Finally, two dimensions have positive and high loadings on the third factor. These variables are mainly related to the lack of having proper sanitation and child health. This can be termed as poor sanitation.

Table 155: Inter-factor correlation

Factors	Factor1	Factor2	Factor3
Factor1	1.0000		
Factor2	0.2616	1.0000	
Factor3	0.3084	0.2848	1.0000

Source: own computation based on Tigray baseline socioeconomic survey (2011).

Table 15 indicates that, the correlation coefficients among the three factors, as implied by the oblique rotation. It appears that factors 1, 2 and 3 are moderately and positively correlated, i.e. poor public services, poor income & health, and poor sanitation, moves together to some extent.

As discussed in the methodology above, individuals are grouped according to the relative (Euclidean) distance between their factorial scores, and the appropriate number of groups or clusters is determined by looking at various statistics. Large values of the pseudo-F index (Calinski and Harabasz, 1974) indicate distinct clustering and one must therefore maximize this statistic. The opposite is true for the pseudo-t2 (Duda and Hart, 1973), and one should choose the number of clusters so that this index is low and has much larger values next to it. It is advisable to look for a consensus among the two statistics, that is, local peak of the pseudo-F statistic combined with a small value of the pseudo-t2 statistic and a larger value of the latter for the next cluster fusion.

Both of these statistics are displayed in table 16 below, where the first 10 cluster groupings can be examined. From table 16 we see that the pseudo-F is maximized for four clusters and the pseudo t2 is maximal for three indicating the presence of four clusters. Thus, in both statistical measures, four clusters seems the solution.

Table 166 : Statistics for determining the number of clusters

Clusters	Pseudo F	Pseudo T-Squared
1	-	27.86
2	27.86	8.87
3	18.41	5621.98
4	1918.23	54.10
5	1486.33	76.42
6	1244.36	582.78
7	1340.72	640.38
8	1551.12	24.30
9	1367.17	27.26
10	1224.42	726.39

Source: own computation based on Tigray baseline socioeconomic survey (2011).

The dendrogram (or cluster tree) in Annex 3 of the appendix presents graphically information concerning which observations are grouped together at various level of similarity (Everitt et al. 2001). At the bottom of the dendrogram, each observation would be considered as its own cluster. As one climbs up in the tree, observations are combined until all are grouped together, the height of the vertical lines indicating the similarity (or dissimilarity) of four groups. A glance at the dendrogram indicates the existence of four clusters.

The average scores of the households pertaining to the various clusters are calculated and the result is shown on table 17 below. Typically the first cluster contains large portion of the sample. The mean scores are found to be negative on all dimensions of poverty indicating that most persons are deprived in all directions. Thus this cluster can undoubtedly be defined as the "multidimensional poor" cluster. A smaller second cluster is then found to have positive mean scores on every dimension. The individuals belonging to this cluster can be called 'non-poor', since most persons are not deprived in any direction. The smaller third cluster is then found to have negative mean score on the first and third factors are multidimensional poor cluster. The very smaller fourth cluster is then found to have positive mean scores on the first and second factors but a negative score on the third factors.

Table 177 : Mean scores on the three factors by cluster

Cluster	Factor1	Factor2	Factor3	Observations	Percentage
1	-2.250210	-0.183020	-0.138950	1,242	56.45
2	2.931081	0.210271	0.182806	955	43.41
3	-3.511435	5.333142	-0.425060	2	0.09
4	2.600419	15.833770	-1.15695	1	0.05

Source: own computation based on Tigray baseline socioeconomic survey (2011).

Table 17 indicates that multidimensional poverty in the study area constitutes 56.45 percent of the population. It can be seen that cluster one has very high negative value (in its absolute sense) in factor one followed by factor two and factor three indicating that these households suffer particularly from public services but less poor income, health and poor in sanitation, and out of the total population 0.09 percent are multidimensional poor by public service and sanitation.

Estimation of poverty by Rural and Urban locations

The poverty measures cluster analyses are decomposed by location specific of the household head and the findings are illustrated in table 18 and table 19. It is evident from the table that rural headed households have higher level of multidimensional poverty than their urban headed households.

Table 18: Rural area Mean scores on the three factors by cluster

Cluster	Factor1	Factor2	Factor3	Observations	Percentage
1	-0.20133	0.068056	-0.00631	1,256	93.59
2	2.940405	-0.99392	0.092086	86	6.41

Source: own computation based on Tigray baseline socioeconomic survey (2011).

Table 18 indicates that multidimensional poverty rural location specific in the study area constitutes 93.45 percent of the population. It can be seen that cluster one has very high negative value (in its absolute sense) in factor one followed by factor two and factor three indicating that these households suffer particularly from public services but less poor income, health and poor in sanitation.

Table 18: Urban area Mean scores on the three factors by cluster

Cluster	Factor1	Factor2	Factor3	Observations	Percentage
1	-0.32133	-0.85056	-0.00423	193	22.49
2	3.940405	-0.86374	0.563052	665	77.51

Source: own computation based on Tigray baseline socioeconomic survey (2011).

Table 19 indicates that multidimensional poverty urban location in the study area constitutes 22.49 percent of the population. It can be seen that cluster one has a negative value (in its absolute sense) in factor two followed by factor one and factor three indicating that these households suffer particularly from poor income, health but less public services and poor in sanitation.

3.4. Comparison of Poverty Analysis Approaches

Unidimensional and multidimensional Poverty comparisons

Table 20 compares the multidimensional poverty approaches and income/expenditure poverty. The main difference between those measures is that the income/expenditure poverty measure provides very conservative estimates of poverty. Using the dual cutoff multidimensional poverty approach in our case the most suitable cutoff for mixed dimensions is k=4, about 69 percent of the total household are deprived in four or more dimensions. On the other hand the unidimensional income/expenditure poverty analysis reveled 41.6 percent of the household were poor. The estimated multidimensional poverty level is much higher than income/expenditure poverty for k-values of 5 or less. The income/expenditure poverty is comparable to the multidmensional poverty only at k = 6. At this point income/expenditure poverty is greater than multidimensional poverty by 2.68 percent. In addition by using the cluster analyiss multidimensional poverty approach 56.45 percent of the household were deprived, but unidimensional income/expenditure poverty approach reveled as stated above. Here is also multidimensional poverty is higher than unidimensional poverty. This suggests that we need to focus our efforts and resources on developing the best possible distinct measures of the various dimensions of poverty deemed relevant to a given setting—aiming for a credible set of multiple indices rather than a single index.

Columns 4, 5, 6 and 7 of table 20 indicate the level of mismatching. Despite being a conservative estimate, income/expenditure poverty makes errors in classifying multidimensional poor households as income non-poor and vice versa. 11 and 9.7 percent of the households classified as income poor are multidimensional non-poor in dual cutoff and cluster analysis respectively. On the other hand 46.2 and 42.6 percent of the households classified as non-poor in income/expenditure poverty are multidimensional poor households in dual cutoff and cluster analysis respectively. The result indicates that in comparing multidimensional poverty cluster analysis is relatively comparable with income poverty.

Table 20: Comparison of unidimensional and multidimensional poverty approaches

Income poverty	Dual cutoff poverty	Cluster Poverty	Percentage of income poor but dual cutoff non-poor	Percentage of income non-poor but dual cutoff poor	Percentage of income poor but Cluster non-poor	Percentage of income non-poor but Cluster poor
41.6	69	56.54	11.01	46.20	9.7	42.6

Source: own computation based on Tigray baseline socioeconomic survey (2011).

5.6.2 Comparison of Multidimensional Poverty Approaches

Table 21 compares the multidimensional poverty approaches. These comparisons were made between the two approaches of multidimensional poverty analysis i.e. The dual cutoff and counting approach developed by Alkire and Foster and cluster multidimensional poverty Analysis Approaches. The main difference between the two measures is that:-

The cluster multidimensional poverty measure provides aggregate estimates of poverty i.e. 56.45 percent of the total population are classified as multidimensional poor. So that, the factor analysis result has identified three dimensions of poverty – poor in public service, poor in income & health, and poor in sanitation. The number of dimensions as well as their relative importance is not determined ex ante but obtained through empirical regularities in the data. The relevance of each dimension is therefore directly dictated by its power in explaining the variance of various deprivation base variables. The population of multiply deprived person is identified by looking at their similarities with respect to their scores on the various dimensions through cluster analysis without the necessity of setting poverty thresholds arbitrarily. The pattern of deprivation and the relations among variables, especially in cluster analysis are not always clear cut, so that some choices must be made based on judgment, rather than on strictly statistical tools.

Whereas the dual cutoff multidimensional poverty measure provides us different estimations of deprivation level using union, intersection and intermediate identification methods. For example the study shows 99.6 percent of the total population is deprived in one or more dimensions and if we take in our case the most suitable cutoff for mixed dimensions is k=4, about 69 percent of the total populations are deprived in four or more dimensions and the incidence of poverty (M_0) at K=4 is 39.9 percent.

In other words the dual cutoff multidimensional poverty measure can display also the result of each dimension i.e. more than 88 percent of the household are deprived in access to energy from electricity and gas, above 60 percent of the household live in poor quality houses, above 58 percent of the population don't have access to electrification and almost 39 percent of the population of Tigray regional state lives in a household with three or more people per room and others. But in case of cluster analysis we can't show such expressions it only indicates the aggregate level of deprivation.

Columns 3 and 4 of table 21 indicate the level of mismatching. Despite being a different multidimensional poverty estimate, dual cutoff poverty makes errors in classifying multidimensional poor households as cluster multidimensional non-poor and vice versa. 17.2 percent of the households classified as dual cutoff multidimensional poor are cluster multidimensional non-poor. On the other hand 13.5 percent of the households classified as non-poor in dual cutoff poverty are cluster poor households. The result shows that comparison of income poverty with the multidimensional poverty approach indicates that, income is relatively comparable with cluster analysis. On the other hand, comparing the multidimensional poverty approach using cluster analysis is less deprived than dual cutoff approach.

Table 191: Comparison of multidimensional poverty approaches

Dual cutoff Multidimensional Poverty	Cluster Multidimensional poverty	Percentage of dual cutoff poor but Cluster non-poor	Percentage of dual cutoff non-poor but cluster poor
69	56.54	17.2	13.5

Source: own computation based on Tigray baseline socioeconomic survey (2011).

4. Conclusions

The general objective of the study is to compare and contrast the Alkire and Foster dual cutoff and the cluster analysis of multidimensional poverty approaches in the study area. The study performs comparison of multidimensional poverty analysis using ten dimensions: education, health, housing quality, electrification, and access to safe drinking water, sanitation, energy for cooking, per capita income, house congestion and child health.

The results of dual cutoff and counting approach developed by Alkire and Foster (2007) poverty analysis show that the estimated poverty index depends on the number of dimensions considered and that the poverty measure decreases with the number of dimensions. This shows that at k=1, 99.6 percent of the total population are deprived in one or more dimensions and at k=2, 94.3 percent of the total population are deprived in two or more dimensions and at k=3, 85 percent of the total population are deprived in three or more dimensions and the most suitable cutoff for mixed dimensions is at k=4, 69 percent of the total population are deprived in four or more dimensions and the incidence of poverty (M_0) at k=4 is 39.9 percent.

The results further suggest that decomposition of poverty by dimensions indicates that lack of source of energy for cooking is the key contributor to multidimensional poverty and next highest contributor are house quality, access of electricity, per capita income, and sanitation and house congestion in each dimension of poverty deprivation. Based on the results, we can conclude that the Alkire and Foster approach can be used to assess the dimensions that drive multidimensional poverty in different contexts.

Whereas, the finding of cluster analysis reveals that about 56.45 percent of the population in regional state of Tigray was in the state of multiple deprivations. The pattern of deprivation and the relations among variables, especially in cluster analysis are not always clear cut, so that some choices must be made based on judgment, rather than on strictly statistical tools. This may generally indicate us the level of deprivation using dual cutoff analysis shows more deprivation in many dimensions than cluster analysis of multidimensional poverty i.e. almost the whole populations are deprived in one or more dimensions.

Income is positively and significantly correlated with all dimensions except with health. However the degree of correlation of income with any of the reaming dimensions is not high. This suggests that multidimensional analysis is indeed important and that a policy targeted to the income poor might not reach other segments of the population deprived in other dimensions.

On the other hand using both multidimensional approaches of poverty analysis the decomposition of multidimensional poverty by location, indicates that multidimensional poverty is more prevalent in rural than urban areas.

Finally, the results in comparison of the dual cutoff and counting approach with that of cluster analysis of multidimensional poverty approach shows that the former one is the best suitable approaches in estimation of multidimensional poverty analysis using different methods of poverty estimation.

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