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THE DIMENSIONS OF POVERTY AND INEQUALITY: A FOCUS ON RURAL HOUSEHOLDS IN ETHIOPIA

von

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1 Introduction

While poverty every where involves people experiencing very real material deprivations, the concept of poverty is used to cover a wide ranging set of interrelated life chances which are valued differently in the diverse cultures and subcultures of the world. This leads ultimately to unresolvable problems of analysis and measurement. However, this does not mean that there is not a lot to be learned about the state, experiences, processes and causes of poverty through thorough conceptual analysis and related careful empirical measurement.

A detailed scrutiny of rural poverty and inequality requires the measurement of well-being. Since it is very difficult, if not impossible, to capture all variables of poverty within the scope of this research, here we focus only on material well-being, which are measured using information on household income, food energy consumption and consumption expenditure. While per capita household calorie consumption and expenditure will be used as a variable to identify and characterise the poor in this study, it should not be considered as an implicit acceptance of these variables as the only appropriate dimensions by which the poor is to be identified. Relying on both, this paper presents the poverty profile, analyses its determinants and inequality in rural Ethiopia.

2 Methodology

2.1 Data Source

The data examined in this paper came from a one-year rural household survey conducted in three districts of Ethiopia during the 1999/2000 cropping season. The study has adopt a stratified random sampling procedure with rural household as an ultimate unit for acquiring first hand information. Three administrative districts, namely Alemaya, Hitosa and Merhabete, were selected purposively to represent major farming systems in Ethiopia.

A structured survey questionnaire was designed to collect relevant information. A total of 149 households have provided complete information for the three-round survey, from which data on demographic characteristics, crop and livestock production, household income, household consumption, and land use and management were gathered. Data on farming activities as well as returns from a total of 540 plots owned by sample households were collected. The visits were executed following a cropping calendar for the major crops in each district.

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2.2 The Empirical Model

2.2.1 The Incidence of Poverty

With the increased awareness and availability of data, various measures of poverty have been developed overtime, among which the FOSTER, GREER and THORBECKE (1984), FGT, class of poverty index is the most commonly applied. Given a vector of suitable measure of well-being, *Y*, in increasing order, Y_1, Y_2, Y_3,..., Yn, where *n* represents the number of households under consideration, the FGT poverty index (P_α) can be expressed as (BAFFOE 1992):

$$P_\alpha = \frac{1}{n}\sum_{i=1}^{q}(g_i / z)^\alpha \tag{1}$$

Where z is poverty line, q is the number of the poor, g_i is shortfall in chosen indicator of well-being. If, for instance, x_i denote the per capita calorie intake of household i, then $g_i = z_i - x_i$ if $x_i < z$; $g_i = 0$ if $x_i \geq z$, and α is the poverty aversion parameter ($\alpha \geq 0$)

The parameter α represents the weight attached to a gain by the poorest. The commonly used values of α are 0, 1, and 2. When we set α equal to 0, then (1) is reduced to the headcount ratio which measures the incidence of poverty. When we set α equal to 1, we obtain P_1 or the poverty deficit. P_1 takes in to account how far the poor, on average, are below the poverty line. Setting α equal to 2 gives the severity of poverty or FGT (2) index. This poverty index gives greater emphasis to the poorest of the poor as it is more sensitive to redistribution among the poor.

2.2.2 The Probability of Being Poor

To characterise the poor in the study areas, a probability model is used in which the chances of falling below the poverty line are linked to household and geographical characteristics which may at the same time be poverty generating factors.

Given the dependent variable of main interest, that a household may be classified as poor or non-poor, a binary logit model can be used for the analysis of the data. Consider that a household is poor (Y=1) if per capita household food consumption is less than 2300 kcal per day or non-poor (Y=0) if the food consumption shortfall is less than or equal to zero. A set of factors, mentioned elsewhere, gathered in a vector X, could explain the response so that:

$$Y_i^* = X'_i\beta + u_i \tag{2}$$

where Y_i^* is the underlying latent variable that indexes the measure of poverty, u_i is the stochastic error term, and β is a column vector of parameters to be estimated. Following GREENE (1993) and assuming that the cumulative distribution of u_i is logistic, a logit model is employed. In this case, the probability of being poor can be given by:

$$Prob(Y_i = 1) = \frac{exp(X_i'\beta)}{1 + exp(X_i'\beta)} \tag{3}$$

Then, the marginal effect of a particular independent variable, X_i, on the probability of the occurrence of the response is given by (MADDALA 1993):

$$\frac{\partial P(Y=1)}{\partial X_i'} = \frac{exp(X_i'\beta)}{\left[1+exp(X_i'\beta)\right]^2}\beta_k \tag{4}$$

Unlike linear models in which the marginal effects are constant, in the case of logit models, we need to calculate them at different levels of the explanatory variables to get an idea of the range of variation of the resulting changes in the probabilities.

2.2.3 Measurement and Decomposition of Inequality

A number of different inequality measures have been proposed in the literature (BOURGUIGNON 1979, COWELL 1999, ATKINSON and BOURGUIGNON 1999, LITCHFIELD 1999). It is recommended that the selected inequality measure should meet some important properties: Pigou-Dalton transfer sensitivity, symmetry, income scale independence, population size independence and decomposability. This study relies on Gini coefficient and Generalized entropy inequality index which satisfy the above properties.

Gini coefficient is based on the concept of Lorenz curve which relates the cumulative proportion of income to the cumulative proportion of income recipients when the recipients are ranked in ascending order of their income. The Gini coefficient is bounded between zero and one. If the income is equally distributed, the Gini coefficient equals zero.

Another widely used class of inequality indicator is a member of the Generalised Entropy (GE) class of inequality measure (COWELL 1995). The General Entropy class of inequality measures have the general formula of:

$$GE(\alpha) = \frac{1}{\alpha^2-\alpha}\left[\frac{1}{n}\sum_{i=1}^{n}\left(\frac{Y_i}{\bar{Y}}\right)^{\alpha} - 1\right] \tag{5}$$

for $\alpha \neq 0$ or 1. In these cases (5) becomes:

$$GE(0) = \frac{1}{n}\sum_{i=1}^{n} log\frac{\mu}{Y_i} \quad ; \; and \quad GE(1) = \frac{1}{n}\sum_{i=1}^{n}\frac{Y_i}{\mu} log\frac{Y_i}{\mu}$$

where n is the number of households in the sample, Y_i is per capita household income of household i, μ is the arithmetic mean per capita income.

Inequality can be decomposed along two dimensions: into the contribution of each component or in to within and between subgroup inequality. The former approach is most relevant to study income inequality by its sources and can be performed using the Gini coefficient (ADAMS and ALDERMAN 1992, BIRTHAL and SINGH 1995). The later can be performed using the GE family indices with $\alpha = 1$, which is equivalent to Theil entropy index of inequality (WORLD BANK 2000) and its decomposition is equivalent to (BAFFAE 1992):

$$GE(1) = \sum_{j=1}^{k}\left[\frac{Y_j}{Y}\right]GE(1)_j + \sum_{j=1}^{k}\left[\frac{Y_j}{Y}\right]ln\left[\frac{Y_j/Y}{N_j/N}\right] \tag{6}$$

where Y is total income, Y_j = total income of the jth group, N_j is number of households in the jth group, $GE(1)_j$ is inequality measure for group j, and k represents the number of groups. The first term in the right and side of equation (6) represents the weighted averages of the inequality found within various groups. Where as the second term measures the between group component of inequality.

3 Empirical Results and Discussion

3.1 Poverty Profile

By any standard, the majority of people in Ethiopia are among the poorest in the world (DERCON and KRISHNAN 1998, IMF 1999, RAHMATO and KIDANU 1999, WORLD BANK 2001). In order to combat such debilitating poverty in view of very scarce resource available to be allocated for the purpose, the poor must be properly identified and an index that takes in to account the intensity of poverty suffered by the poor should be constructed.

3.1.1 Setting the Poverty Line

Large literature exists on approaches to assess poverty. But the question still remains as to where to draw the poverty line. A feature common to all is a significant degree of arbitrariness in the value assigned to the poverty standard. Acknowledging the complexity of assessing poverty in subsistence economies of rural Ethiopia, BEVAN and JOIREMAN (1997) employed various criteria to concluded that none of the measures identifies the poor in a convincing way.

The most popular methods of poverty measures have used the nutritional norm and defined poverty line in terms of minimum calorie requirements (GREER and THOBECKE 1986, AHMED et al. 1991, RAVALLION and BIDANI 1994). The major problems of such approach include determining the minimum food consumption basket that represent the food habit of the poor, the use of value judgements and choice of appropriate price index to deflate their current food expenditure.

Here poverty is presumed to mean lack of command to meet a person's typical food calorie intake just sufficient to meet a predetermined food energy requirement of 2300 kcal per day. Since many combinations of foods could meet this daily requirement, setting this predetermined food energy requirement is not also immune from problems although there are good reasons to use it. It is assumed that regional variations in food consumption patterns are more important than differences observed between the poor and non-poor household within a given district. Therefore, in determining the food poverty line, the consumption data from the survey is used and the general pattern of food consumption at a district level is relied up on, to estimate the quantities of various food items consumed by rural households, and this constitute the reference food basket. Using the Food Composition Table for Use in Ethiopia (EHNRI 1997), the respective quantities were converted in to calories equivalents. Since our aim is to identify a food bundle to attain a 2300 kcal benchmark, the mean values were then scaled in the same proportion as in the reference food basket as in RAVALLION and BIDANI (1994) and DERCON and KRISHMANN (1998).

In order to determine the costs associated with each poverty line, average local prices were applied on each component of the food bundle. The estimated total cost of the food bundle and costs for non-food items, i. e., the poverty line, ranges from ETB 460 to ETB 715 per capita per annum in Merhabete and Alemaya, respectively.

3.1.2 Incidence and Severity of Poverty

Several standard indicators of poverty can be calculated to capture the incidence and severity of poverty on a household or individual basis. The three most commonly employed indices are used in this study, namely: the incidence of poverty, the depth of poverty and severity of poverty (FGT(2)). The incidence of poverty using both per capita household calorie consumption and per capita household expenditure to meet the cost of basic needs criteria is presented in Table 1. The results indicate that 38 % and 43 % of the sample households are deemed poor using the former and the alternative criteria, respectively. Regional comparison of incidence of poverty employing the former criteria shows that the proportion of households living in poverty is markedly the highest in Merhabete. Applying the alternative criteria, though it shows a varying impact on the head count index, it did not reveal any change in ranking of districts.

Table 1: Poverty incidence and severity

District	Head count index		Poverty deficit		FGT(2) index	
	Food energy consumption	Cost of basic needs	Food energy consumption	Cost of basic needs	Food energy consumption	Cost of basic needs
Alemaya	0.30	0.35	0.0305	0.0353	0.0086	0.0074
Hitosa	0.12	0.24	0.0127	0.0352	0.0027	0.0098
Merhabete	0.68	0.66	0.0891	0.1368	0.0148	0.0340
Overall	0.38	0.43	0.0466	0.0734	0.0089	0.0182

The poverty deficit reflects the total deficit of all the poor households relative to the poverty line (RAVALLION and BIDANI, 1994). It is, therefore, a much more powerful measure than the head count ratio because it takes in to account the distribution of the poor below the poverty line. It also reflects the per capita cost of eliminating poverty. The results from the survey reveal that, using both criteria, the depth of poverty is higher in Merhabete, followed by Alemaya and Hitosa, implying that more resource is required to bring the poor households out of poverty in Merhabete than Alemaya and Hitosa. An overall poverty depth of 0.0466 means that if the country could mobilise resources equal to the 4.66 % of the poverty line for every individual and distributes these resources to the poor in the amount needed so as to bring each individual up to the poverty line, then at least in theory, poverty could be eliminated.

Severity of poverty is a measure closely related to the poverty deficit but giving those further away from the poverty line a higher weight in aggregation than those closer to the poverty line. The findings also reveal that poverty in Merhabete is the most sever. Rural poverty in Merhabete is found to be 66 % more sever than overall poverty severity.

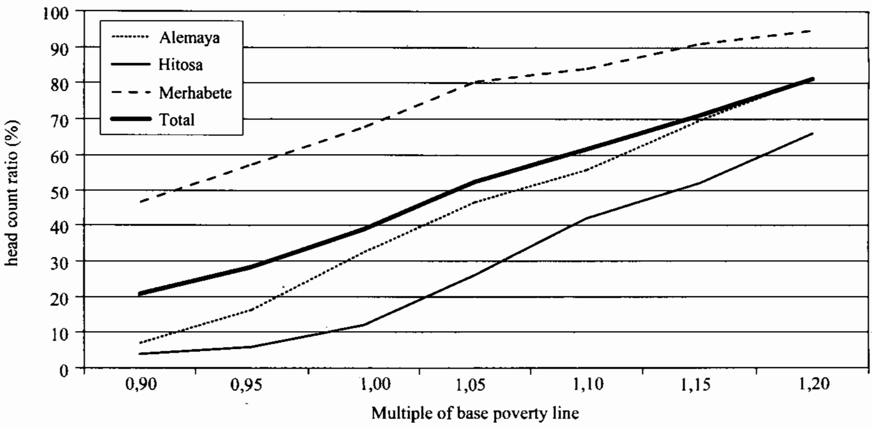
The decomposability property of FGT index allows us to construct Table 2, which reflects the severity of poverty among the poor and also have important policy implications. The numerical results suggest that the severity of poverty is more intense at the lowest decile. More precisely, the results in Table 2 imply that, for instance, if the bottom 30 % of the poor households are correctly identified and made non-poor, then poverty severity will be decreased by 78.65 %, while severity of poverty will decline only by 1 % if the top 30 % of the poor are to benefit from poverty reduction programmes. Therefore, poverty has become sever for the poorest of the poor and appropriate targeting of a specific segment of the poor households will have ist own payoff.

Table 2: Decomposition of severity of poverty by decile

Cumulative percentage of poor households	Severity of poverty (FGT2) for the respective decile	Percent contribution to poverty
10	0.0109	47.08
20	0.0048	67.90
30	0.0024	78.65
40	0.0020	87.02
50	0.0015	93.42
60	0.0008	97.22
70	0.0004	99.02
80	0.0002	99.82
90	0.00003	99.94

Given the arbitrariness in defining the poverty line, it will be of paramount importance to apprehend how the incidence of poverty varies across regions under consideration as assumptions regarding the original poverty line changes. Figure 1 illustrates how incidence of poverty changes as multiples of the original poverty line are considered. It is possible to observe that combination of changes in factors which may result in an increase in original poverty line only by 10 % would bring 42 %, 56 % and 84 % of the households in Hitosa, Alemaya and Merhabete, respectively, to poverty where as the overall poverty incidence increases to 62 %. More over, large segment of the population appears to be concentrated close to the poverty line, as more than 71 % of the households have food energy consumption less than 1.15 times the original poverty line.

Figure 1: Incidence of poverty due to change in poverty line



3.1.3 The Determinants of Poverty

The analysis of determinants of poverty can provide meaningful insight about various poverty-generating factors and the relevance of various policies, such as the feasibility of using targeting devices. For the purpose of analysing determinants of poverty, household poverty is hypothesised to be a function of a household's resource endowment (i. e., land size, land quality, labour, oxen, etc.), gender, age, and education of the household head, composition and size of the household as well as the prevailing physical environment.

The maximum likelihood binary logit regression models have been estimated considering whether a household is poor or non-poor as a response variable. As the data from the three districts are pooled together, in addition to the household characteristics and welfare indicators, a set of dummy variables are included to control for regional locations. The omitted category is Merhabete.

Table 3 regresses the binary response variable, being poor (Prob(P=1)), and presents results of the binary logit. A glance at the results verify that most of the regressors in the model have the signs that conform with our prior expectations. It is also evident that most of the variables are statistically significant at 10 % or lower level. Employing both criteria, the results from the pooled data across regions highlights the importance of household resource endowment in determining poverty. Land holding per adult equivalent and ownership of oxen are both significant in determining the probability of a household to be poor. Household characteristics such as household size and composition have the desired signs but their effect is not found to be statistically significant. This weak association reflects the fact that in rural Ethiopia children, even at the age of six years, contribute to the household labour force and so to its production capacity. Looking after livestock and participating in weeding are among the prime activities of boys, where as fetching water and fuelwood gathering are among the traditional responsibilities of girls.

Table 3: Binary logit coefficient estimates for determinants of Poverty

Variable	Food calorie intake		Costs of basic needs	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
Age of household head (Age)	-0.1257 [a]	0.0750	0.0209	0.0335
Dummy for Alemaya	-9.4884 [b]	4.8556	-7.4594 [c]	1.7646
Dummy for Hitosa	-7.7750 [b]	3.5351	-3.1694 [c]	1.0559
Dependent ratio (Dep)	0.3416	0.7315	0.5770	0.4834
Education of head (Educ)	-2.6397 [a]	1.4379	-1.5500 [c]	0.4854
Per capita expenditure (Exp)	-0.0075	0.0076	---	---
Dummy for sex (Male=1)	2.3788 [c]	0.7603	-1.3340	1.0009
Household size (HHS)	0.4577	0.3397	0.3583 [a]	0.1845
Per capita income (PCI)	-0.0163 [b]	0.0067	-0.0149 [c]	0.0058
Land holding per AE (LMR)	-22.1213 [b]	9.3990	-8.7135 [b]	4.2748
Number of oxen owned (Ox)	-1.8778 [a]	1.1196	-1.8413 [c]	0.6065
Constant	34.3309 [c]	13.5500	6.7383 [c]	2.8269
-2 log Likelihood	128.415		60.728	
Percent correctly predicted	95.30%		91.95	

Note: a, b and c indicate that the coefficients are statistically significant at 0.1, 0.05 and 0.01 level.

The probability of a household being poor tends to diminish as age of the household head increases using per capita household calorie consumption. This can be explained by firstly, asset ownership tends to increase with age; and secondly, the composition of the family changes in time, as those children grow up and either can contribute labour force to various farm activities or leave the household. But note that the sign of the coefficient corresponding to age of household changes when per capita household expenditure is considered to define the poverty line and used as a response variable in the logit model implying that aged household heads have less to spend on household consumption.

The coefficient associated with gender of the household head, apparent in Table 3, could be worth mentioning, given the standard presumptions. While the probability of being poor for male-headed households is higher than the female-headed households employing the per capita food energy consumption, female headed households have higher incidence of poverty if household consumption expenditure is considered as a criteria, although the coefficient is not statistically significant ($P > 0.10$) in the latter case. That means, male-headed households have better capacity to comply with the minimum consumption expenditure required to meet the requirements, but fail to realise it in terms of actual food consumption.

The coefficient on education reflects the prime role that human capital plays in determining poverty. In fact, education is an important dimension of poverty itself, when poverty is broadly defined to include shortage of capabilities and knowledge deprivation. It has important effect on the poor children's chance to escape from poverty in their adult age and plays a catalytic role for those who are most likely to be poor, particularly those households living in rural communities. Education is expected to lead to increased earning potential and improve occupational and geographic mobility of labour. Therefore, it deserves an important place in formulating poverty reduction strategy.

Statistically significant estimates associated with dummy variables for spatial locations imply that households in the three districts differ in their natural resource endowment and other productivity enhancing factors, such as basic infrastructure so that households with similar characteristics in Merhabete experience a higher risk of poverty than those in Alemaya or in Hitosa.

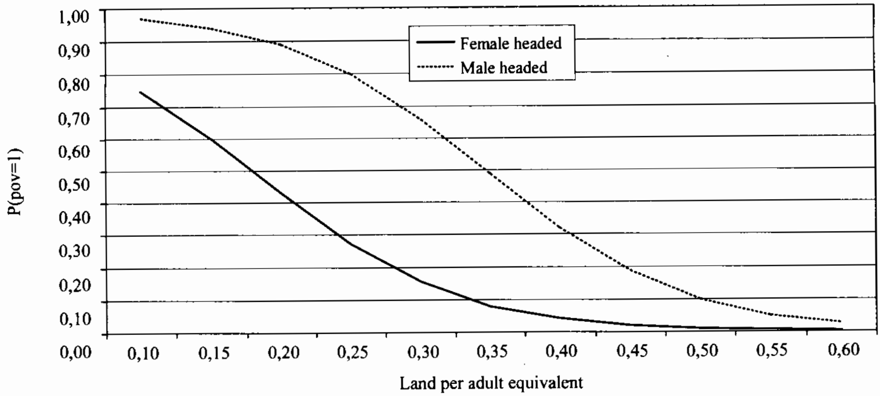
Table 4: The probability of being poor, marginal effect in percent

Explanatory variables	Marginal Effect
Age of household head in years (Age)	-0.28
Dummy for Alemaya district (Alem)	-21.20
Dummy for Hitosa district(Hits)	-17.37
Dependent ratio (Dep)	0.76
Education of household head (Educ)	-5.89
Per capita household expenditure (Exp)	-0.017
Dummy for sex of household head (Male=1)	5.32
Household size in number (HHS)	1.02
Per capita household income (PCI)	-0.036
Land holding per adult equivalent (LMR)	-49.43
Number of oxen owned (Ox)	-4.19

A more appealing interpretation of parameter estimates in a logit model is explaining the marginal effect of each exogenous variable. A possible interpretation of the results presented in Table 4 is that, for instance, it is expected that an additional year for the head of household (as a proxy for experience in farming), all other variables held at their mean values, decreases the probability of a household to be poor by about 0.28 %. Similarly, promoting the household head by one level of education will reduce the risk of poverty by nearly 6 %.

Since our application of the logit model contains some dummy explanatory variables, their respective marginal effects may not be meaningful straight forward (GREENE , 1993). The marginal effects suggested so far generally produce a reasonable approximation to the change in the probability of being poor at a point, such as the mean of the exogenous variable. But at the same time, the mean value of a dummy variable may sometimes be meaningless (for instance, a gender of 0.89). In such circumstances, it is possible to analyse the marginal effect of a dummy variable on the whole distribution by computing the probability of the occurrence of the response.

Figure 2: The effect of LMR on the probability of being poor



Thus, a further illustrative approach to examine parameter estimates in a binary logit model is to assign differing values to a given target characteristic and simulate the resulting probability of being poor while maintaining all other exogenous variables at their mean values. In this context, it is possible to talk about the probability of being poor for a given factor, and comparison can be made across characteristics. This simulation approach is probably the most fruitful in analysing characteristics that allow for higher degree of differentiation.

Figure 2 illustrate how the probability of being poor varies for male-headed and female-headed households over a range of ownership of cultivated land per adult equivalent (LMR) using per capita household calorie consumption as a criteria. At any level of LMR, the marginal effect of gender is given by the vertical distance between the two lines, which ranges from 0.02 at LMR of 0.60 ha to about 0.53 at LMR of 0.25 ha. That is, setting all other exogenous variables at their mean values, and given that cultivated landholding per adult equivalent is 0.25 ha, then households whose head were male were more than 50 % more likely to be poor than those households headed by female.

3.2 Inequality Measurement and Decomposition

Table 5 shows the extent of inequality in per capita household income and calorie consumption measured by Gini coefficients and Theil entropy index and its decomposition by districts. The Gini coeffient for the entire sample households is estimated to be 0.2688 for per capita household income. Where as the corresponding coefficient for per capita household calorie consumption is found to be 0.0950. The results indicate a more equitable distribution relative to most developing countries. This is largely attributed to the economic policies of the previous government which aimed at closing the income/consumption gap between the rich and the poor.

Considering the inequality measure for the three survey districts, inequality ranking employing both the Theil index and the Gini coefficient yield the same order of ranking. Inequality is found to be the highest in Merhabete followed by Hitosa and Alemaya. That is, not only poverty is deep in Merhabete, inequality is also relatively more severe there.

The decomposition of Theil entropy index shows that the contribution of between group component of per capita household income inequality is 8.39 %. This is the inequality that would arise if each person received the average incomes of the subgroup to which he belongs rather than his actual income. This implies that policy measures aimed at reducing inequality existing within each district will reduce inequality in per capita household income by 91.61 %. Policies aimed at reducing inequality between districts, therefore, will have little effect on reducing overall inequality and offer very meagre in terms of recommendation.

Table 5: Within and between districts inequality decomposition

District	Mean per capita household income (ETB)	Per capita household income		Per capita household calorie consumption	
		Theil entropy index	Gini index	Theil entropy index	Gini index
Alemaya	873.00	0.0766	0.1985	0.0128	0.0822
Hitosa	750.00	0.0844	0.2300	0.0105	0.0798
Merhabete	614.00	0.1820	0.3280	0.0098	0.0788
Aggregate	734.00	0.1227	0.2688	0.0145	0.0950
With in		0.1124		0.0109	
% contribution		91.61		75.61	
Between		0.0103		0.0035	
% contribution		8.39		24.39	

The results also indicate that inequality in per capita household calorie consumption is the least in Merhabete with Gini coefficient of 0.0788 and Theil index of 0.0098. where as the relatively largest inequality is observed in Alemaya. The low inequality in consumption in Merhabete may be explained by the fact that poor households in the district can participate in various public works from which they can receive cereals or edible oil for consumption.

Looking at the within and between group components of inequality, the within group component dominates the between group component of inequality, the former accounting for 75.61 %. It can, therefore, be concluded that policies that would reduce inequality persistent within each district will have better payoffs.

4 Conclusions

At the heart of a poverty analysis is constructing a poverty profile, which includes identifying who the poor are, where they are and what their living standard is. Poverty profile has been constructed by dividing the population in to subgroups according to district of residence, and then the proportion of poverty concentrated in each district is determined. The results would lead to think that poverty is to some extent explained by disparities among regions in terms of lack of adequate infrastructure and resource degradation. It is evident from the results that eliminating poverty and inequality within the regions would have larger impact. This can help improve the design of poverty alleviation programs and determine the ways in which a budget can be distributed so as to maximise poverty reduction. Therefore, poverty alleviating programmes should rely on geographic targeting as main device to guide resource allocation.

Actions that ensure gender equality by increasing women's access to assets, education, participation in decision-making and enable them to voice the problems they experience with regard to limited access to resources should be priority for poverty reduction.

The results also reflect how sever the poverty level in rural Ethiopia is. Even though the head count ratio, depth and severity of poverty have shown variation based on the criteria employed, all confirm that poverty is a problem of major concern. The marginal effect analysis of the exogenous variables revealed that, among others, cultivated land per Adult Equivalent, geographical location, education and oxen ownership have greater role in reducing poverty. The simulation of probability estimates showed that, given other characteristics of households, female headed households allocate their available resources in such a way as to obtain more calorie per capita than their counterpart male-headed households.

Even though some variation has been observed between the three districts, both Gini coefficient and Theil entropy index are relatively very low, indicating that with respect to rural Ethiopian households "equality prevail along side sever poverty", i. e., every body is just relatively equally poor.

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