Addis Ababa University, Ethiopian Journal of Business and Economics, EJBE Vol.: 15, No.: 2,
Doi: *https://dx.doi.org/10.4314/ejbe/v12i1.3* **p-ISSN:** ***2311-9772*** **e-ISSN:** ***2410-2393***
Available online: http://ejol.aau.edu.et/index.php/ejbe and https://www.ajol.info/index.php/ejbe

Does the Empowerment Dimension Really Matter in the Measurement of Multidimensional Poverty? Insights from Smallholder Dairy Producers in the Central Highlands of Ethiopia

Abrham Seyoum Tsehay[1]

Abstract

This study examines multidimensional poverty among rural households in Basona Werana Woreda, North Shewa, Amhara Region, using survey data gathered from 262 rural households through a multi-stage sampling design. Employing alternative Multidimensional Poverty Index (MPI) frameworks, the analysis estimates poverty with and without an empowerment dimension under both nested and equal weightings to assess the sensitivity of poverty estimates to indicator composition, weights, and deprivation cutoffs. Household data were analyzed using descriptive methods and a fractional logit regression model to identify the drivers of multidimensional poverty. The results using the default 33% MPI cutoff revealed persistently high levels of deprivation, with poverty incidence ranging from 61.9% to 90.9% depending on the specification. Incorporating empowerment consistently increases measured poverty under nested weights and contributes substantially to overall MPI, highlighting deep structural deficits in agency and collective participation among rural households. Determinant analysis shows that membership in water user associations and input supply groups, access to electricity, larger household size, and lower dependency ratios significantly reduce multidimensional poverty, while female headship, older household heads, and greater distances to basic services exacerbate deprivation. Contrary to expectations, off-farm participation is associated with higher MPI when empowerment is included, suggesting that such activities serve mainly as coping strategies among land-constrained households. Overall, the findings underscore the methodological and policy importance of integrating empowerment into multidimensional poverty measurement and call for rural development strategies that strengthen institutions, infrastructure, and agency-enhancing interventions.

Keywords: Determinants, Multidimensional Poverty, Basona Werana Woreda

[1]Associate Professor of Development Economics, Addis Ababa University, and Corresponding Author E-Mail: abrham.seyoum@aau.edu.et. Cellphone: +251(0) 901958007.

Introduction

For a long time, poverty studies and national poverty estimates globally have primarily relied on unidimensional measurement approaches, such as the monetary method, which defines poverty as a shortfall from a specific income or consumption threshold (Haughton & Khandker, 2009; Wisor, 2012; Evans et al., 2020). However, there is growing recognition of the limitations of monetary measures in adequately capturing the multifaceted nature of poverty (Santos, 2019). Consequently, academics and practitioners increasingly advocate for multidimensional approaches to poverty measurement (Yohannes Mare et al., 2021).

The multidimensional approach to poverty measurement is rooted in Amartya Sen's capability approach, developed in his seminal works of 1976 and 1979. Multidimensional poverty estimation frameworks, such as the Human Development Indices and the Multidimensional Poverty Index (MPI), are designed to capture poverty as a multidimensional phenomenon, reflecting deprivations not only in income but also in education, health, living standards, essential assets, empowerment, and other capabilities essential for a valued life (Alkire, 2007; OPHI, 2018; Atkinson, 2019).

In developing countries, multidimensional poverty estimates have often highlighted significantly higher poverty rates than conventional monetary approaches. This underscores the need for intensified efforts to eradicate poverty in all its forms by 2030, as envisaged in the UN Sustainable Development Goals (SDGs).

Ethiopia, as one of the least developed countries, prioritizes poverty eradication in its national development agenda (MoFED, 2010; UNDP, 2018). Between 2010/11 and 2015/16, Ethiopia made significant progress in poverty reduction, with the share of the population below the national poverty line decreasing from 30% to 24%. Urban poverty reduction was particularly notable, with per capita consumption growing by 6% annually—three times faster than in rural areas, where the poorest 20% experienced minimal growth (World Bank Group, 2023). By 2020, rural poverty rates declined from 30.4% in 2009/10 to 25.6%, while urban poverty rates fell from 25.7% to 14.8% (PDC, 2020).

Despite these achievements, poverty remains a central issue in Ethiopia’s homegrown economic reforms. Based on 2019 data, the MPI revealed that 68.7% of Ethiopia’s population is multidimensionally poor (UNDP, 2023), a figure significantly higher than the Sub-Saharan African average. The situation is exacerbated by challenges such as the COVID-19 pandemic, natural disasters, and ongoing internal conflicts, which have disrupted services, destroyed infrastructure, restricted movement, and heightened inflationary pressures. According to OCHA (2023), Ethiopia's 2023 Humanitarian Response Plan requires \$3.99 billion to address the needs of over 20 million people, including 4.6 million internally displaced persons (IDPs). These challenges further deepen multidimensional poverty and hinder progress toward its eradication.

The Global Multidimensional Poverty Index (MPI) report, released in October 2024, highlights significant disparities between urban and rural areas in Ethiopia. According to the report, 79.7% of the rural population is classified as multidimensionally poor, compared to 39.2% in urban areas. This stark contrast underscores that poverty in Ethiopia extends beyond income deprivation, encompassing multiple dimensions of well-being that require in-depth analysis and targeted interventions.

Given this backdrop, this study aims to assess the multidimensional poverty status of households in Ethiopia, particularly in rural areas where poverty is predominantly concentrated (UNDP, 2018). It seeks to inform policymakers and stakeholders about the prevalence, nature, and determinants of poverty in different regions of the country.

The research focuses on the Basona Werana *Woreda* in North Shewa Zone, Amhara Region—a predominantly rural area reliant on mixed agriculture. While numerous studies on poverty in Ethiopia exist, most employ a monetary approach, failing to capture its multidimensional aspects (Araya et al., 2019; Shaga et al., 2021; Markew & Solomon, 2022). Others use MPI-based approaches but are limited in scope or methodology, focusing on datasets from specific regions or applying global MPIs that exclude empowerment as a dimension (Tilman & Sindu, 2013; Tigre, 2018; Bersisa & Heshmati, 2016; Gebrekidan et al., 2021).

This study contributes to the literature by examining multidimensional poverty among rural households in the central highlands of Ethiopia using two alternative MPI frameworks. Specifically, it estimates MPI with and without the empowerment dimension, applying both nested and equal weightings. This approach highlights the often-overlooked role of empowerment in multidimensional poverty analysis and its implications for poverty eradication efforts in rural Ethiopia. Moreover, unlike most previous studies that treat MPI as either a continuous variable or a binary indicator, this study leverages the fractional nature of MPI values, which range from zero to one. Accordingly, the fractional logit regression model, well-suited for fractional outcomes, is employed to rigorously analyze the determinants of multidimensional poverty. By examining both the prevalence and determinants of multidimensional poverty with and without the empowerment dimension, this study offers methodological insights and policy-relevant evidence to improve understanding of the multifaceted nature of poverty and inform targeted interventions in the study area.

Materials and Methods

Description of the Study Area:

Basona Werana Woreda[2] is one of the districts in North Shewa Zone of the Amhara region surrounding Debre Berhan town, the capital of North Shewa Zone. Formerly known as Debre Berhan Zuria Woreda, it is bordered by Angolalla Tera to the south, the Oromia Region to the southwest, Siyadebrina Wayu to the west, Moretna Jiru to the northwest, Mojana Wadera to the north, Taramaber to the northeast, and Ankober to the east.

Located 130 kilometers north of Addis Ababa, the capital city of Ethiopia, the Woreda lies between 9°38′00″–9°41′00″ N latitude and 39°30′00″–39°32′00″ E longitude (MoA, 2016). According to the 2007 national census conducted by the Central Statistical Agency (CSA), the woreda had a population of 120,930—a 7.81% increase from the 1994 census—with 61,924 men and 59,006 women. Urban inhabitants accounted for 1,219 individuals or 1.01% of the total population.

Based on CSA projections for July 2023, Basona Werana’s estimated population is 147,375, comprising 75,011 males and 72,364 females. With an area of 1,208.17 square kilometers, the Woreda has a population density of 100.09 people per square kilometer, which is below the Zone average of 115.3 people per square kilometer. The Woreda includes 27,753 households, averaging 4.36 persons per household, and 26,918 housing units. The area’s agricultural activities are primarily focused on cereal crops, including teff, wheat, barley, maize, sorghum, and millet, as well as pulse crops such as beans, peas, and lentils. Rural households in the area practice mixed farming, and the Woreda is recognized as one of Ethiopia’s key dairy belts. The Ethiopian government identified Basona Werana as a target area for dairy sector development, offering training programs, advanced dairy technologies, and improved heifers to enhance production. The district holds significant potential for expanding Ethiopia’s dairy sector.

Data Source and Sampling:

[2] *Woreda* is the third level of the administrative divisions of Ethiopia next to regional states and zones. In this study, the words district and woreda are used interchangeably.

The study primarily relies on quantitative data sourced from primary data collection. To complement and substantiate these findings, secondary sources such as government documents, academic articles, and Theses are also utilized. The main data collection method employed is structured interviews, supported by field observations for additional context and insights.

This research is conducted at the household level and hence targets smallholders engaged in mixed agriculture in Basona Werana Woreda. This woreda is one of the 10 woredas of the North Shewa Zone of Amhara National Regional State. In this Woreda, there are 30 rural kebeles and one urban center, namely Debre Berhan Town, which is the capital of the zone. The research follows a multi-stage sampling technique. In the first stage, Basona Werana Woreda was selected purposively since it is located in one of the major milksheds in the country. In the second stage, two rural kebeles, Bakelo and Birbisa, were selected randomly from the 30 rural kebeles in the woreda. In the third and final stage, households were selected from chosen kebeles, using a systematic random sampling proportional to size.

To determine the sample size for this research, Yamane's (1967) formula is employed as shown below:

$$n = \frac{N}{1 + Ne^2} = \frac{1234}{1 + 1234(0.06)^2} = 227$$

Where n denotes the desired sample size, e is set at ± 6% level of precision, and N is the size of the total population from which the sample is drawn. Therefore, based on the formula developed by Yamane (1967), the sample size of 227 farm households was determined for the study. To account for the possible missing response values, Researchers are, therefore, advised to oversample by 10% to 20% of the computed number of samples based on their anticipation of such discrepancies (Naing et al., 2006). In this research, a 15% contingency was assumed from the total sample to achieve the required accuracy. Accordingly, a total sample of 262 farm households, including the contingency, was the sample size of the study. Accordingly, the distribution of the sample from the selected two rural kebeles is shown in the table below.

Table 1: Distribution of Sample Respondents by *Kebeles*

No.	**Name of the *Kebeles***	**Number of households**	**Sample Size**

1	**Bakelo**	934	198
2	**Birbisa**	300	64
	Total	**1234**	**262**

Source: Own Computation (2023)

Methods of Data Analysis:

A variety of both descriptive and econometric analyses have been employed to address the specific objectives of the study. In addition to the use of descriptive statistics to provide an overall picture of the sample smallholders, the multidimensional poverty index (MPI) and Beta regression model were used to address the research objectives.

Measuring Multidimensional Household Poverty: The poverty status of farm households was measured using a Multidimensional Poverty Index (MPI). According to Alkire & Foster (2011), five dimensions are captured to estimate the index, such as education, health, standard of living, wealth, and empowerment. Under these dimensions, 13 indicators were identified based on expediency, obvious normative presumption, data availability, and empirical literature (Alkire, 2007; Alkire & Santos, 2014; UN, 2016; Birhanu, et al., 2021).

Following Alkire & Foster (2011), equal weights were assigned for each dimension due to the absence of compelling reasons to consider one dimension as more important than the other. Accordingly, the multidimensional poverty status of farm households was defined as:

$$p(y_i z) = \begin{cases} 1 \; multidimensional\, poor \; (c_i \geq k), \\ 0 \qquad\qquad\quad otherwise \; (c_i < k), \end{cases}$$

Where, c_i the number of deprivations experienced by the farm household i, and k is the multidimensional poverty cut-off point. A cutoff of 1/3 (33.3%) is used to distinguish between poor and non-poor people. Alternatively, 20%, 40% and 50% cutoff points are used as standard robustness analysis. Table 2 presents dimensions, indicators, deprivation cut-off points, and weights to construct the MPI with the inclusion and exclusion of the empowerment dimension.

Table 2: Dimensions, indicators, deprivation cut-off, and weights

Dimensions	Indicators	Deprivation cut-off	Relative weights			
			With the Empowerment Dimension		Without the Empowerment Dimension	
			Nested Weights	Equal weights	Nested Weights	Equal weights
Education	Adult literacy	No one has completed five years of schooling	1/8	1/12	1/6	1/10
	Child enrollment	No school-age child is attending school	1/8	1/12	1/6	1/10
Health	Health care	No access to health care services	1/8	1/12	1/6	1/10
	Illness	Suffers illness	1/8	1/12	1/6	1/10
Living standard	Electricity	No access to electricity	1/24	1/12	1/18	1/10
	Drinking water	No access to safe drinking water	1/24	1/12	1/18	1/10
	Sanitation	The household has no access to a good toilet or an improved but shared toilet with other households	1/24	1/12	1/18	1/10
	House floor	Floor made with mud, dung, clay	1/24	1/12	1/18	1/10
	Cooking fuel	Use of firewood, dung, and charcoal as fuel	1/24	1/12	1/18	1/10
	Assets	The household does not own Household does not own more than one of these assets: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car or truck	1/24	1/12	1/18	1/10
Empowerment	Decision making	Household decision-making on the use of income is not participatory	1/8	1/12	N/A	N/A
	Cooperative membership	A member of the household is not a member of the cooperatives	1/8	1/12	N/A	N/A

Source: Based on Alkire & Foster (2011) and extended assumptions of equal weighting

Modelling Determinants of Households' Multidimensional Poverty:

Previous studies have used different econometric regression models, such as the multiple linear regression model, probit/logit, censored data model, multinomial, and ordered choice to analyse the determinants of multidimensional poverty. The multidimensional poverty index (MPI) is a composite index measured from three dimensions and 12 indicators following Alkire and Foster (2011) and hence assumes fractional values bounded by values of 0 and 1. The computed values of MPI are continuous fractions with limited concentrations at 0. Hence, for such a response variable, the fractional outcome regression models are suitable for capturing the non-linear relationship between the fractional outcome and the explanatory variables of the model. In this study, the fractional logit regression model has been preferred over Beta regression as the latter doesn't account for bounding values.

The fractional logit model is specified following Papke and Wooldridge (1996). Let P_i denote a fractional response variable bounded in the closed unit interval, $P_i \in [0,1]$, representing a multidimensional poverty index (MPI) score of household i. The fractional logit model specifies the conditional mean of P_i given a vector of covariates X_i as a nonlinear function:

$$E(P_i|X_i) = \Phi(X_i'\beta)$$

where β is a vector of parameters to be estimated and $\Phi(\cdot)$ is the logistic cumulative distribution function defined as

$$\Phi(z) = \frac{exp(z)}{1 + exp(z)}$$

This specification ensures that the predicted conditional mean lies strictly within the unit interval, thereby respecting the natural bounds of the dependent variable without requiring data transformation or truncation.

Following quasi–maximum likelihood (QML) estimation, the log-likelihood contribution for household i is given by:

$$L_i(\beta) = P_i log[\Phi(X_i'\beta)] + (1 - P_i)[1 - \Phi(X_i'\beta)]$$

Under the correct specification of the conditional mean, the QML estimator $\hat{\beta}$ is consistent and asymptotically normal, regardless of the true conditional distribution of P_i, provided standard regularity conditions hold (Papke & Wooldridge, 1996; Wooldridge, 2010). Robust standard errors are typically employed to account for potential heteroskedasticity inherent in fractional data. An important advantage of the fractional logit model is that it naturally accommodates observations at the boundaries without requiring ad-hoc adjustments such as censoring or rescaling. This feature is particularly relevant in poverty analysis, where a non-trivial share of households may be non-poor or fully deprived. Marginal effects are obtained by differentiating the conditional mean with respect to a covariate. X_{ik} $\frac{\partial E(P_i|X_i)}{\partial X_{ik}} = \Phi(X_i'\beta)[1 - \Phi(X_i'\beta)]\beta_k$ and are typically evaluated at sample means or averaged over the empirical distribution of covariates to facilitate interpretation (Wooldridge, 2010; Papke & Wooldridge, 2008).

Results and Discussions

Out of the 262 households interviewed for this study, 252 responses (96%) were valid for analysis, with the remaining 10 responses (4%) excluded due to non-sampling errors. This response rate falls within the contingency margin, ensuring the adequacy of the sample data for analysis. The questionnaire was developed in line with internationally accepted standards and tested instruments, incorporating indicators of MPI. The instruments underwent multiple revisions and validations by professionals and experts in the area.

Descriptive Statistics

Descriptions of Categorical Variables:

The descriptive analysis of categorical variables reveals that the majority of household heads in the study area are male and married, reflecting trends observed in other parts of the country. Over 44% of household heads have attained some level of formal education, while 36.11% are illiterate, and 19.44% have received informal education. The households in the study predominantly engage in farming activities, with limited participation in off-farm and non-farm pursuits.

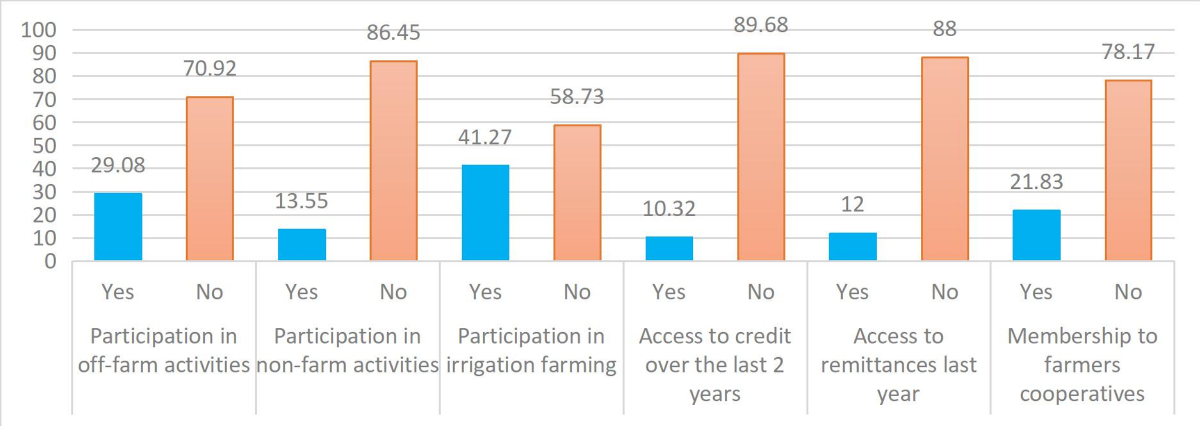

Figure 1: Description of Categorical Variables

The study results show that less than 14% of households engage in non-farm activities, while slightly less than one-third of the sample households participate in off-farm activities. Although smallholders' participation in small-scale irrigation practices is generally limited in Ethiopia, the study area demonstrates a notable exception, with 41.27% of households involved in irrigation practices, indicating that irrigation is relatively common in the region. Access to financial services remains constrained in the study area, as highlighted by the data presented in Table 4 above. Only 10.32% of households accessed credit in the past two years, and just 12% received remittances in the previous year (2022/23 GC). Additionally, less than a quarter of the sample households are members of farmers' cooperatives, suggesting that cooperatives are not well developed in the study area.

Descriptions of Continuous Variables

Table 3 presents the description of some of the continuous variables characterizing sample households. In the study area, the mean age of household heads is 50 years. Those who have attended formal education have completed an average of about seven years of schooling. The average household size is approximately five members, aligning closely with the national average of about five members per household (ILO, 2021).

The average cropland size owned by households in the study area is 0.96 hectares, consistent with the national average farmland size per household. This figure is significantly higher than the averages for Tigray and the Southern Nations, Nationalities, and Peoples' Region (0.49 hectares) but slightly lower than the averages for Amhara (1.09 hectares) and Oromia (1.15 hectares) (Headey et al., 2014). These figures are not expected to change significantly, as there have been no recent land distribution initiatives by the Ethiopian government or regional administrations. The average livestock holding of sampled rural households, measured using the Tropical Livestock Unit (TLU), is 6.4. Meanwhile, the crop diversification index for the sample households is 0.32, indicating a lower-middle level of crop diversification.

Table 3: Description of continuous variables

Variables	Mean (SD)
Head Age (years)	49.45 (12.54)
The highest years of schooling completed by the head	6.55 (2.38)
Household size (number)	4.67 (1.88)
Size of cultivated land (ha)	0.96 (0.72)
Livestock holding in TLU (index)	6.40 (3.43)
Crop diversification (index)	0.32 (0.33)
Diary Commercialization	0.54 (0.40)
Distance to the nearby Primary School	34.41 (21.70)
Distance to the nearby High School	73.57 (33.28)
Distance to nearest Market (walking minutes)	52.68 (28.71)

Source: computed from Survey Data (2023)

The dairy commercialization index based on the Herfindahl measure was found to be 0.54, which falls in a medium or semi-commercialized category of dairy producers following Leavy, J. and C. Poulton (2007); Gebreselassie, S., and Sharp, K. (2008), and Moses Ageya Kembe & Charles Ochola Omondi (2016). On average, it takes households more than 34 minutes to reach primary school; close to 74 minutes to reach the nearby high school, and about 53 minutes to reach the nearby market within walking distance.

Estimation results of rural households' Multidimensional Poverty Status

Table 4 presents the multidimensional poverty status of households computed using the Multidimensional Poverty Index (MPI) developed by Alkire and Foster (2011). The mean MPI values estimated with the inclusion of the empowerment dimension are significantly higher than those estimated without empowerment under both nested and equal weighting schemes, indicating substantial deprivation in empowerment-related indicators. MPI estimates based on equal weights are consistently higher than those based on nested weights, reflecting greater sensitivity to uniformly weighted deprivations. Across all specifications, the minimum MPI value is zero, while the maximum values range between 0.708 and 0.800, suggesting that no household in the sample experiences deprivation across all indicators simultaneously.

Table 4: Multidimensional poverty estimates (Applied MPI cutoff= 33%) (N=252)

MPI Estimation Modalities	Mean	St. Dev.	Minimum	Maximum
Nested Weights				
MPI with empowerment dimension	0.371	0.211	0	0.708
MPI without the empowerment dimension	0.271	0.226	0	0.722
t-test	8.2499 [p-value = 0.0000]			
Equal Weights				
MPI with empowerment dimension	0.466	0.184	0	0.750
MPI without the empowerment dimension	0.382	0.252	0	0.800
t-test	8.9130 [p-value = 0.0000]			

Source: Computed from survey data (2023)

As a robustness check on the extent of multiple deprivations in the study area, additional deprivation cutoffs of 20%, 40%, and 50% are applied alongside the conventional 33% threshold. McNemar's chi-square test is then employed to assess whether MPI estimates differ significantly between specifications with and without the empowerment dimension across the various multidimensional poverty thresholds.

Table 5: Multidimensional poverty estimates

MPI Estimation Modalities	Applied thresholds			
	1/3 (33%)	1/5 (20%)	2/5 (40%)	1/2 (50%)
Nested Weights				
MPI with empowerment dimension (%)	78.97	94.05	52.78	28.17
MPI without empowerment dimension (%)	61.90	82.94	21.43	13.49
McNemar's Chi-square test	26.80	23.06	75.19	31.84
Prob > chi2	0.0000	0.0000	0.0000	0.0000
Equal Weights				
MPI with empowerment dimension (%)	90.87	96.03	73.41	52.38
MPI without empowerment dimension (%)	72.22	98.81	72.22	42.86
McNemar's Chi-square test	47.00	5.44	0.43	16.00
Prob > chi2	0.0000	0.0196	0.5127	0.0001

Source: Computed from survey data (2023)

Table 5 presents the incidence of multidimensional poverty under different MPI specifications, weighting schemes, and deprivation thresholds in the study area. Using the conventional 33% cutoff, 78.97% and 61.90% of households are identified as multidimensionally poor with and without the empowerment dimension, respectively, under nested weighting. These proportions increase to 90.87% and 72.22% when equal weighting is applied to MPI estimates with and without empowerment, respectively. These estimates are broadly comparable with national figures reported by OPHI (2024), which indicate multidimensional poverty rates of 68.7% at the national level and 79.7% in rural Ethiopia.

Similarly, Bantayehu Tamrie and Singh (2021), studying three districts across different agro-ecological zones in rural Ethiopia, report a multidimensional poverty prevalence of 84.2%, while Fisseha Zegeye et al. (2021) find a rate of 57.9% in major teff-growing areas.

Across all deprivation thresholds under nested weighting, the proportion of multidimensionally poor households is consistently and significantly higher when the empowerment dimension is included. Under equal weighting, a similar pattern is observed at the 33% and 50% cutoffs; however, the pattern reverses at the 20% cutoff, and no statistically significant difference is observed at the 40% cutoff. These results suggest that the relative importance of different dimensions varies across the distribution of deprivation, particularly at lower thresholds where deprivations in education, health, and living standards may be more pronounced than those in empowerment. Consequently, although MPI estimates that include empowerment generally indicate higher levels of multidimensional deprivation, the choice of weighting schemes and deprivation cutoffs plays a critical role, and policy implications should therefore be drawn with caution.

Figure 2 illustrates the contribution of different dimensions to the overall MPI under alternative specifications, including with and without empowerment and under nested versus equal weighting schemes. When empowerment is included, it emerges as the largest contributor to MPI under nested weighting and the second-largest contributor—after living standards—under equal weighting. This finding highlights the severity of deprivation in the empowerment dimension, despite its representation by only two indicators compared to five indicators in the living standards dimension. Across all specifications and thresholds, health and education consistently account for the remaining shares of overall multidimensional poverty.

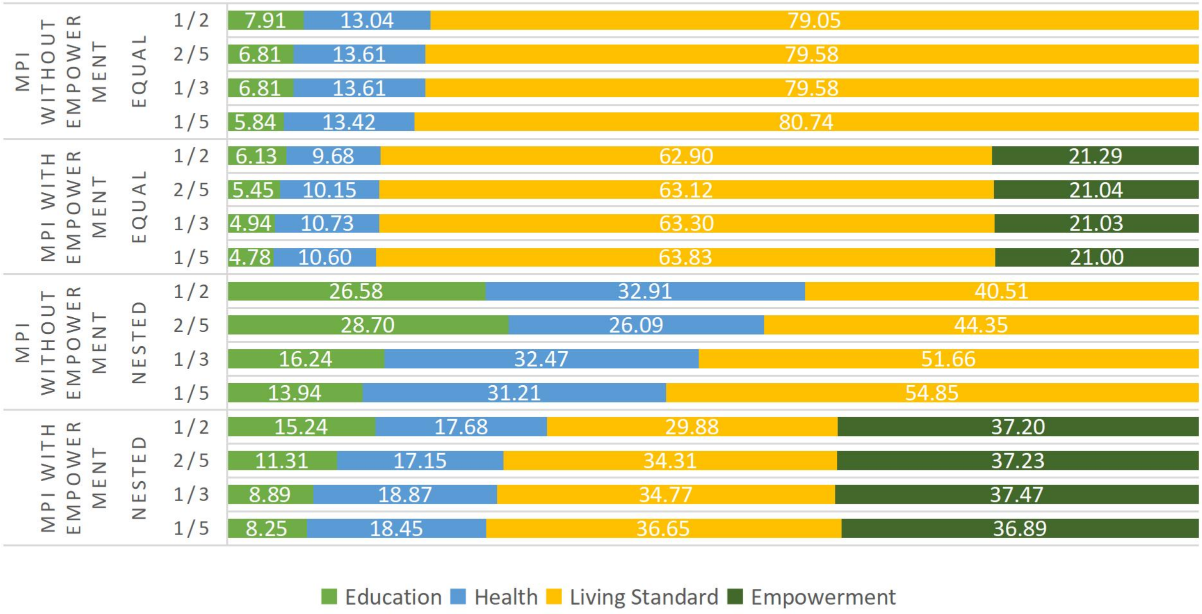

Figure 2: Contributions of dimensions to overall MPI by different weightings and thresholds

Results of the Determinants of Households' MPI with and without Empowerment:

This study estimates four parallel regressions to identify the determinants of multidimensional poverty under MPI specifications with and without the empowerment dimension, using both nested and equal weighting schemes. The MPI without empowerment comprises three core dimensions, while the MPI with empowerment includes a fourth dimension. In all cases, MPI is a weighted average bounded between zero and one, with limited mass at zero, making the fractional logit model the most appropriate estimation approach. Although two-part models were also estimated, they yielded no additional insights, thereby justifying the use of fractional logit regression.

Diagnostic tests support the adequacy of the models. The Wald chi-square statistics indicate overall model significance, link tests confirm correct model specification, and multicollinearity diagnostics using the Collin command show low variance inflation factors. Homoscedasticity is rejected in two of the four regressions, and heteroscedasticity is therefore addressed using robust standard errors. Predicted conditional means lie strictly within the unit interval, ensuring meaningful estimates and fulfills all relevant post-estimation tests. Table 6 reports the fractional logit regression results for MPI with and without empowerment under both weighting schemes.

Table 6: Determinants of Multidimensional Poverty of Households Using Fractional Logit Regression (N = 243)

VARIABLES	MPI without empowerment		MPI with Empowerment	
	Nested Weights dy/dx (SE)	Equal Weights dy/dx (SE)	Nested Weights dy/dx (SE)	Equal Weights dy/dx (SE)
Sex of the Household head (Base: Male)	0.1172(0.1648)	0.2188*(0.1211)	-0.0021(0.1194)	0.1069(0.0794)
Age of Household Head (years)	0.0098(0.0096)	0.0145**(0.0068)	0.0085(0.0070)	0.0114***(0.0042)
The highest years of schooling completed by the head	-0.0044(0.0243)	-0.0042(0.0190)	-0.0127(0.0193)	-0.0053(0.0125)
Off-farm Participation (Base: No)	0.1166(0.1703)	-0.0959(0.1617)	0.2786**(0.1413)	0.0573(0.0935)
Dairy Technology Adoption Index	0.0899(0.3562)	-0.4291(0.2852)	-0.0505(0.2788)	-0.0270(0.1828)
Visit by extension agent last season (count)	-0.0442(0.0771)	-0.0122(0.0729)	0.0651(0.0637)	-0.0210(0.0539)
Access to Irrigation (Base: No)	-0.2083(0.1726)	0.0471(0.1537)	0.0408(0.1215)	0.0899(0.0975)
Participation in Equb (Base: No)	-0.1800(0.1952)	0.0149(0.1457)	-0.2336(0.1421)	-0.0680(0.0954)
Crop land owned (ha)	0.0115(0.1015)	-0.0714(0.0953)	0.0015(0.0811)	-0.0965(0.0686)
Farming experience (years)	-0.0030(0.0096)	-0.0112*(0.0065)	-0.0063(0.0065)	-0.0068(0.0041)
Crop Diversification Index	-0.4195*(0.2399)	-0.3936**(0.2003)	-0.0534(0.1724)	-0.0728(0.1208)
Distance to water source (walking minutes)	0.0004(0.0043)	0.0048(0.0038)	0.0014(0.0034)	0.0054**(0.0024)
Distance to nearby primary school (walking minutes)	0.0063(0.0053)	0.0034(0.0050)	0.0074*(0.0041)	0.0024(0.0032)
Membership in input supply groups (Base: No)	-0.5548**(0.2801)	-0.6010**(0.2562)	-0.8032***(0.2199)	-0.5820***(0.1423)
Membership in water user associations (Base: No)	-0.5991**(0.2406)	-0.7739***(0.2313)	-0.7493***(0.2081)	-0.3842***(0.1287)
Membership in crop marketing group (Base: No)	-0.2147(0.4584)	-0.0923(0.4510)	0.1387(0.5053)	-0.1751(0.3595)
Household size (count)	-0.0685*(0.0405)	-0.0759**(0.0352)	-0.0662**(0.0298)	-0.0597**(0.0234)
Dependency ratio	0.1735(0.1061)	0.2057**(0.0826)	0.2164**(0.0884)	0.1662***(0.0598)
Number of oxen owned by the household (count)	-0.0268(0.0719)	-0.0197(0.0669)	-0.0474(0.0608)	-0.0172(0.0449)
Access to remittance (Base: No)	-0.5840**(0.2893)	-0.6990**(0.2769)	0.1102(0.1731)	-0.0117(0.1284)
Adoption of Improved Cooking Technology (Base: No)	-0.5592***(0.1906)	-0.2136(0.1477)	-0.0838(0.1340)	-0.0423(0.0957)
Access to Electricity (Base: No)	-0.3131**(0.1524)	-0.6386***(0.1414)	-0.2507**(0.1189)	-0.3449***(0.0934)
Village Dummy (Base: Birbisa)	-0.2048(0.1985)	-0.2345(0.1770)	-0.1426(0.1713)	-0.1059(0.1273)
Constant	-0.4597(0.5020)	0.4687(0.4244)	-0.3019(0.4128)	0.1370(0.2814)
Log pseudolikelihood	-132.75032	-143.87627	-148.45012	-159.11488
Wald chi2(23)	89.03	188.28	141.56	211.40
Prob > chi2	0.0000	0.0000	0.0000	0.0000

Source: Computed from Survey Data (2023), *** p<0.01, ** p<0.05, * p<0.1

The fractional logit model across all four specifications yields informative results. Across the models, membership in input supply groups and water user associations, household size, dependency ratio, and access to electricity are found to be significant determinants of multidimensional poverty among the sample households. Other variables exhibit sporadic effects across equations, while extension visits, dairy technology adoption, cropland size, and participation in equb (saving groups) are consistently insignificant across all models.

Members of water user associations have, on average, 38.42 to 77.39% lower MPI values compared to non-members, holding other factors constant. Membership in water user associations likely improves access to water points and promotes awareness of safe water use for drinking, sanitation, and agricultural production, thereby reducing multidimensional poverty. Similarly, membership in input supply groups is associated with 55.48 to 80.32% lower MPI values across the models. This finding is consistent with the role of collective input arrangements in alleviating liquidity and transaction constraints, enabling timely access to productivity-enhancing inputs, and reducing production risk. In the Ethiopian context, where input markets are largely mediated through cooperatives and farmer groups, such arrangements contribute to improvements across multiple MPI dimensions, including living standards and food security.

As expected, households with access to electricity exhibit significantly lower MPI across all models compared to those without electricity. This finding aligns with studies by Sabina Alkire et al. (2020) and Arouna Diallo and Richard Kouame Moussa (2020), underscoring the critical role of electrification in improving rural livelihoods. Household size also emerges as a significant factor across all models. An increase in household size by one member reduces multidimensional poverty by 5.97 to 7.59%, ceteris paribus, while a higher dependency ratio is associated with higher levels of multidimensional poverty, consistent with Chen et al. (2019), Gebrekidan et al. (2021), and Wang et al. (2021). Although the literature presents mixed evidence on the effect of household size on rural livelihoods, the results of this study suggest that larger household sizes are typically associated with greater availability of working labor, thereby enhancing livelihoods and reducing poverty. This interpretation is further supported by a strong positive association (over 68%) between household size and the number of working-age members (15–64 years) in the sample, significant at the 1% level. These findings are consistent with empirical studies by Alemu et al. (2011), Tigre (2018), and Gebrekidan et al. (2021), but contrast with those reported by Anyanwu (2012) and Sultan Asfaw and Gemechu Mulatu (2022). Other variables, including female-headed households, older household heads, and greater distances to primary schools and improved water sources, are associated with higher levels of multidimensional poverty. This is consistent with both theoretical expectations and empirical evidence, as female-headed households often face structural constraints in access to land, labor, credit, and productive assets, while older household heads may experience declining labor capacity and limited adaptability to new livelihood opportunities. Similarly, longer distances to primary schools and water sources increase time and opportunity costs, particularly for women and children, thereby exacerbating deprivations in the education, health, and living standards dimensions of the MPI.

In contrast, greater farming experience, higher levels of crop diversification, access to remittances, and adoption of modern cooking technologies are associated with lower multidimensional poverty. Farming experience enhances managerial capacity and risk management, leading to more stable agricultural production and income. Crop diversification reduces exposure to climatic and market shocks and improves food availability and dietary diversity, thereby lowering deprivation intensity. Remittance income relaxes liquidity constraints and enables households to smooth consumption and invest in human capital and basic services. Finally, the adoption of modern cooking technologies reduces exposure to indoor air pollution and the time burden associated with fuel collection, particularly for women, contributing to improvements in health and living standards. These results are broadly consistent with findings from previous studies in similar rural contexts.

Contrary to a priori expectations and previous studies such as Fassil Eshetu et al. (2022) and Xixi Wu et al. (2024), participation in off-farm activities is associated with higher levels of multidimensional poverty when the empowerment dimension is included and estimated using nested weights. A closer examination of the data reveals that households engaged in off-farm activities tend to own significantly smaller landholdings, indicating that off-farm participation is not driven by diversification or opportunity, but rather functions as a coping or fallback strategy in response to land constraints. In this context, off-farm activities are predominantly low-return, informal, and insecure, generating only modest supplementary income that is insufficient to improve empowerment-related outcomes such as decision-making autonomy and cooperative membership. As a result, off-farm participation in this setting reflects underlying structural deprivation rather than a pathway out of multidimensional poverty.

Conclusion and Recommendation

This study provides robust evidence that multidimensional poverty remains pervasive among rural households in the central highlands of Ethiopia and that its magnitude and structure are highly sensitive to how poverty is conceptualized and measured. Across all specifications, the incidence of multidimensional deprivation is alarmingly high and broadly consistent with national and rural MPI estimates reported by OPHI and related empirical studies. However, the results clearly demonstrate that excluding empowerment from MPI measurement leads to a systematic underestimation of poverty, particularly when nested weighting schemes are applied.
The inclusion of the empowerment dimension not only increases poverty incidence but also fundamentally reshapes the composition of multidimensional deprivation. Empowerment emerges as either the dominant or second-most important contributor to MPI across weighting schemes, despite being represented by fewer indicators than other dimensions. This finding reveals that deprivations related to agency, participation, and collective action are not marginal but central to the lived experience of poverty in rural Ethiopia. It also suggests that conventional MPI frameworks that prioritize education, health, and living standards alone may overlook critical structural constraints that perpetuate poverty over time.

At the same time, the sensitivity of results to weighting structures and deprivation cutoffs highlights an important methodological insight: MPI estimates should not be interpreted as fixed or absolute measures. Differences observed under nested versus equal weights, across different deprivation thresholds; indicate that the relative severity of empowerment deprivation varies across the poverty distribution. This underscores the need for caution when drawing policy conclusions from a single MPI specification and reinforces the value of sensitivity analysis in multidimensional poverty research.

Methodologically, the application of fractional logit regression provides a more appropriate and theoretically consistent framework for analyzing the determinants of multidimensional poverty. The results obtained from this approach are intuitive, stable across specifications, and consistent with broader theoretical expectations, lending credibility to both the estimation strategy and the substantive findings.

The econometric results highlight the central role of collective institutions and basic infrastructure in reducing multidimensional poverty. Membership in water user associations and input supply groups significantly lowers MPI, reflecting the importance of organized access to productive resources, risk-sharing mechanisms, and information flows. Access to electricity similarly emerges as a powerful poverty-reducing factor, confirming its cross-cutting effects on living standards, health, and productive opportunities. Household demographic structure also matters: larger households with more working-age members are less multidimensionally poor, while higher dependency ratios exacerbate deprivation.

Conversely, structural vulnerabilities—such as female headship, older household heads, and greater distances to schools and improved water sources—are associated with higher MPI, reflecting persistent gender, demographic, and spatial inequalities. Importantly, the finding that off-farm participation is associated with higher multidimensional poverty when empowerment is included challenges dominant narratives in the literature. In this context, off-farm activities appear to be driven by land scarcity and necessity rather than opportunity, yielding low and insecure returns that fail to enhance empowerment or reduce structural deprivation.

Overall, the findings carry several important implications for poverty eradication strategies in the study area. First, poverty reduction policies must move beyond sectoral and income-focused interventions and explicitly address empowerment-related deprivations. Strengthening rural institutions that enhance agency, participation, and collective decision-making—such as water user associations, cooperatives, and input supply groups—can yield substantial multidimensional poverty reductions. These institutions not only improve access to resources but also enhance households' capacity to influence outcomes that affect their livelihoods. Second, the strong poverty-reducing effects of access to electricity underscore the importance of accelerating rural electrification as a core component of poverty policy rather than treating it as a complementary infrastructure investment. Electrification generates spillover benefits across multiple dimensions of well-being and should be integrated with agricultural, health, and education interventions. Third, the results suggest that off-farm employment should not be assumed to be an automatic pathway out of poverty. Policies that promote off-farm activities must differentiate between opportunity-driven diversification and distress-driven coping. Without complementary investments in skills, market access, and labor productivity, off-farm employment risks reinforcing, rather than alleviating, multidimensional and empowerment-related poverty. Fourth, spatial and demographic inequalities remain central drivers of deprivation. Reducing distances to schools and improving water sources, and designing gender-sensitive interventions that address constraints faced by female-headed households and older farmers, are critical for inclusive poverty reduction. Fifth, from a measurement perspective, the study demonstrates that MPI design choices matter for both diagnosis and policy prioritization. Policymakers and practitioners should adopt flexible, transparent MPI frameworks that incorporate empowerment and conduct sensitivity analyses across weights and cutoffs to avoid misleading conclusions. Incorporating empowerment into national and subnational poverty monitoring systems would provide a more comprehensive and policy-relevant picture of deprivation in the study area.

Finally, the empowerment dimension in the MPI estimation is captured using only two parameters, which may not adequately reflect the multifaceted nature of household empowerment. Consequently, important aspects of empowerment may be omitted. Future studies could address this limitation by adopting a more comprehensive set of indicators to better capture the empowerment dimension.

Acknowledgement

The study is funded by the Research Office of Addis Ababa University under the Adaptive and Problem-solving Research Fund of the 2022/23 academic year.

References

Alemu, D., Bewket, W., Zeleke, G., Assefa, Y., & Trutmann, P. 2011. Extent and determinants of household poverty in rural Ethiopia: A study of six villages. Eastern Africa Social Science Research Review, 27(2), 21–49. https://doi.org/10.1353/eas.2011.0005.

Alkire, S. 2007. Choosing dimensions: the capability approach and multidimensional poverty, Mansfield Road, Oxford OX1 3TB, UK.: Oxford Poverty & Human Development Initiative, CPRC Working Paper 88.

Alkire, S. & Foster, J., 2011. Counting and multidimensional poverty measurement. Journal of Public Economics, 95(7-8), pp. 476-487.

Alkire, S. & Santos, M. 2014. Measuring acute poverty in the developing world: Robustness and scope of the multidimensional poverty index. World Development, Volume 59, pp. 251-274.

Anyanwu, J. 2012. Accounting for Poverty in Africa: Illustration with Survey Data from Nigeria. Working Paper Series, p. 149.

Araya M. Teka, Gabriel Temesgen Woldu, Zeremariam Fre. 2019. Status and determinants of poverty and income inequality in pastoral and agro-pastoral communities: Household-based evidence from Afar Regional State, Ethiopia, World Development Perspectives, Volume 15,
100123, ISSN 2452-2929, https://doi.org/10.1016/j.wdp.2019.100123.

Arouna Diallo, Richard Kouame Moussa. 2020. Does access to electricity affect poverty? Evidence from Côte d'Ivoire. Economics Bulletin. ffhal-02956563f.

Atkinson, A.B. 2019. Measuring Poverty around the World, Princeton, NJ: Princeton University Press.

Bantayehu Tamrie Alemu & S. P. Singh. 2021. How Does Multidimensional Rural Poverty Vary across Agro-ecologies in Rural Ethiopia? Evidence from the Three Districts, Journal of Poverty, 25:5, 480-498, DOI: 10.1080/10875549.2020.1869659.

Bersisa, M., & Heshmati, A. 2016. Multidimensional measure of poverty in Ethiopia: Factor and stochastic dominance analysis. In A. Heshmati (Ed.), Poverty and well-being in East Africa: A multi-faceted economic approach (pp. 215–238). Springer.

Birhanu, F.Z., A.S. Tsehay, D.A. Bimerew. 2021. The effects of commercialization of cereal crops on multidimensional poverty and vulnerability to multidimensional poverty among farm households in Ethiopia Develop. Stud. Res., 8 (1), pp. 378-395.

Chen, K., Leu, C., & Wang, T. 2019. Measurement and determinants of multidimensional poverty: Evidence from Taiwan. Social Indicators Research, 145(2), 459–478. https://doi.org/10.1007/s11205-019-02118-8.

Evans, M., Nogales, R., and Robson, M. 2020. 'Monetary and multidimensional poverty: Correlations, mismatches, and joint distributions', OPHI Working Paper 133, University of Oxford.

Fassil Eshetu, Jema Haji, Mengistu Ketema & Abule Mehare. 2022. Determinants of rural multidimensional poverty of households in Southern Ethiopia, Cogent Social Sciences, 8:1, DOI: 10.1080/23311886.2022.2123084.

Fisseha Zegeye Birhanu, Abrham Seyoum Tsehay, Dawit Alemu Bimerew. 2021. Heterogeneous effects of improving technical efficiency on household multidimensional poverty: evidence from rural Ethiopia, Heliyon, Volume 7, Issue 12, e08613, ISSN 2405-8440, https://doi.org/10.1016/j.heliyon.2021.e08613.

Gebrekidan, D. K., Bizuneh, A. M., & Cameron, J. 2021. Determinants of multidimensional poverty among rural households in Northern Ethiopia. The Journal of Rural and Community Development, 16(1), 133–151.

Gebreselassie, S., and Sharp, K. 2008. Commercialization of smallholder agriculture in selected Tef-growing areas of Ethiopia. Agriculture and rural development division, Ethiopian Economic Policy Research Institute (EEPRI), Addis Ababa, Ethiopia.

Haughton, J. & R. Khandker, S. 2009. Handbook on Poverty and Inequality. Washington, DC 20433, USA: The World Bank.

Leavy, J. and C. Poulton. 2007. Commercialisations in Agriculture: a Typology. Paper presented at the Fifth International Conference on the Ethiopian Economy, EEA, June 2007, Addis Ababa. www.future-agricultures.org.

Markew Mengiste Neway & Solomon Estifanos Massresha. 2022. The determinants of household poverty: the case of berehet woreda, amhara regional state, Ethiopia, Cogent Economics & Finance, 10:1, DOI: 10.1080/23322039.2022.2156090.

M.E. Santos. 2009. "Challenges in designing national multidimensional poverty measures", Statistics series, No. 100 (LC/TS.2019/5), Santiago, Economic Commission for Latin America and the Caribbean (ECLAC).

Ministry of Finance and Economic Development (MoFED). 2010. Growth and Transformation Plan 2010/11 – 2014/15, Volume I Main Text, Federal Democratic Republic of Ethiopia, Addis Ababa.

Moses Ageya Kembe, Charles Ochola Omondi. 2016. The Infrastructural Development and Commercialization of Smallholder Dairy Farming in Uasin Gishu County, Kenya. Urban and Regional Planning. Vol. 1, No. 4, pp. 77-85. Doi: 10.11648/j.urp.20160104.12.

Naing L, Winn T, Rusli BN. 2006. Practical issues in calculating the sample size for prevalence studies. Arch Orofacial Sci.1:9–14.

OCHA. 2023. Humanitarian Response Plan Ethiopia, Humanitarian Program Cycle February 2023.

OPHI. 2018. 'Global multidimensional poverty index 2018: The most detailed picture to date of the world's poorest people', University of Oxford, UK.

Ormerod, Richard J. 2006. The history and ideas of pragmatism. The Journal of the Operational Research Society 57: 892–909.

Oxford Poverty and Human Development Initiative (OPHI). 2024. Ethiopia: Global Multidimensional Poverty Index country briefing. University of Oxford. https://ophi.org.uk/media/46002/download

Papke, L. E., & Wooldridge, J. M. 1996. Econometric methods for fractional response variables with an application to 401(k) plan participation rates. Journal of Applied Econometrics, 11(6), 619–632.

Papke, L. E., & Wooldridge, J. M. 2008. Panel data methods for fractional response variables with an application to test pass rates. Journal of Econometrics, 145(1–2), 121–133.

Plan and Development Commission (PDC). 2020. Ethiopia 2030: The Pathway to Prosperity Ten-Year Perspective Development Plan (2021 – 2030). Federal Democratic Republic of Ethiopia.

Sabina Alkire, Usha Kanagaratnam, and Frank Vollmer. 2020. Interlinkages Between Multidimensional Poverty and Electricity: A Study Using the Global Multidimensional Poverty Index, OPHI & The Rockefeller Foundation. University of Oxford.

Shaga, H. H., Mega, T. L., and Senapathy, M. 2021. Determinants of Rural Household Poverty: The Case of Sodo Zuria Woreda, Wolaita Zone, Southern Ethiopia. European Journal of Sustainable Development Research, 5(2), em0157. https://doi.org/10.21601/ejosdr/10844.

Sultan Asfaw & Gemechu Mulatu. 2022. Determinants of Households' Multidimensional Poverty: The Case of Nekemte City, Oromia, Ethiopia. European Journal of Business and Management, ISSN 2222-1905 (Paper), ISSN 2222-2839 (Online). Vol. 14, No. 21.

Tigre, G. 2018. Multidimensional poverty and its dynamics in Ethiopia. In: Heshmati A., Yoon H. (Eds) Economic Growth and Development in Ethiopia (pp. 161–195). Springer, Singapore.

Tilman Bruck and Sindu Workneh Kebede. 2013. Dynamics and Drivers of Consumption and Multidimensional Poverty: Evidence from Rural Ethiopia, The Institute for The Study of Labor (IZA) Discussion Paper No. 7364, Bonn, Germany.

UN. 2016. Multidimensional Poverty and its Measurement: Guide on Poverty Measurement, Conference of European Statisticians, 12-13 July 2016. Geneva, Switzerland,

UNDP. 2018. Ethiopia's Progress Towards Eradiating Poverty, Paper Presented to the Inter-Agency Group Meeting on "Implementation of the Third United Nations Decade for the Eradication of Poverty (2028 – 2027)", Addis Ababa, Ethiopia.

UNPD. 2023. Briefing note for countries on the 2023 Multidimensional Poverty Index: Ethiopia.

UNDP & OPHI. 2024. Global Multidimensional Poverty Index 2024. Poverty Amid Conflict. The United Nations Development Programme and Oxford Poverty and Human Development Initiative.

Wang, C., Zeng, B., Luo, D., Wang, Y., Tian, Y., Chen, S., He, X. 2021. Measurements and determinants of multidimensional poverty in Chinna. Journal of Social Service Research, 1–19.

Wisor, S. 2012. Monetary Approaches. In: Measuring Global Poverty. Palgrave Macmillan, London. https://doi.org/10.1057/9780230357471_4.

Wooldridge, J. M. 2010. Econometric Analysis of Cross Section and Panel Data (2nd ed.). MIT Press.

World Bank Group. 2023. Poverty and Equity Brief Ethiopia, Eastern and Southern Africa, povertydata.worldbank.org.

Xixi Wu, Qiangqiang Zhang, Hongyu Ma, and Yujie Hu. 2024. Off-farm employment and multidimensional poverty: empirical evidence from the Yellow River Basin in China, Journal of Rural Sociology, V. 54:01, e20220367, https://doi.org/10.1590/0103-8478cr20220367.

Yamane, Y. 1967. Mathematical Formulae for Sample Size Determination.

Yohannes Mare, Yishak Gecho & Melkamu Mada. 2022. Determinants of multidimensional rural poverty in Burji and Konso area, Southern Ethiopia, Cogent Social Sciences, 8:1, 2068757, DOI: 10.1080/23311886.2022.2068757.