

---

## The Implication of Geospatial and Households Characters on Multidimensional Vulnerability in Rural Ethiopia

By

Zewdu Legesse<sup>1</sup>; Arega Shumetie Ademe<sup>2</sup>

---

### Abstract

*This study examines how household and geospatial factors shape vulnerability to multidimensional poverty in rural Ethiopia, drawing on pooled Ethiopian Socioeconomic Survey data and applying the Feasible Generalized Least Squares (FGLS) approach. Results reveal persistent poverty dynamics: 95% of poor households in 2012 and 97% in 2019 remained vulnerable, while about 6% of previously non-poor households were at risk of falling into poverty. Geographic isolation strongly influenced vulnerability, with each additional kilometer from the nearest main road and market increasing poverty risk by 0.3% and 0.02%, respectively. In contrast, favorable climatic conditions alleviated risks, as a one-unit rise in average annual rainfall reduced vulnerability by 0.5%. Demographic and livelihood characteristics also played a role—each additional year of a household head's age reduced poverty vulnerability by 0.4%, whereas participation in non-agricultural work lowered risk by 2.4% per additional hour spent. Religion influenced outcomes, as non-Orthodox and non-faith households showed lower vulnerability. Regional differences persisted, with households outside Harari more vulnerable than those in Tigray. These findings emphasize the importance of region-specific, socially responsive, and infrastructure-oriented policies to strengthen resilience and reduce rural poverty.*

---

**Keywords:** Multidimensional, Vulnerability, Household, Geo-spatial, Rural

---

### 1. Introduction

#### 1.1. Background of the Study

Poverty remains one of the most persistent socio-economic challenges in developing nations, particularly in rural areas where access to education, healthcare, and economic opportunities is limited (World Bank, 2020; UNDP & OPHI, 2021). In line with the multidimensional view of poverty proposed by Alkire and Foster (2011), deprivation extends beyond income insufficiency to include deficits in health,

---

1 Amhara Region State University, Bahir Dar, Ethiopia

2 Ethiopian Economics Association, Addis Ababa, Ethiopia

education, and living standards. According to the 2021 Global Multidimensional Poverty Index (MPI), approximately 83.5 % of Ethiopia's rural population is classified as multidimensional poor compared with 17.3 % in urban areas (UNDP and OPHI, 2021). This widening rural-urban gap underscores persistent structural inequalities in access to infrastructure, markets, and social services (Beegle, et al., 2016; Dercon et al., 2009). Consequently, the present study focuses on analyzing how household and geospatial characteristics influence expected rural multidimensional poverty in Ethiopia, using pooled data from the Ethiopia Socioeconomic Survey (ESS).

Empirical research on vulnerability in Ethiopia indicates that even non-poor households face a high risk of falling into poverty due to limited social protection systems and heightened exposure to shocks (Calvo and Dercon, 2005; Dercon, 2006; World Bank, 2021). Nearly 40 % of households are reported to be just above the poverty line and are susceptible to shocks such as drought or price fluctuations (World Bank, 2021). However, coverage by formal safety-net programs remains inadequate, reaching only a fraction of those in need (OECD and Policy Studies Institute 2020; Ferdous and Ullah, 2023)

Vulnerability to multidimensional poverty can be defined as the probability that households will experience multiple deprivations in the future due to social, economic, or environmental shocks (Günther, I., and Harttgen, K, 2009). This forward-looking approach complements traditional, static poverty measures by identifying households at risk of slipping into deprivation (Chaudhuri, et al., 2002). In the Ethiopian rural context—where livelihoods depend primarily on climate-sensitive agriculture, land quality, and market accessibility—this dynamic perspective is critical for designing preventive poverty-reduction strategies (DiFalco and Veronesi, 2013).

The distinction between poverty and vulnerability lies in their temporal dimensions: while poverty captures current deprivation, vulnerability assesses future risk (Ligon and Schechter, 2003). A household that is not currently poor may still be highly vulnerable if it lacks resilience to shocks such as drought, illness, or price volatility (Dercon 2006; Calvo and Dercon, 2005). Recognizing this difference is vital for crafting policies that combine immediate poverty alleviation with long-term resilience building (Beegle et al., 2016).

Rural Ethiopia's dependence on rain-fed agriculture and limited infrastructure increases susceptibility to cyclical poverty traps (Dufflo and Banerjee 2011; Loison 2019,). Empirical evidence demonstrates that droughts, soil degradation, and weak market linkages significantly elevate vulnerability among smallholder farmers (Silvestri et al., 2012; Woldehanna and Behrman, 2013). Despite these challenges, comprehensive assessments integrating household-level and geospatial determinants of expected multidimensional poverty remain scarce. This gap motivates the present study, which adopts a multidimensional, spatially informed approach to estimate vulnerability and inform context-specific poverty reduction interventions.

## **1.2. Statement of the Problem**

Although Ethiopia has achieved substantial progress in poverty reduction over the past decade, significant disparities persist between urban and rural regions (CSA 2021; World Bank, 2020). The 2021 Household Consumption and Expenditure Survey (HCES) reported that national income based poverty declined from 29.6 % in 2010/11 to 23.5 % in 2019/20, but rural poverty remains disproportionately high at 25.6 %, compared to 14.8 % in urban areas (CSA, 2021). This persistent rural disadvantage is reinforced by limited infrastructure, lower human capital accumulation, and constrained livelihood diversification opportunities (Bigsten et al., 2003; Kassie et al., 2014).

Beyond income-based measures, multidimensional assessments reveal even higher deprivation. A World Bank (2016) analysis of the Ethiopian Demographic and Health Survey (DHS) showed that 42 % of rural households were deprived in at least three key dimensions—education, health, and living standards—indicating that conventional poverty measures substantially understate vulnerability.

Furthermore, panel-data evidence from the ESS (2011-2016) analyzed by the Ethiopian Development Research Institute (EDRI) reveals that nearly 30 % of rural households initially non-poor fell into poverty within five years (EDRI, 2018). Such downward mobility highlights the fragility of rural livelihoods and the inadequacy of institutional safety nets (Dercon 2006; Beegle et al., 2016). Exposure to crop loss, livestock shocks, and health-related expenses significantly exacerbates this risk (Di Falco and Veronesi 2013; Loison, 2019).

Persistent climatic, economic, and demographic pressures make it essential to develop an integrated understanding of vulnerability to multidimensional poverty that incorporates both household-level characteristics and spatial–environmental conditions. However, empirical studies that jointly integrate household and geospatial variables within a multidimensional framework are still scarce. This study therefore investigates how household and geospatial factors — including labor characteristics, proximity to infrastructure (roads, markets, zonal centers), and climatic indicators (rainfall, temperature, and a wetness index) — influence vulnerability to rural multidimensional poverty. Drawing on pooled ESS panel data, the analysis seeks to produce actionable evidence to inform targeted, climate-resilient rural development policies in Ethiopia.

## **2. Literature Review**

### **2.1. Conceptualizing Multidimensional Poverty and Vulnerability**

Poverty is now widely conceptualized as a multidimensional condition encompassing deprivations across education, health, and living standards, rather than a uni-dimensional lack of income (Alkire, and Foster, 2011). The Multidimensional Poverty Index (MPI) formalizes this understanding by integrating various indicators of wellbeing into a composite measure.

Building on this foundation, vulnerability refers to the probability that a household will fall into or remain in poverty due to exposure to shocks, risks, and limited coping capacity (Calvo and Dercon, 2005; Dercon, 2006); Günther and Harttgen, 2009). It thus captures an ex-ante dimension of welfare risk. In agrarian economies like Ethiopia’s—where livelihoods depend heavily on rainfall and fluctuating markets—vulnerability analysis provides an essential complement to static poverty measurement by highlighting households at risk before they become poor.

### **2.2. Rural Poverty and Household Socioeconomic Characteristics in Ethiopia**

Despite national progress in poverty reduction, rural Ethiopia remains disproportionately affected by multidimensional deprivation. The World Bank (2020) and UNDP and OPHI (2021) report that over 80 % of rural households experience multiple deprivations compared with less than 20 % in urban areas.

Household characteristics are central to explaining these disparities. Education, age, and income diversification tend to enhance resilience, while high dependency ratios and limited asset bases increase exposure to poverty risks (Bigsten et al., 2003; Beegle et al., 2016). Participation in non-agricultural employment significantly reduces vulnerability by smoothing income and reducing dependence on climate-sensitive crops (Kassie et al., 2014; Loison, 2019). However, gender disparities and constraints

faced by female-headed households persist, reinforcing structural vulnerability patterns within rural communities.

### **2.3. Geospatial and Environmental Determinants of Poverty**

Spatial inequality remains a fundamental structural determinant of rural poverty and vulnerability (Kaiser and Barstow, 2022). Households located farther from markets and transportation infrastructure face restricted access to inputs, credit, and information, thereby lowering productivity and welfare outcomes. In Ethiopia, empirical evidence shows that distance to roads and market centers is positively correlated with poverty incidence (Dercon et al., 2009).

Environmental shocks further aggravate this spatial disadvantage: rainfall variability and droughts undermine agricultural yields, worsen food insecurity, and compound poverty (Di Falco and Veronesi, 2013). Integrating geospatial and climatic variables into vulnerability assessment therefore enhances understanding of where and why rural households are most at risk—an insight vital for spatially targeted intervention policies.

### **2.4. Regional and Sociocultural Dimensions of Vulnerability**

Ethiopia's pronounced regional diversity generates unequal vulnerability outcomes. Households in arid and semi-arid regions such as Afar, Somali, and Benishangul-Gumuz exhibit higher risk exposure and weaker coping capacity compared with agriculturally favorable areas such as Tigray and Amhara (Woldehanna and Behrman, 2013).

Beyond ecological variation, social institutions and religious networks influence household adaptation strategies. Communities with strong social capital and collective action mechanisms display greater resilience during crises (Croppenstedt and Muller, 2000). Recognizing these sociocultural differences is therefore critical to designing context-sensitive development and protection programs.

### **2.5. Measuring Vulnerability: Methodological Context**

Recent methodological developments enable estimation of vulnerability as the probability of future poverty using longitudinal data combined with econometric models that account for error heteroskedasticity, such as Feasible Generalized Least Squares (FGLS) (Chaudhuri et al., 2002; Dercon 2006). Datasets like the Ethiopia Socioeconomic Survey (ESS) provide ideal longitudinal coverage for assessing household transitions over time.

However, previous Ethiopian studies often rely on income-based measures or single-dimension poverty indices, overlooking the interaction of geospatial variables (e.g., road proximity, rainfall) with multidimensional deprivation. This omission restricts a holistic understanding of rural vulnerability and its spatial determinants.

### **2.6. Synthesis and Identified Research Gap**

The reviewed literature demonstrates that vulnerability to multidimensional poverty in rural Ethiopia arises from intertwined demographic, economic, and geospatial factors. Older and more educated household heads, diversified income sources, and proximity to infrastructure tend to lower vulnerability, whereas environmental shocks and geographic isolation intensify it.

Yet, few empirical studies simultaneously integrate household and geo-environmental variables within a multidimensional and dynamic econometric framework. This study addresses that gap by utilizing

pooled ESS panel data and applying a three-stage FGLS estimation approach to jointly assess how geospatial accessibility, environmental variation, and household attributes determine vulnerability. The findings will contribute to designing region-specific, resilience-enhancing policy interventions tailored to Ethiopia’s rural context.

### 3. Methodology of the study

#### 3.1. Type and Source of Data

This study will employ secondary pooled data from the Ethiopia Socioeconomic Survey (ESS) spanning the years 2012 to 2019. The primary objective is to examine how household and geospatial characteristics influence vulnerability to multidimensional poverty in Ethiopia. The pooled ESS dataset offers rich household-level data, including information on the age and gender of the household head, household size, presence of children, religious affiliation, and various other demographic and socioeconomic indicators.

Notably, the ESS panel data are supplemented with detailed geospatial variables at the household level. According to the Central Statistical Agency of Ethiopia and the World Bank (2011), these geospatial elements include measurements related to distance, climatological conditions, soil type, terrain characteristics, and other environmental attributes. Integrating such spatially explicit information enhances the capacity to analyze poverty patterns beyond conventional socioeconomic variables. The inclusion of geospatial data is fundamental to understanding the spatial heterogeneity of poverty and identifying environmental and locational factors that heighten household vulnerability. By leveraging both socioeconomic and spatial dimensions, this research aims to generate evidence-based insights to inform more spatially targeted and context-specific poverty reduction strategies in Ethiopia.

#### 3.2. Method of Data Analysis

##### 3.2.1. Measuring Multidimensional Rural Poverty

This study employs the Rural Multidimensional Poverty Index (R-MPI) framework developed by the Food and Agriculture Organization (FAO) and the Oxford Poverty and Human Development Initiative (OPHI, 2022), adapting it to the Ethiopian context through the Alkire-Foster (AF) method (Alkire and Foster, 2011). The R-MPI captures multiple deprivations experienced by rural households across five equally weighted dimensions such as food security and nutrition, education, living standards, rural livelihoods and resources and exposure to risks. Table 1 presents the dimensions and corresponding 16 indicators used to construct the R-MPI.

Table 1 Wellbeing dimension, deprivation indicators and its weight and deprivation cutoffs

Dimensions	Deprivation/Inequality Indicators
Food security and nutrition	Food insecurity and Chilled malnutrition
Education	School attendance and Years of schooling
Living standard	Improved sanitation, Drinking water, Housing, Assets and Electricity
Rural livelihoods and resources	Land certification, Social protection (Assistances), Nonfarm enterprise and Extension services
Risk	Credit denial, Risk of socioeconomic shocks and Risk of climate shocks

Alkire-Foster Methodological Steps:

#### 1. Define Deprivation Cutoffs ( $z_j$ ):

Each indicator has a binary deprivation status, where 1 indicates deprivation and 0 indicates non-deprivation. For instance, a household is considered deprived in food security if it experienced food shortages within the past 12 months; likewise, a household is deprived in livelihoods if no member owns a non-farm enterprise.

Equal weighting is applied across indicators, based on the normative assumption that no single dimension of poverty should be prioritized over others (Alkire and Foster, 2011). This weighting approach has been validated in previous multidimensional poverty studies (Alkire and Santos, 2010).

**2. Calculate Deprivation Score (C<sub>i</sub>):**

For each household *i*, the score is the weighted sum of deprivations:

$$\text{Formula: } C_i = \sum w_j I_j \quad (\text{FOR } J = 1 \text{ TO } 16) \dots\dots\dots 1$$

Where *I<sub>j</sub>* = 1 if deprived in indicator *j*, and *w<sub>j</sub>* is its weight.

**3. Identify the Poor:**

A household is classified as multidimensional poor if its deprivation score meets or exceeds the poverty cutoff (*C<sub>i</sub>* ≥ *K*). Following common MPI literature, this study applies a cutoff of *K* = 33%, meaning that households deprived in at least one-third of the weighted indicators are considered multidimensional poor.

**4. Compute the Rural Multidimensional Poverty Index (R-MPI):**

The R-MPI is the product of the headcount ratio (*H*) and intensity (*A*) of poverty. Headcount ratio (*H*): represents the proportion of the population identified as multidimensional poor. The multidimensional headcount ratio (*H*) is the formal name for the first component and it shows the percentage of the population living in multidimensional poverty.

$$\text{Formula: } H = \frac{\text{Number of poor people (q)}}{\text{Total population (n)}} \dots\dots\dots 2$$

*Intensity (A)*: The intensity (or breadth) of poverty is the second component that denoted by *A* and it indicates the multidimensional impoverished people that is an average deprivation score.

$$\text{Formula: } A = \frac{\sum C_i(K)}{q} \quad (i = 1 \text{ to } q) \dots\dots\dots 3$$

The overall R-MPI is then calculated as:

$$R-MPI = H \times A \dots\dots\dots 4$$

**3.2.2. Method of Vulnerability to Poverty Assessment**

The assessment of Vulnerability to Multidimensional Poverty (VMP) in this study employs the three-stage Feasible Generalized Least Squares (FGLS) estimation technique originally developed by (Amemiya, 1977). This methodology is well recognized in empirical research for its ability to effectively handle econometric challenges such as heteroskedasticity (non-constant error variance) and autocorrelation (correlated error terms). Recent applications in vulnerability and poverty research, including (Marzi et al., 2021) and (Hernández and Zuluaga 2022), have demonstrated the robustness and reliability of this approach. The proven effectiveness of FGLS in addressing statistical inefficiencies motivates its

application in analyzing rural poverty vulnerability in Ethiopia.

The FGLS procedure is implemented through three sequential stages:

### **First Stage: Ordinary Least Squares (OLS) Estimation**

The initial stage involves estimating the baseline model using Ordinary Least Squares (OLS). This step generates preliminary coefficient estimates that describe the linear relationships between household deprivation and its determinants. The residuals obtained from this regression, representing unexplained variations, form the basis for diagnosing heteroskedasticity and autocorrelation in subsequent stages. OLS is employed at this stage due to its conceptual simplicity and interpretability.

### **Second Stage: Variance Estimation**

In the second stage, the residuals from the OLS regression are used to estimate the variance of the error term. This step identifies potential patterns of heteroskedasticity by modeling the squared residuals as a function of relevant covariates. Through this process, we derive estimates of the variance structure across observations, allowing for a more accurate correction of inefficiencies in the final estimation stage.

### **Third Stage: Weighted Least Squares (WLS) Estimation**

The third stage re-estimates the original model using Weighted Least Squares (WLS), based on the variance estimates obtained in the second stage. This involves applying weights that are inversely proportional to the estimated error variances, thereby correcting for heteroskedasticity and ensuring efficiency and consistency of the estimated coefficients. This step significantly enhances the reliability of the regression results and supports valid statistical inference.

To empirically measure Vulnerability to Multidimensional Poverty (VMP), this study adopts the household deprivation score ( $d_{it}$ ) approach, consistent with established methodologies by (Feeny and McDonald 2016) and (Hernández and Zuluaga, 2022). The reduced-form model used to estimate Rural Vulnerability to Multidimensional Poverty (RV-MP) is expressed as:

$$d_{it} = f(Geo_{it}, H_{it}, G_{it}) \dots \dots \dots 5$$

In this equation,  $d_{it}$  represents the household deprivation scores,  $Geo_{it}$  encompasses a vector of geospatial characteristics,  $H_{it}$  is a vector of household characteristics, and  $G_{it}$  is group variables. This formulation allows for a comprehensive analysis that incorporates both individual household factors and broader geographical influences on vulnerability.

In summary, the integration of the FGLS technique with the household deprivation score provides a robust empirical framework for analyzing vulnerability to multidimensional poverty in Ethiopia. By correcting for potential econometric biases and incorporating geospatial as well as household-level factors, this approach yields more reliable and policy-relevant insights into the risk dynamics of rural poverty.

### **3.2.3. Model Specification**

Building on the multidimensional poverty and vulnerability framework described above, this section specifies the empirical model used to estimate Vulnerability to Multidimensional Poverty (VMP) among Ethiopian households. The specification integrates both household-level and geospatial variables,

consistent with the panel structure of the Ethiopia Socioeconomic Survey (ESS) data spanning 2012–2019.

The estimation follows the three-stage Feasible Generalized Least Squares (FGLS) approach set out in Section 3.2.2 to correct for possible heteroskedasticity and autocorrelation.

### 3.2.3.1. Conceptual Model

The relationship between household deprivation and its determinants can be expressed conceptually as:

$$d_{it} = \alpha + \beta_1 DMR_{it} + \beta_2 DIMA_{it} + \beta_3 DIZC_{it} + \beta_4 RA_{it} + \beta_5 EL_{it} + \beta_6 PWI_{it} + \beta_7 HA_{it} + \beta_8 LA_{it} + \beta_9 LANAGAC_{it} + \lambda_1 RS_{it} + \lambda_2 RE_{it} + \varepsilon_{it} \dots\dots\dots 6$$

Where:

- Dependent Variable

- $d_{it}$  — Vulnerability to multidimensional poverty for household  $i$  in time  $t$  (derived from deprivation score).

- Independent Variables

(1) Geospatial Factors:

- $DMR_{it}$  — Distance (km) to the nearest major road.
- $DIMA_{it}$  — Distance (km) to the nearest market.
- $DIZC_{it}$  — Distance (km) to the nearest zonal center.
- $RA_{it}$  — Rainfall (mm) over a 12-month period.
- $EL_{it}$  — Elevation (m).
- $PWI_{it}$  — Potential Wetness Index.

(2) Household Characteristics:

- $HA_{it}$  — Age of the household head (years).
- $LA_{it}$  — Land area in square meters.
- $LANAGAC_{it}$  — Hours spent in non-agricultural activities per week.

(3) Group Variables (Categorical):

- $RS_{it}$  — Religious status of the household head.
- $RE_{it}$  — Region where the household resides.

$\varepsilon_{it}$  (epsilon) denotes the random disturbance term capturing unobserved factors.

Equation (6) therefore represents the theoretical framework linking vulnerability to geospatial accessibility, household endowments, and group-specific characteristics.

### 3.2.3.2. Panel Data Estimation Framework

Given that the ESS dataset is panel (longitudinal)—tracking the same households across survey years—this study incorporates both cross sectional and time dimensions. The corresponding panel model is specified as:

$$d_{it} = \alpha_i + \gamma_t + \beta_1 DMR_{it} + \beta_2 DIMA_{it} + \beta_3 DIZC_{it} + \beta_4 RA_{it} + \beta_5 EL_{it} + \beta_6 PWI_{it} + \beta_7 HA_{it} + \beta_8 LA_{it} + \beta_9 LANAGAC_{it} + \lambda_1 RS_{it} + \lambda_2 RE_{it} + \mu_{it} \dots\dots\dots 7$$

Where:

- $\alpha_i$  captures unobserved household-specific fixed effects, representing time-invariant attributes such as location, cultural practices, or long-term livelihood orientation.
- $\gamma_t$  represents time-specific (year) effects, controlling for national events, macroeconomic shifts, or environmental shocks common to all households during period t.
- $\mu_{it}$  is the idiosyncratic error term.

Equation (7) thus operationalizes the conceptual model by explicitly considering both household-level heterogeneity and temporal variation.

### 3.2.3.3. Vulnerability Estimation and Prediction

Following (Feeny and McDonald 2016) and (Hernández and Zuluaga, 2022), the predicted probability that a household will fall into multidimensional poverty in the future defines its vulnerability. The predictive model can be written as:

$$VMP_i = \Pr( d_{i(t+1)} \geq \tau \mid Geo_{it}, H_{it}, G_{it} ) \dots\dots\dots 8$$

Where:

- $\tau$  (tau) denotes the multidimensional poverty cutoff (33% deprivation).
- $\Pr(\cdot)$  represents the conditional probability function based on parameter estimates derived from Equation (5).
- A household is deemed vulnerable to multidimensional poverty if  $VMP_i \geq 0.5$ , following the convention used in similar studies (Lyons et al., 2021; Marzi et al., 2021).

## 4. Result and Discussion

### 4.1. Estimation of Vulnerability to Multidimensional Poverty

Table 2 illustrates that 50%, 41%, 43%, and 52% of rural residents classified as poor in 2012, 2014, 2016, and 2019, respectively, are projected to remain vulnerable to multidimensional poverty in the coming years. Notably, while the proportion of currently poor individuals vulnerable to poverty decreased in 2014, it has shown a rising trend in the subsequent years. Conversely, among those who were not currently poor, the likelihood of vulnerability to multidimensional poverty increased, with rates of 24%, 30%, 39%, and 30% in 2012, 2014, 2016, and 2019, respectively. Although the number of individuals not currently poor has been declining over the years, a rise is observed in 2019.

The factors contributing to vulnerability include limited access to education, inadequate essential health

services, poor living conditions, and susceptibility to various disasters. Therefore, it is essential to develop multifaceted strategies aimed at alleviating vulnerability to multidimensional poverty.

Table 2 Multidimensional Poverty to Vulnerability

Year	Non-Poor	Percent	Vulnerable	Percent	Non-Vulnerable	Percent
2012	320	0.1	78	24	242	76
2014	217	0.7	65	30	152	70
2016	327	0.11	128	39	199	61
2019	164	0.5	50	30	114	70
Poor						
2012	3025	0.9	1511	50	1514	50
2014	2888	0.93	1187	41	1701	59
2016	2654	0.89	1137	43	1517	57
2019	2876	0.95	1507	52	1369	48

As shown in Table 3, a significant portion of individuals projected to be vulnerable to poverty in the coming years are currently among the impoverished segments of society. This highlights the urgent need for policymakers to focus on addressing multidimensional poverty in rural areas. Furthermore, the table indicates that 95% and 97% of those who will be vulnerable to poverty in the future were already classified as poor in 2012 and 2019, respectively, suggesting a persistent cycle of vulnerability.

Research by (Günther and Harttgen, 2009) and (Azeem et al., 2018), emphasizes that a threshold of over 50% is often used to identify individuals likely to remain vulnerable to poverty for more than one year. This indicates that many people living in poverty in rural Ethiopia are likely to remain trapped in this cycle for an extended period. Given these findings, it is crucial for policymakers to implement targeted interventions that address the root causes of poverty and enhance the resilience of vulnerable populations in rural areas.

Table 3 Vulnerability to Multidimensional Poverty

Year	Non-Vulnerable	Non-Poor	Percent	Poor	Percent
2012	1756	242	14	1514	86
2014	1853	152	8	1701	92
2016	1716	199	12	1517	88
2019	1483	114	8	1369	92
Vulnerable					
2012	1589	78	5	1511	95
2014	1252	65	5	1187	95
2016	1265	128	10	1137	90
2019	1557	50	3	1507	97

The current situation indicates that escaping the poverty trap in rural Ethiopia will pose a significant challenge in the coming years. Therefore, it is essential to develop policies aimed at addressing the deep-rooted poverty in these areas, alongside implementing structural changes in economic sectors. Additionally, data reveals that approximately 6% of individuals who are currently not classified as poor

are projected to become vulnerable to poverty in the near future. To combat this trend, it is crucial to establish a proactive system designed to prevent vulnerability to poverty before it occurs.

#### **4.2. Econometric Analysis of Vulnerability to Multidimensional Poverty**

In this study, we analyzed the factors contributing to vulnerability to poverty in the coming years by incorporating various geospatial data and household characteristics at the household level.

To investigate the relationship between geographic characteristics and vulnerability to multidimensional poverty, this study incorporates a range of spatial variables, including the household's distance from the main road, proximity to the nearest market, distance from zonal centers, average annual rainfall, elevation, and the potential wetness index.

Table 4 indicates that, among the examined variables, the distance of households from the main road exhibits a statistically significant positive relationship with vulnerability to multidimensional poverty. Specifically, it implies that for every kilometer increase in distance from the main road, the vulnerability to multidimensional poverty rises by 0.3%. Similar to this study (Khandker et al., 2009), provided empirical evidence from Bangladesh showing that better infrastructure significantly reduces multidimensional poverty by enhancing mobility and economic participation. These findings underscore the importance of strategic planning and policy interventions aimed at expanding infrastructure and improving road networks to enhance accessibility for remote communities. By doing so, policymakers can mitigate the adverse effects of market distance on poverty and promote inclusive economic growth.

Furthermore, the distance from the nearest market demonstrates a statistically significant positive relationship with vulnerability to multidimensional poverty. This finding suggests that an increase of 1 kilometer in distance from the market correlates with a 0.02% rise in household poverty dynamics. Several studies have established a positive and statistically significant relationship between a household's distance from market centers and its vulnerability to multidimensional poverty. For instance, Smith and Haddad (2000) found that, limited access to markets restricts food security and economic opportunities, thereby exacerbating poverty levels. Similarly, (Escobal and Torero, 2005), demonstrated that rural households located farther from economic hubs face higher deprivation in multiple dimensions, including education, healthcare, and financial services. .

The study reveals a statistically significant negative relationship between distance from the nearest zonal center and vulnerability to multidimensional poverty. Surprisingly, this implies that households located farther from zonal centers are more likely to experience lower levels of poverty. While this finding contrasts with much of the existing literature, it may reflect localized factors such as self-sufficiency in rural areas, targeted rural development programs, or lower living costs in remote regions. For example, a study by (Bigman and Fofack, 2000), highlights that while poverty is generally higher in remote areas, spatial poverty dynamics can vary substantially depending on regional development strategies and resource endowments.

The results of this study reveal a statistically significant negative association between average annual rainfall and household vulnerability to multidimensional poverty. Specifically, a one-unit increase in average annual rainfall is associated with a 0.5% reduction in the likelihood of households experiencing poverty dynamics. This suggests that higher levels of rainfall are associated with a reduction in vulnerability, likely due to enhanced agricultural productivity and increased water availability, both of which are essential for rural livelihoods. Specifically, an increase of 1 millimeter in rainfall is associated with a 5% decrease in vulnerability to multidimensional poverty. Similar results were reported by EJBME, Vol. 8, No. 2, 2026

(Deressa et al., 2008) who found that adequate rainfall contributes to household resilience in the face of poverty in sub-Saharan Africa. Conversely, the results indicate that increases in average temperature are positively associated with heightened vulnerability to multidimensional poverty. Elevated temperatures may exacerbate water scarcity, reduce crop yields, and increase health risks, thereby undermining efforts to reduce poverty. This is consistent with findings by Ahmed et al., (2009), who demonstrated that rising temperature negatively impacts agricultural income and food security, particularly among poor rural households.

The analysis demonstrates a statistically significant negative relationship between age and household vulnerability to poverty. Specifically, each additional year of age is associated with a 0.4% reduction in the likelihood of households experiencing poverty dynamics. This indicates that families with members in their prime age are less vulnerable to poverty. Previous studies have highlighted varying impacts of age on poverty vulnerability, noting that while younger age groups often face greater economic opportunities, older age can lead to increased financial insecurity due to factors such as retirement and health issues. Thus, the negative relationship between age and poverty vulnerability is clear, further investigation is required to unpack the complexities of how aging correlates with economic risk.

This study examines the relationship between the amount of time a household head spends working each week and the household's vulnerability to poverty. It aims to uncover how the time dedicated to work correlates with multidimensional poverty vulnerability. The analysis identifies the connections between non-agricultural tasks (including water harvesting, wood collection, and fencing) —and their impact on vulnerability to poverty. Specifically, when farmers allocate an additional hour to non-agricultural work, vulnerability to poverty decreases by 2.4%. By examining these relationships, the study offers valuable insights into how employment patterns and time allocation impact poverty dynamics within households.

This study's results align with previous research indicating a significant relationship between non-agricultural occupations and poverty reduction in rural areas of Ethiopia. Specifically, the findings suggest that the time a household head dedicates to non-agricultural work is inversely related to the risk of future poverty. This implies that engaging in non-agricultural activities can enhance a family's resilience against poverty.

In comparison to earlier studies, such as those conducted in the Horo Guduru Wollega zone, it has been shown that households participating in non-farm employment experience higher levels of consumption and improved living standards compared to those relying solely on agricultural income (Tesgera et al., 2024). This reinforces the notion that diversifying income sources through non-agricultural work is crucial for reducing vulnerability to poverty in rural settings.

Moreover, the findings are consistent with the broader literature that highlights the importance of non-farm activities in enhancing household income and consumption levels, thereby contributing to poverty alleviation (Woldehanna, 2002). The evidence suggests that non-agricultural occupations not only provide immediate financial benefits but also serve as a buffer against the uncertainties associated with agricultural production, such as climate variability and market fluctuations (Tesgera et al., 2024). Overall, the study underscores the need for policies that promote non-agricultural employment opportunities as a viable strategy for poverty reduction in rural Ethiopia.

This study explores the role of different religions in relation to social and economic issues that contribute to the vulnerability of poverty. These study findings suggest that families adhering to other religions—such as Catholicism, Protestantism, Islam, and various Traditional beliefs—exhibit a lower vulnerability

to poverty compared to Orthodox followers. Additionally, households that do not identify with any faith (non-faith households) are similarly positioned to face lowered poverty risks in the coming years. Specifically, the comparative vulnerability can be summarized as follows: Orthodox followers represent a higher vulnerability to poverty, while Catholic, Protestant, Muslim, Traditional, Pagan, and other faith followers are less vulnerable to poverty compared to Orthodox followers.

This analysis aligns with existing literature that highlights the complex relationship between religiosity and socioeconomic outcomes. For instance, previous studies indicate that religious involvement can influence behaviors that either mitigate or exacerbate poverty, depending on the social context and the specific beliefs held by different religious groups (Joshi et al., 2009; Rogers et al., 2018). Understanding these dynamics is crucial for developing targeted interventions that address the unique challenges faced by various religious communities in the context of poverty.

The findings indicate that vulnerability to poverty varies significantly across different regions. When using the Tigray region as a baseline, most regions exhibit lower vulnerability to poverty, with Harari being a notable exception. Specifically, the Afar, Amhara, Oromia, Somali, and SNNP regions demonstrate significantly lower vulnerability compared to Tigray. In contrast, the Harari and Benshagul-Gumuz region are relatively high vulnerable when compared to Tigray.

Table 4 Econometric Analysis of Vulnerability to Multidimensional Poverty

Variable	Deprivation Score	Variance of deprivation score	Vulnerability to poverty (FGLS model)
Distance from Major Road	= 0.0001***	0.0001***	-0.03***
	(0.0004)	(0.0002)	(0.003)
Distance from Marekt	0.0001	= 0.0001*	0.002**
	(0.0001)	(0.0002)	(0.001)
Distance from Zonal centers	0.0002	0.0001*	-0.001*
	(0.0001)	(0.0021)	(0.001)
Rainfall	= 0.0005	0.0003	= 0.05*
	(0.0002)	(0.0002)	(0.0002)
Elevation	= 0.0003***	= 0.0001	0.0003
	(0.0013)	(0.0001)	(0.0001)
Potential Wetness Index	=0.0002	-0.0002	-0.0013
	(0.0003)	(0.0003)	(0.0015)
Age	= 0.0004***	0.0003*	-0.04***
	(0.0006)	(0.0001)	(0.0001)
Land Size	= 0.0003	0.0003**	-0.0004
	(0.0001)	(0.0001)	(0.0007)
Labor on non- agricultural activity	= 0.0007***	0.0001***	-0.024***
	(0.0001)	(0.0000)	(0.0001)

Religious Status			
Catholic	0.0313**	0.0017	-0.0313**
	(0.0018)	(0.0018)	(0.0106)
Protestant	-0.0003***	-0.0003	-0.0261***
	(0.0006)	(0.0006)	(0.0037)
Muslem	0.0001***	0.0001	-0.0218***
	(0.0006)	(0.0006)	(0.0034)
Traditional	0.0018***	0.0018	-0.0693***
	(0.0021)	(0.0021)	(0.013)
Pagan	-0.001**	-0.001	-0.0384**
	(0.0021)	(0.0021)	(0.013)
Other (S..)	0.0018***	0.0018	-0.087***
	(0.0022)	(0.0022)	(0.0136)
Region			
Afar	-0.0018***	-0.0018	-0.0294*
	(0.0011)	(0.0011)	(0.0066)
Amhara	-0.0002	-0.0002	-0.0053*
	(0.0007)	(0.0007)	(0.0042)
Oromia	-0.0006**	-0.0006	-0.0141**
	(0.0008)	(0.0008)	(0.0046)
Somalie	-0.0034***	-0.0034***	-0.0609*
	(0.001)	(0.001)	(0.0057)
Benshagul..	0.0004	0.0004	0.0085**
	(0.0011)	(0.0011)	(0.0068)
SNNP	-0.0009***	-0.0009	-0.0284*
	(0.0008)	(0.0008)	(0.0047)
Gambelia	-0.0029	-0.0029*	-0.0048*
	(0.0011)	(0.0011)	(0.0068)
Harari	-0.0028***	-0.0028*	0.05*
	(0.0012)	(0.0012)	(0.0069)
Direwda	0.0001	0.0001	-0.0001*
	(0.0012)	(0.0012)	(0.007)
_cons	0.0202***	0.0202***	0.6439*
	(0.0067)	(0.0067)	(0.0407)

Significance level presented as 1 percent (\*), 5 percent (\*\*) and 10 percent (\*\*\*)

## 5. Conclusion and Recommendations

### Conclusion:

This study investigated how household-level and geospatial characteristics shape vulnerability to multidimensional poverty in rural Ethiopia using pooled survey data and robust econometric techniques. The results show strong persistence in poverty-related vulnerability over time. In 2012, about 95% of poor households remained vulnerable, and by 2019 this increased to 97%, indicating that escaping poverty is difficult and that many households remain trapped in conditions that expose them to continued deprivation. In addition, roughly 6% of previously non-poor households were at risk of falling into poverty, highlighting the fragility of rural livelihoods and the importance of preventive policy measures alongside poverty reduction programs.

Geospatial conditions were found to be critical drivers of vulnerability. Greater distance from key infrastructure significantly increased poverty risk: each additional kilometer from a main road raised vulnerability by about 0.3%, while each extra kilometer from a market increased vulnerability by around 0.02%. In contrast, favorable rainfall conditions reduced vulnerability, emphasizing the role of environmental and climatic factors in rural welfare and the importance of resilience to weather shocks.

Household characteristics also mattered. Older household heads were less vulnerable; each additional year of age reduced vulnerability by about 0.4%, suggesting that experience, social capital, and accumulated assets may help households manage shocks. Participation in non-agricultural and supplementary activities (e.g., water harvesting, wood collection, fencing) was associated with lower vulnerability, with each additional hour allocated reducing risk by about 2.4%, underscoring the protective effect of livelihood diversification. Socio-cultural factors were also relevant: compared to Orthodox Christian households, those identifying as Catholic, Protestant, Muslim, traditional faith adherents, or having no religious affiliation showed lower vulnerability. Finally, substantial regional disparities were observed; households outside Harari were generally more vulnerable than those in Tigray, confirming that multidimensional poverty vulnerability is widespread but unevenly distributed across regions.

### Recommendations:

- **Adopt region-specific poverty strategies:** Because vulnerability differs markedly by location, interventions should be tailored to regional conditions.
- **Improve infrastructure and market access:** Expanding rural roads and strengthening market facilities can reduce geographic isolation and improve access to services, employment, and inputs—key pathways for lowering vulnerability.
- **Strengthen climate and environmental resilience:** Promote climate-resilient agriculture through irrigation development, water management, drought-tolerant technologies, and early-warning systems to reduce the welfare impacts of rainfall variability.
- **Support livelihood diversification:** Expand skills training, microfinance, and asset-building initiatives that enable households to develop non-farm income sources, thereby reducing reliance on climate-sensitive agriculture.
- **Enhance social protection:** Scale up targeted safety nets (e.g., conditional cash transfers and shock-responsive support) for vulnerable groups, particularly households exposed to climate risks and other recurrent shocks.

- **Incorporate socio-cultural considerations:** Since religious affiliation correlates with vulnerability differences, programs should be culturally sensitive and may benefit from partnerships with faith-based organizations to improve outreach and effectiveness.

## References

- Alkire, S. (2005). Why the capability approach? *Journal of Human Development*, 6 (1), 115–135. <https://doi.org/10.1080/146498805200034275>
- Alkire, S., Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics*, 95 (7–8), 476–487. <https://doi.org/10.1016/j.jpubeco.2010.11.006>
- Alkire, S., Santos, M. E. (2010). Multidimensional poverty index. OPHI Working Paper 38. Oxford Poverty and Human Development Initiative.
- Amemiya, T. (1977). The maximum likelihood and the nonlinear three-stage least squares estimator in the general nonlinear simultaneous equation model. *Econometrica*, 45 (4), 955–968. <https://doi.org/10.2307/1913820>
- Azeem, M. M., Mugeru, A. W., Schilizzi, S. (2018). Vulnerability to multi-dimensional poverty: An empirical comparison of alternative measurement approaches. *The Journal of Development Studies*, 54 (9), 1612–1636. <https://doi.org/10.1080/00220388.2017.1390976>
- Beegle, K., Friedman, J., De Weerd, J., Gibson, J. (2016). The challenge of measuring hunger through survey methods. *Economic Development and Cultural Change*, 64 (4), 727–758. <https://doi.org/10.1086/686265>
- Bigman, D., Fofack, H. (Eds.). (2000). *Geographical targeting for poverty alleviation: Methodology and applications*. World Bank Publications.
- Bigsten, A., Collier, P., Dercon, S., Fafchamps, M., Gauthier, B., Gunning, J. W., Oduro, A., Oostendorp, R., Pattillo, C., Söderbom, M., Teal, F., Zeufack, A. (2003). Credit constraints in manufacturing enterprises in Africa. *Journal of African Economies*, 12 (1), 104–125. <https://doi.org/10.1093/jae/12.1.104>
- Calvo, C., Dercon, S. (2005). Measuring individual vulnerability: A framework for analysis.
- Chaudhuri, S., Jalan, J., Suryahadi, A. (2002). Assessing household vulnerability to poverty from cross-sectional data: A methodology and estimates from Indonesia.
- Croppenstedt, A., Muller, C. (2000). The impact of farmers' health and nutritional status on their productivity and efficiency: Evidence from Ethiopia. *Economic Development and Cultural Change*, 48 (3), 475–502. <https://doi.org/10.1086/452451>
- Dercon, S. (2006). Vulnerability: A micro perspective. In *Securing development in an unstable world* (pp. 117–146).
- Dercon, S., Gilligan, D. O., Hoddinott, J., Woldehanna, T. (2009). The impact of agricultural extension and roads on poverty and consumption growth in fifteen Ethiopian villages. *American Journal*

- of Agricultural Economics, 91 (4), 1007–1021. <https://doi.org/10.1111/j.1467-8276.2009.01207.x>
- Deressa, T. T., Hassan, R. M., Ringler, C., Alemu, T., Yesuf, M. (2008). Determinants of farmers' choice of adaptation methods to climate change in the Nile Basin of Ethiopia. *Global Environmental Change*, 19 (2), 248–255. <https://doi.org/10.1016/j.gloenvcha.2008.01.002>
- Duflo, E., Banerjee, A. (2011). *Poor economics*. PublicAffairs.
- Escobal, J., Torero, M. (2005). Measuring the impact of asset complementarities: The case of rural Peru. *Cuadernos de Economía*, 42 (125), 137–164.
- Feeny, S., McDonald, L. (2016). Vulnerability to multidimensional poverty: Findings from households in Melanesia. *The Journal of Development Studies*, 52 (3), 447–464. <https://doi.org/10.1080/00220388.2015.1090475>
- Ferdous, J., Ullah, A.A. (2023). *Social safety nets and poverty reduction in developing countries*. Routledge.
- Günther, I., Harttgen, K. (2009). Estimating households vulnerability to idiosyncratic and covariate shocks: A novel method applied in Madagascar. *World Development*, 37 (7), 1222–1234. <https://doi.org/10.1016/j.worlddev.2008.11.00720>. Hernández, J.E., Zuluaga, B.(2022). Vulnerability to multidimensional poverty: An application to Colombian households. *Social Indicators Research*, 164(1), 345–371.
- Joshi, P., Hardy, E., Hawkins, S.(2009). *The role of religiosity in the lives of the low-income population: A comprehensive review of the evidence*.
- Kaiser, N., Barstow, C.K.(2022). Rural transportation infrastructure in low- and middle-income countries: A review of impacts, implications, and interventions. *Sustainability*, 14(4), 2149.
- Kassie, M., Jaleta, M., Mattei, A.(2014). Evaluating the impact of improved maize varieties on food security in rural Tanzania: Evidence from a continuous treatment approach. *Food Security*, 6(2), 217–230.
- Khandker, S.R., Bakht, Z., Koolwal, G.B.(2009). The poverty impact of rural roads: Evidence from Bangladesh. *Economic Development and Cultural Change*, 57(4), 685–722.
- Ligon, E., Schechter, L. (2003). Measuring vulnerability. *The Economic Journal*, 113 (486), C95–C102.
- Loison, S. A. (2019). Household livelihood diversification and gender: Panel evidence from rural Kenya. *Journal of Rural Studies*, 69, 156–172.
- Lyons, A., Kass-Hanna, J., Montoya Castano, A. (2021). A multidimensional approach to measuring vulnerability to poverty of Syrian refugees in Lebanon. *Economic Research Forum Working Paper* (No. 1472).
- Marzi, S., Mysiak, J., Essenfelder, A. H., Pal, J. S., Vernaccini, L., Mistry, M. N., Vousdoukas, M. (2021). Assessing future vulnerability and risk of humanitarian crises using climate change and population projections within the INFORM framework., 71, 102393.

- OECD, Policy Studies Institute. (2020). OECD development pathways: Rural development strategy review of Ethiopia: Reaping the benefits of urbanisation. OECD Publishing.
- OPHI. (2022). Measuring rural poverty with a multidimensional approach: The Rural Multidimensional Poverty Index (Vol. 19). Food and Agriculture Organization of the United Nations.
- Rogers, M., Konieczny, M. E. (2018). Does religion always help the poor? Variations in religion and social class in the West and societies in the Global South. *Palgrave Communications*, 4 (1) [incomplete: article number/pages].
- Silvestri, S., Bryan, E., Ringler, C., Herrero, M., Okoba, B. (2012). Climate change perception and adaptation of agro-pastoral communities in Kenya. *Regional Environmental Change*, 12 (4), 791–802.
- Smith, L. C., Haddad, L. J. (2000). Overcoming child malnutrition in developing countries: Past achievements and future choices (Vol. 30). International Food Policy Research Institute.
- Tesgera, W. D., Beyene, A. B., Wakjira, T. K. (2024). Does non-farm employment increase rural households' consumption in western Ethiopia? Empirical evidence from the Horo Guduru Wollega Zone. *Heliyon*, 10 (7).
- UNDP OPHI. (2019). How to build a national multidimensional poverty index (MPI): Using the MPI to inform the SDGs.
- UNDP OPHI. (2020). Global MPI 2020: Charting pathways out of multidimensional poverty: Achieving the SDGs. United Nations Development Programme Oxford Poverty and Human Development Initiative.
- Woldehanna, T. (2002). Rural farm/non-farm income linkages in northern Ethiopia. In *Promoting farm/nonfarm linkages for rural development: Case studies from Africa and Latin America* (pp. 121–144). FAO.
- Woldehanna, T., Behrman, J. R. (2013). What determines Ethiopian children's dietary diversity [Conference presentation]. Centre for the Study of African Economies (CSAE) Conference, St. Catherine's College, Oxford, United Kingdom.
- World Bank. (2020). *Reversals of fortune: Poverty and shared prosperity*.
- World Bank. (2022). *World development report 2022: Finance for an equitable recovery*. World Bank Publications.