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Determinants of Poverty in Kenya: A Household Level Analysis

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Abstract

Strategies aimed at poverty reduction need to identify factors that are strongly associated with poverty and that are amenable to modification by policy. This article uses household level data collected in 1994 to examine probable determinants of poverty status, employing both binomial and polychotomous logit models. The study shows that poverty status is strongly associated with the level of education, household size and engagement in agricultural activity, both in rural and urban areas. In general, those factors that are closely associated with overall poverty according to the binomial model are also important in the ordered-logit model, but they appear to be even more important in tackling extreme poverty.

Journal of Economic Literature Classification: I30, I32, N97

Keywords: Poverty, Kenya, Africa, Probability Models

I. INTRODUCTION[1]

Poverty in Kenya is pervasive. Table 1 provides a general picture of poverty in Kenya as of 1994. Using a per-adult equivalent measure, the headcount (P_0), the poverty gap (P_1) and severity (P_2) of consumption-poverty indices were 48, 19 and 10 per cent in 1994. The comparable figures for 1997, the latest available, are 52.9, 19.3 and 9.2 per cent [Government of Kenya, 2000]. The figures reported in Table 1 are in general larger than similar indices for Kenya estimated by the Ministry of Finance and Planning [see Government of Kenya, 1998, 2000]. The table also shows that poverty is concentrated in rural areas. The pervasive nature of poverty is one of the reasons for the recent focus on poverty-alleviation policies.

The Government of Kenya has prepared a poverty reduction strategy paper (PRSP) to guide the poverty reduction effort. One major weakness in the government's PRSP is lack of in-depth information for implementing and monitoring the strategy [see Government of Kenya 2001, Alemayehu et al. 2001]. This article should help the government to realise its poverty reduction goals, by laying the foundation for analytical work aimed at an in-depth understanding of poverty, and by establishing benchmark conditions for poverty monitoring.

The remainder of the article is organised as follows. Section II reviews available poverty studies in Kenya. Section III presents the model. Section IV describes the data and Section V discusses the estimation results. Finally, some concluding remarks are made in Section VI.

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II. PREVIOUS POVERTY STUDIES IN KENYA

Analytical work on determinants of poverty in Kenya is at best scanty. Most of the available studies are descriptive and focus mainly on measurement issues. Earlier poverty studies have focused on a discussion of inequality and welfare based on limited household level data [see Bigsten 1981, Hazlewood 1981, House and Killick 1981]. One recent comprehensive study on the subject is that of Mwabu et al. [2000], which deals with measurement, profile and determinants of poverty. The study employs a household welfare function, approximated by household expenditure per adult equivalent. The authors run two categories of regressions, using *overall* expenditures and *food* expenditures as dependent variables. In each of the two cases, three equations are estimated which differ by type of dependent variable. These dependent variables are: total household expenditure, total household expenditure gap (the difference between the absolute poverty line and the actual expenditure) and the square of the latter. A similar set of dependent variables is used for food expenditure, with the explanatory variables being identical in all cases.

Mwabu et al. [2000] justified their choice of this approach (compared to a logit/probit model) as follows. First, the two approaches (discrete and continuous choice-based regressions) yield basically similar results (see below, however); second, the logit/probit model involves unnecessary loss of information in transforming household expenditure into binary variables. Although their specification is simple and easy to follow, it has certain inherent weaknesses. One obvious weakness is that, unlike the logit/probit model, the levels regression does not directly yield a probabilistic statement about poverty. Second, the major assumption of the welfare function approach is that consumption expenditures are negatively associated with absolute poverty at all expenditure levels. Thus, factors that increase consumption expenditure reduce poverty. However, this basic assumption needs to be taken cautiously. For instance, though increasing welfare, raising the level of consumption expenditure of households that are already above the poverty line does not affect the poverty level (as for example measured by the headcount ratio).

Notwithstanding such weaknesses, the approach is widely used and the Mwabu et al. [2000] study identified the following as important determinants of poverty: unobserved region-specific factors, mean age, size of household, place of residence (rural versus urban), level of schooling, livestock holding and sanitary conditions. The importance of these variables does not change whether the total expenditure, the expenditure gap or the square of the gap is taken as the dependent variable. The only noticeable change is that the sizes of the estimated coefficients are enormously reduced in the expenditure gap and in the square of the expenditure gap specifications. Moreover, except for minor changes in the relative importance of some of the variables, the pattern of coefficients again fundamentally remains unchanged when the regressions are run with food expenditure as dependent variable.

Another recent study on the determinants of poverty in Kenya is Oyugi [2000], which is an extension to earlier work by Greer and Thorbecke [1986a,b]. The latter study used household calorie consumption as the dependent variable and a limited number of household characteristics as explanatory variables. Oyugi [2000] uses both discrete and continuous indicators of poverty as dependent variables and employs a much larger set of household characteristics as explanatory variables. An important aspect of Oyugi's study is that it analyses poverty both at micro (household) and meso (district) level, with the meso level analysis being the innovative component of the study.

Oyugi [2000] estimates a probit model using data of the 1994 Welfare Monitoring Survey data. The explanatory variables (household characteristics) include: holding area, livestock unit, the proportion of household members able to read and write, household size, sector of economic activity (agriculture, manufacturing/industrial sector or wholesale/retail trade), source of water for household use, and off-farm employment. The results of the probit analysis show that almost all variables used are important determinants of poverty in rural areas and at the national level, but that there are important exceptions for urban areas [Oyugi, 2000]. These results are consistent with those obtained from the meso-level regression analysis.

It is interesting to compare the implications of the levels [Mwabu et al. 2000] and probit [Oyugi, 2000] regression approaches. From the levels regressions, age, household size, residence, reading and writing and level of schooling are the top five important determinants of poverty at the national level. In the probit model, however, in order of importance the key determinants of poverty are: being able to read and write, employment in off-farm activities, being engaged in agriculture, having a side-business in the service sector, source of water and household size. Region of residence appears to be equally important in determining poverty status in the two approaches. Although the two approaches did not employ the same explanatory variables, this comparison points to the possibility of arriving at different policy conclusions from the two approaches.

III. BINOMIAL AND POLYCHOTOMOUS MODELS OF POVERTY ANALYSIS

The approach we follow intends to explain why some population groups are non-poor, poor, or extremely poor. We identify different population sub-groups in several stages. In the first stage, we identify the poor and non-poor. In the second stage, we examine the probability of being in hard-core poverty conditional on being identified as poor. That is, we also compute the probability of being what we term as 'extremely poor'. This poverty identification process is displayed in Figure 1.

We assumed that the probability of being in a particular poverty category is determined by an underlying response variable that captures the true economic status of an individual. In the case of a binary poverty status (*i.e.* being poor or non-poor), let the underlying response variable y* be defined by the regression relationship:

$$y_i^* = \sum \mathbf{x}_i'\beta \ + u_i \qquad [1]$$

where $\beta' = [\beta_1, \beta_2 ... \beta_k]$ and $\mathbf{x}_i' = [1, x_{i2}, x_{i3} ... x_{ik}]$.

In equation [1], y^* is not observable, as it is a latent variable. What is observable is an event represented by a dummy variable y defined by:

$$\begin{aligned} &y = 1 \quad \text{if } y^* > 0, \text{ and} \\ &y = 0 \quad \text{otherwise} \end{aligned} \qquad [2]$$

From equations [1] and [2] we can derive the following expression:

$$\begin{aligned} \Pr ob(y_i = 1) &= \Pr ob(u_i > -\sum \mathbf{x}_i'\beta) \\ &= 1 - F(-\sum \mathbf{x}_i'\beta) \end{aligned} \qquad [3]$$

where F is the cumulative distribution function for u_i, and $\Pr ob(y_i = 0 | \beta, \mathbf{x}_i) = F(-\sum \mathbf{x}_i'\beta)$.

The observed values of y are the realisation of the binomial with probabilities given by equation [3], which varies with $\mathbf{X}_i$. Thus, the likelihood function can be given by:

$$L = \prod_{y_i=0} [F(-\sum \mathbf{x}_i'\beta)] \prod_{y_i=1} [1 - F(-\sum \mathbf{x}_i'\beta)] \qquad [4a]$$

which can be written as:

$$L = \prod_{y_i=1} [F(-\sum \mathbf{x}_i'\beta)]^{1-y_i} [1 - F(-\sum \mathbf{x}_i'\beta)]^{y_i} \qquad [4b]$$

The functional form imposed on F in equation [4][2] depends on the assumptions made about u_i in equation [1].[3] The cumulative normal and logistic distributions are very close to each other. Thus, using one or the other will basically lead to the same result [Maddala, 1983]. Moreover, following Amemiya [1981], it is possible to derive the would-be estimates of a probit model once we have parameters derived from the logit model. Thus, the logit model is used in this study.

We have specified the logit model for this study by assuming a logistic cumulative distribution of u_i in F (in equations [4a] and [4b]). The relevant logistic expressions are:

$$1 - F(-\sum \mathbf{x}_i'\beta) = \frac{e^{\sum \mathbf{X}_i'\beta}}{1 + e^{\sum \mathbf{X}_i'\beta}} \qquad [5a]$$

[2] The log likelihood function for expression [4a] and [4b] can be written as,

$$l(\beta) = \log L(\beta) = \sum_{i=0}^{n} y_i \log(1 - F(-\sum \mathbf{X}_i'\beta)) + (1 - y_i) \log F(-\sum \mathbf{X}_i'\beta)$$

$$F(-\sum \mathbf{x}_i{}'\beta) = \frac{e^{-\sum \mathbf{X}_i{}'\beta}}{1+e^{-\sum \mathbf{X}_i{}'\beta}} = \frac{1}{1+e^{\sum \mathbf{X}_i{}'\beta}} \quad [5b]$$

As before, $\mathbf{X}_i$ are the characteristics of the households/individuals, and $\boldsymbol{\beta_i}$ the coefficients for the respective variables in the logit regression. Having estimated equation [4] with maximum likelihood (ML) technique, equation [5a] basically gives us the probability of being poor [Prob(y_i=1)] and equations [5b] the probability of being non-poor [Prob(y_i=0)].

After modeling the process that generates the poor or non-poor status, we focus attention on the hard-core poor versus the moderately poor and non-poor. This can be handled by a polychotomous model, more in particular an ordered probit or logit model. This approach is justifiable, because we explicitly make the ordering of the population sub-samples, using total and food poverty lines as cut-off points in a cumulative distribution of expenditure.[4] Since these categories have a natural order, the ordered logit is the appropriate model to be employed in the estimation of relevant probabilities [see Maddala 1983, Amemiya 1985, Greene 1993].[5]

Assuming three categories (1, 2 and 3 and associated probabilities P_1, P_2 and P_3), an individual would fall in category 3 if $u < \boldsymbol{\beta}'\mathbf{x}$, in category 2 if $\boldsymbol{\beta}'\mathbf{x} < u \leq \boldsymbol{\beta}'\mathbf{x} + \alpha$; and in category 1 if $u \geq \boldsymbol{\beta}'\mathbf{x} + \alpha$, where $\alpha > 0$ and *u* is the error term in the underlining response model (see Equation 1). These relationships may be given by:

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[3] This basically forms the distinction between *logit* and *probit (normit)* models.

[4] The method used for computing the poverty lines is given in the Appendix. For lack of a better term we have used the term ‘moderately poor’ to designate those who are poor but not hard-core (or extremely) poor.

[5] Given the nested nature of the categories in our model, nested model seems also a relevant approach. However, such models are relevant in the context when agents make choices and there is dependence among choices. Since our categories do not refer to choices being made, we have opted for the ordered logit model [see Maddala, 1983: 70].

$$P_3 = F(\boldsymbol{\beta}'\mathbf{x}_i)$$
$$P_2 = F(\boldsymbol{\beta}'\mathbf{x}_i + \alpha) - F(\boldsymbol{\beta}'\mathbf{x}_i) \quad [6]$$
$$P_1 = 1 - F(\boldsymbol{\beta}'\mathbf{x}_i + \alpha)$$

where the distribution F is logistic in the ordered logit model. This can easily be generalised for *m* categories [see Maddala 1983]. Assuming the underlying response model is given by:

$$y_i = \boldsymbol{\beta}'\mathbf{x}_i + u_i \quad [7]$$

we can define a set of ordinal variables as:

$Z_{ij}=1$ if y_i falls in the j^{th} category

$Z_{ij}=0$ otherwise (i=1,2,..,n; j=1,2,…,m)

$$\Pr ob(Z_{ij} = 1) = \Phi(\alpha_j - \beta'\mathbf{x}_i) - \Phi(\alpha_{j-1} - \beta'\mathbf{x}_i) \quad [8]$$

where Φ is the cumulative logistic distribution and the α_j's are the equivalents of the α's in equation [6]. The likelihood and log-likelihood functions for the model can be given by equations [9] and [10] respectively, as:

$$L = \prod_{i=1}^{n}\prod_{j=1}^{m}\left[\Phi(\alpha_j - \beta' x_i) - \Phi(\alpha_{j-1} - \beta' x_i)\right]^{Z_{ij}} \quad [9]$$

$$L^* = \log L = \sum_{i=1}^{n}\sum_{j=1}^{k} Z_{ij} \log \Phi\left[(\alpha_j - \beta' x_i) - \Phi(\alpha_{j-1} - \beta' x_i)\right] \quad [10]$$

Equation [10] can be maximised in the usual way, and can be solved iteratively by numerical methods, to yield maximum likelihood estimates of the model [see Maddala 1983].

IV. DATA

The data used are based on the 1994 Welfare Monitoring Survey [Government of Kenya 1998, 2000]. These data were collected for the whole country and covered nearly ten thousand households, comprising about sixty thousand individuals [see Mwabu et al., 2000]. The fundamental rationale behind the choice of a household as a unit of analysis is the assumption of sharing of resources among households. Although the quality of the data we use is in general relatively high, two factors need to be borne in mind in using the results derived from them. First, the results might be affected by the seasonal effect on household expenditure, since seasonality was not controlled for while collecting the data. Second, some districts, especially those from Northeastern province, are underrepresented in the sample.

We used a comprehensive list of explanatory variables which may be grouped into the following categories: *property-related*, such as land and livestock holding; *household characteristics*, such as status of employment, age, gender, educational level, household size; and *others*, such as time spent to fetch water and to obtain energy, place of residence of the household – whether in rural or urban – or in a particular province (see Table 2).

The estimation was made after inflating the number of households in the sample (about 10,000) to that in the total population (nearly 26 million in 1994), using expansion factors. The expansion factors are however adjusted downwards for children in case of adult equivalent-based estimations. The household characteristics are assumed to affect (adult-equivalent) members of the household equally.[6]

V. ESTIMATION RESULTS

Poverty Status: National Sample

According to the estimation results, male-headed households are less likely to be poor. Similarly, the likelihood of being poor is smaller in urban areas than in rural areas. Probably to some extent related to this, people living in households mainly engaged in agricultural activities are more likely to be poor, compared to households in manufacturing activities. In all models the most important determinant of poverty status is the level of education. The effects of this variable are similar across the four models. The coefficient for household size is almost twice as high in the consumption-based as income-based models ones, while the impacts of the sector of employment, as well as the number of animals owned is insignificant in the consumption-based models. Total holding of land does not seem to be important in any of the specifications. An explanation for this may lie on the importance of the quality of land and/or lack of complementary agricultural inputs [see Alemayehu et al. 2001]. Table 3 shows the estimated model and the marginal effects of each explanatory variable on the probability of being poor, based on models in which per adult equivalent consumption is used to

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[6] To save space, we have reported only those results derived from estimates based on poverty defined on the basis of consumption per adult-equivalent. The interested reader is referred to Alemayehu et al. (2001) for per capita and income-based estimates and related details.

estimate poverty. Estimation results using per capita income and consumption are reported in Alemayehu et al. [2001].

Poverty Status: Rural and Urban Sub-Samples

Following the finding that place of residence is associated with level of poverty, we have fitted the model to data for rural and urban areas separately. The estimation results and the marginal effects are given in Table 4. Again the detailed results are given in Alemayehu et al. [2001]. In general, the results show that the factors strongly associated with poverty (level of education, household size, engagement in agricultural activities) are the same in both rural and urban areas. However, the size of the coefficients associated with these regressors is larger in rural areas. Moreover, polygamous marriage seems to worsen poverty in urban as opposed to rural areas. This may point at the larger importance of labour input in rural rather than in urban economic activities. In rural areas all the members of the extended household do often work in agriculture, while in urban areas there may be less scope for all the members of the extended household to be meaningfully engaged. This result does not seem to hold in the consumption-based estimation, however**.** Given the reliability problem with income data and the fact that even the consumption based estimates are not statistically significant at conventional levels, this result may be taken as inconclusive. The consumption-based estimation yield fairly similar results about determinants of poverty, particularly with regard to educational attainment. The coefficients obtained in the latter model are relatively smaller, however. Moreover, factors such as age, size of land holding (albeit with very small coefficients) are found to be statistically significant in this version of the model. Regional dummies for Western and Eastern provinces that are virtually insignificant in the income-based model are found to be statistically significant in the consumption-based version of the model for rural areas. Moreover, working in the urban modern sector seems to reduce the likelihood of being poor.

Ordered Poverty Status: National and Urban-Rural Sub-Samples

Following the discussion in Section 3, we have ordered the sample into three mutually exclusive categories: non-poor (category 1), moderately poor (category 2) and hard-core or extremely poor (category 3), with households in category 3 being most affected by poverty. This classification is based on the poverty and food poverty lines computed from the 1994 Welfare Monitoring Survey (see Appendix).

The estimated model and the marginal effects of the regressors for the consumption-based models are given in Table 5. We noted that the consumption-based model is fairly different from the income-based model. It exhibits regressors with statistically significant coefficients as well as weaker explanatory effects in the case of category 1 (non-poor) and category 2 (poor), respectively [see Alemayehu et al. 2001 for details].[7]

In general, it is interesting to note that those factors that are important in the binomial model are still important in the ordered-logit model. More importantly, by comparing the marginal effects for categories 2 and 3, we note that these variables are much more important in tackling hard-core poverty than moderate poverty.

The ordered logit model is estimated for rural and urban sub-samples too (not reported here, but available on request). Basically the results are similar to those obtained for the national sample. However, the following interesting differences are observed. First, although secondary and university level education are important both in rural and urban areas, primary education is found to be extremely important in rural areas. Second, agriculture as main occupation is more closely associated with poverty in urban areas than in rural areas. This indicates that agriculture being the main occupation is a factor that more strongly differentiates between being poor or non-poor in urban areas. Third, the negative impact of aging is stronger in urban than rural areas. This may reflect the collapse of the extended family network in urban areas, which normally serves as a traditional insurance scheme in Africa. Finally, urban poverty is worst in Western and Northeastern provinces [see Alemayehu et al. 2001].

The ordered-logit estimation of income-based models shows that at the national level the predicted probability of falling in the non-poor category and into moderately and extremely poor categories are 42, 13 and 45 percent, respectively. The corresponding figures for rural areas are similar, while for urban areas they are 58, 19 and 23 percent respectively. This basically shows that for a poor Kenyan residing in rural areas the probability of falling in extreme poverty is much greater than for his/her urban counterpart. A similar pattern is observed when the ordered logit model is estimated using consumption-based data. However, the probability for the first category in general declines while that for the third category rises. This information is summarised in Table 6. The details are given in Alemayehu et al. [2001].

The ordered-logit model results show clearly that determinants of poverty have different impacts across the poverty categories defined. For instance, if we take the most important determinant of poverty status in Kenya, *i.e.* thelevel of education, Table 4 shows that the marginal effect of having a primary level of education are 0.10, -0.03 and -0.07 for non-poor, moderately poor and hard-core poor categories, respectively. The comparable marginal effect figure for secondary level education are 0.25, -0.08 and -0.16; and for university level education 0.36, -0.14 and -0.22, respectively. This shows

[7] The marginal coefficients for category 3 (hard-core poor) are not reported as they could be derived from the sum of the three, which should add to zero. This is because the probabilities of falling in either one of the three categories adds up to one.

that, in general, education is more important for the hard-core poor than for the moderately poor. The relative difference is largest in the case of primary education.

VI. CONCLUDING REMARKS

In this article an attempt has been made to explore the determinants of poverty in Kenya. We have employed both binomial and polychotomous logit models using the 1994 Welfare Monitoring Survey data. Although a number of specific policy conclusions could be drawn from the estimation results, the following policy implications of the study stand out:

First, as expected, we have found that poverty is concentrated in rural areas in general, and in the agricultural sector in particular. Being employed in the agricultural sector accounts for a good part of the probability of being poor. Thus, investing in the agricultural sector to reduce poverty should be a matter of great priority. Moreover, the finding that the size of land holding is not a determinant of poverty status may suggest the importance in poverty reduction not only of improving the quality of land, but also of providing complementary inputs that may enhance productivity.

Second, the educational attainment of the head of the household (in particular high school and university education) is found to be the most important factor that is associated with poverty. Lack of education is a factor that accounts for a higher probability of being poor. Thus, promotion of education is central in addressing problems of moderate and extreme poverty. Specifically, primary education is found to be of paramount importance in reducing extreme poverty in, particularly, rural areas.

Third, and related to the second point above, the importance of female education in poverty reduction should be noted. We have found that female-headed households are more likely to be poor than households of which the head is a men and that female education plays a key role in reducing poverty. Thus, promoting female education should be an important element of poverty reduction policies. Because there is evidence that female education and fertility are negatively correlated, such a policy could also have an impact on household size, which is another important determinant of poverty in Kenya. Moreover, given the importance of female labour in rural Kenya and elsewhere in Africa, investing in female education should be productivity enhancing.

Finally, in line with the three strategies that are outlined in the PRSP and directly related to issues of poverty (economic growth and macro stability, raising income opportunity of the poor, and improving quality of life), the findings in this study point to the importance of focusing on education in general and primary education in rural areas in particular. The study also highlights the higher likelihood of being poor of those who are engaged in the agricultural sector. Thus, the PRSP's strategy of raising income opportunities of the poor should focus on investing in agriculture. Since the macroeconomic environment is important in determining the productivity of such investment, macroeconomic and political stability are a pre-requisite for addressing poverty.

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APPENDIX

Computations of Poverty Lines and Indices

There are a number of studies on the condition of poverty in Kenya, the most important of which being the series of reports published by the Ministry of Finance and Planning. In this paper, we have attempted to follow the method of poverty line determination used by the Ministry of Finance and Planning. This is aimed at allowing for comparison with the results of those studies.

The first step we took is to value the monthly food consumption required to satisfy the 2250 calories that defines the biological minimum required per adult per day. This *food poverty line* is computed by the Ministry of Finance and Planning for 1994 to be Kshs. 874.72 for urban areas and Kshs.702.99 for rural areas per adult per month.

If, for illustration purposes, we take the urban areas, the procedure we adopted is as follows. First we ranked the households according to per adult-equivalent expenditure on food and identified the household that approximately spent Kshs. 874.72 per adult equivalent on food items. Then we computed non-food consumption per adult equivalent, by taking the mean non-food consumption per adult equivalent of those households in the neighbourhood of this particular household (*i.e.* households with food per adult-equivalent food expenditure in a band of +10% and –20% of the food poverty line). Adding this mean non-food consumption, Kshs. 452.24, to the Kshs. 874.72 gives the *poverty line per adult equivalent* of Kshs. 1326.96 per adult per month.

A similar procedure is followed to compute the per capita poverty line. We have used the same Kshs. 874.72 for urban and Kshs. 702.99 for rural food requirement per month per person as the starting point.[8] Taking the same range of households as indicated above, we computed per capita non-food consumption (Kshs. 377.7 and 155.88 for urban and rural areas, respectively). Adding these mean non-food consumption levels to the Kshs. 874.72 and Kshs. 702.99 gives the *per capita* poverty line of Kshs. 1252.7 and 857.88 per month for urban and rural areas, respectively (See Table A.1 for details).

TABLE A.1
POVERTY LINES ADJUSTED FOR PRICE CHANGES
(IN KSHS. PER MONTH)

	1992	**1994**	**1997**
Per capita			
Urban	728.65	1252.7	1552.97
Rural	499.00	857.88	1063.51
Per adult equivalent			
Urban	771.85	1326.96	1645.03
Rural	527.33	906.59	1123.90
Deflators used (1986=100)*	275.07	472.9	586.252

* CPI of December for 1992 and that of June for 1994 and 1997

[8] Notice the assumption of using adult-equivalent requirements for each person in the household. This might be a limiting assumption but is often made due to lack of an alternative.

FIGURE 1
A NESTED STRUCTURE OF POVERTY STATUS

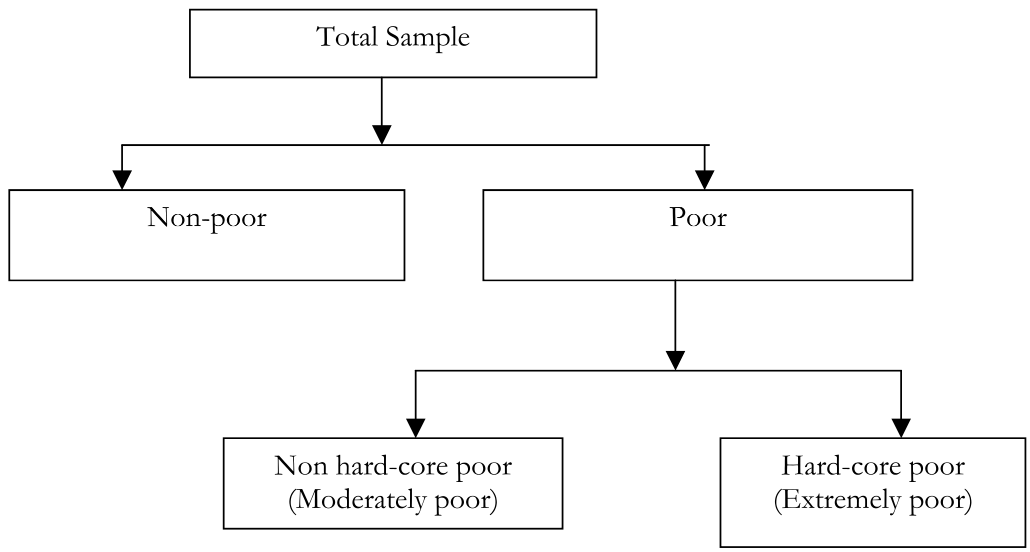

TABLE 1
POVERTY IN 1994
(ESTIMATES BY GOVERNMENT OF KENYA IN BRACKETS)

	Rural		Urban		National	
	Consumption Based	**Income Based**	**Consumption Based**	**Income Based**	**Consumption Based**	**Income Based**
			Per capita income or consumption-based measures			
General poverty						
Headcount ratio	0.64 [0.42]	0.71	0.37 [0.29]	0.52	0.61 [0.40]	0.68
Poverty gap	0.27	0.38	0.13	0.23	0.26	0.36
Poverty severity	0.15	0.26	0.06	0.14	0.15	0.24
Extreme poverty						
Headcount ratio	0.52 [0.25]	0.60	0.20 [0.10]	0.37	0.48 [0.22]	0.56
Poverty gap	0.21	0.30	0.06	0.14	0.19	0.28
Poverty severity	0.11	0.19	0.03	0.08	0.11	0.18
			Per adult equivalent income or consumption-based measures			
General poverty						
Headcount ratio	0.50 [0.42]	0.61	0.27 [0.28]	0.42	0.48 [0.44]*	0.58
Poverty gap	0.20 [0.15]	0.31	0.08 [0.09]	0.17	0.19 [0.14]	0.28
Poverty severity	0.10 [0.08]	0.20	0.04 [0.04]	0.09	0.10 [0.07]	0.18
Extreme poverty						
Headcount ratio	0.36 [0.25]	0.47	0.10 [0.10]	0.23	0.33 [0.22]	0.45
Poverty gap	0.13 [0.08]	0.22	0.03 [0.02]	0.09	0.12 [0.07]	0.21
Poverty severity	0.06 [0.04]	0.14	0.01 [0.01]	0.05	0.07 [0.03]	0.13

Source: Authors' calculations based on Welfare Monitoring Survey 1994 (see Appendix for the method used)
* The 0.40 figure in the 1998 Government of Kenya report is adjusted to 0.44 in the 2000 version.

TABLE 2
DEFINITION OF VARIABLES USED IN THE ESTIMATED EQUATIONS

Variables	Definition	Symbol in the Estimated Equation	Mean	Std dev.
Dependent variable				
Poverty	P=1 if poor, 0 otherwise Poverty estimate based on consumption per adult equivalent	P0_CPAE in binomial logit model; PM_CPAE in ordered logit model		
Explanatory variables				
Sex	Sex = 1 if male, 0 otherwise	SEXD	0.75	0.43
Age and Age square	years	AGE & AGE2	43.11	14.3
Member can read and write	= 1 if yes and 0 otherwise	CANREWTE	0.64	0.48
Marital Status	=1 if married & Monogamy, 0 otherwise =1 if married & polygamy, 0 otherwise	MARYMONO MARYPOLY	0.69 0.10	0.46 0.30
Employment Sector	=1 if formal/public and 0 otherwise	EMPSECD	0.27	0.45
Main occupation of member	=1 if in Agriculture (Commercial farmer, subsistence farmer and pastoralists), 0 otherwise	OCCp	0.56	0.50
Highest level attained (three categories: Primary, Secondary and University)	=1 if in Primary (Standard 1-8 and KCPE) and 0 Otherwise. =1 if in Secondary and certificate (Form 1-4, KCE/KCSE/KAC, Trade test cert I-III and Other Post Secondary cert) and 0 otherwise =1 if in University degree and 0 otherwise	PRIMARD SECONDD UNIVDD	0.37 0.23 0.01	0.42 0.48 0.10
Area of Residence	= 1 if in Rural and 0 otherwise	URBRUR	0.84	0.36
Total holding of land	in acres	TOHOLNOW	3.98	0.31
Number of animals owned	livestock units	ANIMANOW	14.6	56.98

Provincal Dummies: COAST for Coast Province; RIFTV for Rift Valley; WESTERN for Western; EASTERN for Eastern; NEAST for North Eastern, NYANZA for Nyanza and CENTRAL for Central province.

TABLE 3
BINOMIAL LOGIT ESTIMATES FOR CONSUMPTION PER ADULT EQUIVALENT MODEL: NATIONAL SAMPLE

Variables	Estimated Coefficients		Marginal Effects	
	β' s	Z-values	Dy/dx	Z-values
SEXD*	-0.139	-1.50	-0.033	-1.49
MARYMONO*	0.059	0.55	0.014	0.55
MARYPOLY*	-0.146	-1.02	-0.034	-1.04
OCCPD*	0.373	3.85*	0.088	3.94
EMPSECD*	0.004	0.04	0.001	0.04
PRIMARD*	-0.323	-3.93*	-0.076	-3.95*
SECONDD*	-1.062	-10.09*	-0.230	-11.07*
UNIVDD*	-2.608	-4.65*	-0.350	-11.72*
HHSIZE	0.213	13.66*	0.051	13.74*
ANIMANOW	-0.002	-1.01	0.000	-1.01
TOHOLNOW	-0.012	-2.44*	-0.003	-2.44*
URBRUR	0.130	0.92	0.031	0.92
AGE	0.035	2.69*	0.008	2.70*
AGE2	0.000	-2.02**	0.000	-2.02**
COAST*	-0.142	-0.44	-0.033	-0.44
RIFTV*	-0.093	-0.29	-0.022	-0.29
WESTERN*	0.413	1.24	0.101	1.23
EASTERN*	0.270	0.82	0.065	0.81
NEAST*	-0.633	-1.59^	-0.138	-1.74^
NYANZA*	0.000	0.00	0.000	0.00
CENTRAL*	-0.373	-1.14	-0.086	-1.17
Constant	-2.335	-5.29*		

Ratio of Predicted to actual: 61%; Log Likelihood=-6357.1

(*) dy/dx is for discrete change of dummy variable from 0 to 1
*, **, ^ significant at 1, 5 and 10 per cent level.

TABLE 4
BINOMIAL LOGIT ESTIMATES FOR CONSUMPTION PER ADULT EQUIVALENT MODEL BY REGION

	Rural				Urban			
	Estimated Coefficients		Marginal Effects		Estimated Coefficients		Marginal Effects	
Variable	**β**	**Z-values**	**dy/dx**	**Z-values**	**β**	**Z-values**	**dy/dx**	**Z-values**
SEXD*	-0.163	-1.72^	-0.037	-1.42	-0.080	-0.25	-0.120	-2.18**
MARYMONO*	0.127	1.14	0.047	1.53	-0.236	-0.75	-0.013	-0.25
MARYPOLY*	-0.170	-1.16	-0.028	-0.76	0.041	0.08	0.228	2.40*
OCCPD*	0.417	4.19*	0.198	7.72*	1.162	3.05*	0.249	3.20*
EMPSECD*	0.138	1.24	0.048	1.58^	-0.389	-1.91**	0.012	0.28
PRIMARD*	-0.344	-4.02*	-0.068	-3.08*	-0.147	-0.47	-0.017	-0.24
SECONDD*	-1.071	-9.27*	-0.246	-9.78*	-0.989	-3.24*	-0.190	-2.84*
UNIVDD*	-2.951	-4.20*	-0.457	-8.93*	-2.344	-3.18*	-0.362	-8.03*
HHSIZE	0.218	13.55*	0.029	6.79*	0.230	5.06*	0.031	3.42*
ANIMANOW	-0.002	-0.97	-0.001	-4.67*	0.004	0.74	-0.001	-2.05**
TOHOLNOW	-0.010	-2.14**	0.000	0.08	-0.091	-1.85**	-0.009	-1.30
AGE	0.034	2.50*	-0.001	-0.41	0.165	3.18*	-0.002	-0.22
AGE2	0.000	-1.63^	0.000	0.15	-0.002	-3.29*	0.000	-0.20
COAST*	0.377	1.32	-0.013	-0.20	-0.385	-1.16	0.047	0.61
RIFTV*	0.269	1.16	-0.043	-0.82	0.257	0.69	0.046	0.76
WESTERN*	0.810	2.95*	0.042	0.69	0.673	1.25	0.220	2.76*
EASTERN*	0.684	2.67*	0.029	0.51	-0.169	-0.33	-0.033	-0.49
NEAST					-2.553	-2.79*	-0.175	-2.72*
NYANZA*	0.398	1.52	-0.012	-0.21	0.296	0.66	0.000	-0.01
CENTRAL*	0.006	0.02	-0.061	-1.09	0.079	0.20	0.006	0.09
Constant	-2.763	-6.89*			-4.563	-3.64*		

(*) dy/dx is for discrete change of dummy variable
*, **, ^ significant at 1, 5 and 10 per cent level
Rural: Number of observations 9063, Log likelihood -5488.25
Urban: Number of observations 1645; Log likelihood -828.767

TABLE 5
ORDERED LOGIT ESTIMATES USING CONSUMPTION PER ADULT EQUIVALENT: NATIONAL SAMPLE

	The Model		Probability of being Non-poor		Probability of being Moderately Poor	
	Estimated Coefficients		Marginal Effects		Marginal Effects	
Variable	**β**	**Z-values**	**dy/dx**	**Z-values**	**dy/dx**	**Z-values**
SEXD*	-0.104	-1.20	0.025	1.20	-0.006	-1.22
MARYMONO*	0.060	0.60	-0.014	-0.60	0.004	0.59
MARYPOLY*	-0.121	-0.91	0.029	0.92	-0.007	-0.88
OCCPD*	0.315	3.33*	-0.075	-3.40*	0.019	3.31*
EMPSECD*	-0.020	-0.20	0.005	0.20	-0.001	-0.20
PRIMARD*	-0.430	-5.54*	0.101	5.58*	-0.026	-5.23*
SECONDD*	-1.149	-11.22*	0.248	12.29*	-0.075	-10.00*
UNIVDD*	-2.642	-4.81*	0.356	13.80*	-0.139	-10.14*
HHSIZE	0.199	14.82*	-0.048	-14.91*	0.012	11.03*
ANIMANOW	-0.002	-0.97	0.000	0.97	0.000	-0.96
TOHOLNOW	-0.011	-2.55*	0.003	2.55*	-0.001	-2.51*
URBRU	0.291	2.19**	-0.069	-2.19**	0.017	2.17**
AGE	0.041	3.25*	-0.010	-3.26*	0.002	3.19*
AGE2	0.000	-2.76*	0.000	2.77*	0.000	-2.73*
COAST*	-0.166	-0.56	0.039	0.56	-0.010	-0.54
RIFTV*	-0.092	-0.31	0.022	0.31	-0.006	-0.31
WESTERN*	0.375	1.23	-0.092	-1.22	0.019	1.53
EASTERN*	0.289	0.95	-0.070	-0.94	0.016	1.07
NEAST	-0.651	-1.78^	0.143	1.94**	-0.044	-1.73
NYANZA*	-0.029	-0.10	0.007	0.10	-0.002	-0.10
CENTRAL*	-0.401	-1.32	0.093	1.36	-0.026	-1.25
_CUT1	2.379	0.425				
_CUT2	3.140	0.422				

No. of Observations 10708
Log Likelihood=-9426.21

Pm_cpae=

1	**Pr(xb+u<_cut1)**	**0.52**
2	**Pr(_cut1<xb+u<_cut2)**	**0.15**
3	**Pr(_cut2<xb+u)**	**0.33**

(*) dy/dx is for discrete change of dummy variable from 0 to 1
*, **, ^ significant at 1, 5 and 10 per cent level

TABLE 6
PREDICTED PROBABILITIES OF BEING NON-POOR, MODERATELY POOR OR EXTREMELY POOR*

Sample	Income-based Model			Consumption-based Model		
	Probability of being			Probability of being		
	Non-Poor	Poor	Extremely Poor	Non-Poor	Poor	Extremely Poor
National	0.42	0.13	0.45	0.52	0.15	0.33
Rural	0.39	0.11	0.50	0.49	0.15	0.33
Urban	0.58	0.19	0.23	0.72	0.17	0.13

* Figures may not add to 1 due to rounding up [see Alemayehu et al. 2001].