

Assessment of Ethiopian Multidimensional Poverty: Implications for National and Regional Government Policies

*Admassu Tesso Huluka**

**Ethiopian Civil Service University, College of Finance, Development and Management,
Department of Development Management, Associate Professor of Development Studies;
Email: admassutesso@gmail.com; ORCID ID: <http://orcid.org/0000-0002-1946-0977>;
P.O.Box 5648; Addis Ababa, Ethiopia*

Abstract

This study utilizes the Alkire and Foster approach to analyze the Multidimensional Poverty Index (MPI) using data from Ethiopian Demographic and Health Surveys (EDHS) conducted in 2011, 2016, and 2019, aiming to provide detailed insights for national, regional, and local governments to plan and monitor poverty alleviation strategies. The research highlights Ethiopia's significant progress in reducing multidimensional poverty, with prevalence decreasing from 81 percent in 2011 to 64.7 percent in 2019. However, the intensity of poverty has declined more slowly, indicating severe deprivation among those still impoverished. The study emphasizes the need for well-funded and effectively implemented poverty reduction programs, focusing on both prevalence and intensity of poverty. It recommends prioritizing rural development, enhancing agricultural productivity, and addressing gender disparities by supporting female-headed households. Furthermore, the study identifies rising urban poverty and regional disparities, suggesting tailored interventions, conflict resolution, and post-conflict reconstruction, particularly in conflict-affected areas like Oromia, to ensure comprehensive poverty alleviation. Furthermore, enhancing access to quality education and healthcare, improving sanitation and safe drinking water, promoting sustainable farming practices, and fostering economic diversification are crucial to sustaining and accelerating poverty reduction efforts across Ethiopia.

Keywords: *DHS, Education, Ethiopia, Health, Multidimensional poverty, Living standards*

1. Introduction

Poverty alleviation has always been a top priority in national and international development programs (Oxford Poverty and Human Development Initiative, OPHI, 2022; UN, 2018). Most of the 17 goals of the 2030 Agenda for Sustainable Development are coined to address the social, economic, and environmental facets of societal well-being, with a key emphasis on leaving no one behind (UN, 2018). Despite concerted initiatives, multidimensional poverty is increasing. Globally, approximately 1.3 billion individuals are multidimensionally poor, with the majority living in developing countries. Nearly one billion of those 1.3 billion individuals are unable to afford decent housing, sufficient hygiene, and fuels for cooking, and 568 million lack access to safe drinking water (OPHI, 2022).

Currently, access to healthcare, housing, food, and safe drinking water, energy for cooking, housing, and quality education is more difficult than it was when the 2030 Agenda for Sustainable Development was first endorsed. People are frequently left behind in a position to take full advantage of economic expansion, innovation, or globalization, as they face challenges or disadvantages due to a lack of choices and possibilities. Consequently, identifying and strengthening vulnerable population groups is critical for effectively addressing multidimensional poverty (Fahad *et al.*, 2023; Saddique *et al.*, 2023).

Consistent with international initiatives, poverty reduction has long been the priority agenda of the Ethiopian government over the last three decades (EEA, 2021). This effort began with the issuance of Agricultural Development-led Industrialization (ADLI) as a strategy in 2002 (Admassu & Beneberu, 2019).. This strategy envisions rapid and sustained development in agriculture as a prerequisite for sparking and maintaining progress in the rest of the economy. The strategy presumes that the elements influencing the performance of agriculture are associated with broader economic and social initiatives and that boosting agricultural output through advances in technology and trade generates significant demand for the outputs of other sectors, such as fertilizer, transportation, commercial services, and construction (Admassu & Negatu, 2016). Consistent with the ADLI, the Ethiopian government has prepared and implemented a number of five-year national plans, each focusing on poverty reduction: Sustainable Development and Poverty Reduction Program (SDPRP 2002-2005); Plan for Accelerated and Sustainable Development to End Poverty (PASDEP 2005/06–2009/10), the first Growth and Transformation Plan (GTP I 2010/11-2014/15); and the second Growth and Transformation Plan (GTP II-20116-2020).

Despite progress in the Gross Domestic Product (GDP) growth rate, multidimensional poverty remains one of the most serious challenges in Ethiopia. Current evidence shows that the rates of poverty have increased in the country compared to 2015/16, with significant variations among regions (UNDP, 2022a). Evidence also shows that Ethiopia has faced the difficult confluence of a rapidly expanding young population, increasing inflation, an uncertain internal and external setting, including a volatile sub-region, and a generally greater degree of risk – frequently on a large scale – that threatens long-term and inclusive progress in development. As a result, managing a nation's socioeconomic policy agenda has become increasingly challenging and intricate (UNDP, 2022b).

Recognizing the significance of addressing different dimensions of poverty, Ethiopia issued its most comprehensive ten year national plan (the prosperity plan) in 2020 (FDRE, 2021). The prosperity plan is intended to address economic, social, governance, and security concerns, while also providing residents with better choices and decent living conditions. The plan emphasizes a broader definition of poverty that encompasses education, health, and other factors as well as monetary indicators. However, identifying the underlying root causes of multidimensional poverty is a critical first step toward effective poverty reduction (OPHI 2022; UNDP 2022c). Without understanding the root causes and level of multidimensional poverty, assessing the progress of the plan in terms of poverty reduction could be a challenge.

A comprehensive examination of empirical literature on poverty in Ethiopia provides two important conclusions. Firstly, most nationally representative multidimensional poverty studies are very old and highly unlikely to show the current art-of the state (Seff & Jolliffe, 2016; Bizuneh, 2015; Brück & Workneh Kebede, 2021; Dercon & Gilligan, 2008). In addition, these studies also lacked decomposing the determinants of poverty across subpopulations and hence were less likely to be informative for national and regional government policymakers. Second, few existing multidimensional studies are location-specific and, hence, hardly represent the multidimensional poverty reality in other locations in the country (Admasu et al., 2021; EEA, 2021; Mare et al., 2022; Teka et al., 2019). Given the fact that these studies were based on a very limited sample size collected in the form of a cross-sectional study design, they provide neither insight into the dynamisms of multidimensional poverty across various subpopulation groups nor nationally representative. Thus, there is a need to assess the status and contributing factors to the multidimensional poverty at the national and regional levels, urban versus rural dichotomous, and the sex of the household heads.

This study analyzes household-level data from nationally representative large-scale surveys of three rounds of Demographic and Health Survey (DHS) data (2011, 2016, and 2019¹) to investigate how multidimensional poverty changes over time across different subpopulations. The findings of this study offer fresh perspectives on the intricate relationship between household demographic characteristics and poverty dynamics, and how these vary across different regions and living locations, which is necessary for policymakers at both the federal and regional levels.

This study adds three fresh insights to multidimensional poverty research in Ethiopia. First, it develops an MPI at the national, regional, rural vs. urban dichotomy, and gender of headship using the Alkire and Foster (AF) technique (OPHI, 2022), using non-monetary characteristics such as education, health, and living standards. Second, this study used panel data from the 2011, 2016, and 2019 waves of the Ethiopian Demographic and Health Surveys (EDHS) collected from the World Bank and the Ethiopian Central Statistical Authority. Alkire and Santos (2014) discovered that the use of DHS databases is more reliable than any other datasets. Finally, this study provides an analysis of MPI disaggregated by regional state, urban vs. rural dichotomy, and household gender. Such a disaggregated data analysis has practical implications for initiatives aimed at reducing multidimensional poverty based on geography and demographic heterogeneity.

The remainder of this paper is organized as follows. Section 2 describes the data and methods used in the study, including data sources and statistical descriptions, MPI construction, estimation procedures, and descriptive details of the important variables. Section 3 discusses multidimensional poverty estimation and empirical results. Section 4 contains concluding remarks and policy implications for federal and regional governments.

¹ By the time this study is conducted, the most recent DHS database publically available is 2019.

2. Research Methodology

2.1 Analytical Model

To quantify multidimensional poverty, we use the international Multidimensional Poverty Index (MPI), a globally comparable measure of multidimensional poverty in over 100 developing nations (OPHI, 2022). The MPI aims to further Amartya Sen's capability approach, which has pushed for more comprehensive conceptualizations and measures of poverty as deprivation of capability (Sen, 1984, 2000). Several studies empirically justify this concept, noting that the level and change in per capita income or monetary poverty do not always reflect the levels of poverty (Alkire & Santos, 2014; Bersisa & Heshmati, 2021; Brück & Workneh Kebede, 2021; EEA, 2021; Kuhumba, 2012; OPHI & UNDP, 2021; Seff & Jolliffe, 2016; UNDP, 2019b).

Alkire and Santos (2014) discovered that the use of DHS databases is more reliable than any other datasets. MPI's final measure is sensitive to the amount of deprivation among the poor and captures the combined distribution of deprivations, which is a key strength. Furthermore, because the metric is direct, comparisons do not need to be adjusted for price disparities between rural and urban locations or for inflation (Alkire *et al.*, 2022; Alkire & Foster, 2011).

Alkire and Foster's (2011) MPI assessment framework involves four interrelated steps: 1) identification of indicators, 2) assigning values for each dimension (cut-offs), 3) identification of the poor, and 4) measuring multidimensional poverty. Accordingly, we started by choosing the indicators and their cut-off points (Table1). To construct household deprivations, we also incorporated three dimensions of well-being — education, health, and living standards—in accordance with the OPHI methodology, with each dimension weighted to represent one-third of the index (UNDP and OPHI, 2019). Within a given dimension, the individual indicators are equally weighted. The only major difference between the approach followed in this study and the OPHI indices is found in deprivation related to asset ownership. In the OPHI methodology, the asset ownership dimension accounts for deprivations in a car or truck, and does not own more than one of the following small assets: radio, television, telephone, computer, animal cart, bicycle, motorbike, or refrigerator. In contrast, the asset ownership indices in this study account for deprivation in more than two of the following assets: radio, mobile telephone, and animal-drawn cart, land usable for agriculture, livestock, and any form of savings account. This modification of asset ownership deprivation indices is made because MPI allows contextualization of indicators and their cut-offs to specific study areas (Admasu *et al.*, 2021; Alkire *et al.*, 2022; Alkire & Foster, 2011; Gallardo, 2022; Oxford University, 2019).

Table 1 MPI Dimensions, Indicators, and Deprivation Cutoffs

Domains	Indicators	Weights	Deprived if...
Health	Child Mortality	0.17	Any child has died in the family since the last five years (1=yes, 0= otherwise)
	Child nutrition	0.17	Household has at least one child underweight or stunted (1=yes, 0= otherwise)
Education	Child School Attendance	0.17	Any school-aged (child aged 7-15 years is not in school) (1=yes, 0= otherwise)
	Years of Schooling	0.17	No household member has completed six years of schooling (1=yes, 0= otherwise)
Living standards	Electricity	0.06	The household has no electricity (1=yes. 0= otherwise)
	Safe water	0.06	The household does not have access to safe drinking water (1=yes, 0= otherwise)
	Improved Sanitation	0.06	Household has no improved sanitation with WHO Standards (1=yes 0= otherwise)
	Standard Housing	0.06	Household has roof, floor & walls that it is of low quality (1=yes, 0= otherwise)
	Improved Cooking	0.06	The household cooks with dung & wood (1=yes, 0= otherwise)
	Assess ownership	0.06	The household does not own more than two among: radio, mobile telephone, animal-drawn cart, land usable for agriculture, livestock and bank account (1=yes, 0= otherwise)

Source: UNDP & OPHI. (2019). *How to Build a National Multidimensional Poverty Index (MPI): Using the MPI to inform the SDGs*, p150.

The weight of each dimension and indicator is the second step in assessing MPI (UNDP and OPHI, 2019). The values assigned to the indicators and dimensions within MPI are referred to as weights. Weights and cut-offs are crucial in determining the relative value of each deprivation in the final measure (UNDP and OPHI, 2019). To mathematically express the notion of cut-offs and weights, let $\mathbf{Y}$ be a matrix whose entry Y_{ij} denotes the level of indicator j for individual i . Then, it follows for an indicator j and individual i that deprivation occurs when y_{ij} falls strictly below the respective cutoff (OPHI, 2022):

$$y_{ji} < z_j \dots \dots \dots (1)$$

where z_j denotes the deprivation cut-off of the j indicators (Alkire *et al.*, 2022). In this case, all of our indicators are identified as a dummy in which a score of 1 is given if deprived and 0 otherwise.

Different weights (w_j) can be assigned to different indicators depending on their policy relevance (Alkire *et al.*, 2022). The weights are represented in a $1 \times I$ vector, where $w = (w_1, w_2, w_3 \dots \dots w_I)$ with $0 < w_j < 1$ and $\sum_{j=1}^I w_j = 1$. Because we assume that each indicator is viewed as having equal importance, equal weights are assigned to the indicators. This implies that all weights are equal to 1.

Next, poverty was identified in all the dimensions. The household deprivation score for each dimension was calculated by adding the weighted deprivation score for each indicator. After determining the deprivation threshold for each dimension, the poverty status of individual i in a single dimension was obtained according to whether the value of individual i in the dimension was below the deprivation threshold. This means that a household is given a deprivation score of 1 for each indicator if deprived, and 0 otherwise (Alkire *et al.*, 2021, 2022; Alkire & Foster, 2011; Firdausy & Budisetyowati, 2022; Gallardo, 2022).

Next, we identified a multidimensional deprivation score. The sum of the weighted deprivation scores (c_j) of each household was used to identify the poor. The weighted deprivation score is calculated as follows:

$$C_j = w_1 J_1 + w_2 J_2 + w_3 J_3 + w_j J_j \dots \dots \dots (3)$$

Where 'J' refers to the values obtained from each indicator of all dimensions. Finally, the row sum of c_i represents the number of weighted deprivations that individual i faces. Following Alkire and Foster (2011), a household is given a deprivation status score of 1 if deprived in any indicator and a status score of 0 otherwise. To discriminate between poor and non-poor persons, different cut-off methods may be used: *union* approach, *intersection* approach, and *intermediate (dual-cut-off)* approach (Bersisa & Heshmati, 2021; UNDP & OPHI, 2019).

According to the intersection approach, only those persons who are deficient in all indicators at the same time are classified as poor and receive scores of one and zero otherwise. A limitation of this approach is that it results in low incidence rates because it primarily captures only the poorest of the poor. As the number of indicators increases, the chances of being deprived of in all of them at the same time become increasingly remote and hence more likely to underreport the prevalence of multidimensional poverty (UNDP & OPHI, 2019). However, according to the union approach, people are classified as multidimensionally poor if they endure at least one measurable deprivation. The limitation of this approach is that it identifies a larger number of people as poor and, hence, is more likely to overestimate the prevalence of multidimensional poverty (UNDP & OPHI, 2019).

The intermediate (dual-cutoff) approach employs a realistic cutoff point. According to this approach, an increase in a non-poor person's accomplishment level y_{ij} has no effect on the value of the dual cut-off. It is 'deprivation centered' in the sense that a rise in any non-deprived achievement $y_{ij} \geq z_j$ has no effect on the value of the identification function. In other words, a person's poverty status is unaffected by changes in their non-deprived achievement levels (Bersisa & Heshmati, 2021; UNDP & OPHI, 2019). It is also worth noting that in determining who is poor or not poor, the unidimensional poverty evaluation permits a higher degree of non-deprived achievement to compensate for other dimensional deprivations, which is not the case in MPI using the dual-cutoff approach (UNDP & OPHI, 2019). Thus, we used the dual-cut-off approach in this study. Consistent with (OPHI and UNDP (2021), UNDP and OPHI (2019), and UNDP (2021), any household and everyone in it is termed multidimensionality poor if the deprivation score is 0.3333 or greater.

To identify who is poor, the next step is to measure multidimensional poverty. Following Alkire and Foster (2011), we use the simplest multidimensional headcount ratio, defined as

$$H = \frac{\sum_{i=1}^N pk(y_j, Z)}{N} = q / N \dots \dots \dots (4)$$

where q is the number of poor individuals identified with the identification function defined in Equation (3), N is the population size, and H is the percentage of multidimensionally poor people (Alkire *et al.*, 2022; Alkire & Foster, 2011; Dirksen & Alkire, 2021; Hu *et al.*, 2022; Nguyen *et al.*, 2021).

Despite its calculation simplicity, however, the ‘H’ lacks policy relevance, as it fails to increase when a poor person becomes deprived of a new dimension (Alkire & Foster, 2011). H remains unchanged regardless of the number of new dimensions that poor people might be deprived of. Thus, an index that increases with the number of deprivations reported by poor people is required. Let us consider ‘A’ as the ratio of the number of deprivations faced by poor individuals to the number of poor individuals (Alkire *et al.*, 2022; Alkire & Foster, 2011).

$$A = \sum_{i=1}^n \frac{C_j(K)}{\left(\sum_{i=1}^n C_j(K) d \right)} \dots \dots \dots (5)$$

where n represents the number of individuals and d represents the overall dimension of measuring poverty. Here, the numerator shows the number of deprivations faced by individual people, whereas the denominator shows the number of poor people. Finally, the multidimensional poverty index is calculated as the product of the incidence (H) and breadth (A) specified in Equations 4 and 5, respectively.

$$MPI = M_o = H * A = \sum_{i=1}^n \frac{C_j(k)}{(nd)} \dots \dots \dots (6)$$

The multidimensional poverty index (Mo) can be computed using binary, ordinal, or real-valued data, and it has desirable characteristics that increase with the number of deprivations reported by the poor people (Alkire *et al.*, 2022). In this research manuscript, most of our data were binary. Finally, we compared the estimated multidimensional poverty, its prevalence, and intensity changes over time using both OPHI and SLF dimensional indices in the following sub-sections.

2.2 Data sources and collection techniques

Alkire and Santos (2014) discovered that the use of DHS databases is more reliable than any other datasets. Accordingly, panel data from the 2011, 2016, and 2019 waves of the Ethiopian Demographic and Health Surveys (EDHS) were collected from the World Bank and the Ethiopian Central Statistical Authority. The DHS is a nationwide social follow-up survey conducted by the Ethiopian Central Statistical Authority with financial aid from the

World Bank, United Nations Children’s Fund (UNICEF), and United States Agency for International Development (USAID).

Although the first DHS was conducted in 2000 with the second round in 2005, these datasets were not considered for this research because there are important indicators missed for MPI determination. Thus, we used the three most recent waves of datasets: the 2011, 2016, and 2019 DHS datasets. The 2011 DHS was conducted from September 2010 to January 2011, while the 2016 DHS was conducted from January 18, 2016, to June 27, 2016. The latest 2019 DHS was conducted from March 21, 2019, to June 28, 2019. After cleaning and combining the three survey rounds, this study is based on the data analysis of 75,665 sampled respondents from the 2011 round, 73,901 samples from the 2016 rounds, and 40,133 respondents from the most recent 2019 DHS survey round. Because the sample is not self-weighted at the national level, all data in this report are weighted

The shortcoming of all DHS dataset rounds is that the respondents were new throughout each survey round, as each survey was not meant as a follow-up to earlier surveys. As a result, the DHS hardly allowed us to statistically determine whether multidimensional poverty is more transient or chronic at the national and subpopulation levels.

3. Results and Discussions

3.1 Multidimensional Poverty Trends

Our results show that multidimensional poverty continued to decline from a peak of nearly 76 percent in 2011 to 67 percent and 62.7 percent in 2016 and 2019, respectively. Table 2 presents the multidimensional poverty status over time.

Table 2. Multidimensional poverty status over time

Multi-dimensional poverty measures	Survey years (numbers in brackets are percentages)			
	2011	2016	2019	Total
Non- multidimensionally poor	17,114 (24.1)	22,693 (32.95)	14,716 (37.3)	54,523 (30.40)
Multidimensionally poor	53,906 (75.9)	46,181 (67.05)	24,740 (62.7)	124,827 (69.60)
Total	71,020 (100)	68,874 (100)	39,456 (100)	179,350 (100)
Population share	0.393	0.392	0.215	100
Headcount ratio (H)	0.809	0.731	0.647	0.744 ²
Intensity of Poverty (A)	0.585	0.561	0.53	0.565
Adjusted headcount (H*A = MPI=M0)	0.473	0.41	0.343	0.42
Relative contribution to incidence (H)	0.428	0.385	0.187	100
Relative contribution to adjusted headcount (M0)	0.443	0.382	0.175	100

This result is also in line with previous studies that used various datasets and were conducted by Bersisa and Heshmati (2021), Brück and Workneh (2021), Dercon and Gilligan (2008),

² The values of H, A & Mo in the last column shows the overall value of the indices in the population, which is given by the weighted sum of the indices in the three subgroups with weights given by the related population. Example, the last column of head count ratio (H) which is 0.744 is calculated as $[(0.393*0.809)+(0.392*0.731)+(0.647*0.215=0.744)]$.

and Seff and Jolliffe (2016). It is disturbing that a sizable portion of the population is imprisoned in multidimensional poverty.

MPI is a welfare measure that accounts for both the severity and prevalence of poverty. The percentage of people who are multidimensionally poor is shown by the poverty prevalence, which is denoted by (H). From its peak of approximately 81 percent in 2011 to 73.1 percent in 2016 and finally to 64.7 percent in the most recent DHS dataset, this percentage has been falling quickly. This suggests a weighted average of 74.4 percent over the study period. Although the trend indicates that the prevalence of poverty has been decreasing over time, a sizable portion of the population still lives in multidimensional poverty. Other studies (Bersisa & Heshmati, 2021; Brück & Workneh, 2021; Dercon & Gilligan, 2008; OPHI & UNDP, 2021; Seff & Jolliffe, 2016) also support this conclusion. The fact that each period's relative contributions to the incidence and severity of poverty also declined sharply confirms the trend of declining poverty.

The average multidimensional poor person who lacks weighted indicators is depicted by the intensity of poverty (A) (OPHI, 2022). It shows the percentage of weighted deprivations that the impoverished in a community endure relative to the total number of deprivations that the community may encounter. Our results show that the severity of poverty is declining but at a very slow rate compared to its prevalence. The average multidimensionally poor person was deficient in 58.5 percent of the weighted indicators in 2011; this percentage decreased only slightly to 56.1 percent in 2016 and 53 percent in 2019, indicating a weighted average of 56.5 percent.

A weighted average of 42% is implied by the MPI value, which is the product of two measures (the prevalence and intensity of multidimensional poverty), and decreased from 47.3 percent in 2011 to 41 percent in 2016 and 34.3 percent in 2019. The multidimensional poverty index (MPI) is the percentage of the population that has been adjusted for the degree of deprivation experienced. The United Nations Development Programme and Oxford Poverty and Human Development report, which indicate 49.1%, 43.6 percent, and 36.7 percent in 2011, 2016, and 2019, respectively, are comparable to this downward trend (OPHI and UNDP, 2021). The discrepancy in the metrics used to calculate asset ownership may be the primary cause of this moderate difference.

Table 2 shows that the relative contributions of each period to MPI were 44.3 percent, 38.2 percent, and 17.5 percent, respectively, despite the fact that the weighted shares of the population in the datasets of 2011, 2016, and 2019 were 39.3 percent, 39.2 percent, and 21.5 percent, respectively. This unequivocally demonstrates that 2011 contributed five percentage points more than the population share of that year. In comparison, 2019's contribution fell short of its population share by almost four percentage points. This is compelling evidence that more people leave poverty than enter it, confirming the amazing progress made in the multifaceted fight against poverty.

3.2 Multidimensional Poverty Variations by location of residence

MPI is a versatile approach that can be tailored to various contexts and disaggregated into subgroups. A disaggregated MPI analysis can provide the data needed to plan and monitor

a coordinated actionable strategy, identify the poorest, and ensure that no one falls behind (UNDP and OPHI, 2019). It is helpful for governments to use disaggregated and indicator-specific information when designing policy interventions to reduce poverty and leave no one behind. Such data demonstrate distinctions between areas, subgroups, and dimensions in which each group is deprived. It also shows trends in the deprivation of each dimension and indicator. Because it identifies the most deprived areas and poorest groups in a country, together with the deprivation trends in each specific indicator, the information provided by this analysis can improve targeting (Admasu *et al.*, 2021; UNDP & OPHI, 2019; UNICEF, 2021). Accordingly, Table 3 summarizes the poverty prevalence, severity, and contributions of each dimension and indicator for rural and urban areas.

Table 3. Trends of Multidimensional poverty by location of residence

Multi-dimensional poverty measures	Urban			Rural		
	2011	2016	2019	2011	2016	2019
Population share	0.180	0.154	0.271	0.82	0.846	0.729
Headcount ratio (H)	0.372	0.28	0.395	0.905	0.813	0.741
Intensity of poverty (A)	0.460	0.436	0.471	0.596	0.568	0.541
Adjusted headcount (H*A = MPI)	0.171	0.122	0.186	0.539	0.462	0.401
Relative contribution to incidence (H)	0.083	0.059	0.165	0.917	0.941	0.835
Relative contribution to MPI	0.065	0.046	0.147	0.935	0.954	0.853
Relative Contribution to MPI by dimensions and indicators						
Health	0.169	0.185	0.166	0.148	0.144	0.148
Child Mortality	0.029	0.034	0.02	0.025	0.023	0.02
Nutrition	0.139	0.151	0.145	0.123	0.122	0.128
Education	0.313	0.316	0.341	0.345	0.35	0.336
Child School Attendance	0.123	0.119	0.159	0.142	0.137	0.15
Years of Schooling	0.19	0.197	0.182	0.203	0.214	0.187
Living Standard	0.518	0.498	0.494	0.507	0.506	0.516
Electricity	0.04	0.027	0.043	0.091	0.093	0.093
Drinking Water	0.047	0.041	0.059	0.081	0.075	0.071
Improved sanitation	0.112	0.119	0.108	0.088	0.094	0.097
Standard housing	0.115	0.122	0.112	0.093	0.097	0.102
Cooking fuel	0.117	0.121	0.113	0.093	0.097	0.102
Asset ownership	0.087	0.069	0.059	0.061	0.05	0.051

As might be expected, most rural people are trapped in poverty more than urban residents during all survey rounds. In terms of the prevalence and severity of poverty, adjusted head count ratio, and relative contributions, poverty remains largely rural in Ethiopia. The relative contribution of poverty to the MPI was significantly less than the share of the urban population in each survey period. In contrast, the relative contributions of rural people to MPI have been significantly above the share of rural people in each period, implying that poverty is mainly rural dominated in Ethiopia. This finding is consistent with previous studies (Bersisa & Heshmati, 2021; Bizuneh, 2015; Brück & Workneh Kebede, 2021; Dercon & Gilligan, 2008; EEA, 2021; Seff & Jolliffe, 2016).

Although there has been a declining trend in poverty in Ethiopia, it is not uniform across rural and urban areas. Our results show that although rural poverty has been consistently declining in terms of prevalence, intensity, and MPI throughout the study period, there is a

tendency to rise in urban areas during the last survey period. In rural areas, MPI declined from its peak of nearly 54 percent during 2011 to 46.2 percent during 2016, and sharply declined to nearly 40 percent during 2019, showing a nearly 14 percentage point improvement in the period. In contrast, although the MPI declined from its peak of nearly 17 during 2011 to 12.2 percent during 2016, it climbed to nearly 19 percent during the last survey period of 2019, showing two percentage points of worsening poverty in urban areas. This clearly shows that poverty shifted from rural to urban areas in 2019. This could be partly because of the influx of graduate and non-graduate youth job seekers to urban areas and partly because urban areas in Ethiopia were serving as the center of the public uprising against the dictator regime from 2014 to 2018.

We find consistent results across rural and urban areas in terms of the contribution of each factor to multidimensional poverty. Livings standard dimension and its indicators contributed nearly 50 percent to MPI in both rural and urban areas in each period, followed by education and health dimensions. In terms of indicators, years of schooling remained the largest contributor to MPI over time for both urban and rural areas. However, there seem to be vivid variations across urban and rural areas in terms of the second-largest contributor to MPI. While child school attendance remains the second largest contributor to MPI in rural areas, child nutrition is the second most important indicator in urban areas. Overall, however, years of schooling, child nutrition, and school attendance were the three most important contributors to MPI in all cases. Our results also showed that deprivation in the health dimension and its contribution to MPI was more severe in urban areas than in rural areas. This could be partly due to the substantial contributions of health extension agents in several aspects of utilization of maternal health services in rural areas (Medhanyie *et al.*, 2012) and partly because of better access to diverse food groups in rural areas (Admassu & Beneberu, 2019) and, hence, better nutritional status.

In contrast to Seff and Jolliffe (2016), we find fascinatingly consistent results regarding poverty dynamics using each MPI indicator. Some MPI indicators that are found to be transient in the case of urban areas also remain transient in rural areas and vice versa. For instance, child nutrition and three living standard indicators (access to safe drinking water, improved sanitation, and standard housing) were found to be chronic, with most households in rural and urban areas deprived of these indicators during the study period. Throughout all three rounds, most households in both rural and urban areas were consistently deprived of safe drinking water, improved sanitation, and housing. As Seff and Jolliffe (2016) rightly argued, a household is less likely to change its housing quality, sanitation, cooking, and access to safe water over a short period of time than its education and health status. This means that indicators such as housing, improved sanitation, access to improved cooking, and access to safe drinking water are more likely structural poverty and, hence, chronic in nature. However, in terms of their contributions to MPI, access to safe drinking water, improved sanitation, and standard housing are significantly higher in urban areas than in rural areas, implying the relative importance of these indicators to urban people than rural areas.

3.3 Multidimensional Poverty Variations by Sex of Households' Headship

The following table summarizes poverty prevalence, severity, and the contributions of each dimension and indicator by household sex. Contrary to expectations, most male-headed households are trapped in poverty more than female-headed households. In terms of the prevalence and severity of poverty, adjusted head count ratio, and relative contributions, male-headed households are more likely to be trapped in multidimensional poverty than female-headed households in Ethiopia. As can be seen from table 4, the relative contribution of poverty to MPI was significantly less than that of female-headed households in each survey period. In contrast, the relative contributions of male-headed households to MPI were significantly above the share of male-headed households in each period, implying that male-headed households are multidimensionality poorer than female-headed households. This finding is also consistent with previous studies (Bersisa & Heshmati, 2021).

Table 4. Trends of Multidimensional poverty by sex of household head

Multi-dimensional poverty measures	Male			Female		
	2011	2016	2019	2011	2016	2019
Population share	0.804	0.809	0.825	0.196	0.191	0.175
Headcount ratio (H)	0.824	0.742	0.652	0.748	0.684	0.624
Intensity of Poverty (A)	0.590	0.565	0.532	0.559	0.538	0.516
Adjusted headcount ($H \cdot A = MPI$)	0.486	0.419	0.347	0.418	0.368	0.322
Relative contribution to incidence (H)	0.819	0.821	0.831	0.181	0.179	0.169
Relative contribution to MPI	0.826	0.828	0.835	0.174	0.172	0.165
Relative Contribution of subgroups to MPI						
Health	0.158	0.153	0.159	0.111	0.110	0.108
Child Mortality	0.027	0.024	0.021	0.018	0.017	0.017
Nutrition	0.130	0.129	0.138	0.093	0.093	0.091
Education	0.341	0.346	0.333	0.352	0.361	0.360
Child School Attendance	0.143	0.137	0.151	0.131	0.129	0.151
Years of Schooling	0.198	0.209	0.181	0.221	0.232	0.209
Living standards	0.501	0.500	0.509	0.537	0.529	0.532
Electricity	0.087	0.090	0.087	0.087	0.088	0.083
Drinking Water	0.079	0.073	0.069	0.080	0.071	0.071
Improved sanitation	0.088	0.095	0.098	0.095	0.099	0.101
Standard housing	0.094	0.098	0.103	0.098	0.102	0.104
Cooking fuel	0.094	0.097	0.104	0.099	0.101	0.106
Asset ownership	0.059	0.047	0.049	0.078	0.068	0.068

The declining trend in poverty over time also varies according to the gender of the headship. In most cases, there seems to be a more rapid decline in male-headed household multidimensional poverty than in female-headed households. For instance, poverty prevalence, intensity of poverty, and MPI declined for male-headed households by 17 percent, 6%, and 14%, respectively, during the three rounds of the survey. In contrast, these values were 12 percent, 4%, and 10%, respectively, in the case of female-headed households during the same period. This clearly shows that although male-headed households are relatively poorer than their female-headed counterparts, the former are more likely to escape

poverty than the latter. The implication is that female-headed households could remain in multidimensional poverty more than male-headed households in the long run.

Despite significant variation in terms of each dimension and indicators' contribution to MPI by sex of headship, we find consistent results across male-headed and female-headed households in terms of contributing factors to multidimensional poverty. Livings standard dimension and its indicators contributed nearly 50 percent to MPI in the case of male-headed households each year and 53 percent for female-headed households during the same periods. Similarly, the contributions of the education dimensions and their indicators are more pronounced for female-headed households than for male-headed households. By contrast, the contribution of the health dimension and its indicators to the MPI of male-headed households is more significant than that of female-headed households. This implies that female-headed households are more likely to be deprived of long-term assets and are relatively better off in terms of health issues, which are short-term in nature. This further confirms that female-headed households are more likely to be trapped in chronic poverty than male-headed households are

In terms of the indicators, years of schooling and school attendance remained the two largest contributors to MPI over time for both male-headed and female-headed households, followed by child nutrition indicators. However, there seemed to be vivid variations across the two groups in terms of the size of the contributions of the indicator to MPI over time. For instance, while years of schooling contributed nearly 20 percent during the first survey rounds, its contribution to MPI declined to nearly 18 percent during the latest survey round in 2019 for male-headed households. In contrast, the contribution of this indicator to the MPI of female-headed households was nearly 22 percent in 2011, 23 percent in 2016, and dropped slightly to nearly 21 percent in 2019. Conversely, school attendance and child nutrition indicators largely contribute to MPI in the case of male-headed households than for female-headed households each year.

3.4 Multidimensional Poverty Variations by regional states

On average, Afar and Somali regional states are identified with the highest multidimensional poverty index (MPI) score (see figure 1 for details).

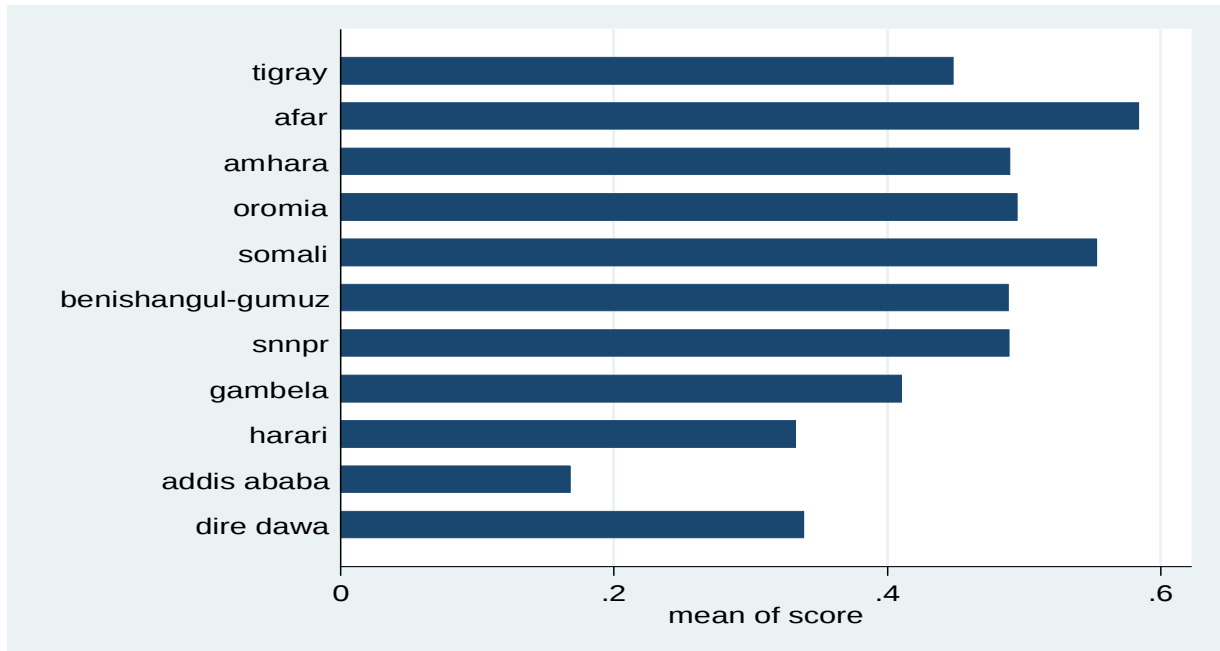


Figure 1. MPI score variation by Ethiopian regional states

Compared to others, the Addis Ababa city administration has a relatively lower MPI score and hence better off in terms of MPI poverty. However, this graph is less informative in identifying the region that is better off in which the MPI dimension is and in which particular year. In essence, the absence of disaggregating the causes of poverty by dimension and indicator might obscure a complete understanding of the nature and causes of poverty. Thus, there is a need to report more detailed disaggregated data analysis by dimension, indicator, and survey period. Table 5 summarizes poverty prevalence, severity, and the contributions of each to MPI by regional state over time.

Table 5. Poverty status by regional states over time

Year	Multi-dimensional poverty measures	Tigray	Afar	Amhara	Oromia	Somali	Benishangul Gulgunuz	SNNPR ³	Gambela	Harari	Addia Ababa	Dire Dawa
2011	Population share	0.066	0.009	0.248	0.389	0.022	0.010	0.209	0.004	0.003	0.037	0.004

³ Note that as all DHS datasets were collected when there were only nine (9) regional states and two self-administered cities in Ethiopia, there is no data disaggregated across the recently established four regional states (Sidama regional; South West Regional states, Central Ethiopia Regional State and South Ethiopia Regional state. Establishment of these four regional states are resulted in dissolving the former Southern Nations, Nationalities, and Peoples' Regional (SNNPR) state.

2019	2016												
	Headcount ratio (H)	Population share	Relative contribution to MPI	Relative contribution to incidence (H)	Adjusted headcount (H*A = MPI=M0)	Intensity of Poverty (A)	Headcount ratio (H)	Population share	Relative contribution to MPI	Relative contribution to incidence (H)	Adjusted headcount (H*A = MPI=M0)	Intensity of Poverty (A)	Headcount ratio (H)
	0.535	0.062	0.051	0.051	0.282	0.527	0.535	0.062	0.062	0.063	0.443	0.578	0.767
	0.845	0.010	0.014	0.013	0.481	0.569	0.845	0.010	0.010	0.009	0.558	0.652	0.856
	0.655	0.204	0.200	0.206	0.335	0.511	0.655	0.204	0.250	0.254	0.476	0.577	0.825
	0.663	0.404	0.419	0.414	0.355	0.535	0.663	0.404	0.406	0.403	0.494	0.589	0.839
	0.889	0.062	0.094	0.085	0.518	0.583	0.889	0.062	0.025	0.023	0.540	0.612	0.882
	0.615	0.011	0.010	0.010	0.318	0.517	0.615	0.011	0.011	0.011	0.497	0.584	0.851
	0.657	0.202	0.201	0.205	0.340	0.518	0.657	0.202	0.222	0.220	0.503	0.590	0.853
	0.515	0.004	0.003	0.003	0.238	0.462	0.515	0.004	0.003	0.003	0.354	0.514	0.689
	0.467	0.003	0.002	0.002	0.239	0.512	0.467	0.003	0.001	0.002	0.264	0.541	0.488
	0.127	0.032	0.005	0.006	0.050	0.394	0.127	0.032	0.007	0.010	0.088	0.419	0.210
	0.525	0.335	0.173	0.003	0.003	0.176	0.525	0.335	0.002	0.002	0.286	0.574	0.498

Relative contribution to MPI	Relative contribution to incidence (H)	Adjusted headcount (H*A = MPI=M0)	Intensity of Poverty (A)
0.051	0.051	0.282	0.527
0.014	0.013	0.481	0.569
0.200	0.206	0.335	0.511
0.419	0.414	0.355	0.535
0.094	0.085	0.518	0.583
0.010	0.010	0.318	0.517
0.201	0.205	0.340	0.518
0.003	0.003	0.238	0.462
0.002	0.002	0.239	0.512
0.005	0.006	0.050	0.394
0.173	0.003	0.003	0.176

We find that the Somali regional state ranked first in terms of poverty prevalence, as indicated by (H), during each of the survey periods, while Addis Ababa ranked the least. poverty prevalence (percentage of people who are multidimensional poor) remains at nearly 88 percent throughout all the survey periods in Somali, while this percentage was 21 percent in Addis Ababa during 2011 and rapidly declined to just 12.7 percent during the last survey period.

In terms of the intensity of poverty (A), the SNNPR regional state ranked first in 2011, with Addis Ababa being the last. The intensity of poverty (A) shows the average multidimensionality poor person deprived of weighted indicators. Thus, in the SNNPR regional state, nearly 56 percent of multidimensionality poor people were deprived of weighted indicators during 2011, while this percentage was nearly 42 percent in Addis Ababa during the same year. From 2016 onwards, the Somali region remained the poorest in terms of poverty severity, with the Dire Dawa city administration being the least affected. This shows that the poorest of the poor (destitute) are mainly in the Somali regional state.

The Oromia regional state ranked first throughout the survey period in terms of its relative contribution to MPI. Throughout this period, the relative poverty contribution of the Oromia regional state exceeds its weighted share of the population. In 2011, the population share of the Oromia regional state was nearly 39%, while its relative contribution to the prevalence of MPI was 40 percent. Similarly, while the population share of this region was 40 percent, its relative contribution to the prevalence and MPI was 41 percent and 42 percent during the last two survey periods, respectively.

The contributions of each dimension and its indicators to the MPI vary across regional states over time. For instance, the Afar regional state ranked first in terms of the largest contribution of health dimensions and two of its indicators (child mortality and child nutrition) to MPI, while the Somali and Gambela regional states were the first in terms of education and living standards contributions to their MPI during the same period, respectively. This implies that while the health dimension was a serious issue for Afar,

education and living standard indicators were critical issues for Somali and Gambela regional states during 2011(please see the annex).

However, during 2016, the Benishangul-gumuz and Harari regional states ranked first in terms of the contributions of health and education dimensions to their MPI, respectively, confirming that deprivations in health and education dimensions are basically transient poverty in nature. In contrast, the Gambela regional state remains the first in terms of the contribution of living standards to its MPI, further confirming that deprivation in the living standard dimension and its indicators imply chronic poverty. Thus, while MPI in regions such as Afar, Benishangul-gumuz, and Harari are transient in nature, people in Gambela are mainly trapped in chronic poverty.

3.5 Socioeconomic Characteristics of Households by their Poverty Status

A thorough examination of the socioeconomic factors of MPI-poor and non-poor households could assist local governments in developing context-specific intervention programs. Our close examination of their socioeconomic data shows that multidimensionally poor people are illiterate, relatively younger, and have a large family size. Table 6 shows the t-test of the socioeconomic characteristics of people across their poverty status based on the 2019 DHS dataset.

Table 6. Socioeconomic characteristics of people across their poverty status

Indicators	MPI Status		t-test	
	MPI poor	Non- poor	t	p> t
Can read & write	0.370	0.756	-93.69	0.000
Age of household head	43.81	45.66	-14.09	0.000
Household size (number)	5.990	5.141	39.19	0.000
Household has at least one member with 6 years of education	0.271	0.989	-209.36	0.000
Household has all school age children up to class 8 in school	0.528	0.968	-113.15	0.000
Household has no child mortality in the last 5 years	0.900	0.994	-40.88	0.000
Household has no child underweight or stunted	0.548	0.982	-112.90	0.000
Household has improved sanitation with WHO Standards	0.063	0.258	-73.78	0.000
Household has drinking water with WHO standards	0.208	0.728	-142.54	0.000
Household has roof, floor & walls that it is not low quality	0.014	0.284	-125.80	0.000
Household has cooking fuel according to WHO standards	0.008	0.220	-111.76	0.000
Household has saving account	0.043	0.317	-108.04	0.000
Household has radio	0.328	0.728	-98.26	0.000
Household has mobile telephone	0.151	0.745	-178.95	0.000
Household owns livestock, herds or farm animals	0.872	0.427	133.64	0.000
Household owns land usable for agriculture	0.781	0.353	113.54	0.000
Household has animal-drawn cart	0.011	0.013	-2.12	0.034
Household has electricity	0.111	0.752	-210.61	0.000
Household highest year of education completed	2.807	3.792	-34.64	0.000
Household has more than 2 small assets including animal cart	0.302	0.562	-63.16	0.000

Although not reported here (for brevity), the socioeconomic differences between the multidimensionally poor and non-poor people are similar across each survey year. Each year, multidimensionally poor people have statistically significant socioeconomic differences from non-poor people. The multidimensionally poor have fewer child school attendances, a large percentage of child school dropouts, more children underweight or stunted, and less access to sanitation and safe drinking water. Unexpectedly, multidimensionally poor people were also identified as having livestock herds and land usable for agriculture. This could be because having livestock herds does not necessarily mean that such assets are productively

used for poverty reduction, as the herds are less likely to get the required quality and quantity of feed and hence less productive. Given the prevalence of severe consecutive drought years affecting pastoralist areas during the last ten years; this finding could be consistent with the reality on the ground, as both livestock and crops are hard-hit by drought and hence less likely to be used for poverty reduction purposes. This finding is consistent with that of Mekuyie *et al.* (2018), who argued that climate change and harsh weather are recognized as serious threats to pastoral farming practices in Ethiopia.

Similarly, having land for agriculture does not necessarily mean that the land is being used productively. Given the low input-low output trap of Ethiopian agriculture, coupled with consecutive drought years affecting the agricultural sector (UNDP, 2022a, 2022b), having land for agriculture does not necessarily mean more productivity. This could also explain why gross domestic product (GDP) originating from agriculture is disproportionately declining, while the share of population in the sector remains above 65 percent (UNDP, 2022a). Over ten years, the average GDP contributions of the agriculture, industry, and service sectors were 38.8 percent, 22.4%, and 39.1%, respectively, while employment in each sector was 72.5 percent, 7.5%, and 20%, respectively (FDRE 2021). This finding also suggests that rural people are more likely to be deprived of important assets, and hence, are more likely to be multidimensionally poor. Table 7 shows the comparisons of socioeconomic characteristics by location of residence using the 2019 DHS dataset.

Table 7. Comparison of socioeconomic characteristics by location of residence

Indicators	Residence area		t-test	
	Rural	Urban	t	p> t
Can read & write	0.42	0.69	-106.53	0.000
Age of household head	44.4	43.8	7.81	0.000
Household size (number)	6.01	5.14	67.22	0.000
Household has at least one member with 6 years of education	0.40	0.84	-178.74	0.000
Household has all school age children up to class 8 in school	0.61	0.87	-110.43	0.000
Household had no child mortality in the last 5 years	0.92	0.97	-32.28	0.000
Household has no child underweight or stunted	0.63	0.86	-93.44	0.000
Household has improved sanitation with WHO Standards	0.06	0.27	-136.44	0.000
Household has drinking water with WHO standards	0.26	0.84	-258.40	0.000
Household has roof, floor & walls that it is not low quality	0.02	0.35	-236.51	0.000
Household has cooking fuel according to WHO standards	0.01	0.30	-230.09	0.000
Household has saving account	0.13	0.53	-196.39	0.000
Household has a radio	0.27	0.55	-113.46	0.000
Household has mobile telephone	0.39	0.85	-194.07	0.000
Household owns livestock, herds or farm animals	0.89	0.25	357.70	0.000
Household owns land usable for agriculture	0.80	0.16	310.58	0.000
Household has animal-drawn cart	0.02	0.02	0.83	0.404
Household has electricity	0.10	0.88	-493.84	0.000
Household highest year of education completed	3.51	4.78	-52.41	0.000
Household has more than 2 small assets including animal cart	0.45	0.46	-2.64	0.008

As expected, there was a statistically significant socioeconomic difference between urban and rural people. Although not reported here, the socioeconomic differences between rural and urban dwelling people were similar across each survey year. Each year, rural people have a low literacy rate, low school attendance, higher student school dropout ratio, less access to sanitation, safe drinking water, and financial services in terms of savings. This finding is also consistent with those of previous studies in Ethiopia (Bersisa & Heshmati, 2021; Bizuneh, 2015; Brück & Workneh Kebede, 2021; Dercon & Gilligan, 2008). As expected, rural people were identified as having livestock herds and land for agriculture, which are less likely to be effective in poverty reduction, as explained above. This, in turn, suggests that rural people are more likely to be multidimensionally poorer than urban people. Table 8 presents a multidimensional poverty comparison across rural and urban areas.

Table 8. Multidimensional poverty status across urban and rural areas⁴

Multidimensional poverty status (%)	type of place of residence		
	Urban	Rural	Total
Non multidimensionally poor	48	52	100
Multidimensionally poor	8.9	91.1	100
Total	18.9	81.1	100
Pearson chi2(1) = 4.8e+04 Pr = 0.000			

As expected, multidimensional poverty status varied significantly across rural and urban areas. While only nine percent of multidimensionally poor people live in urban areas, about 91 percent of multidimensional poor people live in rural areas, and this difference is statistically significant. This trend was similar across all survey years, although the details are not reported here for brevity. This finding is also consistent with those of prior studies (Bersisa & Heshmati, 2021; Brück & Workneh Kebede, 2021; Dercon & Gilligan, 2008; Seff & Jolliffe, 2016). Because rural households are extremely heterogeneous in terms of the sex of heads and hence their socioeconomic possession, it is always recommended to see gender-disaggregated poverty analysis. Table 9 shows the multidimensional poverty comparison across the sexes of household heads.

Table 9. Multidimensional poverty status across sex of household head

Multidimensional poverty status (%)	Sex of head of household		
	Male headed	Female headed	Total
Non multidimensionally poor	28.77	35.55	30.40
Multidimensionally poor	71.23	64.45	69.60
Total	100	100	100
Pearson chi2 (1) = 711.0676 Pr = 0.000			

⁴ Note that we have used importance weighting with all of chi-square tests within this paper. Importance weighting is required to obtain more valuable information even from fewer samples. It is especially useful in precarious situations where some of the categories have a small chance of being extremely good or bad. In these areas of special interest, we can increase the number of samples by a factor f , where f is the sampling weights. Then, in sample weighting, we assigned inverse weights $1/f$ to these sample points, resulting in the same probability distribution across all categories.

As expected, multidimensional poverty varies according to the gender of the household heads. Contrary to some studies (Brück & Workneh Kebede, 2021; Dercon & Gilligan, 2008; EEA, 2021; Seff & Jolliffe, 2016) male male-headed households are more likely to be multidimensionally poorer than female-headed households, and this difference is also statistically significant. While nearly 71.23 percent of male-headed households are multidimensionally poor, this figure is just 64.45 percent for female-headed households. Our findings also support those of Bersisa and Heshmati (2021), who found similar results using different datasets. The next question is why female-headed households are less likely to be multidimensionally poor than male-headed households are. This could be because of their unique socioeconomic status. Table 10 shows a comparison of socioeconomic characteristics by the sex of the headships.

Table 10. Comparison of socioeconomic characteristics by sex of headship

Indicators	Household head		t-test	
	Female	Men	t	p> t
Can read & write	0.505	0.480	9.60	0.000
Age of household head	43.70	44.50	-9.58	0.000
Household size	5.025	6.027	-76.61	0.000
Household has at least one member with 6 years of education	0.529	0.511	6.94	0.000
Household has all school age children up to class 8 in school	0.720	0.660	23.76	0.000
Household had no child mortality in the last 5 years	0.950	0.930	15.11	0.000
Household has no child underweight or stunted	0.770	0.662	42.73	0.000
Household has improved sanitation with WHO Standards	0.123	0.110	7.45	0.000
Household has drinking water with WHO standards	0.474	0.387	33.01	0.000
Household has roof, floor & walls that it is not low quality	0.139	0.091	29.64	0.000
Household has cooking fuel according to WHO standards	0.105	0.076	19.66	0.000
Household has saving account	0.236	0.236	-0.01	0.994
Household has radio	0.299	0.358	-23.28	0.000
Household has mobile telephone	0.510	0.504	2.28	0.023
Household owns livestock, herds or farm animals	0.590	0.771	-77.05	0.000
Household owns land usable for agriculture	0.483	0.686	-79.58	0.000
Household has animal-drawn cart	0.013	0.018	-7.92	0.000
Household has electricity	0.376	0.270	43.45	0.000
Household highest year of education completed	4.101	3.925	6.43	0.000
Household has more than 2 small assets including animal cart	0.339	0.490	-56.82	0.000

With the exception of access to financial institutions in terms of savings account, there has been a statistically significant socioeconomic difference between male-headed and female-headed households. Female-headed households are more likely to be literate, younger, have fewer family sizes, more children's school attendance, fewer student school dropouts, better access to improved sanitation, and safe drinking water. However, female-headed households have fewer small assets, livestock herds, and land for agriculture. Nonetheless, possessions of livestock herds and land for agriculture are not as important for multidimensional poverty reduction in Ethiopia as explained above. Overall, female-headed households were

identified, with almost all parameters positively associated with non-multidimensional poverty. This could be justified by the contributions of long-standing affirmative action policies and gender mainstreaming activities undertaken at almost all government levels.

4. Conclusion and policy recommendations

The study utilizes the Alkire and Foster approach to analyze the Multidimensional Poverty Index (MPI) using Ethiopian Demographic and Health Surveys (EDHS) data from 2011, 2016, and 2019. It aims to provide detailed insights to aid national, regional, and local governments in planning and monitoring poverty alleviation strategies.

Ethiopia has made significant progress in reducing multidimensional poverty, with prevalence falling from 81 percent in 2011 to 64.7 percent in 2019. However, a substantial portion of the population remains impoverished. To sustain and accelerate this progress, the government is advised to enhance and expand poverty reduction programs, ensuring they are well-funded and effectively implemented across all regions.

The intensity of poverty, which measures the percentage of weighted deprivations, has declined more slowly than the prevalence of poverty. This indicates that those who remain poor continue to suffer from severe deprivation. Thus, The government need to focus on interventions that not only reduce the number of people in poverty but also address the severity of their deprivations. This can include comprehensive social safety nets and targeted programs aimed at improving education, healthcare, and living conditions for the poorest.

Multidimensional poverty is predominantly a rural issue in Ethiopia, with rural areas consistently showing higher prevalence and intensity of poverty compared to urban areas. Thus, there is a need to prioritize rural development initiatives that improve access to basic services such as education, healthcare, and clean water. This can involve investing in rural infrastructure, enhancing agricultural productivity, and promoting rural economic diversification.

Male-headed households are more likely to experience multidimensional poverty compared to female-headed households. However, the rate of poverty reduction is faster among male-headed households. Thus, support programs have to ensure that female-headed households do not fall behind. These programs can include economic empowerment initiatives, access to education and healthcare, and measures to promote gender equality in all aspects of life.

Multidimensionally poor households generally have lower literacy rates, larger family sizes, and less access to essential services like sanitation and safe drinking water. Possession of assets like livestock and agricultural land does not necessarily correlate with lower multidimensional poverty due to factors like climate change and inadequate agricultural productivity. Thus, there is a need to enhance agricultural productivity through better access to quality inputs, training, and sustainable farming practices. Addressing climate resilience is crucial for areas heavily dependent on agriculture. Additionally, improving access to education, healthcare, and basic services in these communities will help reduce poverty.

There is a rising trend of urban poverty, particularly due to the influx of young job seekers and socio-political factors. Thus, there is a need to address urban poverty by creating job opportunities and providing affordable housing and essential services. Urban planning should incorporate strategies to accommodate growing populations and mitigate the challenges of rapid urbanization.

Regional disparities exist in deprivation across dimensions. Tailored interventions are necessary to address specific regional challenges. Oromia, despite its resource bases, consistently ranks highest in contributing to MPI, indicating the impact of conflict on poverty. Thus, ending internal conflicts and focusing on post-conflict reconstruction are vital for poverty reduction in most regional states like Oromia.

Annex: Poverty Prevalence, severity & relative contributions of dimensions by regional states

Year	2011							Multi-dimensional poverty measures
	Health	Relative Contribution of subgroups to MPI	Relative contribution to MPI	Relative contribution to incidence (H)	Adjusted headcount (H*A) = MPI=M (O)	Intensity of Poverty (A)	Headcount ratio (H)	Population share
	0.172		0.062	0.063	0.443	0.578	0.767	Tigray
	0.178		0.010	0.009	0.558	0.652	0.856	Afar
	0.146		0.250	0.254	0.476	0.577	0.825	Anhara
	0.149		0.406	0.403	0.494	0.589	0.839	Oromia
	0.163		0.025	0.023	0.540	0.612	0.882	Somali
	0.176		0.011	0.011	0.497	0.584	0.851	Benishangul gumuz
	0.144		0.222	0.220	0.503	0.590	0.853	SNNPR
	0.143		0.003	0.003	0.354	0.514	0.689	Gambela
	0.164		0.001	0.002	0.264	0.541	0.488	Harari
	0.149		0.007	0.010	0.088	0.419	0.210	Addis Ababa
	0.164		0.002	0.002	0.286	0.574	0.498	Diredawa

2019			Asset ownership	Cooking fuel	Standard housing	Improved sanitation	Drinking Water	Electricity	Living standards	Years of Schooling	Child School Attendance	Education	Nutrition	Child Mortality	Health	Relative Contribution of subgroups to MPI	Relative contribution to MPI
Headcount ratio (H)	0.535	0.062	Tigray	0.049	0.105	0.102	0.076	0.087	0.524	0.206	0.106	0.312	0.144	0.020	0.164	0.057	
	0.845	0.010	Afar	0.062	0.089	0.090	0.071	0.081	0.484	0.228	0.124	0.352	0.132	0.031	0.164	0.010	
	0.655	0.204	Amhara	0.051	0.102	0.101	0.077	0.093	0.524	0.229	0.111	0.340	0.120	0.017	0.136	0.229	
	0.663	0.404	Oromia	0.048	0.095	0.093	0.068	0.089	0.489	0.210	0.153	0.363	0.123	0.025	0.148	0.433	
	0.889	0.062	Somali	0.068	0.091	0.084	0.073	0.087	0.496	0.207	0.150	0.358	0.114	0.033	0.146	0.040	
	0.615	0.011	Benishangul-gumuz	0.060	0.101	0.099	0.062	0.091	0.514	0.197	0.113	0.310	0.150	0.027	0.180	0.010	
	0.657	0.202	SNNPR	0.050	0.099	0.094	0.080	0.092	0.515	0.204	0.136	0.341	0.120	0.024	0.144	0.212	
	0.515	0.004	Gambela	0.078	0.116	0.113	0.057	0.091	0.572	0.178	0.086	0.264	0.131	0.033	0.164	0.002	
	0.467	0.003	Harari	0.054	0.103	0.100	0.064	0.051	0.476	0.222	0.137	0.360	0.130	0.034	0.165	0.001	
	0.127	0.032	Addis Ababa	0.102	0.136	0.136	0.011	0.002	0.495	0.231	0.094	0.325	0.140	0.039	0.176	0.003	
	0.525	0.335	Diredawa	0.006	0.096	0.085	0.087	0.058	0.072	0.462	0.227	0.137	0.363	0.147	0.028	0.003	0.174

Asset ownership	Cooking fuel	Stand ard housi ng	Impro ved sanitat ion	Drink ing Water	Electricit y	Living standar ds	Years of Schooling	Child School Attenda nce	Educati on	Nutritio n	Child Mortality	Health	Relative Contribution of subgroups to MPI	Relative contrib ution to MPI	Relativ e contrib ution to incidence (H)	Adjuste d headco unit (H*A = MPI=M O)	Intensit y of Poverty (A)
0.053	0.103	0.099	0.100	0.070	0.082	0.506	0.170	0.124	0.294	0.186	0.014	0.199		0.051	0.051	0.282	0.527
0.069	0.097	0.095	0.093	0.070	0.085	0.511	0.190	0.121	0.310	0.155	0.024	0.179		0.014	0.013	0.481	0.569
0.056	0.108	0.108	0.097	0.067	0.092	0.528	0.210	0.120	0.329	0.129	0.014	0.143		0.200	0.206	0.335	0.511
0.043	0.103	0.102	0.100	0.070	0.086	0.504	0.181	0.171	0.352	0.123	0.021	0.144		0.419	0.414	0.355	0.535
0.069	0.095	0.091	0.091	0.080	0.089	0.516	0.174	0.162	0.336	0.115	0.034	0.148		0.094	0.085	0.518	0.583
0.053	0.107	0.107	0.103	0.051	0.098	0.520	0.183	0.109	0.291	0.154	0.035	0.189		0.010	0.010	0.318	0.517
0.055	0.106	0.107	0.100	0.066	0.081	0.515	0.183	0.149	0.332	0.137	0.017	0.154		0.201	0.205	0.340	0.518
0.086	0.120	0.116	0.116	0.070	0.092	0.600	0.132	0.089	0.221	0.138	0.041	0.179		0.003	0.003	0.238	0.462
0.053	0.106	0.084	0.101	0.076	0.043	0.463	0.199	0.119	0.318	0.186	0.034	0.219		0.002	0.002	0.239	0.512
0.090	0.113	0.129	0.121	0.044	0.011	0.508	0.212	0.098	0.310	0.173	0.010	0.183		0.005	0.006	0.050	0.394
0.072	0.072	0.100	0.089	0.090	0.058	0.075	0.483	0.221	0.123	0.344	0.140	0.033		0.173	0.003	0.003	0.176

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I have no conflicts of interest to disclose

Data Availability Statement

Data generated for this research is available upon formal request from the corresponding author.

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