Abstract
This study proposes to use Demographic and Health Survey (DHS) data to make spatial and inter-temporal multidimensional welfare comparisons for Kenya. We propose to measure well-being in two dimensions; the asset index and nutritional status of women and children. Due to lack of income/expenditure measures in the DHS data, we propose to use inertia approaches to compute a composite measure of wealth to make poverty orderings and inequality comparisons. Dominance approaches of partial poverty orderings will be extended to bi-dimensional dominance to make multidimensional poverty comparisons. We also propose to us the dual cut off and counting approach to measure multidimensional poverty. A child/woman will be considered poor if she comes from a household whose asset index is below an asset poverty line or if her nutritional status is below a certain threshold. Stochastic dominance and a hybrid multidimensional inequality index approaches will be used to make inequality comparisons in a multidimensional setting. The proposed study will fill in the gap left by earlier studies in Kenya that have concentrated on unidimensional monetary poverty measurements. The study is relevant for both Millennium Development Goals and national food and nutrition policy targets.
1. Introduction and Motivation

According to Sen (1985), poverty should be seen in relation to lack of basic needs or basic capabilities. This means that poverty is a multidimensional phenomenon and should therefore be measured by considering multiple indicators of wellbeing. Since Sen’s seminal work, measuring poverty is distinguished into two interconnected exercises: the identification and aggregation tasks. The identification exercise is focused on identifying the poor. Traditional welfare studies measure poverty in terms of deprivation of means, which lead to analysis of monetary indicators (incomes and expenditures). The logic and rationale behind the money-metric approach to poverty is that, in principle, an individual above the monetary poverty line is thought to possess the potential purchasing power to acquire the bundle of attributes yielding a level of well-being sufficient to function. There are several drawbacks of the money-metric approach to poverty measurement. Most important, this approach presupposes that a market exists for all attributes and that prices reflect the utility weights all households within a specific setting assign to these attributes. However, some attributes (public goods) cannot be purchased because markets do not exist and even where markets exist, they are imperfect. Income as the sole indicator of well-being is therefore limited as it typically does not incorporate and reflect key dimensions of poverty related to quality of life. Another drawback of the income approach is that there is no guarantee that households with incomes at or even above the poverty line would actually allocate their incomes so as to purchase the minimum basic needs bundle and therefore households may be non-poor with respect to income but with some members deprived of some basic needs.

In the non-monetary approach, poverty should be viewed as a deprivation of ends (capabilities) and means (functionings) that are intrinsically important (Sen, 1985). Sen recommends that well-being should be assessed based on the positive rights of individuals, and attempts to transpose those rights in a measurable space through the “functioning” concept. Sen’s approach suggests that policies should be evaluated not in their ability to satisfy utility or increase income but to the extent that they enhance the capabilities of individuals and their ability to perform socially acceptable functionings. The non-monetary approach therefore considers well-being in terms of freedoms and achievements and assesses the situation in terms of basic capabilities, such as the ability to be well-fed, educated, healthy, decent, without being overly concerned with information relating to utility per se. The capabilities range from the “absolute deprivation of goods”, in the case of approaches focusing on nutrition or other “basic needs”, to the “relative deprivation of goods” (Townsend, 1979). In this light, poverty indices then have to capture the inability of individuals to achieve a minimal level of capabilities to function.

In aggregation, the individual information is aggregated by means of indices (such as for a population subgroup or at a regional level). Though there are several suggestions extending unidimensional poverty indices to cover multiple dimensions, most formulations end up aggregating all available information into a single measure (see for instance Tsui, 2002 and Bourguignon and Chakravarty, 2003). Emerging literature that theoretically and empirically analyzes poverty as a multidimensional issue uses dominance approaches following Atkinson (1987) and Foster and Shorrocks (1988) in the unidimensional context. An alternative to these studies expand the methods of partial poverty orderings to multidimensional settings (Duclos, 2000).
Sahn and Younger, 2006a, 2006a, 2006c). Another alternative is Alkire and Foster (2008), who propose a counting approach for measuring multidimensional poverty. Their approach is appealing for three reasons: first, it integrates the identification analysis using two cutoffs, where the first is the known dimension-specific threshold for identifying the individuals deprived in that dimension. The second cutoff is the number of dimensions in which an individual has to be deprived to be considered poor. Second, this approach satisfies several desirable properties including decomposability, which is particularly suitable for policy targeting. Third, an investigator has also the freedom to assign different weights to each dimension.

To take into account both identification and aggregation tasks, this project proposes to use nutritional status of children (measured by height for age, weight for age and weight for height) and women (measured by body mass index) to make spatial and inter-temporal welfare comparisons for Kenya using Demographic and Health Survey (DHS) data. Following Sen’s definition of well being, nutrition is a basic capability which is an important indicator of well being worth of study just like other measures of welfare. Child anthropometric measures and body mass index are more direct measures of capability deprivation than income and expenditure and individual well-being in this form can be directly observed. Furthermore, poor nutritional status implies that people suffer from inadequate caloric intake and/or health problems, two important dimensions of wellbeing. In addition, nutrition can be used as a social indicator of the quality of life of the poor because it is quite responsive to socio-economic conditions. Our approach is to measure well-being in wealth (asset index) and nutritional status dimensions. Due to lack of income/ expenditure measures in the DHS data, we use the Sahn and Stifel (2003) asset index to rank children/women by their level of well-being. In our case, a child/woman is considered poor if she comes from a household whose asset index is below an asset poverty line or if her nutritional status is below a certain threshold.

The study also proposes to apply both univariate and multivariate inequality approaches to measure inequalities in child and maternal nutritional status ranked by a composite poverty indicator. Dominance inequality measures will be applied for univariate inequality comparisons, while a hybrid multidimensional inequality index approach (Araar 2008) is proposed for multidimensional inequality comparisons.

2. Main Research Questions:
The proposed research will address two core research questions:
(i) What is the nature of multidimensional poverty measured by women and child nutritional status ranked by a composite poverty indicator in Kenya?
(ii) What has been the spatial and inter-temporal distribution of multidimensional poverty and inequality indices in Kenya?
(iii) What are the policy implications of the distribution in (ii) for Millennium Development Goals and national food and nutrition policy targets?

3. Objectives of the Study
The general objective of the study is to carry out robust multidimensional spatial and inter-temporal poverty and inequality comparisons in Kenya. The specific objectives include:
(i) To construct a composite poverty indicator that provides an aggregate measure of wealth embodying several dimensions.

(ii) To conduct multidimensional poverty and inequality comparisons for child nutritional status ranked by a composite poverty indicator.

(iii) To conduct multidimensional poverty and inequality comparisons for women’s nutritional status ranked by a composite poverty indicator.

(iv) Draw policies relevant for addressing interventions to reduce inequalities in maternal and child nutritional status in Kenya.

4. Scientific Contribution of the Proposed Study

This study has potential to make a major scientific contribution to studies on poverty in Kenya. As far as we know, multidimensional poverty and inequality comparisons have not been conducted in Kenya before. Earlier studies on poverty in Kenya have concentrated on unidimensional poverty comparisons, mostly concentrating on money metric measurements of poverty and determinants of poverty. Recent studies focusing on capability deprivations in Kenya include Kabubo-Mariara, Nd’enge and Mwabu, (2008); Kabubo-Mariara, Karienyeh and Mwangi (2008), Kabubo-Mariara, Araar and Duclos (2008). The first paper analysed determinants of child nutritional status, while the second paper analysed determinants of child mortality but gave a cursory analysis of multidimensional poverty comparisons of child survival and well-being in Kenya. The last paper focused on multidimensional aspects of child well-being.

In Africa and beyond, there are a number of studies that have analyzed multidimensional indicators of poverty, but most studies end up aggregating all available information into a single measure and thus do not differ much from unidimensional approaches. A few and emerging studies have however gone beyond this to use dominance approaches to poverty comparisons (see for instance Duclos et al. 2006a, 2006b, 2006c; Sahn and Stifel, 2002). A more recent approach proposed by Alkire and Foster (2008) takes into account the number of dimensions in which one is poor using two cut offs: within and across dimensions.

In this context, the key contribution of the proposed study includes: (1) The construction of a composite poverty indicator will allow us to study the links between monetary and non-monetary aspects of poverty. (2) Multidimensional poverty comparisons are superior to unidimensional measures in several respects. (i) Unidimensional comparisons can only lead to partial understanding of poverty, and often to unfocused or ineffective poverty reduction programs. They fail to capture many aspects of deprivation, as defined by Sen’s capability approach. (ii) The inclusion of non-monetary measures in multidimensional poverty analysis helps to reveal complexities and ambiguities in the distribution of wellbeing that income based poverty analysis cannot capture. (iii) Multidimensional dominance approach to poverty comparisons facilitate the use of unarbitrary choices of poverty lines and poverty measures and also allow use of poverty comparisons that are robust to the selection of poverty lines and poverty measures. The proposed study will therefore allow us to explore the sensitivity of results to the choice of the threshold distinguishing the malnourished from the well-nourished. Second, unlike other works on multidimensional poverty comparisons, the approach developed by Duclos, Sahn and Younger, (2006a), takes into account sampling variability and the poverty comparisons are therefore statistical, using consistent, distribution-free estimators of the sampling distributions of the
statistics of each poverty comparison. (3) Another potential contribution of the study is in the literature on maternal and child health. As far as we know, there is a dearth of studies on women’s nutritional status in Kenya. Yet good maternal health is of fundamental importance to a country’s well-being and ability to prosper. Protecting the health of mothers safeguards their future contributions to society and ensures the health and productivity of future generations. If the health of mothers is compromised, there will be serious negative consequences for their families (especially children), communities, and the entire process of economic and social development and may even trigger a poverty trap in affected households resulting from effects of negative health shocks. The consequences of poor maternal nutrition are both long term and intergenerational (Meyerhoefer and Sahn, 2007). In children, nutritional deficiencies contribute to high rates of disability, illness and death. They also affect the long term physical growth and development of children, and may lead to high levels of chronic illness and disability in adult life. In addition, high rates of malnutrition jeopardize future economic growth by reducing the intellectual and physical potential (Kabubo-Mariara, Nd’enge and Kirii, 2008).

5. Policy Relevance
The results of the proposed study will be useful to inform policy in several key aspects: Millennium Development Goals (MDGs) focus attention on deprivation in multiple dimensions. Unlike unidimensional poverty comparisons, multidimensional poverty comparisons provide an attractive tool for analyzing such definitions of poverty. The MDGs in Kenya address concerns of high levels of malnutrition through poverty reduction efforts, with the first MDG goal targeting to halve, between 1990 and 2015, the proportion of people whose income is less than 1 US dollar a day. The MDG goal 5 aims at a three quarter reduction in maternal deaths by 2015. Good maternal nutrition is very crucial for lowering maternal mortality especially at child bearing and lactating mothers.

In addition, the proposed study also focuses on issues of concern for the most recent national food and nutrition policy in Kenya which in addition to the first MDG goal, aims at reducing the prevalence of underweight children by half by 2015 and eradicating vitamin A deficiency among children under-five by 2015 (Republic of Kenya, 2005).

Finally, addressing spatial and inter-temporal inequalities in welfare is expected to highlight the interventions that are likely to be important in achieving better nutritional status across regions in Kenya, and would therefore be useful for regional targeting by ranking regions according to their welfare. This would directly impact on the targets of the national food and nutrition policy and the MDGs in Kenya.

6. Methodology
This section outlines the proposed methodology for achieving the research objectives. The methodology focuses on methods for construction of a composite measure of poverty/wealth and the frameworks for carrying out multidimensional poverty and inequality comparisons.

6.1 Construction of the Composite Indicator of Wealth
To achieve objective one, we propose to construct a composite poverty indicator (CPI) that captures multiple aspects of household wealth. This CPI forms the basis of one of the dimensions of the multidimensional poverty comparisons in subsequent sections. We propose to use an index of household assets as the CPI. Like any other composite indicator of wealth, there are some major challenges in constructing an asset index. Most prominent is the difficulty involved in the aggregation of the various types of assets into a single number that represents the sum total of the value of assets. Several aggregation methods have been employed in the literature including entropy and inertia approaches. The inertia approach is a parametric approach to the composite indicator that stems from static mechanisms and is mainly based on multidimensional analysis techniques (Asselin, 2002). The inertia approach uses the principal techniques of factor analysis including principal components analysis (PCA), generalized canonical analysis (GCA) and multiple correspondence analysis (MCA). The inertia approach is less arbitrary than the entropy approach in the definition of the functional form for the composite indicator. The approach also enables an optimal choice among the relevant poverty dimensions.

In the construction of a composite indicator, we not only face the challenge of aggregation but also of definition of a set of weights for each asset. In this study, for each household, we propose to construct an asset index of the form:

\[ A_i = \sum_k \tau_k a_{ik} \]  \hspace{1cm} (1)

where \( A_i \) is the asset index for household \( i \), the \( a_{ik} \)'s are the \( k \) individual assets recorded in the survey for that household, and the \( \tau \)'s are the weights. Most studies use the standardized first principal component of the variance covariance matrix of the observed household assets as weights, allowing the data to determine the relative importance of each asset, based on its correlation with the other assets (Filmer and Pritchett, 2000). The PCA consists of building a sequence of uncorrelated (orthogonal) and normalized linear combinations of input variables, exhausting the whole variability of the set of input variables (Asselin, 2002).

Following Sahn and Stifel (2000, 2003), we propose to use factor analysis (FA) instead of principal component analysis. This is because though similar to principal components, factor analysis has certain statistical advantages: (i) The PCA forces all of the components to accurately and completely explain the correlation structure between the assets. Factor analysis, on the other hand, accounts for the covariance of the assets in terms of a much smaller number of hypothetical common factors (Sahn and Stifel, 2000). (ii) FA allows for asset-specific influences.

\[ \text{The main limitation of the entropy approach is the arbitrary choice of parameters and weights used in the composite indicator functional form. The inertia approach employs a methodology that constructs a composite indicator with the least possible arbitrariness in the definition of the functional form. The categorical weighting consists in quantifying each primary qualitative indicator in a non-linear way, thus without imposing, from the beginning any constraint on a functional form. It also allows making an optimal choice of the pertinent dimensions of poverty while discarding redundant information (Asselin, 2002).} \]
to explain the variances such that all of the common factors are not forced to explain the entire covariance matrix. In many cases, it is assumed that the one common factor that explains the variance in the ownership of the set of assets is a measure of economic status, or welfare. (iii) The assumptions necessary to identify the model using FA are stated explicitly and provide guidance in determining which assets should or should not be included in the index.

The assets to be included in the analysis are ownership of a radio, TV, refrigerator, bicycle, a motorcycle, a car, the household’s source of drinking water (piped or surface water relative to well water); the household’s toilet facilities (flush or no facilities relative to latrine facilities); the household’s floor material (low quality relative to higher quality); and the years of education of the household head (and of respondent if not the head) to account for household’s stock of human capital. The scoring coefficients from the factor analysis will be applied to each household to estimate its asset index and will rank the households on a -1 to 1 scale. To avoid arbitrary assignment of weights to the variables, we propose to rely on the factor loadings results for weights.

6.2 Analytical Framework for Multidimensional Poverty Comparisons

Most of the approaches to poverty measurements are uni-dimensional, identifying the poor by means of a monetary indicator. Emerging approaches however argue that the identification exercise should be extended to not only identify the poor, but also to include adequate dimensions in which the poor are excluded. Identifying the poor in multiple dimensions therefore entails the question of how aggregation should be done. We propose to take into account both the identification and aggregation problems in a multidimensional context using two main approaches: the stochastic dominance approach developed by Duclos, Sahn and Younger (2006) and the dual cut off and counting approach developed by Alkire and Foster (2008). Each of these approaches is discussed below.

6.2.1 Stochastic Dominance Approach

The Duclos, Sahn and Younger (2006) approach extends approaches of partial poverty orderings to multidimensional settings. To illustrate this approach, a good starting point is the works of Chakravarty et al. (1998) and Tsui (2002) and Bourguignon and Chakravarty (2003).3 The authors have developed axioms on multidimensional poverty measures, viewing a multidimensional index of poverty as an aggregation of shortfalls of all the individuals where the shortfall with respect to a given need reflects the fact that the individual does not have even the minimum level of basic needs. Let $z = (z_1, ..., z_k)$ be the k-vector of the minimum levels of the k basic need; $x = (x_1, ..., x_k)$ the vector of k basic needs of the $i^{th}$ person; and $X$ is a matrix summarizing the distribution of k attributes among n persons. The most general form of multidimensional poverty measures can be given by:

$$P(X, z) = F [\pi(x, z)]$$

3 The proposed methods of analysis in this project are the Duclos et al. (2006) and the Alkire and Foster (2008) approaches. For this reason section 6.2 concentrates on these approaches. This study further proposes to compare these multidimensional poverty indices with alternative indices based on Tsui (2002) and Bourguignon and Chakravarty (2003) approaches (presented in the appendix).
where $\pi$ is an individual poverty function that indicates how many aspects of poverty must be aggregated at the individual level. The function $F(.)$ reflects the way in which individual poverty measures are aggregated to yield a global poverty index. The properties of $F(.)$ and $\pi(.)$ will depend on the axioms that the poverty measures have to respect. The desirable axioms include: symmetry, continuity, focus, scale invariance, principle of population, monotonicity, subgroup consistency, subgroup decomposability, factor decomposability, transfer, nondecreasing poverty under correlation increasing arrangement and normality. To establish conditions for the robustness of a poverty measures, some studies assume that the poverty measure does not have to satisfy all the above axioms (see for instance Bourguignon and Chakravarty, 2003; Bibi, 2005; Deutsch and Silber, 2005; Dulcos and Araar, 2006). However, Duclos et al. (2006a) establish conditions for robustness that do not require restrictive conditions on the interval of the different poverty lines.

Following Duclos et al. (2006a), if we assume that we have two measures of well-being; assets $(x)$ and nutritional status $(y)$ and also assuming differentiability, we can show that each of the indicators can contribute to overall well-being. This well-being can be denoted as:

$$
\lambda(x, y) : \mathbb{R}^2 \rightarrow \mathbb{R} \left[ \frac{\partial \lambda(x, y)}{\partial x} \geq 0, \frac{\partial \lambda(x, y)}{\partial y} \geq 0 \right] \tag{3}
$$

Following Duclos, Sahn and Younger, (2006a), we can assume that an unknown poverty frontier separates the poor children/women from the rich, defined implicitly by a locus of the form $\lambda(x, y) = 0$ and is analogous to the usual downward sloping indifference curves. The set of the poor children/women can then be given as:

$$\Lambda(\lambda) = \{(x, y) | \lambda(x, y) \leq 0\} \tag{4}$$

To define the multidimensional poverty indices precisely, let the joint cumulative distribution of $x$ and $y$ be denoted by $F(x, y)$. Focusing on classes of additive multidimensional poverty indices, an additive poverty index that combines the asset index and nutritional status can be defined as $P(\lambda)$ where:

$$P(\lambda) = \int_{\Lambda(\lambda)} \pi(x, y; \lambda) dF(x, y) \tag{5}$$

Where $\pi(x, y; \lambda)$ is the contribution to poverty of an individual with well-being indicators $x$ and $y$ such that:

$$\pi(x, y; \lambda) \left\{ \begin{array}{ll}
\geq 0 & \text{if } \lambda(x, y) \leq 0 \\
= 0 & \text{otherwise.} 
\end{array} \right. \tag{6}$$

In equations (5) and (6), $\pi$ is the weight that the poverty measure attaches to a child/woman inside the poverty frontier. By the poverty focus axiom, $\pi = 0$ for a child/woman outside the poverty frontier. The multidimensional headcount is obtained when $\pi=1$ (Duclos, Sahn and Younger, 2006a).
Modifying the usual unidimensional stochastic dominance curve or FGT poverty index (Foster, Greer and Thorebecke, 1984), a bi-dimensional stochastic dominance surface can be defined as

\[
P^{a_x,a_y}(z_x, z_y) = \int_0^{z_x} \int_0^{z_y} (z_x - x)^{a_x} (z_y - y)^{a_y} dF(x,y) \]  \quad (7)

for integers \(a_x \geq 0\) and \(a_y \geq 0\). The dominance surface can be generated by varying the poverty lines \(z_x\) and \(z_y\) over an appropriately chosen domain, with the height of the surface determined by (7). \(F(x,y)\) is the joint distribution function such as assets and nutritional status. \(P^{1,1}(z_x, z_y)\) generates a cumulative density surface analogous to a poverty incidence curve in a unidimensional analysis. \(P^{2,2}(z_x, z_y)\) can be thought of as a bi-dimensional average poverty gap index (Duclos, Sahn and Younger, 2006a).

The bi-dimensional formulation is only a special case, since there are certain complexities to be taken into account, when expanding the one-dimensional analysis. The issue that has to be dealt with is the distinction between being poor in two (and at the limit all) dimension(s) and in only one dimension. In our context, if an individual either has low assets or poor nutritional status, he/she is poor by a union definition and \(\pi\) will be:

\[
\pi(x_i,z) = \begin{cases} 
0, & \text{if } x_{ij} \geq z_j, \forall j = 1,2,...,k, \\
> 0, & \text{otherwise},
\end{cases} \quad (8)
\]

where \(x_i\) and \(z\) are as defined in equation (2). An intersection definition would consider as poor those who have low assets and poor nutritional status. In this case

\[
\pi(x_i,z) = \begin{cases} 
> 0, & \text{if } x_{ij} \leq z_j, \forall j = 1,2,...,k, \\
0, & \text{otherwise},
\end{cases} \quad (9)
\]

Poverty comparisons in this paper will be based on equation (7) and the results compared with indices derived from appendix equations (A3)-(A6). The comparisons that can be made from (7) are valid for broad classes of poverty functions other than the FGT. Further, the surface will be influenced by the covariance between assets and the nutritional status, because the integrand is multiplicative. The higher the correlation between these two poverty indicators, the higher the dominance surfaces, other things equal.

From (7), we propose to derive a class of bi-dimensional poverty indices which are first order in both assets and nutritional status and possess the important characteristics of being additively separable, non-decreasing in each dimension, anonymous and continuous at the poverty lines\(^4\). Another characteristic is that assets and nutritional status must be substitutes and not complements. This means that the marginal utility of one attribute decreases when the quantity

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\(^4\) See Duclos, Sahn and Younger (2006a) for important features and conditions of bi-dimensional dominance surface.
of another increases (Bourguignon and Chakravarty 2003). Duclos et al. (2006a) have shown that by making further assumptions concerning the general poverty indices, a general form of bi-dimensional poverty indices can be defined. This will further be extended to higher order dominance poverty comparisons. DASP software (Araar and Duclos, 2007) will be used to derive poverty indices and corresponding curves.

6.2.2 Dual Cutoff and Counting approach

The Alkire and Foster (2008) dual cutoff and counting approach to multidimensional poverty measurement follows the Foster, Greer, and Thorbecke (1984) aggregation method and satisfies a set of desirable axioms including ‘decomposability, replication invariance, symmetry, poverty deprivation, dimensional monotonicity’, transfer and rearrangement among others. Like other multidimensional poverty approaches, the approach takes into account both identification and aggregation issues.

Following Alkire and Foster but modifying some of the notation, we start by considering a population of n persons and d > 2 dimensions. Further let \( x_i = [x_{ij}] \) denote the \( n \times d \) matrix of achievements, where the typical entry \( x_{ij} > 0 \) is the achievement of individual \( i = 1,2,\ldots, n \) in dimension \( j = 1,2,\ldots, d \). Each row vector \( x_i \) lists individual \( i \)'s achievements, while each column vector \( x_j \) gives the distribution of dimension \( j \) achievements across the set of individuals. The number of dimensions is assumed to be fixed and given, while \( n \) is allowed to range across all positive integers; so as to allow poverty comparisons to be made across populations of different sizes. The domain of matrices under consideration is given by \( X = \{ x \in R^{nd} : n \geq 1 \} \). If we let \( z_j > 0 \) be the deprivation cutoff (or poverty line) in dimension \( j \), the sum of entries in any given vector or matrix \( v \) can be denoted by \( |v| \), while \( \mu(v) \) is used to represent the mean of \( v \) (Alkire and Foster, 2008).

To identify the poor, we assume all dimensions are equally weighted (an assumption that can be relaxed later). Suppose that a matrix of deprivations \( x^0 = [x^0_{ij}] \) as follows:

\[
\begin{cases}
1 & \text{if } x_{ij} < z_j \\
0 & \text{otherwise}
\end{cases}
\]

for all \( i \) and \( j \), \( x^0_{ij} \) ................................. (10)

Summing each row of \( x^0 \) gives a column vector \( c \) of deprivation counts containing the number of deprivations (\( c_i \)) suffered by individual \( i \).

To identify the poor, the identification function relating to cutoff \( k \) can be defined as \( \rho(x_i; z) \) such that

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5 The approach is said to be a dual cutoff method because it defines some within dimension cutoffs to determine whether an individual is deprived or not in each dimension, and the across dimensions cutoff \( k \) to determine who is to be considered multidimensionally poor. It is also presented as a counting approach, since it identifies the poor based on the number of dimensions in which they are deprived (Alkire and Foster, 2008).
\[ \rho(x, z) = \begin{cases} 1 & \text{if individual is multidimensionally poor} \\ 0 & \text{otherwise} \end{cases} \quad \text{.......................... (11)} \]

The next step is to compare the number of deprivations with a cutoff level \( k \). When each selected dimension has the same weight, the possible values of \( k \) is in the range \( k = 1, \ldots, d \). For any weighting system, let \( \rho_k \) be the identification method such that \( \rho_k(x, z) = 1 \) when \( c_i \geq k \), and \( \rho_k(x, z) = 0 \) when \( c_i < k \). An individual is therefore identified as multidimensionally poor if he/she is deprived in at least \( k \) dimensions.

The aggregation step takes \( \rho \) in equation (11) as given and associates with the matrix \( x \) and the cutoff vector \( z \) an overall level \( M(x; z) \) of multidimensional poverty. The resulting functional relationship \( M : X \times R^d_+ \rightarrow R \) is an index of multidimensional poverty. The first class of multidimensional poverty measures is the headcount ratio defined as:

\[ H = \frac{q}{n} \quad \text{................................................................. (12)} \]

where \( q = \sum_{i=1}^{n} \rho_k(x_i; z) \) i.e. the number of people in set \( z \). As with the usual FGT measures, the share of possible deprivations suffered by a poor individual and the average deprivation share across the poor can be derived from equation (12) by normalizing over the number of dimensions and the number of poor in \( z \). Like the general FGT head count, \( H \) is insensitive to the depth and severity of poverty and violates monotonicity and transfer axioms. In the multidimensional context, it also violates dimensional monotonicity: if a poor person becomes deprived in an additional dimension (in which he/she was not previously deprived), \( H \) does not change (Alkire and Foster, 2008). To deal with this shortcoming, Alkire and Foster propose an adjusted headcount which combines the head count and the average deprivation share across the poor (A) and thus satisfies dimensional monotonicity. This measure is the total number of deprivations experienced by the poor, divided by the maximum number of deprivations that could possibly be experienced by all people \( (nd) \) and is defined as:

\[ M^A = HA = \frac{1}{nd} \sum_{i=1}^{n} c_i \rho_k(x_i; z) \quad \text{................................................................. (13)} \]

If the variables in \( x \) are cardinal, the associated matrix of (normalized) gaps or shortfalls can provide additional information for poverty evaluation. For any \( x \), let \( g_i \) be the matrix of normalized gaps, where the typical element is defined by \( g^1_{ij} = (z_j - x_{ij}) / z_j \) whenever \( x_{ij} < z_j \), while \( g^1_{ij} = 0 \) otherwise. \( g^1 \) is an \( n \times d \) matrix whose entries are nonnegative numbers less than or equal to 1, with \( g^1_{ij} \) being a measure of the extent to which person \( i \) is deprived in dimension \( j \). We can then generalize for any value of \( \alpha > 0 \) to obtain \( g^\alpha \) by raising \( g^1 \) to the power \( \alpha \) such that \( g^\alpha_{ij} = (g^1_{ij})^\alpha \). \( G^\alpha \) can then be expressed as:
\[ G^\alpha = \frac{1}{\sum_{i=1}^{n} c_i \rho_i (x_i; z)} \sum_{j=1}^{d} \sum_{i=1}^{n} g_{ij}^\alpha \rho_k(x_i; z) \]  \hspace{1cm} (14)

The adjusted FGT measure \( M_\alpha = HAG^\alpha \) is defined as

\[ M_\alpha = \frac{1}{nd} \sum_{j=1}^{d} \sum_{i=1}^{n} g_{ij}^\alpha \rho_k(x_i; z) \]  \hspace{1cm} (15)

When \( \alpha = 0 \), \( M_0 \) is the adjusted headcount ratio (\( M_0 \)). When \( \alpha = 1 \), we get the adjusted poverty gap (\( M_1 \)), which is the sum of the normalized gaps of the poor divided by the highest possible sum of normalized gaps. \( M_1 \) summarizes information on the incidence of poverty, the average range of deprivations and the average depth of deprivations of the poor. It satisfies both dimensional monotonicity and monotonicity: if an individual becomes more deprived in a certain dimension, \( M_1 \) will increase. When \( \alpha = 2 \), the measure is the adjusted squared poverty gap. \( M_2 \) summarizes information on the incidence of poverty, the average range and severity of deprivations of the poor. If a poor person becomes more deprived in a certain dimension, \( M_2 \) will increase more the larger the initial level of deprivation for this individual in this dimension. This measure satisfies both types of monotonicity and also transfer, being sensitive to the inequality of deprivations among the poor.

All members of the \( M_\alpha(y; z) \) family are decomposable by population subgroups. If a population is divided into \( n_1 \) and \( n_2 \) subgroups (say rural and urban), the weighted average of the sum of the subgroup poverty levels (population shares as weights) equals the overall poverty level obtained when the whole group is considered:

\[ M(x; z) = \frac{n_1}{n} M(x_1; z) + \frac{n_2}{n} M(x_2; z) \]  \hspace{1cm} (16)

This decomposition can be extended to any number of subgroups. The \( M_\alpha(x; z) \) family presented above assumes that all dimensions receive the same weight. However, the family can be extended into a more general form, admitting different weighting structures. Following Alkire and Foster (2008), let \( w \) be a \( d \) dimensional row vector, whose typical element \( w_j \) is the weight associated with dimension \( j \). Define the matrix \( g^\alpha = [g_{ij}^\alpha] \) to be the \( n \times d \) matrix whose typical element is \( g_{ij}^\alpha = w_j ((z_j - x_{ij}) / z_j)^\alpha \) whenever \( x_{ij} < z_j \), while \( g_{ij}^\alpha = 0 \) otherwise. As illustrated before, a column vector of deprivation counts can be defined, whose \( i \)th entry \( c_i = |g_{ij}^\alpha| \) represents the sum of weights for the dimensions in which person \( i \) is deprived. \( c_i \) varies between 1 and \( d \), and so the dimensional cutoff for the identification step of the multidimensionally poor will be a real number \( k \), such that \( 0 < k \leq d \). When equal weights are used, \( k = \min\{w_j\} \), the identification
criterion corresponds to the union approach, whereas when \( k = d \), the identification criterion corresponds to the intersection approach. Alkire and Foster (2008) also define an intermediate approach when \( 1 < k < d \). In the case of only two dimensions, this criterion will be a combination of these dimensions as proposed by Duclos, Sahn, and Younger (2006). The specification \( w_1 = d / 2 \) and \( w_2 = ... = w_d = d / (2(d-1)) \) is an example of a nested weighting structure in which the overall weight is first split between dimension 1 and the remaining \((d-1)\) dimensions, and then the weight allocated the second group is split equally across the \((d-1)\) dimensions.

The above approach will be applied to measure multidimensional poverty among children in Kenya. The approach requires that \( d > 2 \) or that we have more than 2 dimensions in which the child could be poor. In this case, we consider whether a child is poor in a wealth dimension measured by the asset index and in at least 3 health related dimensions: nutritional status measured by standardized anthropometric measures of height for age (\( haz \)), weight for age (\( waz \)) and weight for height (\( whz \)). The deprivation thresholds for nutritional status follow the United States National Centre for Health Statistics (NCHS) median reference where a cut-off of minus two (-2) standard deviations for \( haz \), \( waz \) and \( whz \) are taken as measures of past/chronic malnutrition, wasting and current/acute malnutrition respectively.

### Choice of Parameter and Weights

One challenge with construction of multidimensional poverty indices is the choice of parameters and weights, yet the ordering of well-being bundles can be very sensitive to the choice of parameters and weights (Decancq and Lugo, 2008). For choice of parameters, suppose we define the individual well-being index as a weighted mean of order \( \beta \) of the transformed achievements \( I_j(x_j) \) such that \( I(X/\beta) = [w_1 I_1(x_1)^{\beta} + ... + w_q I_q(x_q)^{\beta}]^{1/\beta} \). The parameter \( \beta \) captures the degree of substitutability between the transformed achievements. If we let \( \beta = 1 - 1/\sigma \), where \( \sigma \) is the elasticity of substitution, then the smaller the \( \beta \), the smaller the allowed substitutability between dimensions. If \( \beta = 1 \), then the weighted mean of order \( \beta \) is reduced to the arithmetic mean where the dimensions are assumed to be perfect substitutes. When \( \beta = 0 \), the well-being index becomes the geometric mean and has a unit elasticity of substitution between all pairs of dimensions (Decancq and Lugo, 2008). For \( \beta \leq 1 \), the well-being index is weakly convex and reflects a preference for well-being bundles that are more equally distributed. When \( I(X/\beta) \) defined earlier is used to summarize multidimensional poverty or deprivation, a \( \beta \geq 1 \) is more appropriate. If \( \beta \) goes to \(-\infty(+\infty)\), the elasticity of substitution becomes 0 and the well-being indices become the minimum (maximum) of the transformed achievements across the dimensions. In this paper, for simplicity we assume that \( \beta = 1 \). This implicitly assumes that the poverty indices we propose to compute should be sensitive to multiple deprivations.

The main methods of weighting in multidimensional poverty measurement include equal weights, frequency-based weights, most favourable weights, multivariate statistical weights, regression based weights and normative weights (Decancq and Lugo, 2008). None of these methods has been proved to be the best, and most approaches to poverty measurement do not provide suitable methods to address the weighting issue. Instead, they give the latitude to assign
weights to each dimension in a normative way (Batana, 2008). Caution is however advanced on
the trade-offs that arise from using different weighting methods and the need for robustness tests
to determine the impact of specific value of weights on poverty indices (Decancq and Lugo,
2008). The most commonly used approach to weighting is equal weighting. Though convenient,
equal weighting is far from uncontroversial (Decancq and Lugo, 2008; Alkire and Foster, 2008).
According to Atkinson (2003), equal weights is an arbitrary normative weighting system that is
appropriate in some but not in all situations. This paper proposes to assign equal weights to the
asset index and nutrition. However, for child nutrition, we however propose to move to general
weights where nutrition is assigned equal weight with asset index, but the nutrition specific
weight will then be divided equally between each of the three nested dimensions of child
nutrition (Batan, 2008; Alkire and Foster 2008).

6.3 Analytical Framework for Inequality Comparisons
6.3.1 Uni-dimensional Inequality Comparisons
This study proposes to carry out both univariate and multivariate inequality comparisons. For
univariate analysis, we propose to measure inequality in the composite indicator of well-being
(assets index) using the absolute rather than the usual Gini index because the asset index assumes
negative values for the poorer groups. The absolute Gini index can be defined as:

\[ AI = I \times \mu \]  

where I is the usual relative Gini coefficient and \( \mu \) is the average of assets.

The absolute Gini can be defined in-terms of the magnitude of relative deprivation, that is, the
difference between the desired situation and the actual situation of a child/woman (Moyes, 1987;
Araar, 2006). The relative deprivation of child/woman i compared to child/woman j can be
defined as follows:

\[ \delta_{i,j} = (y_j - y_i)_+ = \begin{cases} 
 y_j - y_i & \text{if } y_i < y_j \\
 0 & \text{otherwise.} 
\end{cases} \]  

where \( y_k \) is the asset index for child k. The expected deprivation of child/woman i equals to:

\[ \bar{\delta}_i = \frac{\sum_{j=1}^{N} (y_j - y_i)_+}{N} \]  

where N is the total number of children under five years/women in the sample. The AI can be
written in the following form:

\[ AI = \sum_{i=1}^{N} \frac{\delta_i}{N} = \bar{\delta} \]
The functional form of the absolute Gini coefficient presented in equation (20) shows that this coefficient is the average of the expected relative deprivation. This AI posses all the important inequality axioms and most important all axioms are consistent and continue to be so when the mean is negative or equal to zero (see Araar 2006 for a detailed discussion of the axioms of the absolute Gini index). This AI satisfies the all inequality axioms including symmetry, population, Pigou-Dalton transfer, invariance to constant adding, constance to proportional adding and most important all axioms are consistent and continue to be so when the mean income is negative or equal to zero (Araar 2006).

The contribution of each child/woman to total inequality depends on her expected relative deprivation. When child/woman k belongs to group g, her average relative deprivation can be written as:

\[ \tilde{\delta}_k = \phi_g \delta_{k,g} + \bar{\delta}_{k,g} \]  
\[(21)\]

\[ \delta_{k,g} = \frac{\sum_{j=1}^{N-K_g} (y_k - y_j)_+}{N} \]  
\[(22)\]

Where \( \phi_g \) is the population of children’s/women’s share of group g, \( K_g \) is the number of children/women that belong to the group g, \( \delta_{k,g} \) is the expected relative deprivation of child/woman k at the level of group g and \( \bar{\delta}_{k,g} \) is the expected relative deprivation of k at the level of its complement group. Araar (2006) has shown that by using equations (21) and (22), the decomposition of the Gini index takes the form:

\[ AI = \sum_{g=1}^{G} \phi^2 A_{g} + AI(\mu_g) + R \]  
\[(23)\]

where R is a residual or a group asset overlap.

Analogous to the absolute Gini Index, we propose to use the absolute Lorenz curve to test for inequality dominance. Moyes, (1987) and Araar (2006) have shown that the absolute inequality in distribution A dominates that of B if and only if:

\[ AL_A(p) < AL_B(p) \quad \forall p \in [0,1] \]  
\[(24)\]

where \( AL_D \) is the absolute Lorenz curve for the distribution D, such that

\[ AL_D(p) = \int_0^p (y_D(q) - \mu_D) dq \]  
\[ = GL_D(p) - p \mu_D \]  
\[(25)\]
where $GL_D$ is the generalised Lorenz curve for the distribution $D$. Using the above analogy, the absolute concentration curve can also be derived from the usual concentration curve to measure progressivity in nutritional status.

### 6.3.2 Multidimensional Inequality Comparisons

There are a number of multivariate inequality indices proposed in the literature, mostly springing from generalizations of the univariate inequality indices proposed by Atkinson (1970) and Kolm (1969). These include Maasoumi index (1986, 1999); Tsui index (1995, 1999) and Bourguignon index (1999). While these indices satisfy some of the most important inequality axioms and properties (Lugo, 2005), they are not defined for negative values. Examples of indices that can allow for negative achievements as a special case include Tsui’s and Kolm-Pollak [Kolm (1969, 1976)– Pollak (1971)]. A later development is the generalized Gini absolute inequality indices based on Gini social evaluations introduced by Gajdos and Weymark (2005). These indices are however insensitive to correlation among dimensions of entitlements. Araar (2008), however proposes a hybrid index of inequality that assumes sensitivity to both uni and multidimensional inequality. We propose to use this approach in this paper.

Araar’s hybrid multidimensional inequality (MDI) index takes the following form:

\[
MDI_A = \sum_{i=1}^{k} \left[ \tilde{\lambda}_i AI_k + (1 - \tilde{\lambda}_i) AC_k \right] \tag{27}
\]

Where $\tilde{\lambda}_k$ is a vector of parameters, $AI_k$ and $AC_k$ denote the absolute Gini and absolute coefficient of concentration respectively. Araar has shown that $MDI_A$ obeys a set of desired properties for MDI indices. In addition, this hybrid index posses several other properties. Specifically, it is robust for proportional bounded values since $I_k \geq C_k$. It also obeys the Uniform Pigou-Dalton Majorization principle for all $\tilde{\lambda}_k \in [0,1]$ and the Uniform Majorization Principle for the same set. The index further obeys Tsui’s(1999) Correlation Increasing Majorization axiom and finally it is decomposable by components.

The attraction of the hybrid index lies in that it has a flexible functional form that reflects the multi-aspects of social preferences and is therefore easily interpretable. The index also allows for establishment of a complete order for social welfare functions. Furthermore, the index is multi-level decomposable by components, which is important for policy targeting for addressing uni- and multi dimensional forms of inequality simultaneously (Araar, 2008). DASP software (Araar and Duclos, 2007) will be used to derive both univariate and multidimensional inequality indices and curves.

### 7. The Data Types and Sources

To achieve the objectives of the study, we propose to use three rounds of DHS data for the period 1993-2003. The DHS are nationally representative samples of women aged 15 to 49 and

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6 The authors are very grateful to Abdelkrim Araar and Suman Seth for very useful insights on multidimensional inequality indices.
their children and is rich in information on demographic, nutrition and health information and is therefore adequate to answer the key research questions of this proposal. The three surveys, while relatively comparable differ in a number of ways. The 1993 KDHS collected information on 7,540 women aged 15-49, and 6,115 children aged less than 60 months from 7950 households in the months of February to August 1993. The 1998 KDHS collected information on 7,881 women aged 15-49, and 5,672 children aged less than 60 months from 8,380 households in the months of February to July 1998. The 2003 KDHS covered 8,195 women aged 15-49 and 5,949 children aged less than 60 months from 8,561 households in the months of April to August, 2003. All surveys covered both rural and urban populations. The surveys collected information relating to demographic and socio-economic characteristics for all respondents and more extensive information on pre-school children.

The Demographic and Health Surveys utilized a two-stage sample design. The first stage involved selecting sample points (clusters) from a national master sample maintained by Central Bureau of Statistics (CBS) the fourth National Sample survey and Evaluation Programme (NASSEP) IV. The 1993 and 1998 KDHS selected 536 clusters, of which 444 were rural and 92 urban from seven out of the eight provinces in Kenya. The 1993 survey collected data from 34 districts, while the 1998 survey collected from 33 districts. In 2003, a total of 400 clusters, 129 urban and 271 rural, were selected, drawn from all eight provinces and 69 districts. For 2003, 65 of the districts were taken from the seven provinces sampled in the earlier surveys, but the sample is equally representative due to creation of new districts from previously surveyed districts. From the selected clusters, the desired sample of households was selected using systematic sampling methods.

8. Consultation and Dissemination Strategy

8.1 Proposed Research

In order to ensure that the results reach the targeted audience and contributes towards achievement of the policies outlined in section 5, it is important to ensure that there is adequate link between the research and policy. To facilitate this, the project team has discussed the proposal with policy makers from two Ministries: Ministry of State for Planning, National Development and Vision 2030, and Ministry of Public Health. The choice of the policy mentors is guided by the expected policy relevance of results and the likely consumers and implementers. In the Ministry of State for Planning, National Development and Vision 2030, we have established contact with policy makers involved in poverty reduction, food and nutrition policy. In the Ministry of Public Health, we are liaising with policy makers dealing with maternal and child health issues. We have also established contact with the Social Policy Advisor for Budgetary Control in the Ministry of Finance. This advisor is in charge of implementation of UNICEF supported programs and will therefore act as a crucial link with UNICEF-Kenya. He will be instrumental in our collaboration with UNICEF over implementation of results from our previous PEP project and this proposed project.

To reach out to the research community, working papers of the study will be presented and discussed at various research forums including seminars at the host institution and also for peer review at PEP workshops. Working papers will also be presented and discussed in other relevant national, regional and international conferences. To ensure a wider reception and thorough peer review, we shall target the following international conferences: UNICEF/Graduate Program on
International Affairs (UNICE/GPIA); Child Poverty Network Conferences; Centre for the Study of African Economies (CSAE); Human Development Capability Association (HDCA); World Institute for Development Economics Research /United Nations University (WIDER/UNU). In addition, we will look out for all other major conferences related to the issues investigated in this study.

Policy briefs will be made available to policy makers, non-governmental and civil society organisations in Kenya. The final report of our study will be made available in the form of a PEP working paper as well as working papers for the School of Economics. Excerpts of the study will also be submitted to journals listed in ECONLIT for publication.

8.2 Previous Research

The results of the previous PEP project by the team leader (et al.) were presented at the UNICEF/GPIA conference on ‘Rethinking Poverty: Making policies work for children’ in April 2008. Some aspects of the paper had earlier been presented at an AERC workshop on ‘Reproductive Health, Economic Growth and Poverty Reduction’ held in Nigeria in October 2007. The paper had also been accepted for presentation at a conference on ‘Poverty and Social Exclusion: Dynamics and Multidimensional Issues’ held in Barcelona in November 2007, but was not presented due to lack of funds. A version of the paper was also presented at the HDCA conference on ‘Equality, Inclusion and Human Development’ held in Delhi in September 2008. An extract of the paper is also expected to be presented at an International conference on ‘Child Poverty and Disparities: Public Policies for Social Justice’ in Cairo, Egypt, 17 and 18 January 2009.

In Partnership with the East African Regional IDRC office, the team is in the process of organizing a PEP National Policy conference to disseminate the research findings. The workshop is tentatively scheduled for late January 2009. The workshop will also feature presentation of results of Young Lives Project Ethiopia (YLE). YLE was designed to help policy-makers and planners in Ethiopia improve the quality of children’s lives and is part of a four country, multi-donor project, coordinated by Save the Children UK. The study sought to record changes in child poverty over a 15-year period through a longitudinal survey. The first phase of the YLE was financed by DFID, while IDRC supported the second phase, focusing on the impacts of the Ethiopian governments’ growth Strategies on its policies to achieve universal primary education and child nutrition. The workshop will also act as a pre-inception workshop for a Child Poverty Research Network, a proposal developed jointly by PEP and Save the Children UK. The objective will be to share ideas of the network and proposed research with the aim of soliciting partners and interested participants. The conference will target: policy makers from all relevant Government Ministries (including, but not limited to poverty reduction strategies, food and nutrition policy, and child health issues); other stakeholders including UNICEF; UNDP; USAID; World Bank; and other development partners. We will also invite a few, carefully selected senior researchers in research and academic institutions.

The team has already produced a PEP working paper and a policy brief based on the working paper. In addition, we have extracted 3 journal papers, all under publication review:


9. Prior Training and Experience of Team members

Dr. Kabubo-Mariara is currently associate director and senior lecturer in the School of Economics, University of Nairobi. She is a development economist by training and has wide research experience in poverty, labour market and income distributional issues. She also researches on development and environment economics with a bias on the interaction between poverty and environmental variables. Dr. Kabubo-Mariara has won several research grants in her areas of specialization from both local and international organizations, including PEP and the African Economic Research Consortium (AERC). Participation in collaboration projects, both locally and internationally has played an important role in enhancing her research capacity. Currently, she is the team leader of a collaborative research project on ‘Reproductive Health, Economic Growth and Poverty Reduction in Africa’, funded by the AERC. In this project, the team is investigating the consequences of fertility for child health. She has been a visiting scholar to Cornell University (1998, 2004 and 2005) under the African Economic Research Consortium collaborative project on poverty, labour market and income distribution issues in Sub-Saharan Africa, where she worked on both monetary and non-monetary measures of poverty(education and child nutritional status for Kenya). She also participated in a study visit to Laval University under the PEP project where she received some basic training on multidimensional poverty analysis. In August-September 2008, Dr. Kabubo-Mariara attended the Human Development Capability Association (HDCA) Summer School on ‘Capability and Multidimensional Poverty: Measurement and Analysis’ where she gained very useful knowledge on multidimensional poverty analysis.

Dr. Anthony Wambugu is a lecturer of Economics in the School of Economics, University of Nairobi. He received his M.A. degree from the University of Botswana and Ph.D. from the University of Gothenburg, Sweden under African Economic Research Consortium training fellowships. He conducts research on labour and human capital (health, education and nutrition) issues with a bias on utilization and impact on individual and household incomes. Current research includes, studying the link between prenatal and postnatal care; the impact of education on incomes and the relationship between employment and poverty. He has been a visiting scholar to the Centre of African Economies, Oxford University in 2002. In his research, Dr. Anthony Wambugu uses large scale household surveys and firm-level surveys and STATA computer software package. He has little previous experience in poverty analysis.
Ms. Esther Kimani holds a B.A. (Hons.) and Masters degree in Economics from the University of Nairobi. Currently she is a graduate assistant with the School of Economics, University of Nairobi. Her research interests are in the field of development economics, with a focus on household welfare and environmental issues. She has experience with field surveys and data entry but little experience with data analysis and report writing.

Ms. Susan Musau holds a B.A. (Hons.) in Economics from the University of Nairobi. Currently she is an M.A. Economics student in the School of Economics, University of Nairobi. She has no prior research experience.

10. **Expected Capacity Building for Researchers and Institutions**
This study has potential to build capacity in two ways: at the individual and institutional levels. At the individual level, Kimani and Musau (both female under 30 years) will participate as trainees and will benefit from the study in several ways: (i) Learn how to use large survey datasets (ii) Improve literature review skills (ii) Get first exposure to poverty analysis. (iii) Learn how to use various statistical software including STATA, DASP and get exposure to other training materials available from PEP to enhance analytical capacity. (iv) Develop report writing skills. (v). It is also expected that they will thereafter use this knowledge in their postgraduate research.

Wambugu has prior research experience in analysis of human capital, but no experience with core poverty analysis. Given his training background, he has the capacity to quickly grasp and apply new methodologies. By participating in this project, he expects to get exposure to poverty analysis and also learn about multidimensional poverty comparisons. Kabubo-Mariara expects to learn a lot more about multidimensional poverty comparisons through training and collaboration with PEP supervisors.

At the institutional level, the knowledge gathered by the two core researchers will be used in teaching and further research in the School of Economics. This will broaden the School’s research capacity and also pave way for increased collaboration between PEP (including PEP-Africa) and the School. It is also expected that the trainees may thereafter use this knowledge in doctoral research.

Kabubo- Mariara will be in charge of the overall implementation of the project and in training the junior researchers on all aspects of the projects. Wambugu will backstop the lead researcher and will specifically train the junior researchers on handling large data sets, literature review and use of STATA software. The junior researchers will participate in all aspects of the project under the guidance of the other researchers.

11. **Ethical, Social, Gender or Environmental Issues/Risks.**
We are not aware of any ethical, social, gender or environmental issues arising from the proposed study.

12. **List of Projects in Related Areas Involving Team Members.**
The lead researcher has participated in several projects on poverty in Kenya, focusing on both monetary and non-monetary measures of poverty and also the link between poverty and the environment. Some of the most relevant projects (and output) include:


**2003-2006: Collaborative AERC poverty project.** Output-


References


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Appendix: Alternative Multidimensional Poverty Indices

This appendix presents a brief review of alternative multivariate poverty comparisons to be explored in this paper, namely approaches developed by Tsui and Bourguignon & Chakravarty. In closely related approaches, Tsui (2002) and Bourguignon and Chakravarty (2003), extend the class of sub-group consistent poverty index to the multidimensional context. In particular, Tsui (2002) extends standard univariate axioms of unidimensional poverty indices to derive axioms tailored to the multivariate poverty context. These axioms include: continuity; symmetry; replication invariance; monotonicity; subgroup consistency; and ratio-scale invariance and are complemented with poverty specific properties of strong poverty focus, poverty criteria invariance, poverty non-increasing minimal transfer, and poverty non-decreasing rearrangement (Tsui 2002). Multidimensional poverty measures that satisfy these properties take the form (maintaining the same notation as in section 6.2):

\[ P_1(x;z) = \frac{1}{n} \sum_{i=1}^{n} \left[ \prod_{j=1}^{k} \left( \frac{z_j}{\min\{x_{ij};z_j\}} \right)^{\alpha_j} - 1 \right] \] \hspace{0.5cm} \text{(A1)}

where \( \alpha_j > 0, i=1,2,\ldots,k \), and the parameter \( \alpha \) has to be chosen to maintain convexity of the functions and

\[ P_2(x;z) = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{k} \delta_j \ln \left[ \frac{z_j}{\min\{x_{ij};z_j\}} \right] \] \hspace{0.5cm} \text{(A2)}

with \( \delta_j > 0, i=1,2,\ldots,k \)

Tsui then derives a class of nontrivial multidimensional poverty indices that satisfy the basic poverty index axioms if and only if there exists some strictly increasing function of \( P \) given by:

\[ P_{i1}(x;z) = \prod_{i=1}^{k} \left( \frac{z_j}{\min\{x_{ij};z_j\}} \right)^{\alpha_j} - 1 \] \hspace{0.5cm} \text{(A3)}

and

\[ P_{i2}(x;z) = \sum_{j=1}^{k} \delta_j \ln \left[ \frac{z_j}{\min\{x_{ij};z_j\}} \right] \] \hspace{0.5cm} \text{(A4)}

with \( P_i = 0 \) only for those above the poverty line in all dimensions. \( \alpha_i \) represents the contribution that the relative shortfall in attribute \( j \) makes to the individual’s poverty. The implicit poverty index (the first moment of the discrete empirical distribution of \( P_i \)) takes the form:

---

7 These studies have been criticized on the basis of aggregating the multiple measures of wellbeing into a one-dimensional index, thereby returning to a univariate analysis. To avoid that Duclos et al. (2006) suggested expanding poverty comparisons based on dominance criteria to cover multidimensional settings.
\[ P(x; z) = \frac{1}{n} \sum_{i=1}^{n} p_i \]  

Bourguignon and Chakravarty (2003) propose similar axioms to those of Tsui, but replace subgroup consistency with the separability axiom and allow for correlation increasing transfer to have either an increasing or decreasing effect on the evaluation of poverty, depending on the nature of the attributes involved. They derive a component poverty line based multidimensional poverty index that takes a general CES-like form:

\[
P^\beta(x; z) = \frac{1}{n} \sum_{i=1}^{n} \left( \sum_{j=1}^{k} w_j \left[ \max \left\{ 1 - \frac{x_{ij}}{z_j} ; 0 \right\} \right] \right)^{\gamma/\alpha + \beta} \]

In this case poverty shortfalls in univariate dimensions are aggregated into some average shortfall with a particular value of \( \alpha \) and \( \beta \). Multidimensional poverty is then defined as the average of that aggregate shortfall, raised to the power \( \alpha \), over the whole population. With \( \alpha = 0 \), \( P^\beta \) becomes a multidimensional headcount. With \( \alpha = 0 \), \( P^\beta \) becomes a multidimensional poverty gap, obtained by some particular averaging of poverty gaps in the two dimensions. \( P^\beta \) satisfies the non-decreasing poverty under correlation increasing switch or the converse property depending on whether \( \alpha \) is greater or less than \( \beta \) (Bourguignon and Chakravarty, 2003).