

# Chapter 8

## Multidimensional Poverty and Its Dynamics in Ethiopia

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**Abstract** Traditional one-dimensional income or consumption expenditure-based poverty measures provide a biased and incomplete guide to addressing poverty. Recent research trends are shifting from one-dimensional to multidimensional poverty analyses. This paper uses Alkire and Foster (Understandings and misunderstandings of multidimensional 793 poverty measurement. Springer Science +Business Media, Berlin, 2011) method of multidimensional poverty analysis using data from four rounds of the Ethiopian Demographic and Health Survey. Our study concludes that multidimensional poverty is high in Ethiopia in general and in rural Ethiopia in particular. In Ethiopia, multidimensional poverty has been decreasing moderately over time but still a large proportion of its population is under the multidimensional poverty line. Living standards contribute the most (more than 85%) to multidimensional poverty while education contributes about 14% and health contributes the least (less than 1%). Among the indicators that this paper uses in multidimensional poverty, there is high deprivation in sanitation, cooking fuel, floor and electricity. Further, sanitation and cooking fuel deprivations are increasing but education deprivation and school attendance deprivation have been decreasing over time. Level of education, having a bank account and the number of working age family members reduce multidimensional poverty but the number of children under 5-years and dependent family members (dependency ratio) increase Ethiopian households' multidimensional poverty.

**Keywords** Poverty · Ethiopia · Multidimensional poverty · Deprivation

**JEL Classification Codes** C250 · C430 · I320

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## 8.1 Introduction

Ethiopia is the second most populous country (after Nigeria) in Africa with a diverse population mix of ethnicity and religion. Large proportions of its population live in rural areas and are engaged in agriculture which accounts for 43% of its gross domestic product (CSA 2009). Coffee and other agricultural products are the main export commodities and Ethiopia is one of the least urbanized countries in the world (CSA 2009).

Poverty is a development challenge for most developing countries (Dercon et al. 2009) and poverty reduction is an important priority for their governments. Ethiopia adopted the Plan for Accelerated and Sustainable Development to end Poverty (PASDEP) to attain the millennium development goals (MDGs) by 2015. The first Growth and Transformation Plan (GTP-I) was developed to bring about rapid and broad-based growth to eventually end poverty (MOFED 2010). Despite all these steps, according to a government report in 2016 (GTP II 2016) around 25% of the population was still living under the poverty line.

Measuring the poverty level is the first step in poverty reduction strategies. Earlier approaches to the measurement of poverty are one-dimensional. They are based on a single indicator, usually income or consumption expenditure, showing the level of deprivation. These monetary measures separate the population between poor and non-poor through the identification of thresholds or poverty lines. Although income measures of poverty have been used frequently, they have some limitations because human life is affected not only by income but also by other dimensions of life like education and health. Therefore, a poverty analysis should also take into consideration these other dimensions. Literature on multidimensional poverty is growing fast (for example, Adetola 2014; Alkire and Foster 2011; Alkire and Santos 2010; Bourguignon and Chakravarty 2003; Dhongda et al. 2015; Hishe Gebreslassie 2013; Maasoumi and Xu 2015).

In a country like Ethiopia where poverty is deep rooted, a rigorous multidimensional poverty measure, trend development and a dynamic adjustment analysis of poverty are important to understand the poverty history of the country. In addition, this will help shed light on whether poverty reduction strategies implemented by federal and regional governments so far have been effective in reducing multidimensional poverty so that appropriate poverty reduction policies can be designed in the future.

Our study uses the Demographic and Health Survey (DHS) data for 2000–2014 and examines the extent, trends and dynamics of multidimensional poverty in the country across regions and over years in the components most relevant and locally feasible. It uses the Alkire and Foster (2011) method of multidimensional poverty index (MPI) measure, adapting the method on which MPI is based to better address local realities, needs and available data.

## 8.2 Research Motivation

Earlier approaches to the measurement of poverty have some limitations which are mainly related to the way in which they measure income, market failure and how household incomes are used for household members' (women and children's) wellbeing.

While using income or consumption expenditure as a measure of poverty, parts of a household's income including home production and consumption of goods and services may not be reported correctly. This lack of accuracy is attributed to the absence of records and because of tax reasons leading to unreliable statistics. Even if measured and reported, a household's income as a measure of poverty relates only to the resources required to achieve wellbeing and not necessarily to the outcomes, that is, the final condition of an individual.

Some markets do not exist in developing countries (in particular, those related to provision of public goods) and others operate imperfectly. The use of income as a measure of poverty assumes that markets and prices exist for all goods and services. Hence, income poverty measures at best provide only an incomplete and biased guide to addressing poverty. Accounting for multidimensional poverty reduces biases and provides a good picture of the households' wellbeing.

The logic behind the income approach is that a household above the income poverty line possesses potential purchasing power to acquire a bundle of goods and services yielding a level of wellbeing that is sufficient to function (Thorbecke 2008). The income or consumption measure indicates the means, not the end. It is not the amount of tuition fee that determines the level of education, rather the level of education or knowledge acquired that determines the productive capacity of an individual, a household and society. It is not the amount of money that one spends on medical services but the number of days of illness, maternal deaths and child mortality that we are able to reduce which will determine the level of healthcare. Therefore, emphasis has to be shifted from the means to the end.

Poverty arises because poor people's lives can be affected by multiple deprivations that are all of importance (Sen 1992). Hence, arguing against a single monetary dimension (income or consumption) as a sufficient proxy of human welfare to other non-monetary values such as health, education, contribution of the public sector and political participation will result in shifting focus from the means to the end.

Besides the relevance of the multidimensional poverty measure in indicating human wellbeing, more data (for example, DHS data) on non-income dimensions is available today. Further, methodologies for a multidimensional measurement have advanced considerably in recent years and created new possibilities of measuring multidimensional poverty at the national, regional and sub-regional levels. The poverty measure at one point of time or year does not indicate whether poverty reduction policies implemented by federal and regional governments have been effective in reducing multidimensional poverty. Repeated cross-sections with time invariant common characteristics or panel data are required to investigate the

dynamics of poverty. Poverty is a stochastic phenomenon; poverty trends and its dynamic analysis are very essential. Thus, it is important to know the history and the dynamics of poverty based on which appropriate national and regional policies can be designed.

In Ethiopia most previous researches have been one-dimensional (Berisso 2016; Woldehanna and Hagos 2013). There are some multidimensional poverty researches but they are very general and overlook the differences within the country, regions and ethnic groups. Ambel et al. (2015) consider health, education and standard of living. However, they examine poverty diminution by diminution and thus ignore the interdependence and correlation between dimensions and do not come up with a multidimensional poverty index.

Bruck and Workneh (2013) computed a multidimensional poverty index in Ethiopia but did not include some living standard indicators like electricity, sanitation and cooking fuel in their analysis. Using Ethiopia Demographic and Health Survey data, Alemayehu and Addis (2014) found the multidimensional poverty index; however, his research did not consider variations within regions and the poverty trend and its dynamics over time. Others have focused on some deprivation and under-estimated deprivations in other dimensions. Bersisa and Heshmati (2016) focus on energy poverty and do not show poverty changes over time.

Our study examines multidimensional poverty levels in Ethiopia and changes across regions and over time in the components most relevant and locally feasible. It uses the multidimensional poverty measure (Alkire and Foster 2011) method. Adapting the method on which MPI is based helps us address local realities, needs and the available data better.

Our study is different from the others in three aspects. First, it uses the most recent and the four rounds EDHS cross-section data from 2000 to 2014 for measuring MPI. Second, it estimates MPI in these four round periods and conducts trend and dynamic analyses and makes decompositions along time, regions and dimensions. Third, in earlier multidimensional poverty researches, having any two assets or more regardless of the type of assets made households non-deprived of assets. In our study, the living standard indicator—assets—is divided into three categories: information assets, mobility assets and livelihood assets. A household is non-deprived in assets if it owns at least one of the assets from two or more asset categories. This is a new empirical perspective in an analysis of multidimensional poverty.

## 8.3 Literature Review

### 8.3.1 Poverty

Poverty has to be defined appropriately or it should at least be understood conceptually before it can be measured (Thorbecke 2008). Literature defines poverty in

different ways and there is no consensus on the definition. According to the basic needs approach, poverty is insufficiency of resources and opportunities to satisfy basic human needs. The World Bank (2014) says that 'poverty is pronounced deprivation in well-being.' Wellbeing in this sense means an individual or household's command over commodities in general. It focuses on whether households or individuals have enough resources to meet their needs. Poverty in this case is measured mainly in monetary terms. This is the starting point for most analyses of poverty. The second view is whether people are able to obtain basic consumption goods such as food, shelter, clothes, healthcare and education. In this approach, the emphasis shifts from resources (money) to outcomes.

Other authors define poverty in different ways. Foster et al. (2013), define poverty as the absence of acceptable choices across a broad range of important life decisions, as well as lack of freedom to be or to do what one wants. The inevitable outcome of poverty is insufficiency and deprivation across many of the facets of a fulfilling life.

The most comprehensive and logical attempt to capture the concept of poverty is Sen (1992) capability and functioning approach where wellbeing comes from the capability to function in society, poverty is seen as lack of pre-requisites of a self-determined life and the 'lack of capabilities' to function or manage one's life. People are considered poor when they lack key capabilities and so have inadequate income, education, poor health, low self-confidence and powerlessness. The human rights-based approach emphasizes that respect for human rights is a necessary condition for various social and economic outcomes. It challenges, to some extent, the approach that poverty be measured by a one-dimensional criterion based on income and/or consumption expenditure and therefore it addresses the multidimensional nature of poverty beyond the lack of income (UNDP 2013).

Poverty is a challenge for developing countries and requires worldwide efforts and collaborations to reduce it. Extreme poverty is observed in all parts of the world and this is a global challenge including in developed countries. In 2013, 767 million people were estimated to be living below the international poverty line of US \$1.90 per person per day (The World Bank 2016). Almost 10.7% of the global population was poor by this standard of which Sub-Saharan Africa's share was about 41% showing that poverty is still widespread in Africa (Chen and Ravallion 2008). In 2013, the World Bank adopted two ambitious goals: end global extreme poverty by reducing the poverty headcount ratio from 10.7% in 2013 to 3% by 2030 and promote shared prosperity in every country in a sustainable way (The World Bank 2016). These two goals are part of a wider international development agenda and are closely related to the United Nation's sustainable development goals (SDGs). According to the World Bank, extreme poverty decreased over time and between 1990 and 2015 the percentage of the world's population living in extreme poverty fell from 37.1 to 9.6%. However, it will take another 100 years to bring the world's poorest up to the previous poverty line of \$1.25 a day.

### **8.3.2 *Multidimensional Poverty***

There has been a shift of focus from the one-dimensional nature of poverty to its multidimensional nature in measuring poverty. Considering the multidimensional nature of poverty has become increasingly important over recent years and different contributions to this have been made. In addition to money income or consumption expenditure, human lives and wellbeing are affected by different dimensions such as health and education. A one-dimensional measure of poverty using income or consumption expenditure presupposes that a market exists for all goods and services; however, often markets do not exist for many goods and services or they function imperfectly (Bourguignon and Chakravarty 2003; Thorbecke 2008; Tsui 2002) and therefore, monetary values cannot be assigned to particular aspects of wellbeing (Hulme and McKay 2008; Thorbecke 2008). Also, having sufficient income for purchasing a basic basket of goods does not directly imply that it is also spent on that basket of goods (Thorbecke 2008). Individual wellbeing is a multidimensional notion (Stiglitz et al. 2009), individuals care about many different aspects of their lives, including their material standard of living, health and schooling. As stated by Alkire and Santos (2011) low income, poor health, inadequate education, job insecurity, disempowerment and precarious housing are clear manifestations of multidimensional poverty. The components of poverty change across people, time and context but multiple domains are involved. Empirical literature documents a mismatch between monetary and non-monetary deprivations (Berenger and Verdire-Chouchane 2007; Hishe Gebreslassie 2013; Tran et al. 2015). This difference is attributed to a possible bias in the single dimensional measure of poverty. A study in India by Stewart et al. (2007) found that 53% of the Indian children living in income-poor households were not malnourished and 53% of the malnourished children were not living in income-poor households.

### **8.3.3 *Measurements of Poverty***

It is important to identify who the poor are and where they live for measuring the level of poverty so that resources can be directed at them more effectively for addressing poverty. The measurements paint a picture of the magnitude of the problem and can help identify programs that will work well in addressing poverty (Foster et al. 2013). Governments can be accountable for their policies and researchers can explore the relationships between poverty and other economic variables (Foster et al. 2013).

Poverty has often been measured using income or consumption expenditure and can thus be measured in relative, absolute and subjective terms. Relative poverty measures a household or individual's income relative to a certain average income (for example, mean, median), while absolute poverty measures individuals' or households' incomes relative to a certain income threshold (poverty line). The

subjective approach defines poverty as subjective judgments of an individual of what constitutes socially acceptable minimum standards of living in society. People value their poverty status within their society using different dimensions and indicators. Thus, this approach provides more information than relative and absolute measures of poverty and is therefore multidimensional in nature or perspective.

The World Development Reports introduced poverty as a multidimensional phenomenon, and the Millennium Declaration and MDGs have been highlighting multiple dimensions of poverty since 2000. The first wellbeing measure on a worldwide scale was the Human Development Index (HDI). The Human Development Report ranks countries by HDI, which consists of their achievements in economic and social spheres such as life expectancy, educational attainments and income. The Human Poverty Index (HPI) developed by the UN was to complement HDI, however in 2010 HPI was substituted by the UN's multidimensional poverty index (UNDP 2013).

The multidimensional poverty index measures a range of deprivations such as inadequate living standards, lack of income, poor health, lack of education, disempowerment and threat of violence (Alkire and Santos 2010) and is currently used in more than 100 countries. In academic literature, interest in multidimensional poverty measurement is growing (Alkire and Foster 2011). Effective multidimensional poverty measures have practical applications such as they can replace or supplement the income or consumption poverty measure. Dimensional decomposability of the multidimensional poverty measure can help monitor the level and composition of poverty and also help evaluate the impact of programs (for example, health and education programs). The multidimensional poverty measure gives more policy relevant information as it can single out the effect of each dimension on poverty and policies for reducing poverty should rely on a multidimensional analysis of poverty (Adetola 2014).

The dashboard approach is a starting point for measuring the multidimensionality of poverty to assess the level of deprivation in the dimensions separately; it applies a standard uni-dimensional measure to each dimension (Alkire et al. 2011; Ravallion 2011). The dashboard approach tries to find deprivation indices for all indicators considered in a multidimensional poverty analysis. The dashboard approach has the advantage of increasing the set of dimensions considered, offering a rich amount of information and potentially allowing the use of the best data source for each particular indicator and for assessing the impact of specific policies (such as nutritional or educational interventions). However, this approach has some significant disadvantages. First, dashboards do not reflect joint distribution of deprivations across the population precisely and because of this they are marginal methods (Alkire et al. 2015).

In literature, the distinction between being poor in all dimensions and in only one dimension has been referred to as the intersection and union definitions of poverty. This can be illustrated using an example drawn from Duclos and Younger (2006). The authors state that if wellbeing is measured in terms of all dimensions then a person can be considered poor if his achievement in each dimension is less

than the poverty threshold set for that particular dimension. This is defined as an intersection definition of poverty and will generally produce untenably low estimates of poverty. In contrast, a union definition considers an individual to be poor only if her achievement in one of the dimensions were to fall below its respective threshold. This is very commonly used and may lead to exaggerated estimates of poverty. In between these two extremes the most widely used measure of multi-dimensional poverty currently is the multidimensional poverty index (MPI).

MPI uses different dimensions and indicators. A poverty cut-off is set for each indicator and finally the multidimensional poverty cut-off is set by combining all the indicators based on the weight assigned to each indicator. There are several main features of MPI that can be used as important tools for a poverty analysis. First, MPI can be expressed as a product of the incidence of poverty (Headcount ratio  $H$ ) and the intensity of poverty or the average deprivation score ( $A$ ) among the poor. Second, the MPI measure can be decomposed across population sub-groups which can be geographic regions, ethnic or religious groups. We use this feature to create poverty measures for regions within a country. Third, MPI can be broken down into the indicators in which the poor people are deprived (Alkire and Foster 2011). In other words, it is possible to compute the contribution of each indicator to the overall poverty.

## 8.4 Data and Methodology

### 8.4.1 Data

Our research used the Ethiopian Demographic and Health Survey (EDHS) data. EDHS is conducted by the Ethiopia Central Statistical Agency (CSA) with support from the worldwide Demographic and Health Survey (DHS) project. DHS is a comprehensive dataset that consists of samples from all regions in the country (nine regional states and two city administrations) which represent the national population of Ethiopia.

DHS is cross-section data collected almost every five years. The first round was in 2000; the second in 2005; the third in 2011; and the most recent was in 2016. The data collected contains information on household characteristics, households' dwelling units such as the source of water, type of sanitation facilities, access to electricity, types of cooking fuel and others.

The DHS data for 2016 has not yet been released. Hence, as an alternative we used the Ethiopia Mini Demography and Health Survey (EMDHS) of 2014. However, in the Mini 2014 DHS, the variable 'types of cooking fuel' was not collected and the 2014 analysis does not include types of cooking fuel. We make necessary adjustments for that. In our research the unit of analysis is a household, a household has common resources and takes decisions that affect almost all its members.



### 8.4.1.1 Components of Multidimensional Poverty

There is no fixed list of what should be included in a MPI (Ravallion 2011). The list is open and the most important thing is the process through which the components are selected (Alkire et al. 2011). This must be agreed upon with a certain degree of consensus. Such a consensus may derive from participatory experiments, a legal basis, international agreements such as the MDGs or human rights and empirical evidence regarding people's values. Statistical relationships or the correlation between the variables must also be explored and understood.

We selected MPI's indicators after a thorough consultation process involving experts in all the three dimensions (Alkire et al. 2011). The ideal choices of indicators had to be reconciled with what was actually possible in terms of data availability. We used three dimensions and 10 indicators suggested by Alkire and Foster (2011)—health, education and living standard. The deprivation dimensions and indicators used in our multidimensional poverty analysis are listed in Table 8.1.

**Table 8.1** MPI's dimensions and indicators

Dimensions	Indicators	A household is deprived of the indicator if:
Health	Child mortality	One or more child died in the household after the last survey
	Nutrition	There is child malnutrition in the household and/or adult malnutrition in the household after the last survey
Education	Highest grade obtained	No household member who is 13-years or older has completed six years of schooling
	School attendance	Any school age child in the household is not attending school in the academic year
Living standard	Electricity	The household has no access to electricity
	Sanitation	There is no facility/bush/field, or sanitation facilities are open to the public or shared with other households
	Sources of water	A household's source of water is an unprotected spring, well, river/dam/lake/pond/stream and others
	Floor materials	The floor material of the house is earth, sand, dung and others
	Cooking fuel	The cooking fuel used by a household is charcoal, firewood, straw, dung and others
	Asset ownership	A household has at most one asset in one of the three asset categories: access to information (phone mobile or fixed), radio, TV); asset for easy mobility (bicycle, motorbike, motorboat, car, truck or animal wheel cart); asset for livelihood (refrigerator, agricultural land or livestock (at least one cattle or at least one horse or at least two goats or at least two sheep, or at least 10 chicken)

#### 8.4.1.2 The Weight of the Indicators

In a multidimensional poverty analysis, there is no general consensus not only on multidimensional poverty dimensions but also on relative weights of indicators and the substitution between attributes (Decancq and Lugo 2013; Maasoumi and Xu 2015; Ravallion 2011). Next to the identification of dimensions and indicators of multidimensional poverty, the crucial problem is assigning suitable weights to the indicators (Berenger and Verdire-Chouchane 2007). Weights play a crucial role in aggregating and determining the trade-off between the dimensions (Decancq and Lugo 2008). The equal weight approach has been used by different authors (Atkinson 2003; Alkire and Foster 2011; Dhongda et al. 2015; Salazar et al. 2013). However, this approach is controversial and it has its share of critics (Decancq and Lugo 2008). Most multidimensional poverty indicators are assumed to be correlated and the equal weight approach fails to consider these correlations and therefore multidimensional poverty dimensions cannot have similar importance or weight (Ravallion 2011). One of the options for an alternative method is to use individual preferences as a weighting scheme (Decancq et al. 2014; Takeuchi 2014). In this weighting scheme, the relative importance and trade-off among dimensions are left to the individual. The problem with this approach is that individuals may not reveal their real preferences (Takeuchi 2014). Following this criticism other weighting approaches such as parametric or statistical approaches have been used. Statistical techniques are widely used in designing poverty measures and in giving a weight to each indicator (Maggino and Zumbo 2012). Key techniques include descriptive and model based methods. Descriptive methods are the principle component analysis (PCA), the multiple correspondence analysis (MCA) and cluster analysis (CA). Model based methods are the latent class analysis (LCA), the structural equation model (SEM) and factor analysis (FA).

The main difference between PCA and MCA is the scale of the variables used. PCA is used when variables are of cardinal scale, while MCA is appropriate when variables are categorical or binary. The model-based methods are latent variable models and cover latent class analysis (LCA), factor analysis (FA) and more generally, structural equation models (SEMs). When the indicators are ordinal, binary or categorical, a more suitable multivariate technique for a lower-dimensional description of the data is a correspondence analysis (CA).

Like PCA, FA is also used as a data reduction method; however, there is a fundamental difference between the two methods. PCA is a descriptive method that attempts to interpret the underlying (latent) structure of a set of indicators on the basis of their total variations (common variation and unique variation), while FA is a model-based method that focuses on explaining the underlying common variance across indicators instead of total variance. The observed dimensions are a manifestation of the factors and have been used by different authors (Decancq and Lugo 2008; Noble et al. 2007). Since the factor analysis (FA) model makes no prior assumptions regarding the pattern of relationships among the observed indicators (Alkire et al. 2015), it can be used for cardinal and categorical data. Further, it considers the correlation between indicators and removes or reduces redundancy or

duplication from a set of correlated variables. Our research uses the factor analysis model to determine the weight of the indicators.

In finding the weight of the indicators using factor analysis, if the observed variables are  $X_1, X_2, \dots, X_n$ , the common factors are  $F_1, F_2, \dots, F_m$  and the unique factors are  $e_1, e_2, \dots, e_n$ , the variables may be expressed as a linear function of the factors:

$$\begin{aligned}
 X_1 &= a_{11}F_1 + a_{12}F_2 + a_{13}F_3 + \dots + a_{1m}F_m + a_1e_1 \\
 X_2 &= a_{21}F_1 + a_{22}F_2 + a_{23}F_3 + \dots + a_{2m}F_m + a_2e_2 \\
 &\vdots \\
 X_n &= a_{n1}F_1 + a_{n2}F_2 + a_{n3}F_3 + \dots + a_{nm}F_m + a_n e_n
 \end{aligned}
 \tag{8.1}$$

The model assumes that each observed variable is a linear function of these factors with a residual variable. The model produces the maximum correlation and seeks to find the coefficients  $a_{11}, a_{12}, \dots, a_{nm}$ . The coefficients are weights or factor loadings in the same way as regression coefficients. The factor loadings give us the strength of the correlation between the variables and the factor.

It is possible to solve Eq. 8.1 for the factor score so as to obtain a score for each factor for each subject. The equation is of the form:

$$\begin{aligned}
 F_1 &= \lambda_{11}X_1 + \lambda_{12}X_2 + \lambda_{13}X_3 + \dots + \lambda_{1m}X_m \\
 F_2 &= \lambda_{21}X_1 + \lambda_{22}X_2 + \lambda_{23}X_3 + \dots + \lambda_{2m}X_m \\
 &\vdots \\
 F_n &= \lambda_{n1}X_1 + \lambda_{n2}X_2 + \lambda_{n3}X_3 + \dots + \lambda_{nm}X_m
 \end{aligned}
 \tag{8.2}$$

In this model, each factor is a weighted combination of the input variables. The main idea behind this model is that the factor analysis seeks to find factors such that when these factors are extracted, there remain no correlations between variables as the factors account for the correlations.

### 8.4.2 Aggregation of MPI

We have n-households in each round representing the population of interest and d-indicators for selected dimensions for which  $d \geq 2$ . Once the data is available and the range of dimensions and indicators have been selected, we have achieved the level matrix of dimension  $(n \times d)$  of n-households and d-indicators of the selected dimensions. Let  $\sum Y = [Y_{ij}]$  denote the  $n \times d$  matrix of achievement for i household across j dimension. The typical entry in the achievement  $Y_{ij} \geq 0$  which represents individual i's achievement in indicators j. Each row vector

$Y_i = (Y_{i1}, Y_{i2}, \dots, Y_{id})$  gives household  $i$ 's achievements in the different dimensions  $j$  across individuals and the column vector  $Y_j = (Y_{1j}, Y_{2j}, \dots, Y_{nj})$  gives the achievements of all households in the sample on  $j$  indicator.

In MPI we have the deprivation cut-off and the poverty cut-off. A deprivation cut-off vector  $z = (z_1, \dots, z_d)$  (deprivation cut-offs for each dimension) is used to determine whether a household is deprived in that indicator. If a household's achievement level in a given dimension  $j$  falls short of the respective deprivation cut-off  $z_j$ , the household is said to be deprived in that indicator and will have a value of 1. If the household's level of achievement is at least as great as the deprivation cut-off, the household is not deprived in that indicator and will have a value of 0 in that indicator. Finally, we have a deprivation score matrix of  $(n \times d)$  dimension with values of 0 and 1.

Following Nawaz and Iqbal (2016) each household is assigned a deprivation score ( $C_i$ ) based on the weighted sum of the deprivations experienced in each indicator. The deprivation score of each household lies between 0 and 1.

The deprivation score of each household ( $C_i$ ) is calculated by:

$$C_i = W_1I_1 + W_2I_2 + \dots + W_dI_d \quad (8.3)$$

where,  $I_i = 1$  if the household is deprived in indicator  $i$  and 0 otherwise, and  $W_i$  is the weight attached to indicator  $i$  with  $\sum_{i=1}^d W_i = 1$ .

A column vector  $C = (C_1, \dots, C_n)$  of the deprivation score reflects the breadth of each household's deprivation.

A second cut-off, which in the Alkire and Foster methodology is called the poverty cut-off, is the share of (weighted) deprivations that a household must have to be considered multidimensionally poor and is denoted by  $k$ . A household is considered poor if its deprivation score is equal to or greater than the poverty cut-off,  $C_i \geq K$ . In MPI, a household is identified as poor if it has a deprivation score greater than or equal to 1/3 (33%) (Alkire and Santos 2011; OPHI 2013).

MPI is an index designed to measure poverty. Following Alkire and Foster (2011), method the structure of the adjusted headcount measure of MPI combines two key pieces of information: the proportion or incidence of households whose share of weighted deprivations is  $k$  or more and the intensity of their deprivation: the average deprivation that poor households' experience. Formally, the first component is called the multidimensional headcount ratio (H):

$$H = \frac{q}{n} \quad (8.4)$$

Here  $q$  is the number of households that are multidimensionally poor and  $n$  is the total population. However, the headcount ratio (H) violates dimensional monotonicity (Bruck and Workneh 2013). To solve dimensional monotonicity of the headcount ratio, Alkire and Foster (2011) developed the second component of MPI called the intensity (breadth) of poverty (A). It is the average deprivation score of multidimensionally poor households and can be expressed as:

$$A = \frac{\sum_{i=1}^n C_i(k)}{q} \tag{8.5}$$

where,  $C_i(k)$  is the censored deprivation score of household  $i$ , and  $q$  is the number of households that are multidimensionally poor. MPI is the product of both incidence (H) and severity or depth (A) components:

$$MPI = H \times A \tag{8.6}$$

### 8.4.2.1 Decomposition by Sub-groups

One good feature of MPI is that it can be decomposed by population sub-groups such as regions, zones, rural/urban or ethnic groups, depending on the sample design. For example, if there are  $n$  sub-groups by which the survey is represented, the decomposition is:

$$MPI_{country} = \frac{n_1}{N} MPI_{n_1} + \frac{n_2}{N} MPI_{n_2} + \dots + \frac{n_n}{N} MPI_{n_n} \tag{8.7}$$

where,  $n_i$  denotes the population sub-group (regions, zones or rural/urban) and  $N$  denotes the total population ( $n_1 + n_2 + \dots + n_n = N$ ). This relationship can be extended for any number of groups, as long as their respective populations add up to the total population.

Given Eq. 8.7, we can easily compute the contribution of each sub-group to overall poverty by using the formula:

$$\text{Contribution of sub-group } (n_i) \text{ to MPI} = \frac{\frac{n_i}{N} MPI_{n_i}}{MPI_{country}} \times 100 \tag{8.8}$$

When a sub-group’s contribution to poverty exceeds its population share, it suggests that there is a seriously unequal distribution of poverty in the country or the region with some regions/sub-regions/ethnic groups bearing a disproportionately high share of poverty.

The average annual absolute change of each indicator  $X$  can be computed by using the formula:

$$\Delta X_{t-s} = (X_t - X_s)/(t - s) \tag{8.9}$$

where,  $X_t$ , denotes the performance or MPI of a country or a region in period  $t$  and  $X_s$  is the performance or MPI of a country or region in period  $s$ . The average annual change of each indicator  $X$  is:

$$\Delta\%X_{t-s} = ((X_t - X_s)/X_s)/t - s \quad (8.10)$$

The estimated percentage of absolute or relative changes for different sub-groups provide information about the effects of various policies aimed at reducing poverty. A change in MPI over time can provide information about changes in the incidence or intensity of poverty levels or their combined changes. Following Apablaza and Yalonetzky (2011) we decompose the change in MPI as:

$$\Delta\%MPI_{t-s} = \Delta\%H_{t-s} + \Delta\%A_{t-s} + (\Delta\%H_{t-s} * \Delta\%A_{t-s} * (t - s)) \quad (8.11)$$

#### 8.4.2.2 Decomposition by Indicators

MPI can also be decomposed by indicators. An easy way of doing this is by computing the censored headcount ratio in each indicator. We can get the censored headcount ratio by adding up the number of people who are poor and deprived in that indicator and dividing this by the total population. Once all the censored headcount ratios have been computed, we can find the multidimensional poverty index of a country as:

$$MPI_{country} = W_1CH_1 + W_2CH_2 + \dots + W_{10}CH_{10} \quad (8.12)$$

Here  $W_1$  is the weight of indicator 1 and  $CH_1$  is the censored headcount ratio of indicator 1, and so on for the other nine indicators, with  $\sum_{i=1}^d W_i = 1$ . From Eq. 8.12 one can compute the contribution of each indicator to overall poverty by:

$$Contribution\ of\ indicator\ i\ to\ MPI = \frac{W_iCH_i}{MPI_{country}} \times 100 \quad (8.13)$$

If a certain indicator's contribution to poverty widely exceeds its weight, it suggests that there is relatively high deprivation in this indicator as compared to the other indicators and this requires appropriate policy interventions.

#### 8.4.3 Determinants of Multidimensional Poverty

Besides the extent of multidimensional poverty and its dynamics, we are also interested in identifying the determinants of multidimensional poverty. These are essential for reducing multidimensional poverty. There are different household characteristics that determine a household's poverty status (Adetola 2014; Berenger and Verdire-Chouchane 2007; Berisso 2016). We consider the variable family size of the household, number of children under 5-years, age of the household head and the education level of the household.

Because of differences in job opportunities and the uneven distribution of infrastructure across the country, people living in different places such as the capital city, small cities, towns, the countryside or rural areas are exposed to different levels of multidimensional poverty. Therefore, place of residence needs to be controlled for. Livestock are important assets for rural people as they are used as food, drought animals and a source of cash. We used a tropical livestock unit to represent livestock assets of the households.

In the AF method of multidimensional poverty, the households' deprivation score ( $c_i$ ) is compared with the multidimensional poverty cut-offs ( $k$ ). If the deprivation score is greater than or equal to the poverty cut-off ( $c_i \geq k$ ), a household is considered to be multidimensionally poor. This is represented by the binary variable ( $y_i$ ) that takes the value 1 or 0 as:

$$y_i = \begin{cases} 1 & \text{if and only if } c_i \geq k \\ 0 & \text{otherwise} \end{cases} \tag{8.14}$$

The binary variable ( $y_i$ ) occurs with probability  $p_i$ , which is conditional on the explanatory variables ( $x_i$ ) and is represented as:

$$p_i = pr(y_i = 1) = pr(y_i = 1|x_i) \tag{8.15}$$

The outcome variable has only two values (binary). Therefore, we use the logistic regression model which is a limited-dependent variable model. The logit of  $p_i$  is the natural logarithm of odds that the binary variable ( $y_i$ ) takes a value 1 rather than 0 which is the relative probability of being multidimensionally poor. The logit model is a linear model for the natural logarithm of the odds Eq. 8.16:

$$\ln \frac{p_i}{1 - p_i} = \eta_i = \beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik} \tag{8.16}$$

In our logistic model,  $y_i$  is the dependent variable,  $y = 1$  indicates that a household is multidimensional poor, which is our variable of interest and  $p$  is probability of success. In this case the  $p$ -value indicates the probability that a household is multidimensionally poor,  $x$  is the independent variable and  $\beta$  is the coefficient to be estimated.

The coefficient  $\beta_j$  is the change in the logit due to a one-unit increase in  $x_j$  while holding all other explanatory variables in the model constant.  $e^{\beta_j}$  gives the odds ratio associated with a one-unit increase in  $x_j$ .

The logit model is also a multiplicative model for the odds as in:

$$\frac{p_i}{1 - p_i} = e^{\eta_i} = e^{\beta_0} (e^{\beta_1})^{x_{i1}} \dots (e^{\beta_k})^{x_{ik}} \tag{8.17}$$

The conditional probability  $p_i$  is then given as:

$$p_i = \frac{1}{1 + e^{-\eta_i}} = \frac{1}{1 + e^{-\sum_{j=0}^k \beta_j x_{ij}}} \quad (8.18)$$

The logistic regression estimation results of determinants of multidimensional poverty for the three rounds of DHS data is presented in Table 8.2. We performed the model specifications, goodness of fit and multicollinearity tests.

## 8.5 Results and Discussion

Our multidimensional poverty analysis' results show that multidimensional poverty is high in Ethiopia in general and in rural Ethiopia in particular (Table 8.6). Because of the traditional farming system in rural Ethiopia and given that a bulk of the rural population derives its livelihood from agriculture, poverty is by and large a rural phenomenon (Alemayehu et al. 2014; GTP II 2016). In 2000, MPI in rural Ethiopia was very high (0.913) relative to urban Ethiopia (0.245). Over time, poverty in rural Ethiopia has been decreasing moderately (Fig. 8.1). But in urban Ethiopia multidimensional poverty has not been decreasing; instead it has been increasing over time. Ethiopia was committed to attaining the MDGs by 2015. It developed the first Growth and Transformation Plan (GTP-I) which was designed to maintain rapid and broad-based growth and eventually to end poverty. Despite all these steps, multidimensional poverty in Ethiopia has remained high. Our MPI estimation results are almost similar to UNDP's internationally comparable MPI measures (Tables 8.6 and 8.7).

Comparisons of regional multidimensional poverty show that even though there were some differences over years, the multidimensional poverty level was high in almost all the regions of the country. In particular, multidimensional poverty was the highest in Amhara, Afar, Somali and Tigray regions in 2000; in Afar, Tigray,

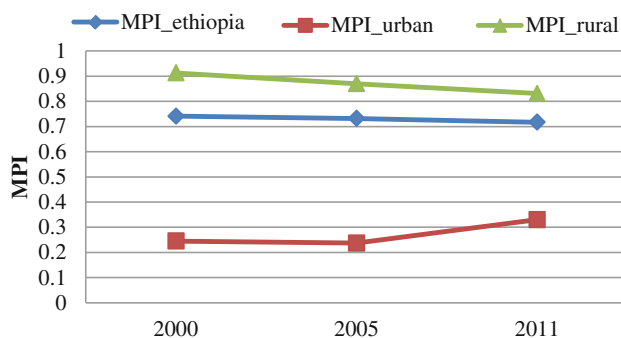


Fig. 8.1 MPI trends in rural and urban Ethiopia over the years, 2000–2011



Amhara and Somali regions in 2005; and in Somali, Benishangul and SNNP regions in 2011. Whereas Addis Ababa, Dire Dawa and Harari regions were among the regions where multidimensional poverty was relatively lower (Table 8.6).

Out of the nine regions in Ethiopia (excluding the two city administrations), Tigary, Amhara, Oromia and SNNP regions constituted about 90% of the total population of the country (CSA 2010). Hence, a poverty analysis of these regions can give us a good picture of multidimensional poverty in Ethiopia. Multidimensional poverty is very high in these regions; however, moderate reduction has been observed in Amhara, Oromia and Tigary regions, but in SNNP there is no such reduction in multidimensional poverty (Figs. 8.2 and 8.3).

One advantage of MPI is that it makes it possible to see the contribution of each region or sub-group to multidimensional poverty. The contributions of regions to overall (country) multidimensional poverty indicate that the regions contributed different shares to multidimensional poverty. For example, in 2000, 2005 and 2011,

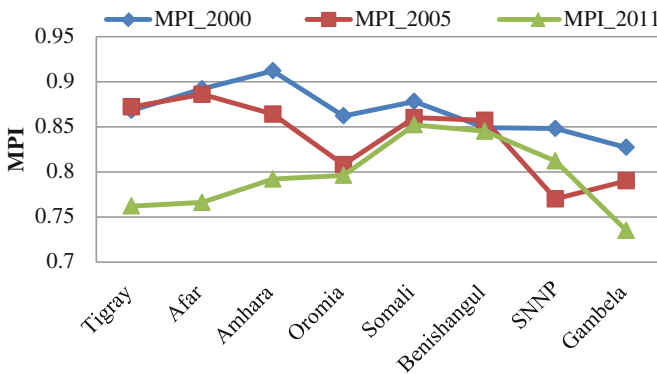


Fig. 8.2 Development of regional MPI in Ethiopia over the years, 2000–2011

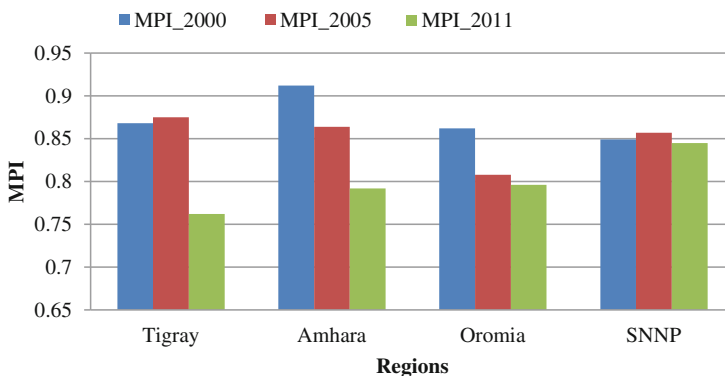
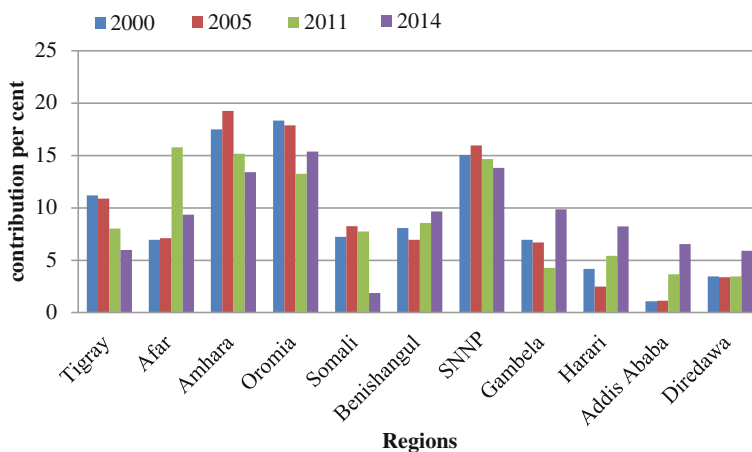


Fig. 8.3 Multidimensional poverty of selected regions over the years, 2000–2011



**Fig. 8.4** Regions' contribution to MPI and its development over time, 2000–2014

Harari, Addis Ababa and Dire Dawa regions contributed less to multidimensional poverty as compared to their population shares, whereas Amhara and Oromia regions contributed more to multidimensional poverty (Table 8.11; Fig. 8.4). In 2014, Tigray, Somali, SNNP, Amhara, Dire Dawa and Addis Ababa contributed less to multidimensional poverty. Whenever a sub-group or region's contribution to poverty exceeds its population share, it suggests that there is a seriously unequal distribution of poverty in the country. This may be because of differences in policy and its implementation or both. If the same poverty reduction policy is implemented over years, the regions contribute differently to overall multidimensional poverty which implies that there are differences in the way in which the regions implement the policy or in the effects of the policy. Heterogeneity in region's ability to escape poverty can be used to design region specific poverty reduction policies to speed up regional equalities.

Tigray region's contribution to multidimensional poverty has been decreasing over time while Addis Ababa's contribution has been increasing over time (Figs. 8.4 and 8.6).

When we consider the contribution of different dimensions to multidimensional poverty, living standards contributed the most (more than 85%) followed by education (14%) and health (less than 1%) (Table 8.8).

Among the indicators used in our multidimensional poverty analysis, we found high deprivation in sanitation, cooking fuel, floor and electricity. Further, sanitation and cooking fuel deprivations increased over time, but education deprivation and school attendance deprivation decreased over time (Fig. 8.5). These results are in line with other recent studies, for example, Alemayehu et al. (2015), which indicate that the proportion of population deprived in multiple indicators has declined but deprivation in some indicators of multidimensional poverty are quite high in Ethiopia (Fig. 8.5).

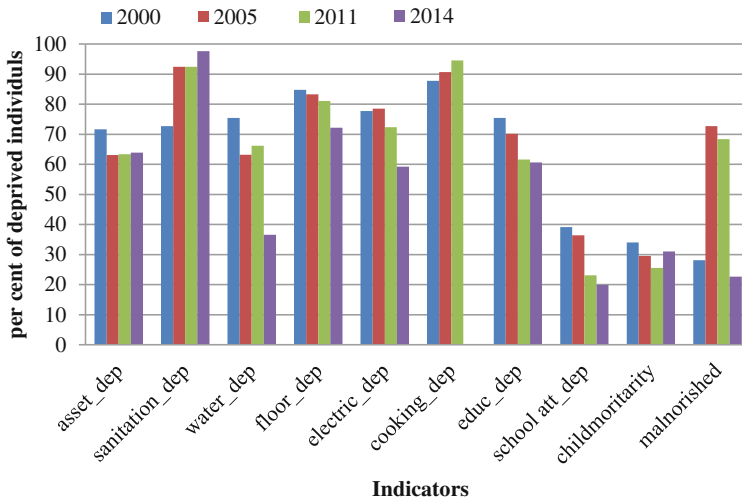


Fig. 8.5 Indicator-wise deprivation in the population

Our multidimensional poverty dynamic results show that in 2005, the highest annual MPI change was in Harari region (about a 3.7% reduction relative to 2000) whereas, in 2014 the highest annual MPI change was in Tigray region (about a 16% reduction). On the contrary, Addis Ababa’s annual multidimensional poverty change increased from 3.4% in 2005 to 16% in 2014 relative to the previous survey year (see Table 8.10).

### 8.5.1 Econometric Model’s Results

In addition to the computation of MPI and its decomposition by regions and indicators, it is very important to identify determinants of multidimensional poverty to identify areas of interventions in multidimensional poverty reduction efforts. Our logistic model estimation results show that the family size (fsize) coefficient was negative and significant (Table 8.2), which indicates that as the family size increased the likelihood of failing into multidimensional poverty decreased. This finding is different from other studies, for example, by Bruck and Workneh (2013) which shown that family size matters in consumption poverty (the larger the family size the higher is the probability that a household will fall into consumption poverty) but family size has no significant impact on multidimensional poverty. However, on the contrary, some studies indicate a direct relationship between poverty and family size (Adetola 2014; Berisso 2016). One possible reason for this is that most people in Ethiopia are living in rural areas and are engaged in traditional agriculture. Traditional agriculture, by its nature, is labor intensive. Hence, all working age (even under-age) rural household family members engage in family

farm activities in one way or another. Therefore, households' with more family members who are actively involved in family farm activities can manage their family farms easily and the more economically active household members in a family, the less likely the family is to fall into poverty.

The number of children under 5-years-old (*childrenunder5*) and dependency ratio (*depratio*) were positive and significant, implying that as the number of children under-5 and number of dependent family members increased a household's probability of being poor also increased. As expected education of the household head (*educ*) was negative and significant because as people get more educated they become more productive and earn more which makes them less likely to be poor. This is also consistent with other findings (Adetola 2014; Berenger and Verdire-Chouchane 2007).

People usually like to invest in human capital at a young age as they have enough time to get returns. Earnings increase with age as new skills and knowledge are acquired through life and work experiences and also by investing in human capital (education). So, during young ages or economically active ages, households' probability of multidimensional poverty decreases as age increases. Adetola (2014) states that an increase in household age reduces the household's likelihood of being multidimensional poor initially at a threshold and then it increases.

The dummy variable—bank account—is negative; those households which had bank accounts were less poor as compared to those who did not have a bank account. We also considered place of residence as a variable in our analysis. In 2000 and 2005 households in the countryside, towns and small cities were poorer compared to households in large cities (the reference area) as their coefficients were positive and significant. Data on place of residence was not available for 2011, so as an alternative, we used residence (rural/urban). Households in the rural areas were poorer than those in urban areas.

Region is dummy variable and *region1\_Tigray* is base or reference region. In 2005 and 2011 (except Afar in 2005), no region was significantly better than Tigray as far as multidimensional poverty is concerned and some regions like Afar, Amhara and Somali had intense multidimensional poverty.

### ***8.5.2 Multidimensional Poverty Index Robustness to Change in Weight of Indicators***

We estimated MPI using factor analysis weights which take into consideration the correlation among indicators. We also used the equal weight approach as an alternative. In this approach each dimension is equally weighted at one-third; each indicator within a dimension is also equally weighted. Then we verified if the rankings were stable using both approaches. We calculated the correlation coefficients using different ranking methods—Pearson's correlation coefficient,

**Table 8.2** Logistic regression model estimation results of the determinants of multidimensional poverty-coefficients

Multidimensional poverty	Round1_2000	Round2_2005	Round3_2011
Fsize	-0.4993***	-0.3706***	-0.3079***
Childrenunder5	0.9074***	0.6536***	0.2082
Age (household head age)	-0.0040	-0.0159***	-0.0233***
Educ.	-1.1776***	-0.2134***	-0.0833*
TLU	0.9682***		-0.0151
Land for agriculture_1 (0 = No, 1 = yes)	0.6416***	0.8611***	0.5448
Sex_2dummy (1 = Male, 2 = female)	-0.1744	0.1169	-0.0451
Place of residence-dummy (capital or large city is the reference)			
Small city	1.9615***	0.2296*	
Town	4.7096***	2.4594***	
Countryside	8.9348***	6.6189**	
Regions dummy (Tigray_1 is the reference)			
Afar_2	-0.1526	-0.1543	0.9875***
Amhara_3	0.8522**	1.8270**	3.5669***
Oromia_4	0.9508***	0.6753	0.7255
Somali_5	0.4325	1.4830	2.0259***
Benishangul_6	2.1498***		
SNNP_7	-0.1742	1.0721*	0.1592
Gambela_12	2.2209***	0.6639	0.5866
Harari_13	-0.6238	0.4407	0.3575
Addis_14	(omitted)	(omitted)	0.4153
Dire Dawa_15	-1.2098***	0.2333	-0.1379
Depratio		0.2590**	0.6722***
Bankaccout_1dummy (0 = No, 1 = yes)		-2.0827***	-1.3829***
Hecland			-0.0016**
Residence_2 dummy (1 = urban, 2 = rural)			4.9809***
Cons.	0.8011***	-0.3451	2.4084***
N	13,811	5367	2335
Chi2	9653.8885	3131.1694	798.95555
Bic	2296.9858	1275.7274	803.5593

\* $p < 0.1$ ; \*\* $p < 0.5$ ; \*\*\* $p < 0.01$

Spearman’s rank correlation coefficient and Kendall’s rank correlation coefficient (Tau-b). As a starting point, we estimated the correlation coefficient of the deprivation score of households’ in the two weighting systems and found that the correlation in Ethiopia in general and in rural/urban Ethiopia in particular was large enough to conclude that there was a strong rank correlation of deprivation scores of households in the two weighing systems (Table 8.3).

Changing the indicators' weight affected the multidimensional poverty index. We compared the correlation coefficient of the multidimensional poverty index of regions in Ethiopia for a change in weights of indicators for 2000–2011. Interestingly, the correlation coefficient obtained between the two alternative weighting systems was high and the regions ranking remained quite stable, thus one region had higher poverty than the other regions regardless of the weighting system used (Table 8.4).

### 8.5.3 Sensitivity Analysis of MPI to Different Choices

A multidimensional poverty analysis is based on certain selected dimensions and indicators. Once we had identified the dimensions and indicators we aggregated them using weights and finally we categorized people or households into multidimensionally poor or non-poor based on an agreed poverty cut-off.

#### 8.5.3.1 Sensitivity to Change in Weights of Indicators

We used a factor analysis to determine the weights of the indicators. We used a factor analysis and equal weight for comparison and sensitivity analysis purposes. Multidimensional headcount ratio and multidimensional poverty index (MPI) were different when equal weight and factor analysis weights were used (Tables 8.5, 8.6,

**Table 8.3** Correlation of deprivation score (ci) of households using equal weight and factor analysis weight

Regions	Correlation coefficient measures used	Deprivation score Correlation coefficients for years, 2000–2011		
		2000	2005	2011
Ethiopia	Pearson	0.823	0.825	0.778
	Spearman	0.865	0.837	0.809
	Tau-b	0.744	0.695	0.553
Rural Ethiopia	Pearson	0.583	0.626	0.600
	Spearman	0.758	0.718	0.692
	Tau-b	0.646	0.580	0.553
Urban Ethiopia	Pearson	0.802	0.802	0.778
	Spearman	0.818	0.784	0.692
	Tau-b	0.661	0.644	0.659

**Table 8.4** Regions' correlation coefficient of MPI using equal weight and factor analysis weight

Correlation coefficient measures used	MPI correlation coefficients for years, 2000–2011		
	2000	2005	2011
Pearson	0.9914	0.9880	0.9860
Spearman	0.9297	0.8678	0.9297
Tau-b	0.8242	0.7889	0.8242

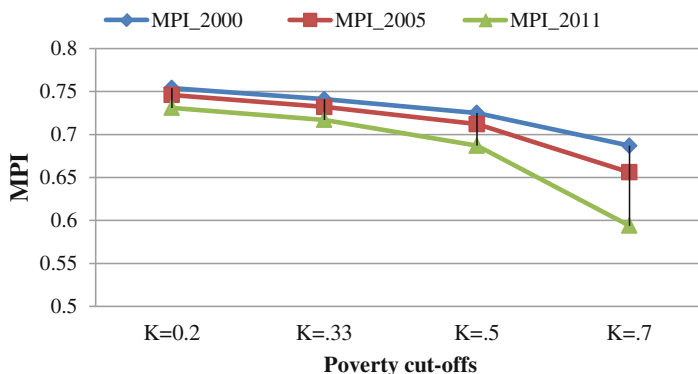
8.7, 8.8, 8.9, 8.10, 8.11 and 8.12). The headcount ratio (H) using a factor analysis weight was greater than that of equal weight (except in 2005). Similarly, MPI using a factor analysis weight was greater than that of equal weight in each year. These differences are mainly because of the differences in weights given to the indicators. Thus, the multidimensional poverty analysis is sensitive to the weights attached to the indicators (Decancq and Lugo 2008).

### 8.5.3.2 Sensitivity to Change in Poverty Cut-offs (K)

The Alkire and Foster method of multidimensional poverty index which we used has two cut-offs: deprivation cut-off ( $z_i$ ) and poverty cut-off ( $k$ ). Poverty cut-off is used to identify those households as multidimensionally poor if their weighted deprivation score ( $c_i$ ) is greater than or equal to the poverty cut-off  $k$  ( $c_i \geq k$ ). In the Alkire and Foster method, a household is multidimensionally poor if its deprivation score is greater than or equal to 33%. The change in multidimensional poverty for some selected poverty cut-offs ( $k = 0.2, k = 0.5, k = 0.7$ ), relative to the benchmark poverty cut-off ( $k = 0.33(33\%)$ ), indicated that a decrease in multidimensional poverty was relatively higher for an increase in poverty cut-off compared to an increase in poverty when there was a decrease in the poverty cut-off. We found that the proportion of the multidimensional poor was less sensitive to downward as opposed to upward revisions of the poverty cut-off (Fig. 8.6).

**Table 8.5** Multidimensional poverty: with equal weight and factor analysis weight

Years	H	A	MPI
<i>Aggregation with equal weight</i>			
2000	0.832	0.645	0.531
2005	0.877	0.667	0.585
2011	0.809	0.632	0.511
<i>Aggregation with factor analysis weight</i>			
2000	0.843	0.879	0.741
2005	0.872	0.839	0.732
2011	0.908	0.789	0.717



**Fig. 8.6** Sensitivity of MPI to the change in poverty cut-off (K)

## 8.6 Conclusion and Recommendations

Despite efforts to reduce it, multidimensional poverty is still high in Ethiopia. Though urban multidimensional poverty is on the rise, poverty mainly remains a rural phenomenon. The dynamics of a multidimensional poverty analysis indicate that poverty in rural Ethiopia is decreasing, but this has not been observed in urban Ethiopia. Even though Ethiopia is an agrarian country and a majority of its population lives in rural areas, the poverty reduction policy of the country should also consider urban poverty (Fig. 8.7).

The intensity and depth of poverty is different in different regions of the country and level of multidimensional poverty reduction is not the same in all the regions. There is unequal distribution of poverty in the country with some regions bearing a disproportionately high share of the poverty. Regions in Ethiopia are different in social, cultural and resource endowments. Poverty reduction policies and implementation strategies need to consider these differences. Regional heterogeneity should be taken into consideration when designing region specific poverty reduction policies to speed up regional equalities. In some regions (for example, Afar, Somali and Bensihangul) multidimensional poverty is very high relative to the other regions. Poverty reduction policies in these regions do not seem to be as effective as in the other regions of the country. This results in regional differences in the prevalence and intensity of poverty within the country which raises the question of equity. Poverty reduction interventions require identifying determinants of multidimensional poverty. Level of education, having a bank account and more working family members in a household reduce multidimensional poverty. On the other hand, number of children under-5, number of dependent family members and households' engagement in agriculture increase multidimensional poverty. Multidimensional poverty is sensitive to the weight of the indicator and the poverty cut-offs used for the analysis.



**Table 8.6** Multidimensional poverty index (MPI) and the 95% confidence interval for the 2000–14 (unequal weight)

	2000		2005		2011		2014	
	MPI (0.003)	95% confidence interval (0.736, 0.746)	MPI (0.004)	95% confidence interval (0.725, 0.739)	MPI (0.005)	95% confidence interval (0.708, 0.726)	MPI (0.017)	95% confidence interval (0.483, 0.551)
Ethiopia	0.741 (0.003)	(0.736, 0.746)	0.732 (0.004)	(0.725, 0.739)	0.717 (0.005)	(0.708, 0.726)	0.517 (0.017)	(0.483, 0.551)
Urban	0.245 (0.005)	(0.236, 0.254)	0.237 (0.007)	(0.224, 0.250)	0.330 (0.008)	(0.314, 0.346)	0.403 (0.020)	(0.334, 0.472)
Rural	0.913 (0.001)	(0.911, 0.915)	0.870 (0.018)	(0.866, 0.874)	0.831 (0.003)	(0.825, 0.837)	0.490 (0.035)	(0.451, 0.521)
<i>Regions</i>								
Tigray	0.868 (0.005)	(0.858, 0.878)	0.872 (0.006)	(0.860, 0.884)	0.762 (0.015)	(0.733, 0.791)	0.397 (0.053)	(0.293, 0.501)
Afar	0.892 (0.006)	(0.881, 0.903)	0.886 (0.008)	(0.870, 0.902)	0.766 (0.012)	(0.743, 0.789)	0.700 (0.061)	(0.581, 0.819)
Amhara	0.912 (0.003)	(0.905, 0.919)	0.864 (0.006)	(0.855, 0.873)	0.792 (0.009)	(0.774, 0.810)	0.501 (0.054)	(0.394, 0.608)
Oromia	0.862 (0.004)	(0.855, 0.869)	0.808 (0.006)	(0.797, 0.819)	0.796 (0.010)	(0.777, 0.815)	0.525 (0.041)	(0.444, 0.606)
Somali	0.878 (0.006)	(0.866, 0.890)	0.860 (0.010)	(0.841, 0.879)	0.852 (0.010)	(0.832, 0.872)	0.248 (0.065)	(0.121, 0.375)
Benishangul	0.849 (0.005)	(0.839, 0.859)	0.857 (0.006)	(0.845, 0.869)	0.845 (0.008)	(0.829, 0.861)	0.607 (0.062)	(0.485, 0.729)
SNNP	0.848 (0.004)	(0.840, 0.856)	0.770 (0.006)	(0.757, 0.783)	0.812 (0.008)	(0.797, 0.827)	0.501 (0.047)	(0.410, 0.592)
Gambela	0.827 (0.006)	(0.816, 0.838)	0.790 (0.010)	(0.770, 0.810)	0.735 (0.020)	(0.695, 0.775)	0.691 (0.068)	(0.559, 0.823)

(continued)

Table 8.6 (continued)

	2000		2005		2011		2014	
	MPI (0.012)	95% confidence interval (0.474, 0.522)	MPI (0.019)	95% confidence interval (0.368, 0.442)	MPI (0.018)	95% confidence interval (0.570, 0.638)	MPI (0.060)	95% confidence interval (0.520, 0.756)
Harari	0.498 (0.012)	(0.474, 0.522)	0.405 (0.019)	(0.368, 0.442)	0.604 (0.018)	(0.570, 0.638)	0.638 (0.060)	(0.520, 0.756)
Addis Ababa	0.083 (0.005)	(0.073, 0.093)	0.097 (0.007)	(0.083, 0.111)	0.251 (0.010)	(0.231, 0.271)	0.271 (0.055)	(0.164, 0.378)
Dire Dawa	0.401 (0.012)	(0.377, 0.425)	0.434 (0.019)	(0.397, 0.471)	0.580 (0.032)	(0.517, 0.643)	0.643 (0.056)	(0.534, 0.752)

Source Author's computations using DHS data

**Table 8.7** Headcount (H), intensity (A) and multidimensional poverty index (MPI) of Ethiopia by regions for the 2000, 2005, 2011 and 2014 (equal weight)

Regions or residence	2000			2005			2011			2014		
	H	A	MPI	H	A	MPI	H	A	MPI	H	A	MPI
Ethiopia	0.823	0.645	0.531	0.877	0.667	0.585	0.809	0.632	0.511	0.658	0.523	0.344
Urban	0.386	0.476	0.184	0.494	0.472	0.233	0.374	0.499	0.187	0.463	0.449	0.208
Rural	0.974	0.668	0.651	0.877	0.666	0.585	0.944	0.645	0.612	0.718	0.538	0.386
<i>Regions</i>												
Tigray	0.943	0.655	0.618	0.978	0.692	0.677	0.847	0.614	0.520	0.462	0.449	0.208
Afar	0.945	0.699	0.661	0.974	0.733	0.714	0.874	0.693	0.606	0.875	0.569	0.498
Amhara	0.967	0.645	0.624	0.979	0.692	0.677	0.905	0.617	0.558	0.813	0.510	0.415
Oromia	0.929	0.645	0.599	0.942	0.667	0.628	0.894	0.660	0.590	0.686	0.519	0.356
Somali	0.949	0.681	0.639	0.943	0.719	0.678	0.977	0.684	0.668	0.445	0.533	0.234
Benishangul	0.938	0.639	0.600	0.972	0.681	0.662	0.954	0.632	0.603	0.789	0.560	0.442
SNNP	0.918	0.651	0.597	0.930	0.665	0.618	0.902	0.609	0.549	0.606	0.558	0.338
Gambela	0.911	0.602	0.549	0.957	0.630	0.603	0.830	0.596	0.494	0.647	0.533	0.345
Harari	0.599	0.599	0.359	0.596	0.577	0.344	0.740	0.556	0.412	0.625	0.547	0.342
Addis Ababa	0.229	0.422	0.097	0.363	0.426	0.155	0.264	0.476	0.126	0.429	0.367	0.157
Dire Dawa	0.535	0.589	0.315	0.654	0.613	0.401	0.600	0.673	0.404	0.667	0.553	0.369

*Source* Author's computations using DHS data

**Table 8.8** Percentage contribution of multidimensional poverty dimensions to multidimensional poverty index, by years and regions (unequal weight)

Regions or residence	2000					2005					2011					2014				
	Living stand.	Educ.	Health	Total	Living stand.	Educ.	Health	Total	Living stand.	Educ.	Health	Total	Living stand.	Educ.	Health	Total	Living stand.	Educ.	Health	Total
Ethiopia	85.74	13.72	0.54	100	86.22	13.13	0.64	100	87.87	11.52	0.61	100	85.76	13.60	0.64	100				
Urban	85.81	13.61	0.58	100	87.33	11.98	0.69	100	90.47	8.95	0.58	100	93.87	5.75	0.37	100				
Rural	85.73	13.74	0.54	100	86.14	13.22	0.64	100	87.56	11.83	0.61	100	83.46	15.83	0.56	100				
<i>Regions</i>																				
Tigray	85.58	13.91	0.51	100	86.55	12.86	0.59	100	89.05	10.46	0.48	100	82.00	17.45	0.56	100				
Afar	85.29	14.09	0.63	100	84.58	14.85	0.56	100	85.68	13.64	0.68	100	84.54	14.91	0.55	100				
Amhara	85.71	13.79	0.50	100	86.21	13.13	0.66	100	88.66	10.72	0.63	100	82.08	17.03	0.89	100				
Oromia	85.92	13.51	0.57	100	86.52	12.84	0.65	100	87.23	12.14	0.64	100	85.91	13.64	0.45	100				
Somali	84.61	14.96	0.44	100	84.95	14.58	0.46	100	86.22	13.13	0.66	100	91.13	8.33	0.54	100				
Benishangul	85.89	13.58	0.53	100	86.26	13.02	0.72	100	87.37	11.96	0.67	100	82.12	17.26	0.62	100				
SNNP	86.32	13.12	0.56	100	86.39	12.87	0.72	100	89.88	9.55	0.57	100	86.42	12.91	0.67	100				
Gambela	88.06	11.38	0.56	100	88.89	10.47	0.64	100	91.18	8.24	0.59	100	89.65	9.81	0.54	100				
Harari	84.78	14.66	0.57	100	85.01	14.32	0.68	100	86.34	13.20	0.46	100	88.81	10.35	0.84	100				
Addis Ababa	80.08	19.27	0.64	100	84.49	14.72	0.79	100	89.90	9.55	0.55	100	92.84	7.07	0.08	100				
Dire Dawa	83.92	15.15	0.57	100	85.32	13.96	0.72	100	86.87	12.55	0.59	100	83.65	15.05	1.29	100				

Source Author's computations using DHS data

**Table 8.9** Percentage contribution of multidimensional poverty dimensions to multidimensional poverty index, by years and regions (equal weight)

Regions or Residence	2000					2005					2011					2014				
	Living stand.	Educ.	Health	Total	Living stand.	Educ.	Health	Total	Living stand.	Educ.	Health	Total	Living stand.	Educ.	Health	Total	Living stand.	Educ.	Health	Total
Ethiopia	46.68	34.79	18.53	100	43.00	30.00	27.00	100	45.99	26.33	27.68	100	46.08	31.19	22.73	100				
Urban	39.02	33.14	27.83	100	35.84	24.90	39.30	100	44.50	18.57	36.93	100	65.80	14.66	19.54	100				
Rural	47.43	34.45	17.62	100	43.47	30.00	26.00	100	46.17	27.29	26.53	100	42.95	33.82	23.23	100				
<i>Regions</i>																				
Tigray	47.58	35.47	16.95	100	44.3	29.6	26.10	100	48.87	24.64	26.49	100	48.60	32.71	18.69	100				
Afar	45.24	34.18	20.58	100	42.0	34.56	23.41	100	42.09	28.75	29.16	100	47.37	31.58	21.05	100				
Amhara	48.48	35.29	16.23	100	43.8	29.44	26.76	100	47.91	24.95	27.14	100	41.25	35.25	23.50	100				
Oromia	47.13	34.76	18.12	100	43.52	29.80	26.67	100	44.43	29.17	26.40	100	44.75	33.15	22.10	100				
Somali	45.66	38.26	16.08	100	42.91	34.43	22.66	100	43.63	29.75	26.63	100	21.87	39.06	39.06	100				
Benishangul	47.52	34.22	18.26	100	43.76	28.01	28.23	100	47.26	25.46	27.29	100	43.44	33.94	22.62	100				
SNNP	47.23	34.50	18.26	100	42.15	30.18	27.67	100	49.37	23.52	27.11	100	44.10	32.61	23.29	100				
Gambela	50.25	28.30	21.44	100	46.57	23.94	29.50	100	50.91	18.37	30.72	100	57.83	24.10	18.07	100				
Harari	44.84	34.83	20.32	100	39.21	29.41	31.38	100	45.49	29.91	24.59	100	51.22	24.39	24.39	100				
Addis Ababa	24.37	38.71	36.93	100	26.55	26.48	46.97	100	42.55	19.88	37.58	100	74.75	15.15	10.10	100				
Dire Dawa	40.85	36.48	22.67	100	37.9	30.73	31.34	100	44.89	28.70	26.41	100	39.76	30.12	30.12	100				

Source Author's computations using DHS data

**Table 8.10** Multidimensional poverty index (MPI), absolute annual change and relative annual change in MPI relative to the previous survey years in Ethiopia, by Rural/Urban and regions

Regions or residence	MPI_2000	MPI_2005	Annual change		MPI_2011		Annual change		MPI_2014		Annual change	
			Absolute	Relative (%)	Absolute	Relative (%)	Absolute	Relative (%)	Absolute	Relative (%)		
Ethiopia	0.741 (0.003)	0.732 (0.004)	-0.002**	-0.24	0.717 (0.005)	-0.003**	-0.34	0.5 (0.017)	-0.067**	-9.30		
Urban	0.245 (0.005)	0.237 (0.007)	-0.002	-0.65	0.33 (0.008)	0.016***	6.54	0.49 (0.020)	0.053**	16.16		
Rural	0.913 (0.001)	0.87 (0.002)	-0.009***	-0.94	0.831 (0.003)	-0.007***	-0.75	0.403 (0.035)	-0.143**	-17.17		
<i>Regions</i>												
Tigray	0.868 (0.005)	0.872 (0.006)	0.001	0.09	0.762 (0.015)	-0.018***	-2.10	0.397 (0.053)	-0.122**	-15.97		
Afar	0.892 (0.006)	0.886 (0.008)	-0.001	-0.13	0.766 (0.012)	-0.020***	-2.26	0.7 (0.061)	-0.022	-2.87		
Amhara	0.912 (0.003)	0.864 (0.005)	-0.010***	-1.05	0.792 (0.009)	-0.012***	-1.39	0.501 (0.054)	-0.097**	-12.25		
Oromia	0.862 (0.004)	0.808 (0.006)	-0.011***	-1.25	0.796 (0.01)	-0.002	-0.25	0.525 (0.041)	-0.090**	-11.35		
Somali	0.878 (0.006)	0.86 (0.01)	-0.004	-0.41	0.852 (0.01)	-0.001	-0.16	0.248 (0.065)	-0.201**	-23.63		
Bemishangul	0.849 (0.005)	0.857 (0.006)	0.002	0.19	0.845 (0.008)	-0.002	-0.23	0.607 (0.062)	-0.079**	-9.39		
SNNP	0.848 (0.004)	0.77 (0.006)	-0.016***	-1.84	0.812 (0.008)	0.007***	0.91	0.501 (0.047)	-0.104**	-12.77		
Gambela	0.827 (0.006)	0.79 (0.01)	-0.007***	-0.89	0.735 (0.02)	-0.009**	-1.16	0.691 (0.068)	-0.015	-2.00		
Harari	0.498 (0.012)	0.405 (0.02)	-0.019***	-3.73	0.604 (0.018)	0.033***	8.19	0.614 (0.055)	0.003	0.55		
Addis Ababa	0.083 (0.005)	0.097 (0.007)	0.003	3.37	0.251 (0.01)	0.026***	26.46	0.373 (0.056)	0.041	16.20		
Dire Dawa	0.401 (0.012)	0.434 (0.019)	0.007	1.65	0.58 (0.032)	0.024***	5.61	0.471 (0.060)	-0.036	-6.26		

Source Author's computation using DHS data, standard errors in parentheses, \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$

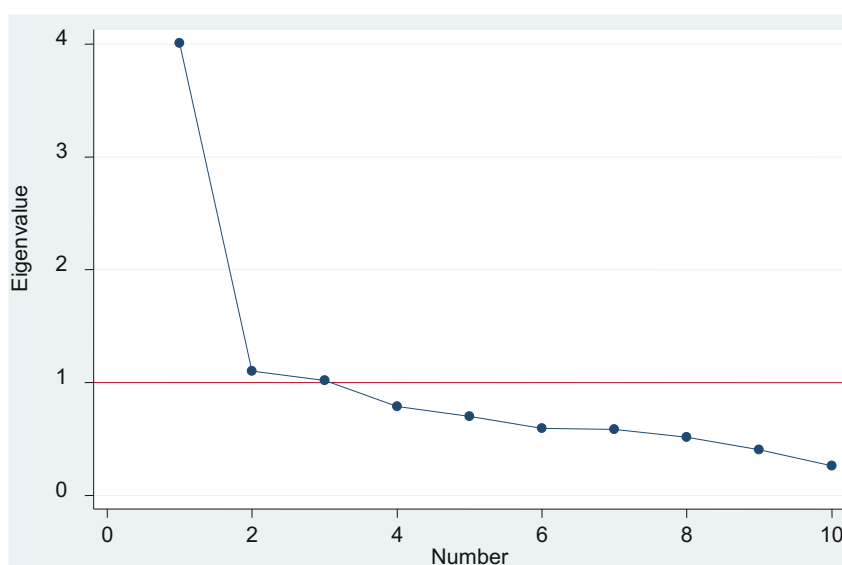
**Table 8.11** Population share and multidimensional poverty contribution of regions

Regions	2000			2005			2011			2014		
	%	Contr.	Diff.	%	Contr.	Diff.	%	Contr.	Diff.	%	Contr.	Diff.
Tigray	9.55	11.18	1.63	9.15	10.89	1.74	7.55	8.03	0.48	7.79	5.98	-1.81
Afar	5.79	6.96	1.17	5.87	7.10	1.23	14.77	15.78	1.01	6.98	9.35	2.37
Amhara	14.19	17.49	3.3	16.34	19.25	2.91	13.73	15.16	1.43	13.85	13.42	-0.43
Oromia	15.78	18.35	2.57	16.22	17.88	1.66	11.94	13.26	1.32	15.15	15.37	0.22
Somali	6.10	7.23	1.13	7.04	8.26	1.22	6.51	7.74	1.23	3.90	1.87	-2.03
Benishangul	6.96	8.08	1.12	5.96	6.96	1.00	7.25	8.55	1.30	8.23	9.65	1.42
SNNP	13.14	15.04	1.63	15.21	15.97	0.76	12.96	14.67	1.71	14.29	13.83	-0.46
Gambela	6.24	6.96	1.90	6.22	6.70	0.48	4.17	4.27	0.10	7.36	9.85	2.49
Harari	6.19	4.16	-2.03	4.50	2.49	-2.01	6.44	5.42	-1.02	6.98	8.21	1.23
Addis Ababa	9.66	1.08	-8.58	7.80	1.13	-6.49	10.42	3.66	-6.76	9.09	6.55	-2.54
Dire Dawa	6.41	3.46	-2.95	5.69	3.38	-2.31	4.28	3.47	-0.81	6.49	5.92	-0.57

*Note* %—population percentage share of the regions; *contr.*—region's multidimensional poverty contribution; *diff.*—difference between multidimensional poverty contribution and population percentage share

**Table 8.12** Factor analysis/correlation

Factors	Eigen value	Difference	Proportion	Cumulative
Factor 1	4.00854	2.90402	0.4009	0.4009
Factor 2	1.10452	0.08387	0.1105	0.5113
Factor 3	1.02065	0.23047	0.1021	0.6934
Factor 4	0.79018	0.08903	0.0790	0.6924
Factor 5	0.70115	0.10428	0.0701	0.7625
Factor 6	0.59687	0.00881	0.0597	0.8222
Factor 7	0.58806	0.07026	0.0588	0.8810
Factor 8	0.51780	0.11043	0.0518	0.9328
Factor 9	0.40737	0.14251	0.0407	0.9735
Factor 10	0.26486	–	0.0265	1.0000

**Fig. 8.7** Screen plot of eigenvalues after factor

Poverty reduction policies should focus on living standard indicators as these indicators contribute the most to multidimensional poverty in almost all regions in the country. There is high deprivation in sanitation, cooking fuel, floor and electricity in Ethiopia; thus, these indicators require careful interventions by federal and regional governments to reduce multidimensional poverty.

Poverty is multidimensional and thus a response to poverty should involve many sectors and stakeholders. Collective effort is the right approach and should be scaled up and practiced more extensively.



Our analysis used a household as the unit of analysis. However, in Ethiopia where there is high ethnic and cultural diversity, intra-household inequalities (between men and women, adults and children) may be severe. Our household multidimensional poverty analysis did not take into consideration intra-household inequalities because of unavailability of data at an individual level. A multidimensional poverty analysis at the individual level provides potential for future research when individual level data is available. Multidimensional issues such as an analysis of child poverty and nutrition based poverty are also potential research areas.

## References

- Adetola, A. 2014. Trend and determinants of multidimensional poverty in rural Nigeria. *Journal of Development and Agricultural Economics* 6 (5): 220–231.
- Alemayehu, A., M. Parend, and Y. Biratu. 2015. Multidimensional poverty in Ethiopia, change in overlapping deprivations. Poverty Research Working Paper, 7417. The World Bank Group.
- Alemayehu, G., and Y. Addis. 2014. *Growth, poverty and inequality in Ethiopia, 2000–2013: A macroeconomic appraisal*. A chapter in a Book to be published by Forum for Social studies, FSC, Department of Economics, Addis Ababa University.
- Alkire, S., and J. Foster. 2011. *Understandings and misunderstandings of multidimensional poverty measurement*. Berlin: Springer Science+Business Media.
- Alkire, S., and M.E. Santos. 2010. Acute multidimensional poverty: A new index for developing countries. OPHI Working Paper, 38.
- Alkire, S., and M.E. Santos. 2011. The multidimensional poverty index. OPHI Research in Progress.
- Alkire, S., J. Foster, and M.E. Santos. 2011. Where did identification go? *Journal of Economic Inequality* 9 (3): 501–505.
- Alkire, S., J.E. Foster, S. Seth, M.E. Santos, J.M. Roche, and P. Ballon. 2015. Multidimensional poverty measurement and analysis: Overview of methods for multidimensional poverty assessment. OPHI Working Papers, 84.
- Ambel, A., P. Mebta, and B. Yigezu. 2015. Multidimensional poverty in Ethiopia: Change in overlapping deprivations. Policy Research Working Paper 7417. The World Bank Group.
- Apablaza, M., and G. Yalonetzky. 2011. Measuring the dynamics of multiple deprivations among children: The cases of Andhra Pradesh, Ethiopia, Peru and Vietnam. Paper submitted to CSAE conference, March.
- Atkinson, A.B. 2003. Multidimensional deprivation: Contrasting social welfare and counting approaches. *Journal of Economic Inequality* 1: 51–65.
- Bersisa, M., and A. Heshmati. 2016. Multidimensional measure of poverty in Ethiopia: Factor and stochastic dominance analysis, in A. Heshmati A. (ed.), *Poverty and well-being in East Africa. Economic studies in inequality, social exclusion and well-being*. Cham: Springer.
- Berisso, O. 2016. Determinants of consumption expenditure and poverty dynamics in Urban Ethiopia: Evidence from panel data, in A. Heshmati (ed.), *Poverty and well-being in East Africa. Economic studies in inequality, social exclusion and well-being*. Cham: Springer.
- Berenger, V., and A. Verdire-Chouchane. 2007. Multidimensional measures of well-being: Standard of living and quality of life across countries. *World Development* 35 (7): 1259–1279.
- Bourguignon, F., and S. Chakravarty. 2003. The measurement of multidimensional poverty. *Journal of Economic Inequality* 1 (1): 25–49.
- Bruck, T., and S. Workneh. 2013. Dynamics and drivers of consumption and multidimensional poverty: Evidence from Rural Ethiopia. Discussion Paper No. 7364.

- Chen, S., and M. Ravallion. 2008. China is poorer than we thought but no less successful in the fight against poverty. Policy Research Working Paper WPS4621.
- CSA (Central Statistical Agency). 2009. *The 2007 population and housing census of Ethiopia: National statistical summary report*. Addis Ababa, Ethiopia: CSA.
- CSA (Central Statistical Agency). 2010. *The 2007 population and housing census of Ethiopia: National statistical summary report*. Addis Ababa, Ethiopia: CSA.
- Dhongda, S., Y. Li, P. Pattanaik, and Y. Xu. 2015. Binary data, hierarchy of attributes, and multidimensional deprivation. *Journal of Economic Inequality* 14: 363–378.
- Decancq, K., M. Fleurbaey, and F. Maniquet. 2014. *Multidimensional poverty measurement with individual preferences*. Princeton: Princeton University Williams, Economic Theory Center Research Paper.
- Decancq, K., and M.A. Lugo. 2013. Weights in multidimensional indices of wellbeing: An overview. *Econometric Reviews* 32 (1): 7–34.
- Decancq, K., and M.A. Lugo. 2008. Setting weights in multidimensional indices of well-being. Working Paper, University of Oxford, Department of Economics.
- Dercon, S., D. Gilligan, J. Hoddinott, and T. Woldehanna. 2009. The impact of roads and agricultural extension on consumption growth and poverty in fifteen Ethiopian villages. *American Journal of Agricultural Economics* 91 (4): 1007–1021.
- Duclos, D.S., and S. Younger. 2006. Robust multidimensional poverty comparisons. *Economic Journal* 116 (514): 943–968.
- Foster, J., S. Seth, M. Lokshin, and Z. Sajaia. 2013. *A unified approach to measuring poverty and inequality: Theory and practice*. The World Bank. <https://doi.org/10.1596/978-0-8213-8461-9>.
- GTP II. 2016. *Growth and Transformation plan II (GTPII) (2015/16–2019/20)* (vol. 1). Addis Ababa: Federal Democratic Republic of Ethiopia, National planning commission, main text.
- Hishe Gebreslassie, G. 2013. Multidimensional measures of poverty analysis in urban areas of Afar regional state. *International Journal of Science and Research (IJSR)*, 6.
- Hulme, D., and A. McKay. 2008. Identifying and measuring chronic poverty: Beyond monetary measures? In *The many dimensions of poverty*, ed. N. Kakwani, and J. Silber, 187–214. Palgrave: Macmillan.
- Maasoumi, E., and T. Xu. 2015. Weights and substitution degree in multidimensional well-being in China. *Journal of Economic Studies* 42 (1): 4–19.
- Maggino, F., and B.D. Zumbo. 2012. *Measuring the quality of life and the construction of social indicators, Handbook of social indicators and quality of life research*. Springer Science +Business Media, pp. 201–238.
- Ministry of Finance and Economic Development (MOFED). 2010. *Growth and transformation plan, 2010/11–2014/15*. Addis Ababa, Ethiopia: Ministry of Finance and Economic Development.
- Nawaz, S., and N. Iqbal. 2016. Education poverty in Pakistan: A spatial analysis at district level. *Indian Journal of Human Development* 10: 270–287. <https://doi.org/10.1177/0973703016674081>.
- Noble, M., D. McLennan, K. Wilkinson, A. Whitworth, H. Barnes, and C. Dibben. 2007. *The English indices of deprivation 2007. Communities and local government*. London.
- OPHI (Oxford Poverty and Human Development Initiative). 2013. *How multidimensional poverty went down: Dynamics and comparison*. Oxford: University of Oxford.
- Ravallion M. 2011. On multidimensional indices of poverty. The World Bank Development Research Group. Policy Research Working Paper 5580.
- Salazar, R., B. Duaz, and R. Pinzon. 2013. *Multidimensional poverty in Colombia, 1997–2013*. Institute for Social and Economic Research, ISER working paper series.
- Sen, A.K. 1992. *Inequality re-examined*. New York: Russell Sage Foundation.
- Stewart, F., R. Saith, and B. Harriss White. 2007. *Defining poverty in the developing world*. Basingstoke: Palgrave Macmillan.
- Stiglitz, J.E., A. Sen, and J.P. Filtoussi. 2009. Report by the Commission on the Measurement of Economic Performance and Social Progress, Mimeo.

- Takeuchi, L.R. 2014. Incorporating people's value in development: Weighting alternatives. Development progress, World Bank Photo Collection.
- The World Bank. 2014. *The World Bank Annual Report 2014*. Washington, DC: The World Bank. Available at: <https://openknowledge.worldbank.org/handle/10986/2009>.
- The World Bank. 2016. *The World Bank Annual Report 2016*. Washington, DC: The World Bank. Available at: <https://openknowledge.worldbank.org/handle/10986/24985>.
- Thorbecke, E. 2008. Multidimensional poverty: Conceptual and measurement issues. In *The many dimensions of poverty*, ed. N. Kakwani, and J. Silber. New York: Palgrave Macmillan.
- Tran, V., S. Alkire, and S. Klasen. 2015. Static and dynamic disparities between monetary and multidimensional poverty measurement: Evidence from Vietnam, Oxford Poverty & Human Development Initiative (OPHI), Working Paper, No. 97.
- Tsui, K.Y. 2002. Multidimensional poverty indices. *Social Choice and Welfare* 19 (1): 69–93.
- UNDP. 2013. *Human development report 2013. The Rise of the South: Human progress in a diverse world*. United Nations Development Programme.
- Woldehanna, T., and A. Hagos. 2013. Dynamics of welfare and poverty in rural and urban communities of Ethiopia. An International Study of Child poverty, *Yongs Lives*, Working Paper 109.