What Explains Household Poverty in the Rural Areas of the Hadiya Zone in Ethiopia?

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Abstract

The study sought to examine the factors contributing to household poverty in the rural area of Misrak Badawacho district within the Hadiya Zone of the Central Ethiopia Region. A cross-sectional survey approach was adopted for the research. A representative sample of 240 households was selected by employing a multi-stage sampling approach. The selection process involved systematic random sampling from four sub-districts (kebeles). The data collection involved a questionnaire survey, key informant interviews, and focus group discussions. The collected data were analyzed using descriptive and inferential techniques. Specifically, descriptive statistics, the logit model, and the FGT (Foster, Greer, and Thorbecke) poverty index-based measures were employed. The results reveal that the poverty threshold in the area was approximately 7,981.4 Ethiopian birr per adult equivalent consumption expenditure per year. Based on this estimated threshold, the poverty index showed that 44.6% of the surveyed households live below the poverty threshold. The respective poverty gap and severity were found to be 9.4% and 3.33%. The econometric findings from the simple logit model suggested that education attainment, the size of actual cultivated land, ownership of livestock, oxen possession, non-agricultural activities income, the contact frequency with extension agents, and agricultural inputs use had a strong negative relationship with poverty levels and were statistically significant. In contrast, factors such as gender, family size, poor health conditions, and distance from the market were positively associated with higher poverty levels. Therefore, it is essential to implement policies that promote the adoption of agricultural technologies, improve the availability of productive resources, strengthen rural-urban market connections, and enhance health services as effective strategies for reducing poverty in rural areas.

Keywords: Poverty, Consumption approach, Factors, logit model

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1. Introduction

1.1. Background

Poverty is an important social concern in Sub-Saharan Africa(SSA) as it is in most developing countries. In 2015, 75% of the countries in SSA had poverty rates higher than 18%. Out of the world's total (28) poorest countries, SSA consists of 27, and all of them have a rate of poverty higher than 30%. In 11 countries, all in SSA, more than half of their populations live in extreme poverty (Khan et al., 2020). In every region except SSA, the average poverty rate is less than 18%. However, in SSA, about 41% (or 413 million people) live below the International Poverty Line (IPL) (World Bank, 2018).

In Ethiopia, one of the least developed countries in the world (Mare et al., 2022), around 30% of its population lives below the World Bank's 2USD per day poverty line, with over 27 million people facing extreme poverty or occasional food insecurity. Poverty is a bit more common in rural areas, with 30%, compared to 26.1% in urban areas (*Ibid*). A survey done by the Central Statistical Agency (2017), found that in 2015/16, about 23.5% of people were living below the poverty line. This number is higher in rural areas, at 25.6%, than in urban areas, at 14.8%. The poverty gap index, which shows how much people are below the poverty line on average, was 6.7%. In rural areas, this gap is 7.4%, which is more than double the gap in urban areas, which is 3.6%. The poverty severity index, which shows how bad the poverty is, is 2.8% nationally. In rural areas, this is 3.1%, which is much higher than in urban areas, at 1.4%.

About a quarter of people in Ethiopian live below the national poverty line. Ethiopia's poverty index, which examines various forms of hardship, is significantly worse than the one that solely considers income. Around 88.2% of people face several types of hardship, and 67% live in very severe poverty. When it comes to income inequality, the top fifth of the population earns five times more than the poorest fifth. (UNDP, 2016). Poverty in Ethiopia is reflected in low per capita income, low literacy rates, low primary school enrollment, limited access to health services, inadequate access to sanitation and safe water, and high infant, child, and maternal mortality rates. It also results in a shorter life expectancy (CSA, 2017). These conditions are even more pronounced in the study area, Misrak Badawacho Woreda, Hadiya Zone, in central Ethiopia, as observed in our research and local reports. Poverty is a major obstacle for farming households.

By examining important demographic and socio-economic factors, we aimed to better understand the situation in this rural area. Understanding the context and designing effective anti-poverty programs is crucial. Any successful poverty reduction initiative depends on accurately identifying and addressing the characteristics of the poor. Therefore, understanding the nature, causes, and extent of rural poverty is essential for developing effective and successful government interventions to reduce deprivation in rural settings. With this in mind, the objective of the study was to examine the socio-economic factors resulting in the probability of falling into poverty in rural Ethiopia and contribute to the broader understanding of poverty research.

2. Methodology

2.1 Research and Sampling Design

The study used data collected from a cross-sectional survey design. The target population of the study was households located in the rural Badewacho district of the Hadiya zone in Ethiopia. A total of 240 representative participants were selected through systematic sampling from four sub-districts within the Badewacho district. The 1977 Cochran formula was employed to get the size of the sample as:

$$n = \frac{z^2pq}{e^2} ---------------(1)$$

According to Cochran (1977), the desired level of precision in a study can be determined by considering the acceptable amount of sampling error in the estimates. This decision is based on the level of risk the study should take when using the research data to conclude. Precision is usually expressed as a percentage. The highest level of precision corresponds to a 5% margin of error, the middle level to 7%, and the lowest to 10%, associated with confidence levels of 95%, 93%, and 90%, respectively.

A reasonable 6% margin of error at a 95% level of confidence was chosen, and the proportion of a particular attribute in the population, denoted as p = 0.5, was estimated.

$$n = \frac{1.96^2 * 0.5 * 0.5}{0.06^2} = 266.8 -------------(2)$$

Where the number of samples is represented by n, Z^2 is the normal curve value that provides an area of α in the tails; (1 – α) is the level of confidence sought, like 95%. e is the level of accuracy you want, p is the estimated share of a certain feature in the population, and q is 1 minus p. The Z value comes from statistical tables that show the area under the normal curve. For example, Z equals 1.96 for a 95% confidence level.

Hence, to estimate the sample size, we calculated it as:

Z^2= the critical value for a two-tailed test at a 95% confidence level (1.96)

e = Margin of error between the sample and population size (0.06), Zegeye (2017)

To find out the final sample size, we looked at the total population in the study area. Because of that, we used Cochran's (1977) correction formula to determine the exact sample size needed for the study. **Ns =**

$$\frac{n}{1+\frac{n}{N}} = \frac{266.8}{1+\frac{266.8}{2376}} = 240 \qquad ---------------------(3)$$

The adjusted sample size, denoted as Ns, is derived from the sample size calculated using Cochran's (1977) method. In this context, n stands for the number of households we collected data from using this method, and N is the population of households in the four sub-districts, as the finance and economic development office's report of the district indicated. The total population size is approximately 23,455, comprising 11,617 males and 11,838 females. However, the total number of households is 2,376, with 1,422 being from the lowland (Kolla) and 954 from the midland (Woinadega) areas, as per the MBWFEDO report (2018).

So, the number of households included in this study was decided to be 240. We used a method called systematic sampling to pick the people who would take part. In this approach, the first person is chosen randomly, and then others are selected in a regular, set pattern. If there are N total people in the group and we need to choose n of them, we calculate the sampling interval, denoted as R, is calculated as R = N/n (Singh & Masuku, 2012). In this study, every 10th household was included in the sample, with the starting point selected randomly from the range of 1 to 10.

In the study area, the total number of households was 2,376, of which 954 were located in the midland (Woinadega) and 1,422 in the lowland (Kolla) regions. The sample size of 240 households was distributed among each kebele in proportion to the proportion of households present in each kebele.

Table 1. Samples taken from each Kebele

Name of Kebeles	Total population/kebele			Households/kebele			Sample by household			Agro ecology
	Men	Women	Sum	Men	Women	Sum	Men	Women	Sum	
Ajeba-Chalfo	2149	2117	4266	460	34	494	47	3	50	Woina-Dega
Kanchara	2646	2748	5394	429	31	460	44	3	47	
Edo	3207	3338	6545	738	57	795	74	6	80	Kolla
Shirko-Gafarso	3615	3635	7250	600	27	627	60	3	63	
Total	11617	11838	23455	2227	149	2376	225	15	240	

Source: own computation (2019)

Misrak Badawacho Woreda is divided into thirty-six (36) sub-districts, which collectively consist of 28,640 households. Out of these, 6,635 are located in urban areas, while the remaining 22,005 are in rural areas. The households' primary source of living is agriculture. The group of people from whom the samples were taken are rural families in the woreda who mainly rely on mixed farming to support their living. A multi-stage sampling approach was used to choose the total number of samples. Initially, the district was intentionally selected because it is known for having a high poverty prevalence. In the second stage, the woreda was divided into two agroecological zones—woyna-dega and Kolla—to ensure the sample households were representative. In the third stage, four kebeles (sub-districts)—Ajeba-Chalfo, Kanchara, Edo, and Shirko-Gafarso—were selected using a stratified random sampling technique, based on their agro-climatic conditions. Finally, households were selected through systematic random sampling to ensure homogeneity in agricultural practices, settlement patterns, topography, and lifestyle..

Once the sampling frame was identified, which is a full list of all households in each chosen kebele, gathered from kebele leaders, managers, and development agents, 240 rural households were carefully selected from the kebeles. The selection was done in a way that matched the proportion of households in each kebele, as shown in Table 1.

2.2 Data source, type, and method of collection

We have mainly used primary data sources, supported by secondary data. The first-hand primary data were gathered using key informant interviews (KII), a structured questionnaire survey, and focus group discussions (FGD). The collected data via survey questionnaires are primarily quantitative, while the information gathered through KIIs and FGDs is mainly qualitative.

2.3 Data Analysis Methods Employed

The data gathered was looked at and understood using methods that involve numbers and economic analysis. Simple stats like percentages, ratios, averages, and how spread out the numbers are were used to show what the people in the study are like. A method called FGT helped look at how bad poverty is, how big the gap is between poor and non-poor families, and how many people are poor. This was done by looking at how much money families spend. Also, a type of economic analysis called logistic regression was used to find out what causes poverty. All the number work was done using a program called STATA 16.

Information from group discussions and interviews with key people was also used. These helped explain any unclear parts or missing parts from the number-based findings. The group discussions let people talk about their daily lives, and the interviews gave extra details that helped check and confirm how poverty in the area being studied. An econometric model, specifically a logistic regression was employed to analyze the probability of being poor in a rural area where the study was conducted.

2.3.1 Econometric Model Specification

No economic model can perfectly show how poverty connects to the factors that cause it. Because of this, the best model to use is the one that most accurately shows and predicts the link between the main topic being studied and the other related factors. There are many different econometric models that researchers use in their studies, especially when the outcome they're looking at has only two possible outcomes. These models include the logistic, probit, and normal log-linear regression models, among others.

The logit and probit models are the most common types of models used when the outcome is a yes or no type of response, such as whether a household is in poverty. These models help show how different factors relate to the outcome. According to Gajarati (1995) the probit model is often used as an alternative to the logistic model in such studies.

Even though the two models are very similar, they have some important differences. The logistic model has a slightly flatter shape at the ends compared to the probit model, which rises more quickly towards the edges. Even though both models give similar results, the binary logit model is often liked more because it's easier to understand and interpret the results.

The study employed a binary logit model to look at how a household's poverty status is connected to different factors. A household is considered to be poor (Y = 1) if its total spending per adult equivalent each year is below the poverty line. If a household spends more than the poverty line, they are not considered poor (Y = 0), which means they have little or no money left after covering their basic needs..

The statistical equation is specified as: $Y_i = \beta_0 + \sum_{i=0}^{n} \beta_i X_i + \varepsilon_i$ ———————————— 5

Where; Y_i refers the dependent variable that measures poverty; Y_i =1 if $Yi < 0$, 0 if $Yi \geq 0$

n = represents the number of independent variables; β_0= refers the intercept;

βi = vector of coefficients for all the independent variables ε_i= the error terms; and

X_i = indicates the independent variables (determinants for poverty).

So, the binary dependent variable takes two values: 1 if the household is below the poverty line, 0, otherwise. The probability of being under poverty depends on a set of explanatory variables X, which have the following probabilities,

Prob (Y_i=1) = F (βX) ———————— 6

Prob (Y_i=0) = 1– F (βX) − − − − − − − − − −7

Where F refers the cumulative distribution function for ε_i, therefore, the logistic regression equation can be presented as: Logit (P) =$In\left[\frac{P}{1-P}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_n X_n - - - - - 8$

Where: β_0, β_1, β_2, …, β_n are the parameters to be estimated, such as the age and educational attainment of the head of the household, household size, etc, and P is the chance of the household being poor. Before fitting the logit model, the presence of multicollinearity and heteroscedasticity was checked to ensure that both were addressed. Additionally, robustness checks were carried out.

Multicollinearity test: Before beginning the logit model, the presence of multicollinearity among the explanatory variables has to be checked. This is because multicollinearity can have a big impact on how accurate the estimates of the model's parameters are. The Variance Inflation Factor (VIF) is a good measure of multicollinearity among continuous explanatory variables (Gujarati, 1995). All the continuous explanatory variables were included as predictors. For the regressions, the coefficient of determination (R^2) was calculated. This is a common method to detect multicollinearity using the VIF, which is calculated as:

VIF = $\frac{1}{1-R^2_{xz}} - - - - - - - - - - - - - -9$

Where R^2_{xz} is the relationship between X and Z variables.

VIF measures how much the variance of an estimator is increased because of multicollinearity. As the value of R^2_{xz} gets closer to 1, the VIF increases without bound. This means that as collinearity becomes more severe, the variability of the estimator also increases, and in extreme cases, it can become very large. When there is no collinearity between the variables X and Z, the VIF equals 1. A VIF value above 10 suggests a potential issue (Gujarati, 2004).

Additionally, there might be a linear relationship between categorical variables, which can also result in multicollinearity or a strong association. To identify such issues, contingency coefficients were calculated using the survey data..

In addition, a linear relationship might exist between qualitative variables, potentially causing multicollinearity or a strong correlation. To identify this issue, contingency coefficients were calculated using the survey data.

The following method was employed to determine the contingency coefficients:

$$C = \sqrt{\frac{x^2}{\mathrm{n}+x^2}} - - - - - - - - - - - -(10)$$

Where: x^2 = is the value of the chi-square test; C = refers to the Contingency coefficient; and n = is the size of the sample.

The Contingency Coefficient varies from 0 to 1. The interpretation is the same as VIF. I.e, 0 indicates no relation and increasing to 1 indicates the existence of a relationship.

Heteroscedasticity test: The existence of the heteroscedasticity issue can lead to parameter estimates that are not reliable or consistent. It is not appropriate to rely on standard t and F tests for forming confidence intervals or conducting hypothesis tests when heteroscedasticity is present, as this results in inflated variances and broader confidence intervals. In summary, if we continue to use standard estimation methods in the presence of heteroscedasticity, the conclusions drawn from the model may be incorrect or misleading. Therefore, the Breusch-Pagan test is commonly used to detect heteroscedasticity, as recommended by Gujarati (2004).

Robustness (predictive) power of the model: The ability of a model to correctly forecast results is important for its usefulness in econometric analysis. This forecasting ability is checked by comparing the model's predictions with the real data. Unlike the linear regression model, which uses the F-test to check how well it fits, the log-likelihood ratio test is used to check how good the model's fit is, as mentioned by Liao (1994).

2.3.2 Poverty Analysis

This study used the expenditure approach to examine poverty. The reason for choosing this method is that consumption is thought to change more steadily than income. It is easier to observe, remember, and measure compared to income, and people are less likely to adjust their reported income figures. To calculate a household's consumption expenditure, first, the food bundle needed to meet the minimum food energy requirements is identified. Then, an additional amount is added to cover non-food basic needs. The value of the food someone eats is figured out by looking at today's local prices to set the food poverty line. The money given for other basic needs, like clothing or shelter, is based on how poor people usually spend their money..

In 2015/16 the food and non-food poverty line for the country was calculated as birr 7,184 per adult equivalent per year by HICE 2015/16 and MoFED (2015). This figure was used as a reference to identify the poverty threshold for the area. To account for inflation, a simple mathematical method was applied. The average inflation rate for the country during the period 2016 to 2018 was used to adjust the poverty line.

The base year 2015/16 inflation rate was 10.12% (World Bank, 2017). Using this rate, a straightforward calculation was performed to determine the current poverty line.

The poverty line for the area was estimated by assuming: $R^1 = R^0 + \mathrm{r} * R^0$ ————— 11

Let R^0, be the initial inflation rate (for the year 2015/16 as the initial inflation rate),

R^1, represents the current adjusted inflation rate, and **r** is the annual average inflation growth rate for 2016 to 2018. (2016 (7.26%), 2017 (8.6%), and 2018 (13.4%) (UNDP 2018)) = 7.26+8.6+13.4 =Average 9.75 %).

Using this, the calculation becomes, $R^1 = R^0 + \mathrm{r} * R^0$ = 0.1012 + 0.0975*0.1012 = 0.111. To find out the current poverty line for the study area, the adjusted inflation rate was used. This means it is the cost of basic items needed to survive based on the 2015 poverty line adjusted for inflation. The following formula was used to calculate the new poverty line:

Let P^1 be the new poverty line and P^o be the base year's (2015) poverty line of the country, and, R^1 is the price adjusted for inflation.

Thus, $P^1 = P^o + R^1 * P^o$ = 7184 birr+ 0.111*7184birr = 7981.4 birr ——————————— 12

The FGT index (1984) was employed to assess the severity, incidence, and level of poverty in the area. The index uses three main measures: the Head Count Index (P0), which shows the percentage of people living in poverty; the Poverty Gap Index (P1), which tells us how far on average the poor are below the poverty-line; and the Poverty Severity Index (P2), which looks at both how deep the poverty is and how it is spread among the poor. These measures are calculated using Q, the number of people with earnings below the poverty threshold, and N, the total population number.

The Head Count Index (P0) represents the percentage of the poor in the population. However, it provides no information about how far below the poverty line the poor are or whether the poor are uniformly affected, or if there is variation in their levels of poverty. It also doesn't say if all poor people are equally poor or if some are much poorer than others. It is given by PCI $= P_0 = \frac{Q}{N}$ ————— 13 this can be rewritten as: $P\alpha (Z, Y) = \frac{1}{N}\sum_{i=1}^{Q}\left[\frac{Z-Yi}{Z}\right]^{\alpha}$

where **Pα** is the measure of the poverty (poverty index), **Z** is the poverty line, **Y_i** refers to the amount of expenditure of people living below the poverty line, **N** is the total number of people, **Q** is the number of people taken as poor, typically those below the poverty threshold, and **α** is the Poverty aversion parameter, i.e., the weight attached to the sensitivity and severity of the poor; its commonly used values are 0, 1, and 2 as mentioned by Araya in 2010.

Poverty Gap Index (P_1) The poverty gap index shows how deep poverty is; it is the difference between the poverty line and the average income of people who are poor, measured as a percentage of the poverty line" (FGT, 1984). It uses the mentioned variables and defines the poverty gap **(G_i)** as the difference between the poverty line(**Z**) and the actual income **(Y_i)** of individuals living in poverty, with the gap taken to be zero for non-poor individuals. Algebraically, the poverty gap (PG) has been calculated in the following way:

$$pG = P_2 = \frac{1}{N}\sum_{i=1}^{Q}\left[\left(\frac{G_i}{Z}\right)\right] ------------14 \quad \text{Where } G_i = \frac{1}{N}\sum_{i=1}^{Q}\left[\frac{Z-Y_i}{Z}\right]$$

Poverty Severity Index (P_2): It is referred to as the square of the poverty gap index. This index assesses the depth of poverty by calculating the difference between the income of the poor and the poverty line, squaring this difference, and then taking the average. (FGT, 1984). Compared to the poverty gap index, this measure is more reflective of the severity of poverty because it takes into account the level of inequality among the poor (Tassew et al, 2008). It was calculated as follows: $PS = P_2 = \frac{1}{N}\sum_{i=1}^{q}\left[\frac{Z-Y_i}{Z}\right]^2 --15$

To assess poverty, the aforementioned indices along with consumption-based measures were computed. A dummy dependent variable was established for the binary logit model, and its influencing factors were identified and presented in Table 2, along with the corresponding hypotheses drawn from related literature.

Table 2. Definitions and Measurements of all variables for the Binary logit model

Code of variables	**Type**	**Definition and measurement of variables**	**Expected sign** **Sign (+or-)**
The dependent variable			
POVSTAT	Dummy	Whether the Household is in Poverty or not (1=poor 0=non-poor)	
Explanatory Variables			
AGEHH	Continuous	The age of the Head of the Household (in years)	+ve/-ve

SEXHH	Dummy	Sex of the Head of the Household (1=Woman 0, otherwise)	+ve
MSHH	Dummy	The household head's marital status (1=married, 0 if not)	+ve
FSHH	Continuous	Family size of the HH	+ve
DEPRATIO	Continuous	Dependency ratio in the household in Adult Equivalent	+ve
EDULEVHH	Continuous	HH's educational level in years completed	-ve
HEALSHH	Continuous	The status of health of the household head	+ve
OFFNFINC	Continuous	Non-farm and off-farm income earned in birr/year	-ve
FRQEXNSE	Continuous	Number of extension contacts days/month	-ve
LVSTOWN	Continuous	HH Livestock ownership in TLU	-ve
DSTMRKT	Continuous	Distance to the market center in kilometers	+ve
LANDHLD	Continuous	Land-holding in hectares of the household	-ve
OXOWN	Continuous	HH Oxen ownership in number	-ve
AGINPUT	Dummy	Agricultural input utilization status of the HH	-ve
CRDTUTZ	Continuous	Credit accessed by the HH in birr per year	-ve

3. FINDINGS AND DISCUSSION

3.1 Measuring the Incidence and Extent of Household Poverty

Poor and non-poor households were identified to understand how many people are living in poverty and how widespread it is in Misrak Badawacho Woreda. To do this, the existing poverty threshold for the district was used. For the year 2015/16, the food and non-food poverty lines were calculated as 3,772 and 3,412 birr per year per adult equivalent, respectively. The poverty line was fixed at 7,184 birr per adult equivalent per year (HICE 2015/16).

In 2018/19, the poverty line was updated based on the national poverty line (7,184 birr) and adjusted for inflation. This led to a new poverty line of 7,981.4 birr per adult per year member of a household. This line, along with the actual per-adult consumption spending, is used to calculate consumption poverty indices. Real per-adult consumption is found by dividing the nominal consumption expenditure by the nutritional calorie-based adult equivalence family size, which takes into account differences in age and gender.

The consumption expenditure for both food and non-food items of each household is calculated and then divided by the household size to find the annual consumption per household member. The minimum food poverty line was set based on the minimum number of calories needed per adult per day, which was determined to be 3,236 kilocalories, matching the usual diet of households in the area. Based on this, the estimated food and non-food poverty lines were calculated from survey data. The food poverty line was found to be 6,224 birr per adult per year (70.4%), and the non-food line was found to be 2,618 birr per adult per year (29.6%) (see Table 3 below). The food poverty line has been interpreted and used to determine the expenditure needed to meet basic non-food needs.

The 2015/16 HICE surveys, initiated at the national level, showed that the food share in rural areas was 53.6% with an average of 3,155 kilocalories. This was the lowest in the Central Ethiopia region (former South Region), which had a food share of 59.1% with an average of 3,875 kilocalories (HICE surveys, 2015/16). In rural areas, a significant portion of total consumption is allocated to food items rather than non-food items. A high proportion of total expenditure on basic food consumption suggests that people in rural areas may be food insecure. Moreover, the findings of this study indicate that food expenditure is significantly higher than non-food expenditure, as shown in previous studies. In the study area, the regional and national levels of food expenditure as a proportion of total expenditure were found to be 70.4%, 59.1%, and 53.6%, respectively. The kilocalorie share of food consumption in the study area was found to be 3,236.06, which is less than the regional figure of 3,875 and greater than the national figure of 3,155 kilocalories.

Table 3 Sample household food and non-food consumption status.

Expenditure category	Gram/ day/ adult	*Average kcal/ Gram	Kcal/ day/ adult	Calorie %share	Mean price/kg/litter	Poverty line value/year	Expenditure %share
Teff	30.78	3.589	110.51	3.41	26	292.21	3.31

Barely	4.52	3.36	15.18	0.469	25	41.23	0.47
Wheat	2.51	3.28	8.23	0.25	20	18.31	0.21
Maize	570.95	3.58	2044.	63.16	10	2083.98	23.57
Haricot bean	37.78	3.4	128.45	3.97	10	137.9	1.56
Millet	15.83	3.46	54.76	1.69	12	69.32	0.78
Kocho	51.26	1.9	97.39	3.01	20	374.2	4.23
Fino	5.71	3.3	18.84	0.58	30	62.50	0.71
Kik	1.25	3.4	4.25	0.131	50	22.80	0.26
Shiro	4.77	3.4	16.23	0.501	50	87.13	0.99
Pasta	12.33	4.12	50.81	1.57	20	90.02	1.02
Misir	3.63	3.4	12.34	0.38	65	86.08	0.97
Meat	2.5	3.68	9.156	0.28	250	227.03	2.57
Butter	0.59	3.87	2.28	0.070	250	53.84	0.61
Milk	12.2	3.87	47.11	1.456	25	111.1	1.26
Egg	1.21	3.66	4.44	0.137	60	26.55	0.30
Oil	9.3	3.87	35.98	1.11	30	101.82	1.15
Vegetable	78.2	3.87	302.8	9.36	30	856.76	9.69
Pepper	2.89	0.933	2.70	0.083	100	105.5	1.2
Salt	13.71	1.78	24.40	0.754	12	60.04	0.68
Coffee	16.63	1.103	18.34	0.567	100	607.1	6.87
Sugar	4.5	3.85	17.32	0.535	30	49.26	0.56
Honey	0.75	2.61	1.96	0.061	35	9.6	0.11
Spices	1.67	2.97	4.97	0.153	50	30.51	0.35
Fruit	56.56	3.6	203.6	6.29	30	619.3	7.004
Total	942		3236	100			
Food Expense						6223.98	70.4%
Non-food Expense						2618.2	29.6%
Total						8842.18	100

Source: Own computation (2019) Adopted from FAO (2011)

3.2 FGT Method of Analysis

The Foster, Greer, and Thorbecke (1984) Index was often used to study poverty. It helped analyze three things: the level of poverty, how many people are poor, and how severe the poverty is in the area being studied. The three measures of poverty in the FGT (1964) index are:-

Headcount Index (P_0): - This is the share of the population whose consumption is below the poverty line in the district, i.e. $P_0 = \frac{Q}{N} = \frac{107}{240} = 0.446 \; or \; 44.6\% ------------3$

Poverty gap Index (P_1): "The poverty gap index measures, on average, who falls below the poverty line, and is a percentage of the poverty line" FGT (1984).

$$P_1 = \frac{1}{N}\sum_{i=1}^{Q}\left[\frac{Z - Y_i}{Z}\right] \frac{1}{240}\sum_{i=1}^{Q}\left[\frac{7981.4 - Y_i}{7981.4}\right] = \frac{1}{240}\,(22.54)$$
$$= 0.0939 \; or \; 9.4\% \quad --------4$$

Poverty Severity Index (P_2): - "The poverty severity index measures variation in the poverty level of individual households," FGT (1984).

$$P_2 = \frac{1}{N}\sum_{i=1}^{q}\left[\frac{Z-Y_i}{Z}\right]^2 = \frac{1}{240}\sum_{i=1}^{q}\left[\frac{7981.4-Y_i}{7981.4}\right]^2 = \frac{1}{240}\,(7.98) = 0.0333 or 3.33\% --------5$$

Table 4 shows that the poverty incidence in the study area is 0.446, meaning that 44.6% of the households surveyed are poor and unable to satisfy the basic needs of their family members. This suggests that 44.6% of the sampled households are living in absolute poverty within the study area. This rate is significantly higher than the regional and national rural poverty rates, which are 21.9% and 25.6%, respectively (CSA, 2017).

The rural poverty status (RPOVSTAT) is defined as being poor if a person's income is less than 7,981.4 birr per year, and non-poor if it is equal to or greater than 7,981.4 birr per year. According to this definition, out of 240 sampled households, 107 (44.6%) were classified as poor, while 133 (55.4%) were classified as non-poor.

Table 4: Depth, Incidence, and Severity of the Poverty Status

Indexes	The district	Regional (2015/16)	National (2015/16)
Headcount Index (P_0)	44.6%	21.9%	25.6%
Poverty Gap Index (P_1)	9.4%	8.2%	7.4%

Poverty Severity Index (P_2)	3.33%	3.5%	3.1%

Source: Own computation (2019)

The overall level of poverty in the district was measured as 0.094, which means that, on average, each household needs to access up to 9.4% of the poverty line resources to reach the poverty line. In other words, the average distance between the poor and the poverty line is 9.4% of the set poverty line (7,981.4 birr) in the area. This suggests that an average of 9.4% of total household consumption is necessary to lift the poor out of poverty. This poverty gap is greater than both the regional and national rural poverty gaps for the year 2016, which were 8.2% and 7.4%, respectively (CSA, 2017).

The poverty severity index for the study area was found to be 0.0333, which is 3.33% lower than the threshold level. This means that the gap between the poorest families in the area is not too big. The severity index value is lower than the regional severity index of 3.5% but higher than the national severity index of 3.1% for the year 2016 (CSA, 2017).

Table 5 FGT Poverty measures by Kebele

Kebele	Poor	Non-poor	Observations	%Share	P_0	P_1	P_2
Ajeba-Chalfo	22	28	50	20.6%	44%	14.5	6.6
Kanchara	17	30	47	15.9%	36.2%	5.8	1.6
Edo	38	42	80	35.5%	47.5%	8.4	2.8
Shirko-Gafarso	30	33	63	28.04%	47.6%	9.3	2.7
	107	133	240	100	44.6%	9.4	3.33

Source: Own computation (2019)

In Table 5, a comparison was conducted among the kebeles using the three indicators. Column 6 of the table indicates that the poverty incidence (P0) is the highest in Edo & Shirko-Gafarso (47.5%) and lowest in Kanchara (36.2%). Furthermore, the poverty gap or deficit (P1), presented in column 7, represents the total shortfall of all poor households compared to the poverty line as pointed out in a similar study by (Ravallion and Bidani, 1994). This measure gives more useful information than the headcount index because it looks at how poverty is spread among households that are below the poverty line. It also shows the average amount of money needed to lift all the poor people out of poverty. The survey shows that the deepest poverty is in Ajeba-Chalfo, with 14.51%, followed by Shirko-Gafarso at 9.3%, Edo at 8.42%, and Kanchara at 5.8%. This suggests that more resources would be needed to eliminate poverty in Ajeba-Chalfo compared to Shirko-Gafarso, Edo, and Kanchara. The sample estimation results from the study areas indicate an overall poverty depth of 0.0939. This means that if resources equivalent to 9.4% of the poverty line could be mobilized for each individual and distributed to the poor in the required amount to bring them up to the poverty line, then, in theory, poverty could be eradicated.

3.3 Demographic Characteristics of Sample Households and Poverty

3.3.1 Sex and Poverty

Table 6 Sex distribution profile of Households and poverty

Sex of HH	Poor household		Non-poor		Total		P-value	χ2
	N = 107	Percent	N = 133	Percent	N=240	Percent		
Male	95	88.8%	131	98.5%	226	94.2%	0.001	10.1802
Female	12	11.2%	2	1.5%	14	5.8%		
Total	107	100%	133	100%	240	100%		

Source: Own computation (2019)

The results of this study also reveal that out of 14 female-headed households included in the research, 12 (which is approximately 85.7%) were classified as poor, as shown in Table 6. In contrast, among the 226 male-headed households, only 95 (around 42%) were found to be poor. This suggests that female-headed households are more likely to experience poverty compared to male-headed households. A t-test conducted as part of the analysis indicates that the association between gender and poverty status is statistically significant at the 1% level.

3.3.2 Poverty status by family size

Table 7 Family Size Profile of Sample Households

Demographic profile	Poor households (107)				Non-poor households (133)				p-value	t-value
	mean	std. dev.	Min	max	mean	Std. dev.	min	max		
Family Size	6.72	2.24	2	18	5.39	2	1	10	0.00	-8.84

Source: Own computation (2019)

The average adult equivalent family size across the households surveyed was 5.98 persons, with a standard deviation of 2.2. This suggests that the average adult equivalent family size for rural households in the study area is greater than both the regional and national averages of 4.2 and 4.0, respectively (EDHS, 2016). The smallest and largest household sizes observed were 1 and 18 persons, respectively. However, when looking at the mean adult equivalent family sizes of poor and non-poor households, they were 6.72 and 5.4, respectively, as shown in Table 7. This indicates that households with larger family sizes are more likely to be poor compared to those with smaller family sizes in the study area. A chi-square test ($\chi^2 = 0.000$) confirmed that there is a strong and statistically significant association between household size and poverty status at the 1% level.

3.4 Povert status by Socio-Economic Characteristics

Table 8 Cultivated land, livestock and Oxen ownership, and poverty Profile

Socio-Economic Profile	Poor households (107)				Non-poor households (133)				p-value	t-value
	Mean	Std. Dev.	Min	max	Mean	Std. dev.	min	max		
Land	0.68	0.4	0.12	2	1.1	0.46	0.5	3	0.000	7.35
Livestock	1.94	1.66	0.01	12	4.33	2.4	1	14	0.000	8.7
Oxen	0.42	0.61	0.00	3	1.2	.60	0	3	0.000	9.87

Source: Own computation (2019)

3.4.1 Cultivated Land Holding of the Household and Poverty

Land is not only important for farming but also serves as a key indicator of the living standards of rural households, distinguishing between those who are poor and those who are not. According to the survey findings, the average land area owned by the sampled households is 0.91 hectares. All the households in the study used rain-fed farming methods rather than irrigation-based techniques. When looking specifically at the poor and non-poor groups, the poor had an average of 0.68 hectares of cultivated land, while the non-poor had an average of 1.1 hectares. This difference in land holdings between the two groups is statistically significant at the 1% level of significance (Table 8).

3.4.2 Household Livestock Ownership Excluding Oxen and Poverty

Livestock is regarded as a form of security in times of crop failure and also provides an extra source of income for families living in rural areas (Adugna and Wagayehu, 2013). In this study, the ownership of livestock and oxen by rural households, along with their access to agricultural inputs and distance from the nearest market, were taken into account. For rural households, keeping large animals serves as a way to manage unexpected risks of food shortages by offering immediate income from on-farm sales, which helps them buy both food and other necessities for their family members. The livestock owned by the sample households was measured using TLU (Total Livestock Unit). The findings show that the average number of livestock owned by the sample households was 3.27 TLU. As shown in Table 8, the average livestock ownership for the poor and non-poor groups of households was 1.94 TLU and 4.33 TLU, respectively. The difference in the average livestock holdings between the poor and non-poor groups was found to be statistically significant at the 1% level.

3.4.3 Oxen Ownership and Poverty

Owning oxen along with access to land is a crucial factor that enables the efficient use of both land and labor resources, which in turn helps rural households to avoid food poverty. The data also shows that poor households own an average of 0.42 oxen, while non-poor households own an average of 1.2 oxen. The difference in the number of oxen owned between these two groups is statistically significant at the 1% level.

3.5 Econometric Results

The econometric model used in this study is binary logistic regression. To identify the most relevant predictors of the dependent variable, fifteen explanatory variables were included in the model. These consist of twelve continuous variables and three dummy variables. The choice of these factors was based on both existing theories and previous research findings. The dependent variable in the model is POVSTAT, which represents the poverty status of households. It takes a value of 1 if the household is classified as poor and 0 otherwise.

Out of the fifteen explanatory variables included in the binary logistic regression model, eleven variables—nine continuous and two dummy variables—were found to be statistically significant in determining the poverty status of rural households. Among these eleven significant variables, seven were highly significant at the 1% level of significance. These include sex, family size, educational level, livestock holding, off-farm/nonfarm income, distance from the market, and agricultural input utilization. Two variables, namely health and oxen holding, were significant at the 5% level of significance, while two other variables, cultivated land and frequency of extension service, were significant at the 10% level of significance. An econometric analysis was conducted for each variable, including the calculation of marginal effects.

Marginal effects were estimated after performing the binary logistic regression. Since the logit model is not linear, the marginal effect of each independent variable on the dependent variable is not constant and varies depending on the values of the independent variables. Therefore, marginal effects serve as a way to summarize how a change in the response variable is related to a change in a covariate. For categorical variables, the effects of discrete changes are calculated. The marginal effects for these variables indicate how the probability of the dependent variable being 1 changes when the corresponding independent variable changes from 0 to 1, while keeping all other variables constant. For continuous independent variables, the marginal effect measures the instantaneous rate of change, as described by Greene (1993).

Table 9 Marginal effects after logistic regression

Variable	Marginal effects (dy/dx)	Std. Err	Z	P value	X
AGRHH	-0.017	0.015	-1.17	0.241	47.867
SEXHH*	0.814	0.120	6.75	0.000	.058
MSHH*	0.857	1.291	0.66	0.507	.961
FSHH	0.307	0.111	2.75	0.006	5.983
DEPRATIO	0.199	0.258	0.77	0.440	.709
EDLVLHH	-0.152	0.051	-3.01	0.003	4.961
HEALHH	0.295	0.127	2.32	0.020	1.104
LANDHLD	-0.731	0.402	-1.82	0.069	.911
LVSTOWN	-0.198	0.082	-2.42	0.016	3.267
OXOWN	-0.323	0.168	-1.91	0.056	.850
OFFNFINC	-0.037	0.014	-2.72	0.007	9.151
FREQEX~E	-0.213	0.126	-1.69	0.091	2.508
DSTMRKT	0.269	0.102	2.63	0.009	5.804
AGINPUT*	-0.811	0.161	-5.05	0.000	.717
CRDTUTZ	-0.124	0.088	-1.40	0.161	.665
1%, 5%, and 10% significance level, respectively					

Number of observations	240	Pseudo R2	0.868	
LR chi2(15)	286.20	Log-likelihood	-21.846	
Prob > chi2	0.000			

Source: Own computation (2019)

As it is clear from the above binary logistic regression table 9, all of the predictor variables in the binary logit estimates agree with the expected signs. Following the background information on the binary logit estimate, a detailed explanation of all explanatory variables is presented below.

Sex of the Household Head (SEXHH): As anticipated, there is a positive and statistically significant association between sex and the poverty status of households at the 1% level of significance. Female-headed households have an 81.4% higher probability of being poor compared to male-headed households. The likelihood of poverty decreases when the household is led by a male, as reported by Frew (2018). This suggests that households led by females are more likely to experience poverty than those led by males. The findings of this study align with this observation, showing that male-headed households tend to be less poor than female-headed ones. Additionally, the descriptive analysis indicates that most female-headed households struggle to meet essential needs and are classified as poor.

Household Family Size (FSHH) ***the FGT poverty index***: The size of a household's family was found to have a positive relationship, and this association is statistically significant at the 1% level. This positive link suggests that as family size increases, the likelihood of a household being poor rises, or the chance of not being poor decreases. This finding aligns with the study by Zegeye (2017), which also noted that larger households are more likely to experience poverty. The marginal effect of 30.7% for family size indicates that, assuming all other factors remain constant, the risk of being poor increases by 30.7% for each additional adult equivalent in family size. This supports the hypothesis that family size plays a significant role in determining the poverty status of a household. It further highlights the importance of managing population growth in the region under study.

Household Head's Educational Attainment (EDULVLHH): As shown in the binary logit estimation results presented in Table 9, there is a negative and statistically significant relationship between education and the likelihood of a household being poor, at the 1% significance level. When the educational level of the household head increases by one grade, the chance of the household being poor decreases by 15%, assuming all other factors remain unchanged. Numerous empirical studies have demonstrated that an educated workforce is more likely to secure employment with better income and effectively engage in business activities, as they possess the knowledge and skills necessary for such opportunities. The descriptive analysis in this study also supports this notion, indicating that households with higher educational attainment are less likely to experience poverty. This suggests that the connection between education and poverty is consistent and reliable. These findings align with previous research conducted by Frew (2018) and Melese et al. (2017).

Cultivated Land Holding (LANDHLD): The model results indicate that the amount of cultivated land a household owns is negatively connected to their poverty status, and this relationship is statistically significant at the 10% level. This suggests that as the size of a farm increases, the likelihood of the household being non-poor also rises. This finding supports the idea that farmers with larger plots of land are more likely to escape poverty compared to those with smaller landholdings, as larger farms typically enable greater food production. This increased production leads to higher income and wealth, which in turn allows for more investment in agricultural inputs. Such investments can further boost food production, ultimately improving the living conditions of farming households.

When the size of landholding increases by one hectare, the probability of a rural household being poor decreases by 73% in the study area. This could be due to the fact that higher landholdings are associated with increased income and consumption levels. This suggests that a household's capacity to achieve a stable economic situation is closely tied to the agricultural potential of the land they own. The findings align with the study by Adugna and Sileshi (2013), who also found that landholding plays a significant role in helping rural households move out of poverty, with the variable being significant at the 1% level.

Household Livestock Ownership Excluding Oxen TLU (LVSTOWN): Livestock ownership is associated with a lower likelihood of being poor, and this relationship is statistically significant at the 1% level. This negative connection arises because the size of livestock represents a crucial resource for rural households. Households that own larger quantities of livestock are more likely to generate higher incomes through livestock production. This income allows them to buy sufficient food and other necessary goods, especially when other households face resource shortages. The average marginal effect suggests that, all else being equal, a reduction of one TLU in total livestock holdings increases the probability of a household being poor by 19.8%. Conversely, an increase of one TLU in livestock holdings decreases the probability of poverty by 19.8%. These findings align with Krishnan's (2000) research, which shows that households with significant physical capital, such as livestock, tend to experience lower poverty rates and are more likely to improve their economic status over time..

Oxen Ownership (OXOWN): Oxen ownership is linked to a lower likelihood of rural household poverty and this relationship is statistically significant at the 5% level. The study found that as the number of oxen owned by a household increases, the chance of being classified as poor decreases. This suggests that rural households with more oxen are more likely to escape poverty. One reason for this is that these households may engage in sharecropping agreements with other households that have sufficient land but no oxen. Through such arrangements, they can produce enough food not only to meet their own needs but also to have a surplus. Additionally, households that own oxen can cultivate larger areas of land compared to those without oxen, which leads to increased agricultural output. The findings indicate that, assuming all other factors remain constant, the probability of being poor decreases by an average of 32.3% for each additional oxen owned. This aligns with the findings of Alemayehu Geda (2006).

Agricultural Input Utilization Status of the Household (AGINPUT): The use of agricultural inputs was found to have a negative relationship with poverty status, and this association is statistically significant at the 1% level. Households that utilize improved agricultural inputs are more likely to experience food security compared to those that do not use them. These improved inputs contribute to increased productivity and higher levels of crop production. Specifically, the use of essential inputs such as fertilizer in crop production, at the rate of one quintal, significantly reduces the likelihood of poverty by 81% among rural households in the study area.

4. CONCLUSION AND RECOMMENDATIONS

4.1 Conclusion

The level, gap, and intensity of poverty (44.6%, 9.4% & 3.33%) in the study area are greater than the 2015/16 national rural poverty indicators, which are 25.6%, 7.4% & 3.1%, respectively. Likewise, these levels are significantly higher than the regional rural poverty rates, which stand at 21.9% compared to 8.2%. However, the overall intensity of poverty in the study area is lower than the regional intensity, which is 3.5%. On average, allocating about 9.4% of the resources required to meet the poverty line can assist poor households in fulfilling their essential needs within the study area.

A binary logistic regression model indicated that nearly eleven (11) variables (nine (9) continuous and two (2) dummy variables) were statistically significant in determining the poverty status of rural households. Among these eleven (11) significant variables, four (4) factors—such as sex, family size, distance from the market, and health status—were found to have a positive and strongly significant relationship with poverty at 1% and 5% levels of significance. On the other hand, seven (7) variables, including agricultural input usage, educational level of the household head, off-farm/non-farm income, livestock ownership, oxen ownership, cultivated land size, and frequency of extension contact, exhibited a negative relationship with poverty and were significant at 1%, 5%, and 10% levels of significance.

The implication is that enhancing the factors that contribute positively to poverty will help reduce the burden of poverty in rural areas. In addition, improving the factors that negatively influence poverty can lead to better poverty outcomes for rural households

4.2 Recommendations

There are many factors that contribute to rural poverty. These factors suggest that an integrated and coordinated approach is necessary for addressing broader issues of rural development, especially the issue of rural poverty. Therefore, the following points represent key areas for intervention and policy development to enhance the living conditions of households in the study area.

- Female-headed households are more likely to experience poverty compared to male-headed households. The study found a significant relationship between poverty status and the head of the household. Thus, future poverty reduction efforts should focus more on female-headed households. These households need improved skills through various training programs to increase their income.

Therefore, the local administration should take steps to economically empower female-headed households, helping them generate sufficient income to support their families.

- Family size can influence the level of poverty in a household. The study highlights the need to reduce fertility rates. This suggests the importance of controlling population growth in the study area through family planning and other innovative strategies.
- The education level of household heads is negatively and significantly related to rural poverty. A more literate head has a greater chance of escaping poverty because they can better understand how to manage a household and lead a better life. Investing in human capital through education is crucial for achieving positive labor returns. Therefore, there is a need for an integrated approach to education that is centered on the needs of rural communities. This education should promote literacy in areas related to livelihood and health. Formal institutions like adult education programs, along with the expansion of health facilities, can contribute to creating literate and healthy households, which are essential for reducing poverty.
- In addition, greater possession of physical assets like farmland and livestock is strongly associated with better household welfare. Expanding farmland size and improving the quality of cultivated land through watershed management, conservation practices, and efficient use of agricultural inputs can significantly improve land productivity. Implementing inter-resettlement programs can also help by improving access to agricultural land and other natural resources, thus enhancing food security and income sources in the short term.
- Promoting off-farm and non-farm activities, along with the use of technology, can also contribute to poverty reduction. Enhancing access to rural financial services can help farmers overcome capital constraints, enabling them to purchase farm oxen, inputs, and participate in trade. Therefore, increasing financial access for poor farmers should be a key area of intervention and policy.
- Improved market access can increase household income and reduce the likelihood of poverty. Thus, efforts should be made to create local markets and improve transportation and other infrastructure, which will help reduce the time and cost of accessing markets.
- The frequency of contact with extension workers is also negatively related to rural poverty, meaning that households that interact with extension services have better access to new technologies that can improve their livelihoods. Extension workers play an essential role in transferring knowledge and technology from research institutions to farmers. Therefore, investing in extension programs through capacity-building initiatives can strengthen the connection between research, extension, and farmers, leading to more effective poverty reduction strategies.

In general, poverty reduction strategies should be targeted and tailored to specific locations and households, as poverty is often individual-centered rather than a general issue. Therefore, programs that improve the income and well-being of individuals, households, and specific localities should be implemented selectively.

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Data Availability:

The data will be available upon request.

Conflict of Interest

There is no Conflict of interest in submitting this manuscript for publication in this journal.

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