# Determinant of Poverty in Ethiopia

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***Abstract***

*Poverty has turned out to be a great global social and economic problem. In Ethiopia, it is multifaceted and deep rooted. This study attempts to analyze the impact of socioeconomic and demographic characteristics of households on poverty in Ethiopia, using the latest Household Income, Consumption and Expenditure Survey (HICES) 2010-11. The study employs a logistic regression model to identify determinants of wellbeing of the household by considering per capita consumption as a dependent variable. Different households are classified as either poor or non-poor on the basis of absolute per capita consumption of Birr 3781. Results show owner of agricultural land, head (self-employed or employed in formal sector) are more likely to exit from poverty line. The results also reveal that female headed households, large family size and high dependency ratio are adversely affected.*

**Keywords:** Poverty, Household, Per Capita Consumption, Determinants, Logistic Regression.

**JEL classification:** C8

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## 1. Introduction

Achieving sustainable economic growth with a focus on combating poverty has become the key development goal for governments around the world, as reflected in the Millennium Development Goals, Goal 1; *"eradicate extreme poverty and hunger"*. In this objective, analysis of poverty aroused the interest of researchers, public authorities and international organizations. The specificities of developing economies, in particular the dualism between the urban and rural areas incites to identify the determinants of poverty with a view of designing policies and strategies to alleviate poverty that persists in most of these countries. Poverty in Ethiopia has many manifestations. The Human Development Index (HDI) for 2014 (based on estimates of 2013), which takes life expectancy, adult literacy, primary schooling and per capita income is 0.435 which is low in comparison of Rwanda, Uganda and Sub-Saharan Africa and rank of Ethiopia is 173 out of the 177 countries. According to most recent multidimensional poverty index estimation, 88.2% of the populations of Ethiopia are multi-dimensionally poor while an additional 6.7% are near multidimensional poverty. The MPI, which is the share of the population that is multidimensional poor, adjusted by the intensity of deprivations, is 0.537. Rwanda and Uganda have MPI is of 0.352 and 0.359 respectively.

By any standard, the majority of people in Ethiopia are among the poorest in the world (Dercon and Krishnan, 1998; IMF, 1999; Rahmato and Kidnanu, 1999; World Bank, 2001). Poverty seems to persist in large sections rural society as well as urban sections with little hope for a substantial improvement of the living conditions of the rural poor as well as urban poor in the near future. In order to combat such debilitating poverty considering very scarce financial resources available to be allocated for the purpose, we have to understand the determinants of poverty in rural and urban Ethiopia. For this, the poor must be properly identified and an index taking the intensity of poverty suffered by the poor into account needs to be constructed.

Analytical work that scrutinizes poverty profiles is best scanty. Even the available ones are mostly descriptive focusing on explaining the extent of poverty and mostly associated with studies that relate to food entitlement failure (see Webb *et al.*, 1992; Webb and Von Braun, 1994). Among those studies, Beevan and Joireman (1997) adopt a sociological approach towards the measurement of poverty on the meaning and use of different measurements.

Using micro level panel data from villages in rural Ethiopia, Dercon (2001) analyses the determinants of growth and changes in poverty during the initial phases of the economic reform (1989-1995) making use of a standard decomposition of income and poverty changes. His empirical results indicate that overall, consumption grew and poverty fell substantially during the period under consideration and that on average the poor have benefited more from reforms than the non-poor households, even though the reforms did not deliver similar benefits to all the poor. He argues that the main factors driving changes are relative price changes, resulting in changes in the returns to land, labour, human capital and location. Bogale et al. (2005) investigated the determinants of rural poverty in Ethiopia on the basis of survey data of three districts namely Alemaya, Hitosa and Merhabete and found that nearly 40% of the sample households live below poverty line with an average gap of 0.047.

The Ethiopian Ministry of Finance and Economic Development (MoFED) assessed the 1999/2000 Household Income and Consumption Expenditure (HICE) and welfare Monitoring Survey results and concluded that the incidence of poverty is higher in rural than in urban areas with poverty head count ration of 45.4 and 36.9%, respectively (MoFED). However, as compared to 1995/96 level, poverty incidence increased by 11.4% in urban areas and declined by 4.42% in rural areas in 1999/2000.

Most of these studies aim to assess the extent of poverty and explain relative changes which occur in the incidence of poverty due to policy changes. The article aims to add discussion by examining the socio- economic and demographic characteristic of households on poverty in rural and urban

Ethiopia. We analyze the latest Household Income, Consumption and Expenditure Survey (HICES) 2010-2011 and estimate determinants of poverty using a maximum likelihood binary logistic regression model considering whether a household is poor or non-poor as a response variable. This allows us to derive further meaningful insight about various poverty – generating factors that determine the persistence of poverty in Ethiopia and the relevance those specific policies can play in alleviating poverty.

## 2. Data Source and Research Methodology

### *2.1. Data Source*

The data used in this study has been taken from the 2010-11 Household Income, Consumption and Expenditure Survey (HICES) for Ethiopia. The survey covered both rural and urban areas of the country which was conducted from 8 July 2010 through 7 July 2011.

For the purpose of representative sample selection, the country was divided into three broad categories, i.e., rural, major urban centers and other urban areas categories. Therefore, each category of a specific region was considered to be a survey domain for which the major findings of the survey are reported. However, Harari and Dire Dawa have rural and urban categories, only; while Addis Ababa has only urban areas divided into10 sub-cities considered as survey domain or reporting levels.

### *2.2. Poverty Line*

Large literature exists on approaches to assess poverty. However, the question still remains as where to draw the poverty line. Ideally, the poverty line should be based on a basket of goods and services including food and nutrition, as well as clothing, housing and health care and education that can be considered basic needs (Baffoe, 1992). Greer and Thorbecke (1986) apply the cost of food consumption corresponding to the recommended daily allowance of calories and provide the profile and decomposition of food poverty among Kenyan smallholders.

Economic theories suggest that per capita expenditure is the best indicator of welfare, but this presupposes that households, as consumers, maximize a continuous utility function defined over commodities (Glewwe, 1987). Bevan and Joierman (1997) employed personal wealth ranking, community wealth ranking and consumption poverty, and concluded that none of the indicators applied identifies the poor on a convincing way.

The most popular method of poverty measurement have used the nutritional norm and defined poverty in terms of minimum calorie requirements (Dandekar and Rath, 1971; Osmani, 1982; Greer and Thorbecke, 1986; Ahmed *et al.*1991; Ercelawn, 1991; Ravallion and Bidani, 1994).

In the absence of an invariably acceptable national poverty line for Ethiopia, we decided to use the official poverty line constructed by MoFED in 2010/2011. That is, a household is deemed as living in poverty if the per capita consumption is less than equal Birr 3781 otherwise the household will be considered as non-poor.

### *2.3. Definitions of Variables Used in the Study*

The dependent variable of our study is binary variable i.e it takes value 1 for poor and 0 for non-poor. To know the impact of independent variables on poverty we have considered the following socio- economic and demographic variables i.e independent variables.

**Table 1: List of Variables and their Description**

| **Independent (Explanatory) Variables** | |
|---|---|
| SEX | Sex of the Household Head (0 = Male, 1 = Female) |
| AGE | Age of the Household Head (in year) |
| FSZ | Number of Household Members (Family Size) |
| FSZSQ | Family Size Squared |
| AREA | Place of Residence of Household (0 = Urban, 1 = Rural) |
| NWOR | Number of Working Members/Productive Age (between 15 and 64 years inclusive) |
| AGRL | Household Having Agricultural Land (0 = No, 1 = Yes) |
| DEPR | Dependency Ratio $= \frac{\text{People of (Age 14 and Below + Age 65 and Above)}}{\text{People Above Age of 15 and Below Age of 64}}$ |
| | Head of the Household Has No Education (NSCH = 0)** |
| EDLEV | Head of the Household Completed Elementary School (CMPE = 1) |
| | Head of the Household Completed Secondary School (CMPS = 2) |
| | Head of the Household Completed College/University & Above (CCUA = 3) |
| | Head of the Household is Single (SINGLE= 0)** |
| MARST | Head of the Household is Married (MARRIED = 1) |
| | Head of the Household is Divorced/Widowed (DIVSEW = 2) |
| | Head of the Household is Employed in Informal Sector (INFOE = 0)** |
| EMPST | Head of the Household is Employed in Formal Sector (FORME = 1) |
| | Head of the Household Head is Self-Employed (SELFE = 2) |

Note: ** implies reference category

## *2.4. Method of Data Analysis*

The data set was analysed using bivariate and multiple logistic regression analyses. Bivariate analysis was done in order to identify which characteristics independently related to socioeconomic status (poverty level) were using Pearson's chi-square tests of associations as given below.

$$\chi^2 = \frac{\sum_{i=1}^{r}\sum_{j=1}^{c}(O_{ij} - E_{ij})^2}{E_{ij}} \sim \chi^2_{\sim}(r-1)(c-1) \quad \textbf{(1)}$$

Where: $O_{ij}$ is the observed value in the $i^{th}$ row and $j^{th}$ column

$E_{ij}$ is the expected value of the $i^{th}$ row and $j^{th}$ column cell

$r$ = is number of row and $c$ = is number of column.

Given the dependent variable of main interest that a household may be classified as poor or non-poor, a binary Logistic regression model is useful when the outcome (dependent) is binary, meaning zero or one, with one being success. Suppose in multiple logistic regression case, a collection of $p$ explanatory variables be denoted by $\mathbf{x}' = (1, x_1, x_{2,} ..., x_p)$. Furthermore, let $\text{®}_i$ denotes the conditional probability that the $i^{th}$ household is below the poverty line. Thus, the model for which the outcome variable is binary, can be written as:

$$y_i = \text{®}_i + \text{£}_i ; i = 1, 2, ..., n \qquad \textbf{(2)}$$

Where:

$$\text{®}_i = \frac{\exp(z_i)}{1 + \exp(z_i)} \qquad \textbf{(3)}$$

with $z_i = {}_0 + {}_1 x_{1i} + {}_2 x_{2i} + ... + {}_p x_{pi} = \mathbf{X}'\boldsymbol{\beta}$. Here $\boldsymbol{y}$ is n×1 vector of response having $y_i$ = 0 if the household is not-poor and $y_i$ = 1 if the household is poor, **X** is an n× (p+1) design matrix of explanatory variables, $\boldsymbol{\beta}$ is a (p+1) ×1 vector of parameters, $\boldsymbol{\varepsilon}$ is also an n×1 vector of unobserved random errors. The quantity $\text{®}_i$ is the probability for the $i^{th}$ covariate satisfying the important requirement $0 \le \text{®}_i \le 1$. Then, the log-odds of having $y$ = 1 for given $\boldsymbol{x}$ is modeled as a linear function of the explanatory variables as:

$$E(\mathbf{y} / \mathbf{x}) = \ln\left(\frac{\text{®}_i}{1 - \text{®}_i}\right) = {}_0 + {}_1 x_{1i} + {}_2 x_{2i} + ... + {}_p x_{pi} \qquad \textbf{(4)}$$

The function $® _i = \dfrac{\exp(\mathbf{X}'\boldsymbol{\beta})}{1+\exp(\mathbf{X}'\boldsymbol{\beta})}$ is known as logistic function. The most commonly used method of estimating the parameters of a logistic regression model is the method of Maximum Likelihood (ML) instead of Ordinary Least Square (OLS) method.

## 3. Results and Discussion

### *3.1 Model Selection for National Data*

The model at National level with all variables is shown in the Table 2.

**Table 2: Logistic Estimate of Poverty at National Level (Full Model)**

| Variable | Parameter Estimate | Standard Error | Wald Chi-Square | Pr > Chi-Square | Odds Ratio |
|---|---|---|---|---|---|
| INTERCEPT | -7.245 | 0.1527 | 2250.574 | 0.0001 | |
| DEPR | 0.186 | 0.0368 | 25.706 | 0.0001 | 1.205 |
| NWOR | -0.095 | 0.0384 | 10.878 | 0.0010 | 0.910 |
| FSZ | 1.017 | 0.0384 | 702.694 | 0.0001 | 2.766 |
| FSZSQ | -0.050 | 0.0025 | 389.424 | 0.0001 | 0.951 |
| AGE | -0.007 | 0.0011 | 48.636 | 0.0001 | 0.992 |
| SEX | 0.471 | 0.0401 | 137.893 | 0.0001 | 1.602 |
| AGRL | -0.297 | 0.0503 | 34.925 | 0.0001 | 0.743 |
| AREA | 1.655 | 0.0359 | 2128.093 | 0.0001 | 5.234 |
| DIVSEW | 0.443 | 0.0789 | 31.521 | 0.0001 | 1.557 |
| MARRIED | 0.409 | 0.0448 | 83.274 | 0.0001 | 1.505 |
| CMPE | -0.168 | 0.0400 | 17.724 | 0.0001 | 0.845 |
| CMPS | -0.413 | 0.0650 | 40.342 | 0.0001 | 0.388 |
| CCUA | -0.669 | 0.0860 | 60.528 | 0.0001 | 0.515 |
| SELFE | -0.445 | 0.0495 | 81.040 | 0.0001 | 0.640 |
| FORME | -0.208 | 0.0820 | 6.350 | 0.0120** | 0.812 |

** Significant at 5% level of significance

The calculated value e of the likelihood ratio test statistic is

$$G^2 = 32854.561 - 23431.280 = 9423.281$$

For $\alpha = 0.05,$ we have $\chi^2_{0.05}(15) = 24.996$, since $G^2 = 9423.281 > 24.996$ and the *p*-value for the test is $P\left(\chi^2(15) > 9423.281\right) = 0.000$ which is significant at the *α* = 0.05 level. Thus, we reject the null hypothesis and conclude that at least one and perhaps all 15 coefficients are different from zero.

The Table 3 exhibits AIC, SC, R-Square and number of parameters to be estimated for null and full model, respectively.

**Table 3: Model Selection Criteria**

| Model | AIC | SC | R-Square | No. of Parameters |
|---|---|---|---|---|
| Null | 32855.561 | 32859.005 | - | 1 |
| Full | 23463.280 | 23502.392 | 0.3991 | 16 |

The Table 3 reveals that the full model have the lowest value in both criterion (AIC and SC) which is the indication of a better fit model by adjusting for the number of explanatory variables and the number of observations. The R-square value for the full model is 39.91%. The estimated logit model for household level determinants of poverty at National level is as given below:

$$\begin{aligned}\mathrm{logit}(\hat{\pi}_i) &= -7.25 + 0.186\mathrm{depr} - 0.095\mathrm{nwor} + 1.02\mathrm{fsz} - 0.05\mathrm{fszsq} - 0.007\mathrm{age} + 0.471\mathrm{sex} \\ &- 0.297\mathrm{agrl} + 1.66\mathrm{area} + 0.443\mathrm{divsew} + 0.41\mathrm{married} - 0.168\mathrm{cmpe} - 0.413\mathrm{cmps} - 0.669\mathrm{ccua} \\ &- 0.4376\mathrm{selfe} - 0.21\mathrm{forme} \qquad .\mathrm{Model} - \mathrm{I}'\end{aligned}$$

Another way to analyze the effects of independent variables to know the probability of being poor is the change of odds ratio as the independent variables change. The odds ratio is defined as the probability of being poor divided by the probability of not being poor. Table 2 (the last column) shows the odds ratios for each independent variable at National level.

As it is evident from Table 2 that the variables dependency ratio (DEPR), family size (FSZ), household head being female (SEX), marital status (DIVSEW and MARRIED) and living in the rural area (AREA) have odd ratios greater than one, which means that these variables are positively correlated with the probability of being poor. On the contrary, the variables number of working members (NWOR), agricultural landholding (AGRL), family size squared (FSZSQ), age of household head (AGE), having completed elementary education (CMPE), having completed secondary education (CMPS), having college education and above (CCUA), being self-employed (SELFE) and being household head employed in formal sector (FORME) all have odd ratios lower than one, which means that these variables are negatively correlated with the probability of being poor.

## *3.4. Model Diagnostics*

In model diagnostics we are concerned with goodness fit of the model.

### *3.4.1 Goodness-of-Fit of the Models (H-L Tests)*

The goodness-of-fit measures how effectively the model describes the response variable. Now, we can test the reduced model to see if it is a good fit. The following table gives H-L test Statistics (2000) (summary for Model (National)).

**Table 4: Hosmer and Lemeshow Goodness-of-Fit Tests**

| | **National** |
|---|---|
| H-L test statistic ($\hat{C}$) | 2.223 |
| P-value | 0.9734 |
| No. of observations | 27827 |

For $\alpha = 0.05$, we have $\chi^2_{0.05}(8) = 15.507.$

Since $\hat{C}_{National} = 2.223$ are all less than the tabulated value 15.507, we do not reject $H_0$, and conclude that the fitted models fit the data adequately well. Thus, the goodness-of-fit test with *p*-values 0.9734 indicates that there is insufficient evidence to claim that the models do not fit the data adequately. If the *p*-value is less than our accepted α-level (5% in this case), the test would reject the null hypothesis of an adequate fit. So our models fit the data well.

### *3.4.2 Classification Table*

In order to assess the predictive power of the models, a classification table of correct and incorrect predictions was constructed, based on the predicted probability of being poor for each data. A probability equal or greater than 0.5 was interpreted as a prediction of a household being poor, while a probability lower than 0.5 was interpreted a prediction of a household being non- poor. Table 5 shows the classification for the models. In this table, "D" represents the number of poor households in the sample while "~D" represents the number of non- poor cases in the sample. The symbol "+" represents the number of households predicted as poor by the model while "-" represents the number of no- poor cases predicted by the model.

As it can be seen in the Table 5, the models sensitivity rate (percent of poor cases correctly predicted by model) are 55.3%, 27.26% and 77.79%, while the models specificity rate (percent of non-poor cases correctly predicted by the model) are 90%, for National.

The false positive rate for households classified as poor by the model at National level is 31.6 percent, which means that 31.6 percent of the number of households predicted as poor by the model are in fact non-poor. The false negative rate for households classified as non- poor by the model is 15.95 percent, which means that 15.95 percent of households predicted as non-poor by the model are in fact poor.

**Table 5: Classification Table of Correct and Incorrect Predictions for National [Urban] Rural**

| Classified | True | | |
|---|---|---|---|
| | D | ~D | Total |
| + | 4272 [613] 4252 | 1974 [1001] 1859 | 6246 [1614] 6111 |
| - | 3443 [1636] 1214 | 18138 [14257] 2995 | 21581 [15893] 4209 |
| Total | 7715 [2249] 5466 | 20112 [15258] 4854 | 27827 [17507] 10320 |

| | **National** |
|---|---|
| Sensitivity | 55.30% |
| Specificity | 90.10% |
| Positive predictive value | 68.40% |
| Negative predictive value | 84.05% |
| False + rate for true ~D | 9.82% |
| False – rate for true D | 44.63% |
| False + rate for classified + | 31.60% |
| False – rate for classified - | 15.95% |
| Correctly classified | 80.53% |

The positive predictive value rate of the National model is 68.4 percent, which means that 68.4 percent of the total number of predicted poor households is in fact poor. Negative predictive rate is 84 percent, meaning that 84 percent of the total number of non-poor cases predicted by the model is in fact non-poor. As a whole, the National model correctly predicts 80.53

percent of cases. Sensitivity and specificity rely on a single cut point to classify a test result as positive.

### *3.5 Diagnostic Plots*

One way of looking at the model adequacy is to graph studentized Pearson and deviance residuals against predicted probabilities. The studentized Pearson residuals and deviance residuals are plotted against the estimated logistic probability respectively and in all case, the lower smooth approximates a line having zero slope and intercept. Any significant departure from this suggests that the model may be inadequate and potential outliers may have dramatic impact on the fit of the model (Sarkar et al 2011).

It is to be mentioned here that the reduced model also passes the model checking procedure.

## 4. Discussions of the Results

The data has been analyzed at National level. Ethiopia, like other developing countries is subject to the threat of high population growth rate. This high growth accompanied by the high unemployment rate and low female labor force participation rate poses a serious threat to the households. High dependency ratio (DEPR) and larger family size (FSZ) contribute positively to the probability of becoming a poor household for national level. The coefficients for both of these variables are positive and significant at 5% level of significance. The coefficient of family size squared (FSZSQ) is however negative and significant, controlling for the fact that very large families can also have potential earners and can reduce the poverty through larger participation in the work force. However, this situation is not highly desirable due to the fact that the odds ratio are at a very low level of less than 1% in reducing the probability of being poor for national level. The odd ratio of the variable dependency ratio (DEPR) shows a contribution of 20.5%

in increasing the likelihood of being poor where as family size (FSZ) contributes 76.6%.

Number of working household members/productive age (NWOR) has a potential in reducing the probability of remaining in the poor household category. Sex of household head i.e being female (SEX) positively affects the likelihood of remaining poor. Several studies have discussed the phenomenon of the feminization of poverty, which is said to exist if poverty is more prevalent among female-headed households than among male-headed households. This situation might be due to the presence of discrimination against women in the labor market, or it might be due to the fact that women tend to have lower education than men and they are paid lower salaries. Using a probit model, Meron (2003) found that female-headed households are poorer and more vulnerable to poverty than male-headed households in Urban Ethiopia.

Looking at the results of logistic regression estimated national level; we reach at the same conclusion as Meron (2003) since the sign for sex of the head (SEX) is positive and statistically significant at 5% level of significance. Moreover, the odd of being poor for female-headed households are 1.602 (OR = 1.602 with $p$-value = 0.0001) times in comparison to male-headed households. Conversely, we can say that the odd of being poor for those male-headed are 0.6242 (OR = 0.6242, given by the reciprocal of 1.602) times for those headed by female.

It is argued that poverty increases at old age as the productivity of the individual decreases and the individual has few savings to compensate for this loss of productivity and income. This is more likely to be the case in developing countries like Ethiopia, where savings are low because of low income. However, the relationship between age and poverty might not be linear, as we would expect that incomes would be low at relatively young age, increase at middle age and then decrease again. Therefore, according to life-cycle theories we would expect to find that poverty is relatively high at young ages, decreases during middle age and then increases again at old age.

For the case of Ethiopia based on 1999/00 Household Income, Consumption and Expenditure Survey (HICES) and Welfare Monitoring Survey (WMS), Tassew (2008) finds that age of the household head (AGE) is relevant in explaining poverty. Using the 2010/11 HICES and the methodology developed above we reach at the same conclusion as Tassew (2008) and age of the head is statistically significant in explaining poverty at National level. Various researchers have identified the linkages between education and poverty. A base hypothesis is that higher education negatively affects poverty. That the coefficients on the educational attainment of household head (CMPE, CMPS and CCUA) are all negative and statistically significant at 5% level of significance for the three models.

The level of education is grouped into four categories ranging from illiterate to higher education (college and above). The odds of being poor with education level elementary school (CMPE), secondary school (CMPS) and college and above (CCUA) was found to be 0.845, 0.388 and 0.515 times that of illiterate (no schooling-reference category) respectively, implying that household head with higher educational attainment (CCUA) exhibited a lower chance to be poor as compared to the illiterate household head for National.

The result of marital status for national level indicates that divorced/widowed and married clients are 55.7% and 50.5% more likely to be poor respectively than single (never married-reference category) clients, implying clients whose marriage ended because of death of a partner or due to some disagreement are found to have a significantly high likelihood of being poor in Ethiopia.

Employment status of the household head is one of the determinants of household's poverty status. Self-employed household head (SELFE) are about 64% less likely to be poor than those employed in informal sector (INFOE) which is the reference category. Household's which are headed by the one who is employed in formal sector (FORME) are about 81% less likely to be poor than those works in informal sector (INFOE) at country level (Model-I).

Last but not certainly the least, the ownership of agricultural land of household (AGRL) significantly help in lowering the possibility of being poor. The results show that households having agricultural (farming) land have 74.3%, 89.3% and 63.2% less chances to be remain as a poor. The possible reason might be that the most of the population majorly employed in agricultural sector; the agricultural sector therefore is a big sector of employment in rural area especially as compared to urban area of the country.

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