



Dynamics and Determinants of Household Poverty in Ethiopia: A Correlated Random Effect Approach

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Abstract

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Despite the implementation of the numerous programs, strategies and policies in developing countries, poverty has remained a persistent challenge. This study investigates the dynamics and determinants of household poverty in Ethiopia using two waves of panel data from the Ethiopian Socioeconomic Survey (2019 and 2022) and a correlated random effect logistic regression model. The results reveal that the incidence, gap, and severity of poverty have increased over time in Ethiopia. Rural and female-headed households are disproportionately affected, reflecting persistent spatial and gender-based disparities. Transition analysis further indicates that 31.64% of households experienced chronic poverty, 43.92% of households were in transitory poverty and 24.44% households remained sustainably non-poor. The regression results indicate that family size ($\beta = 0.318, p = 0.000$), age of household heads ($\beta = 0.006, p = 0.010$), participation in productive safety net program ($\beta = 0.361, p = 0.000$), being from Amhara region ($\beta = 0.982, p = 0.000$), being from rural areas ($1.115, p=0.000$), year dummy and being from SNNP region ($\beta = 0.732, p = 0.000$) are positively and significantly related with poverty. But, male-headed households ($\beta = -0.317, p = 0.000$), and education level of household heads ($\beta = -0.615, p = 0.000$) are negatively and significantly related with poverty in Ethiopia. This study is limited by its focus on a unidimensional welfare indicator, and by the exclusion of the Tigray region from the analysis. These findings highlight the need for multidimensional, region-specific, and gender-sensitive interventions to curb poverty, including expanding rural infrastructure, improving agricultural productivity, enhancing educational opportunities, and redesigning PSNP to focus not only on short-term consumption smoothing but also on long-term investment in agricultural and non-agricultural activities.

Keywords: Correlated random effect Model, Endogeneity, Foster-Greer-Thorbecke, Ethiopia, Poverty

1. INTRODUCTION

One of the most urgent issues facing low-income nations, particularly those in Sub-Saharan Africa, is poverty. In sub-Saharan Africa, nearly 460 million people are below the global poverty line (World Bank, 2022). Over the past 20 years, Ethiopia's economy has grown rapidly, making it one of the biggest in Sub-Saharan Africa. However, the nation's reliance on rain-fed agriculture, susceptibility to climate shocks, and structural labor market constraints have made it difficult to reduce poverty, income inequality, and unemployment (UNDP, 2022; IMF, 2023). Regarding the definition and assessment of poverty, there are two schools of thought in economic literature: monetarist and non-monetarist.

The monetarist definition and assessment of poverty is based on a single statistic, such as income or consumption levels in relation to a predetermined poverty line. Its proponents believe that monetary indicators that show control over commodities and services are an excellent way to quantify welfare (Ravallion, 2019). In order to identify the poor, this approach focuses on setting thresholds, such as national or worldwide poverty lines (World Bank, 2022). In order to provide policymakers with a clear yardstick for poverty reduction targets, monetary metrics should be kept objective, quantifiable, and comparable across populations and time periods (Alkire et al., 2020). However, this method of characterizing and quantifying poverty is questioned since it may oversimplify poverty by neglecting dimensions like social inclusion, health, and education that go beyond income.

The non-welfarist perspective on poverty, on the other hand, emphasizes multifaceted metrics that capture more dimensions of well-being than just money and consumption. Sen's capacity approach, which emphasizes the significance of people's freedoms and opportunities to live the lives they value, is the foundation of this strategy (Sen, 2018). According to this perspective, poverty encompasses not only lack of finance but also lack of access to certain crucial aspects of life such as health, education, empowerment, and living standards. Proponents of this perspective contend that multidimensional measurements of poverty are more accurate in reflecting the complex reality of poverty, particularly in developing nations where income-based metrics may mislead or understate hardship. Consequently, in both national and international

poverty assessments, the non-welfarist viewpoint has become much more prominent (Alkire & Foster, 2011; UNDP, 2023).

There are also different theories regarding the drivers of poverty namely; individual, cultural, structural and geographic theories. Individuals become poor because of their own decisions, according to the individual theory, which connects poverty to personal characteristics like intelligence, character, or effort (Banerjee & Duflo, 2019). The cultural theory of poverty which assumes that culture is static, sees poverty as a socially transmitted culture with values, norms, and behaviors that sustain deprivation across generations (Small, Harding, & Lamont, 2018). The geographical theory of poverty contends that underprivileged regions encounter systemic obstacles like inadequate infrastructure, low investment, and environmental limitations, which perpetuate poverty cycles in spite of overall economic expansion (World Bank, 2020; OECD, 2021). Still, the structural theory of poverty focuses on the social, political, and economic system which causes individuals to have inadequate resources with which to realize their income and well-being (UN DESA, 2020).

Ethiopia has adopted a number of development approaches since the socialist state collapsed in 1991 in an effort to transition its economy from agricultural to industry and attain sustainable growth. While the Plan for Accelerated and Sustained Development to End Poverty (PASDEP, 2005–2010) concentrated on creating jobs through labor-intensive industries and small businesses, the Sustainable Development and Poverty Reduction Program (SDPRP, 2002–2005) prioritized infrastructure, health, education, and agriculture (MoFED, 2002). Aiming to drive structural transformation toward industry and higher-value services, the Growth and transition Plans (GTP I, 2010–2015; GTP II, 2015–2020) came next (NPC, 2016). Despite all of these initiatives, the Ethiopian economy continues to perform poorly on a number of fundamental metrics and is susceptible to shocks (World Bank, 2022). Ethiopia's human development index of 0.47 places it 173rd out of 189 countries, below the sub-Saharan African average (UNDP, 2021).

Ethiopian poverty is still disproportionately affecting rural households, women-headed households, and peripheral regions, and it is highly unequal across gender, geography, and rural-urban lines (CSA & World Bank, 2020; UNDP, 2022). When creating inclusive solutions, it is

essential to comprehend poverty dynamics, or how households enter and exit poverty, as this provides deeper insights than static metrics (Dang & Dabalen, 2022). This study uses two waves of the Ethiopian Socioeconomic Survey (2019 and 2022) to investigate changes in poverty indices, break down poverty by gender, region, and place of residence, and use panel logistic regression to look at the factors that influence transitions. While regional and rural-urban decompositions show glaring disparities associated with geography, conflict, and reliance on agriculture (UNDP, 2021; World Bank, 2022), gender-based decomposition emphasizes the ongoing vulnerability of women-headed households because of social and labor market barriers (UN Women, 2022). This study, hence, offers fresh insights into Ethiopia's poverty dynamics and determinants, which can help shape more sustainable and equitable policies to reduce poverty.

Though some previous studies have examined the extent and determinants of poverty in developing countries (Cherif et al., 2024; Esrael et al., 2025; Mupaso et al., 2024), they have used cross-sectional data, which did not show the dynamics of poverty, and did not decompose poverty by regions, rural, and urban areas. This research, therefore, fills this gap by exploring the dynamics and drivers of poverty in Ethiopia using two years of panel data (2019 and 2022) from the Ethiopian Socioeconomic Survey. Specifically, this study aimed to answer the following research questions:

- a. What are the patterns and dynamics of unidimensional poverty in Ethiopia between 2019 and 2022, and how do households transition into and out of poverty during this period?
- b. What socioeconomic, demographic, and structural factors determine the incidence and persistence of poverty among Ethiopian households?

The remaining sections are organized as follows. The second section presents the data and the methodology of the study; the third section deals with the results and discussion, while the fourth section presents the conclusion and policy implications.

2. DATA AND METHODS

2.1. Data Sources and Types of Variables

The Ethiopian Socioeconomic Panel Surveys (ESPS4 and ESPS5), which were carried out in 2019 and 2022, are the basis for this poverty study. All nine regional states as well as the two

city administrations, Addis Ababa and Dire Dawa, were included in the 2019 survey (ESPS4), which was used as the baseline for later waves. 565 enumeration locations yielded a sample of 6,094 households, 219 of which were urban and 316 of which were rural (Central Statistical Agency of Ethiopia, 2020). With the exception of Tigray, all areas and the two city administrations were covered by the fifth wave (ESPS5), which was carried out between September 12, 2021, and June 30, 2022, 4,959 households, 220 of which were rural and 215 of which were urban, were randomly selected from 435 enumeration regions for the interviews (Ethiopian Statistical Service & World Bank, 2022). Both surveys are nationally representative, providing reliable national and regional estimates for rural and urban areas. Though the ESPS4 (2019) contains 6,094 sample households and the ESPS5 (2022) contains 4,959 sample households, a balanced panel is created here by keeping the households which appear in both waves through unique identification numbers of the households. As a result, the final data set used for analysis is comprised of 4,959 households, whereas 1,135 households who did not participate in the 2022 survey wave were dropped from the analysis.

The real consumption per adult equivalent data employed in this analysis is provided directly by the Ethiopian Socioeconomic Surveys (ESS) Waves 4 (2019) and 5 (2022), both of which have been made real by adjusting for inflation and regional price differentials. However, poverty lines for food and general consumption have been provided only for the base year 2016, at 3,772 Birr and 7,184 Birr respectively. As there are no updated official poverty lines in years 2019 and 2022, the poverty lines in 2016 are converted to 2019 and 2022 poverty lines using GDP deflators from the National Bank of Ethiopia reports in years 2016, 2018, and 2022. As a result, the adjusted poverty line for food consumption is 4,979.04 Birr for 2019 and 9,618.60 Birr for 2022, whereas the adjusted general poverty line amounts to 9,482.88 Birr and 18,319.20 Birr, respectively. Specifically, the adjusted poverty line is calculated as:

$$PL_{adj} = PL_{base} * \frac{GDP\ deflator_t}{GDP\ deflator_b}$$

Where PL_{adj} is an inflation adjusted poverty line, PL_{base} is the base year poverty line, $GDP\ deflator_t$ is the GDP deflator for the target years (2019 or 2022), and $GDP\ deflator_b$ is the GDP deflator for the base year or the year of poverty line (2016). In this paper, data from two

waves of Ethiopian Socioeconomic Panel Survey (ESPS) have been used, that is, ESPS4 (2019) and ESPS5 (2022). The survey conducted in 2019 is considered the base for the other waves. The ESPS4 survey included 6,094 households (Central Statistics Agency of Ethiopia, 2020) while the ESPS5 covered 4,959 households (Ethiopian Statistical Service and World Bank, 2022). For the purpose of balanced panel analysis, only 4,959 households participating in both surveys based on unique household ID numbers are selected. For poverty analysis, the main variable is real household consumption expenditure per adult equivalent. The variable is calculated as follows; first, total household consumption expenditures are divided by adult equivalence scales that adjust calories per individual depending on their age and gender. The obtained figures are then deflated using price indices to calculate real consumption per adult equivalent.

2.2. Poverty Lines and Measurement

The measurement of poverty remains controversial in development economics due to the differences in definition and measurement approach. While some scholars emphasize monetary measures such as income and expenditure, others highlight non-monetary dimensions like access to health, education, and basic services, or employ both methods (Alkire & Foster, 2011). The first task in poverty analysis is the determination of the poverty line or threshold to classify people in to poor and non-poor. The poverty line is defined as the minimum income or consumption necessary to meet basic needs such as food, clothing, and shelter (Ravallion, 1992).

While the absolute poverty line fixes a threshold of essential goods and services across regions, relative poverty line adjust to average or median consumption levels of the broader population (World Bank, 2018; Atkinson, 2019). The poverty line is used to identify who is poor and to distinguish differences across countries, regions, and households. To quantify poverty, researchers often apply the Foster-Greer-Thorbecke (FGT) indices (Foster, Greer, & Thorbecke, 1984), which capture incidence, depth, and severity of deprivation. The head count index is given as follow:

$$P_0 = \frac{Q}{N} \quad (1)$$

Where P_0 , Q and N refer to the incidence of poverty, number of poor households and the total sample households respectively. It measures the proportion of individuals below the poverty line,

though it treats all the poor equally. The poverty gap which shows the average shortfall from the poverty line is computed using equation 2 as follow:

$$P_1 = \frac{1}{N} \sum_{i=1}^q \left(\frac{Z - C_i}{Z} \right) \quad (2)$$

Where Z is the poverty line, C_i is the consumption level of i^{th} household, q is the number of poor households. The severity of poverty is measured by taking the square of the poverty gap and it gives more weight to the poorest thereby accounting for inequality among the poor (Alkire et al., 2015).

$$P_2 = \frac{1}{N} \sum_{i=1}^q \left(\frac{Z - C_i}{Z} \right)^2 \quad (3)$$

These three measures provide a comprehensive framework for understanding not just how many people are poor, but also the intensity and distribution of poverty. The inflation adjusted poverty line was calculated by deflating the most recent poverty line because the official poverty line for the survey years (2019 and 2022) is not available. If a household's actual consumption per adult equivalent is less than the inflation-adjusted poverty line, the household is said to be below the absolute poverty line. Absolute food poverty is defined as 4979 and 9619 Ethiopian Birr per year per adult equivalent for 2019 and 2022, respectively, while absolute general poverty line is defined as 9483 and 18,319 Birr per year per adult equivalent for 2019 and 2022. The general and food poverty lines in Ethiopia from 2016 were adjusted to create these lines.

2.3. Model Specification

This study employed a panel data model to identify the determinants of household poverty in Ethiopia. The general panel data model is specified by including the individual heterogeneity effect as follow:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \mu_i + u_{it} \quad (4)$$

where subscript i denote household, t denotes time, X_{it} refers to a vector of explanatory variables, μ_i refer to individual heterogeneity effect and u_{it} is the random error term. The above model can be estimated by logistic fixed effect model or correlated random effect logistic model. First, if equation #1 is estimated by logistic fixed effect model, it can control for individual heterogeneity effect (Wooldridge 2010). But the logistic fixed effect model has a limitation that it does not estimate the effect of any variable that does not vary across time. Second, to solve the

limitation of fixed effect model, it has been proposed to estimate within effects in random-effects models (Allison, 2009; Wooldridge 2010). The model which estimates the within effects in the random effect model is called correlated random effect model (CREM) logistic regression. This model simultaneously estimates the within effect and the between effect in panel data analysis, and it enables us to test the equivalence between the within and the between effects. The logistic correlated random effect model is mathematically specified as follow:

$$Y_{it} = \beta_0 + \beta_1(\ln X_{it} - \ln \bar{X}_i) + \beta_2 c_i + \beta_3 \bar{X}_i + \mu_i + U_{it} \quad (5)$$

In equation #5, β_1 measures the within effect or the fixed effect estimate (Mundlak 1978) while β_3 measures the between effect. Besides, β_2 measures the effect of time invariant observed variables on the dependent variable. For the estimate of β_2 to be unbiased, $E(\mu_i/X_{it}, c_i) = 0$ and $\mu_i \sim (0, \delta_{\mu}^2)$. One merit of the CREM logistic regression is its ability to test for equivalence of within and between estimates. This test, which is referred to as an augmented regression test (Jones et al. 2007, 217), can be used as an alternative for the Hausman specification test. If between and within effects are the same, that is, $\beta_1 = \beta_3$, then the data supports the use of random effect model. The dependent variable in equation #5 (Y_{it}) is a binary variable which assumes value of 1 for poor household and 0 otherwise. The explanatory variables include AGE, representing the age of the household head; FS, the household family size; and MALE, a dummy variable equal to 1 if the household head is male and 0 if female. Rural is a location dummy taking the value 1 for households in rural areas and 0 for those in urban areas, while Amhara is a regional dummy equal to 1 if the household head is from Amhara region and 0 otherwise, EDUC denotes the education level of the household head, SNNP is a regional dummy which takes 1 for households from SNNP region and 0 otherwise, CL is a dummy variable indicating participation in casual labor, and PSNP captures participation in the Productive Safety Net Program.

2.4. Variables and Hypotheses

Age of household head is continuous and measured in years in this research. The age of household head is expected to be positively related with poverty. At a higher age, household head may suffer from health problem, and productivity may also decrease (Deressa & Zerihun,

2022). Previous studies also found positive and significant association between age of household head and poverty as elderly households may not be able to diversify their sources of income. Poverty status is highly influenced by the gender of the head of the home. Households headed by men typically have greater access to networks, jobs, and productive resources, which lowers the risk of poverty. Cultural barriers and limited resources disproportionately affect households led by women (World Bank, 2022; Bachewe et al., 2021).

Large family size increases consumption needs relative to available resources and often raises dependency ratios, making households more vulnerable to poverty (Taffesse & Hassen, 2022). While larger families can provide labor, in rural Ethiopia this effect is often outweighed by the pressure on household consumption. Being from rural areas is also expected to positively related with poverty as households in rural areas may have limited access to markets, public services, and information. However, households from urban areas are less vulnerable to poverty since they mainly participate in non-agricultural activities (Bezu & Barrett, 2021). Reliance on casual or daily wage labor is often a sign of livelihood insecurity, low human capital, and lack of stable income sources, all of which are strongly linked to poverty (Hirvonen et al., 2022). Households relying on casual labor typically face unstable employment and low wages. Households with educated heads are more likely to adopt modern technologies and diversify livelihoods.

Due to their reliance on rain-fed agriculture, inadequate infrastructure, and restricted access to social services and markets, Ethiopian rural households are more vulnerable to poverty (MoF, 2023). In general, urban households have more access to nonfarm jobs and a wider variety of income sources. By offering food or monetary transfers in return for labor, PSNP participation aims to lower poverty. Although PSNP increases food security in the near term, research shows that its impact on reducing poverty is ambiguous and may even be positively correlated with poverty because poorer households are more likely to participate in the program (Berhane et al., 2022). Education reduces poverty by improving agricultural output, expanding access to off-farm work, and enhancing human capital (Asfaw et al., 2021).

3. RESULTS AND DISCUSSION

3.1. Descriptive Results

As shown in Table 1, there have been significant changes in Ethiopian household spending habits between 2019 and 2022. The real annual food expenditure per adult equivalent (AE) increased from 12,215.57 to 13,500.26 ETB while the total expenditure mounted from 16,140.83 to 17,163.28 ETB. The ongoing food price inflation in Ethiopia also disproportionately impacted food consumption in comparison to non-food spending as reflected in Table 1 (WFP, 2023).

Table 1. Descriptive Statistics of Variables

| 2019 | Observations | Mean | SD |
|---|--------------|-----------|-----------|
| Real annual food expenditure per AE | 4849 | 12215.565 | 11640.294 |
| Real annual nonfood per AE | 4849 | 2694.931 | 4085.454 |
| Real annual expenditure on education per AE | 4849 | 480.647 | 3069.418 |
| Real annual expenditure on utility per AE | 4849 | 749.685 | 1402.772 |
| Real annual total expenditure per AE | 4849 | 16140.828 | 14735.631 |
| Adult Equivalent | 4849 | 3.593 | 1.856 |
| Household size | 4849 | 4.396 | 2.272 |
| Credit | 4849 | 0.126 | 0.332 |
| Productive Safety Net Program | 4849 | 0.114 | 0.336 |
| Non-farm Participation | 4849 | 0.112 | 0.315 |
| Gender | 4849 | 0.688 | 0.463 |
| Age | 4849 | 42.893 | 14.821 |
| Marital Status | 4849 | 0.712 | 0.453 |
| 2022 | | | |
| Real annual food expenditure per AE | 4849 | 13500.262 | 13673.338 |
| Real annual nonfood per AE | 4849 | 2677.835 | 4188.438 |
| Real annual expenditure on education per AE | 4849 | 335.87 | 1086.678 |
| Real annual expenditure on utility per AE | 4849 | 649.309 | 1338.043 |
| Real annual total expenditure per AE | 4849 | 17163.277 | 16229.826 |
| Adult Equivalent | 4849 | 3.802 | 1.971 |
| Household size | 4849 | 4.591 | 2.349 |
| Credit | 4849 | 0.203 | 0.402 |
| Productive Safety Net Program | 4849 | 0.17 | 0.376 |
| Non-farm Participation | 4849 | 0.129 | 0.335 |
| Gender | 4849 | 0.687 | 0.464 |
| Age | 4849 | 45.236 | 14.604 |
| Marital Status | 4849 | 0.734 | 0.442 |

Own Computation from ESPS4 and ESPS5 (2025)

Conversely, real non-food expenditure per AE decreased little from 2,694.93 ETB in 2019 to 2,677.84 ETB in 2022, remaining nearly constant. This suggests that household allocations to non-food goods may have been limited by rising food prices. Food prices may have crowding-out effects on critical services and human capital investment, as seen by the significant drop in utility expenditure and education spending per AE (from 480.65 ETB in 2019 to 335.87 ETB in 2022) (FAO et al., 2022).

There was also a slight change in household demographics and livelihood indicators over time. In line with demographic transition patterns seen in Ethiopia's rural and urban areas, the mean adult equivalent increased from 3.59 to 3.80 and the average household size increased from 4.40 to 4.59 (CSA, 2022). While participation in the Productive Safety Net Program (PSNP) increased from 11.4% to 17.0%, access to credit improved significantly (12.6% in 2019 to 20.3% in 2022), reflecting efforts by the government and donors to reduce vulnerability in the face of economic shocks, such as the COVID-19 pandemic and disruptions caused by conflicts (World Bank, 2023). Non-farm participation also rose slightly, underscoring its growing role as a coping and diversification strategy for rural households. Demographic characteristics such as age, gender composition, and marital status remained relatively stable, highlighting that observed changes in welfare and livelihood access are largely policy and market driven rather than demographic shifts. Additionally, non-farm participation increased marginally, highlighting its expanding function as a coping and diversification tactic for rural households. Age, gender composition, and marriage status were among the demographic factors that stayed mostly constant, indicating that market and policy forces, rather than demographic changes, are primarily responsible for the observed changes in welfare and livelihood availability.

Table 2. Poverty Incidence, Gap and Severity in 2019 and 2022

| | 2019 | | 2022 | |
|------------------------|--------------|--------|--------------|--------|
| | Observations | Mean | Observations | Mean |
| General Poverty | | | | |
| Poverty incidence | 4849 | 0.3782 | 4849 | 0.6937 |
| Poverty gap | 1834 | 0.3711 | 3364 | 0.4638 |
| Poverty severity | 1834 | 0.1876 | 3364 | 0.2683 |
| Food Poverty | | | | |
| Poverty incidence | 4,849 | 0.2093 | 4849 | 0.4971 |
| Poverty gap | 1015 | 0.3207 | 2410 | 0.3815 |
| Poverty severity | 1015 | 0.1462 | 2410 | 0.1953 |

Own Computation from ESPS4 and ESPS5 (2025)

The findings show a dramatic rise in the incidence, gap, and severity of both general and food poverty between 2019 and 2022. Food poverty incidence more than doubled from 20.9% to 49.7%, while general poverty incidence rose from 37.8% in 2019 to 69.4% in 2022. In a similar vein, both measures' poverty gap and severity indices increased, indicating that not only did more households drop below the poverty line, but that the impoverished also become worse off. These results stand in contrast to previous research conducted in Ethiopia, which showed that agricultural expansion, rural development initiatives, and pro-poor policies have contributed to a long-term drop in poverty during the previous few decades (World Bank, 2020; Hirvonen et al., 2021). Recent data, however, indicates that shocks like the COVID-19 pandemic, war, inflation, and shocks connected to climate change have undone gains and exacerbated poverty (Hirvonen et al., 2022; Baye & Minten, 2023). Therefore, a concerning pattern of welfare deterioration is highlighted by the observed rises in both general and food poverty between 2019 and 2022, highlighting the need for Ethiopia to implement new and more robust poverty reduction policies. In both 2019 and 2022, rural households experienced far worse than urban ones, and they faced a greater decline in all three metrics between the two years. This means that not only did more rural households fall below the poverty line, but they also fell deeper below it and became relatively poorer than urban households. In 2019, the rural general poverty incidence (57.74%) was much higher than the urban incidence (20.99%), rising to 85.08% in 2022 versus 56.06% in urban areas; the rural poverty gap increased from 0.3975 to 0.5313 while the urban gap increased from 0.3097 to 0.3770; and the rural poverty severity increased from 0.2078 to 0.3305 relative to an increase from 0.1408 to 0.1881 in urban areas.

Table 3. Decomposition of Poverty Indices by rural and Urban in 2019 & 2022

| | 2019 | | 2022 | |
|------------------------|---------------------|---------------------|---------------------|---------------------|
| General Poverty | Rural (2220) | Urban (2629) | Rural (2225) | Urban (2624) |
| Poverty incidence | 0.5774 | 0.2099 | 0.8508 | 0.5606 |
| Poverty gap | 0.3975 | 0.3097 | 0.5313 | 0.3770 |
| Poverty severity | 0.2078 | 0.1408 | 0.3305 | 0.1881 |
| Food Poverty | | | | |
| Poverty incidence | 0.3180 | 0.1175 | 0.6400 | 0.3757 |
| Poverty gap | 0.1054 | 0.0348 | 0.2652 | 0.1255 |
| Poverty severity | 0.0487 | 0.0153 | 0.1419 | 0.0591 |

Own Computation from ESP54 and ESP55 (2025)

Similar but more pronounced trends can be seen in food poverty, where the incidence of food poverty increased from 31.8% to 64.0% in rural areas and from 11.8% to 37.6% in urban areas. The gap and severity of food poverty in rural areas also increased significantly more than in urban areas, indicating greater calorie/consumption deficits among the impoverished in rural areas. These spatial patterns align with recent national evidence that the disruptions caused by COVID-19, high inflation and food price shocks, localized conflict, and weakened real incomes reversed long-term poverty reduction gains after 2019. These factors affected both urban households (through price spikes and income losses) and rural livelihoods (through crop and market shocks), but left rural households more vulnerable and further from recovery.

Although the decline was not uniform across Ethiopia's regions, regional poverty generally increased between 2019 and 2022. While rural-dominated regions like Oromia, Amhara, SNNP, Afar, and Somali saw the largest increases in both the poverty gap and severity, indicating deeper and more entrenched shortfalls among the poor, traditionally less-poor and more urbanized regions like Addis Ababa, Harari, and Dire Dawa saw sharp increases in poverty incidence. Absolute poverty rose in many regional states during this time, according to data from national LSMS surveys and related studies.

Rural areas were disproportionately affected, and smaller areas like Gambella, Benishangul-Gumuz, and Somali showed especially significant relative increases in incidence and inequality (Mekasha, 2025; World Bank, 2024). These results are consistent with new research showing that rising food prices, inflation, climatic shocks, and violence have eroded previous advances in reducing poverty, making the poor in many areas not only more numerous but also less wealthy overall (Mekasha, 2021; World Bank, 2024). In conclusion, regional patterns changed from earlier convergence of welfare improvements to a more fragmented geography of poverty by 2022. This highlighted the need for regionally tailored interventions, with urban centers seeing rapid increases in incidence and rural-majority regions facing increasing depth and severity of poverty (Goshu, 2024; Mekasha, 2025).

Table 4. Decomposition of General and Food Poverty Indices by Regions in 2019 & 2022

| General Poverty | 2019 | | | 2022 | | |
|---------------------|-----------|--------|----------|-----------|-------|----------|
| | Incidence | Gap | Severity | Incidence | Gap | Severity |
| Afar | 0.315 | 0.121 | 0.063 | 0.676 | 0.312 | 0.182 |
| Amhara | 0.541 | 0.190 | 0.091 | 0.771 | 0.407 | 0.247 |
| Oromia | 0.396 | 0.131 | 0.061 | 0.803 | 0.405 | 0.244 |
| Somali | 0.453 | 0.177 | 0.090 | 0.779 | 0.390 | 0.229 |
| Benishangul Gumuz | 0.414 | 0.137 | 0.062 | 0.729 | 0.355 | 0.208 |
| SNNP | 0.576 | 0.266 | 0.153 | 0.790 | 0.418 | 0.254 |
| Gambela | 0.452 | 0.183 | 0.097 | 0.696 | 0.319 | 0.183 |
| Harar | 0.208 | 0.062 | 0.028 | 0.652 | 0.289 | 0.165 |
| Addis Ababa | 0.137 | 0.034 | 0.013 | 0.439 | 0.086 | 0.022 |
| Dire Dawa | 0.233 | 0.071 | 0.031 | 0.602 | 0.238 | 0.128 |
| Food Poverty | | | | | | |
| | 2019 | | | 2022 | | |
| Afar | 0.0819 | 0.0275 | 0.0124 | 0.254 | 0.097 | 0.049 |
| Amhara | 0.1309 | 0.0365 | 0.0097 | 0.314 | 0.125 | 0.065 |
| Oromia | 0.0818 | 0.0229 | 0.0097 | 0.316 | 0.124 | 0.064 |
| Somali | 0.1468 | 0.0525 | 0.0260 | 0.311 | 0.116 | 0.057 |
| Benishangul Gumuz | 0.1077 | 0.0253 | 0.0092 | 0.276 | 0.101 | 0.052 |
| SNNP | 0.2040 | 0.0769 | 0.0382 | 0.324 | 0.133 | 0.070 |
| Gambela | 0.130 | 0.044 | 0.0199 | 0.239 | 0.095 | 0.048 |
| Harar | 0.045 | 0.012 | 0.006 | 0.063 | 0.086 | 0.044 |
| Addis Ababa | 0.039 | 0.010 | 0.037 | 0.062 | 0.010 | 0.002 |
| Dire Dawa | 0.053 | 0.014 | 0.006 | 0.171 | 0.063 | 0.049 |

Own Computation from ESPS4 and ESPS5 (2025)

When comparing poverty by gender, it is evident that while both male- and female-headed households saw their circumstances deteriorate between 2019 and 2022, male-headed households continuously suffered marginally greater levels of poverty. With comparable trends for the poverty gap and severity, the general poverty incidence increased from 39.2% to 70.9% among families headed by men and from 34.7% to 66.0% among households headed by women. The prevalence of food poverty rose for both categories as well, rising from 19.9% to 46.5% for families headed by women and from 21.4% to 51.1% for homes headed by men. Even while poverty increased significantly for everyone, male-headed households' levels of poverty remained somewhat higher, indicating that their relative poverty decreased with time while the gender gap reduced.

Table 5. Decomposition of Poverty Indices by Gender in 2019 & 2022

| | 2019 | | 2022 | |
|------------------------|-------------|---------------|--------------|--------------|
| | Male (3337) | Female (1512) | Male (3,332) | Female(1517) |
| General Poverty | | | | |
| Poverty incidence | 0.3923 | 0.3472 | 0.7092 | 0.6598 |
| Poverty gap | 0.1452 | 0.1296 | 0.3343 | 0.2944 |
| Poverty severity | 0.0738 | 0.0647 | 0.1953 | 0.1658 |
| Food Poverty | | | | |
| Poverty incidence | 0.2137 | 0.19974 | 0.5114 | 0.4654 |
| Poverty gap | 0.0687 | 0.0636 | 0.1980 | 0.1711 |
| Poverty severity | 0.0312 | 0.0292 | 0.1022 | 0.0859 |

Own Computation from ESPS4 and ESPS5 (2025)

Widespread vulnerability is demonstrated by the findings, which show that 31.6% of households are chronically poor, 43.1% are transitorily poor, and only 24.4% are sustainably non-poor under general poverty. With 14.6% of people living in chronic poverty, 41.5% in transitory poverty, and 43.9% in sustainable non-poverty. Food poverty, on the other hand, is less enduring, indicating that food insecurity is more temporary and shock-driven. In general, food poverty represents temporary vulnerabilities, whereas chronic poverty is more noticeable in overall welfare.

Table 6. Entry and Exit of People from Poverty in Ethiopia

| General Poverty | Chronic poverty | Transitory poverty | Sustainable non-poor |
|------------------------|-----------------|--------------------|----------------------|
| Number | 3068 | 4260 | 2370 |
| Percentage | 31.64 | 43.92 | 24.44 |
| Food poverty | | | |
| Number | 1,412 | 4,026 | 4260 |
| Percentage | 14.56 | 41.51 | 43.93 |

Own Computation from ESPS4 and ESPS5 (2025)

3.2. Regression Results

Based on a sample of 9918 observations, the correlated random effect logistic regression or the Mundlak approach offers important insights on determinants of household Poverty in Ethiopia. The correlated random effects (CRE) logistic regression, which has alternatively been referred to as the Mundlak approach, plays an important role in panel data analysis by relaxing the highly unlikely assumption that the independent variables are independent of the unobserved individual component in the case of random effects estimation. Through the inclusion of the time mean of time varying regressors, the CRE logistic regression approach captures the correlation between the two, ensuring unbiased results while still providing estimates for time invariant variables,

unlike the fixed effect method. On the other hand, it offers a powerful tool for disentangling between within and between unit effects while serving as a means of testing the random effects specifications. In the correlated random effects logistic regression, the Mundlak test checks whether the mean of the regressors is jointly equal to zero, and thus supports the standard random effects assumption of no correlation between regressors and the unobserved individual effects. The Mundlak test result in Table 7 (chi-square statistic = 36.0 and p-value = 0.000) reject the null hypothesis of no relationship between the variables under study. The implication here is that there exists a relationship between the explanatory variables and unobserved individual effects. This renders the standard random effects approach inconsistent and invalid. Therefore, the better alternative is the correlated random effects logistic regression specification.

Table 7. Regression Results of Correlated Random Effect (CRE) or Mundlak Model

| Correlated Random-Effects Logistic Regression | | | | | Number of observations= 9918 | |
|---|--------------------------------------|------------|---------|---------|--------------------------------------|------------|
| Wald chi2(12) = 1441.13 | | | | | Number of Groups=4,959 | |
| Prob > chi2 = 0.0000 | | | | | | |
| Poverty determinants | Correlated Random Effect (CRE) Model | | | | Marginal Effects | |
| | Coefficient | Std. Error | t-value | p-value | Coefficients | Std. Error |
| Family size | 0.318 | 0.019 | 16.66 | 0.000 | 0.051 | 0.003 |
| Age of HH | 0.006 | 0.003 | 2.59 | 0.010 | 0.001 | 0.000 |
| Mean family size | 0.143 | 0.024 | 5.97 | 0.000 | 0.023 | 0.004 |
| Mean age of HH | -0.003 | 0.004 | -0.97 | 0.334 | -0.001 | 0.001 |
| Amhara | 0.982 | 0.085 | 11.61 | 0.000 | 0.157 | 0.013 |
| SNNPR | 0.732 | 0.086 | 8.56 | 0.000 | 0.117 | 0.013 |
| Rural | 1.115 | 0.057 | 19.41 | 0.000 | 0.178 | 0.009 |
| PSNP | 0.361 | 0.080 | 4.49 | 0.000 | 0.058 | 0.013 |
| Male | -0.317 | 0.059 | -5.37 | 0.000 | -0.051 | 0.009 |
| Education | -0.615 | 0.061 | -10.04 | 0.000 | -0.098 | 0.009 |
| Casual labor | 0.142 | 0.100 | 1.42 | 0.157 | 0.023 | 0.016 |
| Year dummy | 1.841 | 0.066 | 27.98 | 0.000 | 0.295 | 0.007 |
| Constant | -3.289 | 0.166 | -19.80 | 0.000 | | |
| /lnsig2u | -1.2220 | 0.3983 | | | | |
| Sigma_u | 0.5428 | 0.1081 | | | | |
| Rho | 0.0822 | 0.0301 | | | | |
| Mundlak Test | Chi2 value: 36.00, Prob > chi2=0.000 | | | | Variance inflating factor (VIF)=1.45 | |

Source: Own Computation (2025)

The estimation results of the correlated random effects (CRE) logistic regression showed that the regression is jointly significant (Wald $\chi^2 = 1441.13$, $p < 0.001$), thus indicating a relatively good

fit for panel data. A multicollinearity test revealed no significant multicollinearity between explanatory variables (VIF=1.20). The family size is positively associated with poverty ($\beta = 0.318$, $p < 0.001$) implying that a large family will likely be poor since high dependency ratios affect household poverty adversely because resources become scarce (World Bank, 2022; UNDP, 2023). This finding is in agreement with research by Deressa et al. (2020), which links larger family sizes to increased poverty risk due to higher dependency ratios. The household head's age shows a positive and significant effect on poverty ($\beta = 0.006$, $p < 0.010$) implying that older household heads are at a higher likelihood of being poor owing to their inability to produce income and labor (World Bank, 2022).

Two dummy variables were created based on the two regions Amhara and SNNP, considering other regions as the base category. It is seen that the two variables carry positive values, implying that the odds of becoming poor are greater for households living in these regions relative to the base category. The above outcome is backed by literature in empirical research and descriptive statistics. One reason for the above result could be based on the geographical and structural perspectives of poverty. Geographical perspective explains poverty from the standpoint of the specific disadvantage faced by certain geographical regions in terms of location, infrastructure, and market accessibility (Zhou & Liu, 2022), whereas the structural perspective takes a broader approach. So, disparities across regions are apparent, and households in Amhara ($\beta = 0.982$, $p < 0.001$) and SNNP ($\beta = 0.732$, $p < 0.000$) have a higher probability of being poor than those in the reference group. This observation is supported by research showing spatial inequalities and unbalanced economic development in Ethiopia (World Bank, 2022; UNDP, 2023). Being rural raises the probability of poverty ($\beta = 1.115$, $p < 0.001$), which could be attributed to various structural factors like inadequate infrastructure and lack of basic amenities (UNDP, 2023).

The probability of participating in PSNP is significantly correlated with poverty ($\beta = 0.361$, $p < 0.000$). This can be explained by the proper targeting of the poor by the programme and not an increase in the poverty level, which is widely documented in social protection intervention analysis (World Bank, 2022). The participation of male-headed households has a negative

correlation with poverty ($\beta = -317$, $p < 0.000$). This may imply the gender differences in resource possession, labor market participation, and income generation potential (UNDP, 2023).

The probability of being impoverished has a strong negative relationship with education ($\beta = -0.615$, $p < 0.001$). High educational levels enhance income generation through productive capacities and employment, thus lowering poverty rates. Education is a key driver of productivity, employment, and income (World Bank, 2022; UNDP, 2023). A study conducted by Berisso (2016) found that education lowers both chronic and transient poverty, higher education levels are closely linked to lower poverty incidence. The dummy for the year is statistically significant ($\beta = 1.841$, $p < 0.001$), implying that poverty increases over time, possibly due to macroeconomic issues, inflation, or other factors that may influence household well-being (World Bank, 2023). The analysis reveals that it is critical to consider both observable and unobservable heterogeneity when modeling panel data (Wooldridge, 2021; Baltagi, 2021). The significant positive coefficient suggests a sharp rise in the incidence of poverty in 2022, most likely as a result of macroeconomic shocks like inflation and the COVID-19 pandemic (Mekasha, 2021). Therefore, this study emphasizes how poverty in Ethiopia is complex and influenced by household characteristics, education, work, social safety programs, and geographical disparities. According to the findings, methods for reducing poverty may benefit from focused interventions that address these issues. The calculated value of the standard deviation of the random effect ($\sigma_u = 0.543$) represents moderate levels of heterogeneity among people with respect to their log odds of the outcome variable. From the intra-class correlation ($\rho = 0.082$), we observe that only 8.2% of the variation comes from the unobserved heterogeneity of the household, indicating some panel effects.

4. CONCLUSION

The dynamics and causes of household poverty in Ethiopia were examined in this study using two waves of panel data from the Ethiopian Socioeconomic Survey (2019 and 2022) and a correlated random effect (CRE) logistic model. The findings consistently show that poverty has been worse over time in terms of incidence, disparity, and severity, with Amhara and SNNP regions experiencing higher poverty level compared to other regions. Besides, rural households and female-headed households continue to experience disproportionately high rates of poverty,

highlighting ongoing gendered and spatial disparities in welfare outcomes. According to the dynamic analysis of poverty, 24.44% of households stayed persistently non-poor, 43.92% experienced transitory poverty, and 31.64% experienced chronic poverty.

The identified determinants offer additional understanding of the dynamics of household welfare. The likelihood of poverty was greatly increased by having a larger family, being from rural area, being a member of the Productive Safety Net Program (PSNP) and being older household head. On the other hand, there was a clear correlation between education and a lower likelihood of poverty, underscoring the importance of education as a means of escaping poverty. These results highlight the multifaceted nature of Ethiopian poverty and its strong correlation with structural and demographic factors, necessitating focused interventions in addition to broad policy initiatives.

The study suggests enhancing gender-sensitive and region-specific poverty reduction strategies in light of these findings. Reducing rural poverty requires building secure non-farm employment possibilities, enhancing agricultural productivity and developing rural infrastructure. All levels of education should be given top priority, with a focus on empowering women via literacy and skill development. The positive relationship between the PSNP and poverty highlights the successful targeting of poor households by the program, meaning that it is achieving its intended purpose. Therefore, there is no need for changes in the present targeting process but rather a need for improvements. The program can be scaled up alongside complementary livelihood assistance programs to allow the beneficiaries to graduate out of poverty.

According to the results obtained from the perspective of geographic, individual, structural, and cultural theories of poverty, the fight against poverty in Ethiopia will require a combined effort from different stakeholders. The government and its development partners must ensure that they build robust social safety nets and increase opportunities for education, healthcare, infrastructure, and employment creation. The regional and local governments must tackle spatial inequalities by focusing on rural development, resilience-oriented farming techniques, and increased market access. Individually, there is a need for capacity building and entrepreneurship initiatives.

This study has also some limitations. First, the research was limited in its capacity to capture longer-term poverty dynamics and potential cyclical impacts because it mainly relied on two survey waves (2019 and 2022). Second, the study concentrated on household-level features while leaving out community-level elements that could significantly influence poverty outcomes, such as infrastructure, market accessibility, and climate shocks. Third, the research is carried out by adopting a unidimensional welfare approach that emphasizes consumption expenditure and considers welfare through financial terms alone. Fourth, this study does not test the attrition effect since only few observations were omitted to form balanced panel data. A multidimensional welfare approach, which considers aspects such as education, health, and standards of living, may give a better perspective of welfare and poverty. Hence, additional waves of panel data should be used in future studies to offer deeper insights into the long-term patterns of poverty. Understanding how environmental shocks affect household welfare would also be improved by integrating meteorological and geographical factors. Investigating intra-household dynamics, such as decision-making and asset ownership based on gender, would also help explain why gender differences in poverty still exist.

Competing interest: the authors declare no competing interests.

Data availability: data used in this research can be available on reasonable request.

Ethics and Consent to Participate declarations missing: Not applicable since the study used secondary data.

Author contribution: FE was involved in conceptualizing, designing the research protocols. He also was involved in data analysis, designing the methodology, prepared the manuscript, and edited the final manuscript.

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-

Appendix 1: Regression Results

```
. xtlogit poor hh_size age mean_hh_size mean_age amhara snnp rural psnp sex educ causal2 year_dummy, re vce(cluster household_id2)
```

Fitting comparison model:

```
Iteration 0: Log pseudolikelihood = -6697.0008
Iteration 1: Log pseudolikelihood = -4921.1366
Iteration 2: Log pseudolikelihood = -4911.8746
Iteration 3: Log pseudolikelihood = -4911.8614
Iteration 4: Log pseudolikelihood = -4911.8614
```

Fitting full model:

```
tau = 0.0 Log pseudolikelihood = -4911.8614
tau = 0.1 Log pseudolikelihood = -4909.8011
tau = 0.2 Log pseudolikelihood = -4910.0739
```

```
Iteration 0: Log pseudolikelihood = -4909.8011
Iteration 1: Log pseudolikelihood = -4908.76
Iteration 2: Log pseudolikelihood = -4907.9937
Iteration 3: Log pseudolikelihood = -4907.9925
Iteration 4: Log pseudolikelihood = -4907.9925
```

Calculating robust standard errors ...

```
Random-effects logistic regression      Number of obs   =   9,698
Group variable: household_id2          Number of groups =   4,849

Random effects u_i ~ Gaussian          Obs per group:
                                         min =         2
                                         avg =        2.0
                                         max =         2

Integration method: mvaghermite        Integration pts. =   12

Wald chi2(12) = 1441.13
Log pseudolikelihood = -4907.9925      Prob > chi2     = 0.0000
```

(Std. err. adjusted for 4,849 clusters in household_id2)

| poor | Coefficient | Robust std. err. | z | P> z | [95% conf. interval] | |
|--------------|-------------|---------------------|--------|-------|----------------------|-----------|
| hh_size | .3182268 | .0191026 | 16.66 | 0.000 | .2807863 | .3556672 |
| age | .0064857 | .0025089 | 2.59 | 0.010 | .0015683 | .0114032 |
| mean_hh_size | .142885 | .0239305 | 5.97 | 0.000 | .0959821 | .1897878 |
| mean_age | -.0034445 | .0035661 | -0.97 | 0.334 | -.0104338 | .0035449 |
| amhara | .982033 | .084596 | 11.61 | 0.000 | .8162279 | 1.147838 |
| snnp | .73221 | .0855616 | 8.56 | 0.000 | .5645124 | .8999076 |
| rural | 1.115124 | .0574605 | 19.41 | 0.000 | 1.002503 | 1.227744 |
| psnp | .3607457 | .0802669 | 4.49 | 0.000 | .2034255 | .5180659 |
| sex | -.3169076 | .0590124 | -5.37 | 0.000 | -.4325698 | -.2012455 |
| educ | -.6145412 | .0612367 | -10.04 | 0.000 | -.7345629 | -.4945195 |
| causal2 | .1415363 | .0999437 | 1.42 | 0.157 | -.0543497 | .3374223 |
| year_dummy | 1.840708 | .0657863 | 27.98 | 0.000 | 1.711769 | 1.969647 |
| _cons | -3.288935 | .1661022 | -19.80 | 0.000 | -3.61449 | -2.963381 |
| /lnsig2u | -1.222024 | .3983273 | | | -2.002731 | -.4413167 |
| sigma_u | .5428013 | .1081063 | | | .3673774 | .8019906 |
| rho | .0821964 | .0300499 | | | .0394081 | .1635341 |

```
. test mean_hh_size mean_age
```

```
( 1) [poor]mean_hh_size = 0
( 2) [poor]mean_age = 0

      chi2( 2) =   36.00
      Prob > chi2 = 0.0000
```

. vif

| Variable | VIF | 1/VIF |
|--------------|------|----------|
| hh_size | 2.28 | 0.439071 |
| mean_hh_size | 2.26 | 0.441786 |
| age | 2.09 | 0.477546 |
| mean_age | 2.06 | 0.484377 |
| rural | 1.25 | 0.800420 |
| educ | 1.13 | 0.883756 |
| sex | 1.09 | 0.915707 |
| amhara | 1.07 | 0.936496 |
| psnp | 1.07 | 0.938577 |
| snp | 1.06 | 0.942299 |
| year_dummy | 1.06 | 0.946845 |
| causal2 | 1.02 | 0.980005 |
| Mean VIF | 1.45 | |