Multidimensional Poverty in Kenya: Analysis of Maternal and Child Wellbeing*

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Abstract
This paper generates multidimensional poverty profiles for women and children over a ten year period-1993 to 2003. Demographic and Health Survey data are utilized to advance the measurement of poverty in Kenya in four ways: First the paper constructs a composite poverty index (CPI). Second, it applies the Alkire and Foster (2007) approach to the measurement of multidimensional poverty based on the CPI and health status. Third, stochastic dominance approaches are used to make poverty orderings across groups. Fourth, the bi-variate Probit model is applied to explore the correlates of multidimensional poverty. The results show that: the distribution of poor women and children differ across groups, space and time; and the CPI and rural areas contributed more than health and urban areas respectively to multi-dimensional poverty. Results further suggest that understanding the correlates of wellbeing in a multidimensional context can generate policy insights for improving human capital investments.

Key words: Multidimensional poverty, composite poverty indicator, child health, stochastic dominance, Kenya.

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1. Introduction
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. In his seminal work, Sen (1976) referred to a two-stage process of measuring poverty, namely identification and aggregation. The identification stage 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 wellbeing sufficient to function.

However, the money-metric approach to poverty measurement has several drawbacks. The main drawback is that, 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 wellbeing 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 (Thorbecke, 2008).

Another approach to poverty measurement is the non-monetary approach. Sen (1985) and others have argued, however, that poverty should be viewed as a deprivation of ends rather than of means. It is indeed the ends (or, in Sen’s terminology, one’s capabilities to be well) that are intrinsically important for one’s well-being. Sen’s approach also suggests that policies should be evaluated not by their ability to satisfy utility or to increase income but to the extent that they enhance the capabilities of individuals and their ability to perform socially acceptable functioning. The non-monetary approach therefore considers wellbeing in terms of freedoms and achievements and assesses wellbeing 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). Consequently, poverty indices must capture the inability of individuals to achieve a minimal level of capabilities to function.

In the aggregation stage, individual level information is aggregated by means of indices (such as for a population subgroup or at a regional level). Although there are several suggestions extending unidimensional poverty indices to cover multiple dimensions, most formulations end up aggregating individual level information into a single measure (see for instance Tsui, 2002).

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2 Functionings are the “beings and doings” of a person whereas capabilities are the various combinations of functionings that a person can achieve. Capability is thus a set of vectors of functionings reflecting the person’s freedom to lead one type of life or another (Sen, 1985).
and Bourguignon and Chakravarty, 2003). Emerging literature that analyzes poverty as a multidimensional issue uses dominance approaches following Atkinson (1987) and Foster and Shorrocks (1988) in the unidimensional context (see for instance Duclos et al. 2006a, 2006b, 2006c; Sahn and Stifel, 2002). Duclos, Sahn and Younger, (2006a, 2006b, and 2006c) extend the methods of partial poverty orderings to multidimensional settings. Another alternative is Alkire and Foster (2007), 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. The first is the known dimension-specific threshold for identifying the individuals deprived in that dimension. The second 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, like in several other multi-dimensional poverty measures, an investigator has the freedom to assign different weights to each dimension.

This study analyses multidimensional poverty for women and children in Kenya. The focus on women and children is motivated by the fact that they comprise the largest proportion of the poor and vulnerable population in Kenyan. The study is further motivated by the potential debilitating long-term effects of maternal and child poverty on long term growth and development of children. Poverty comparisons are based on nutritional status and a household composite poverty indicator (CPI) Following Sen’s definition of wellbeing, child anthropometric measures and body mass index, both indicators of food and health deprivation, are considered more direct measures of capability deprivation than income and expenditure. Individual wellbeing 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. Unlike incomes and expenditures, these measures of wellbeing are also easily assessed at the individual rather than the household level.

A child/woman is considered poor if she comes from a household whose CPI is below a pre-determined poverty line and/or if her nutritional status is below a certain threshold. Stochastic dominance analysis is also carried out. In addition, a bi-variate Probit model of multidimensional poverty is estimated. Based on the findings, the paper suggests policies for improving maternal and child nutritional status in Kenya. The study contributes to the literature in three ways. First, it constructs a CPI, which allows the ranking of maternal and child health. This CPI is close to a deprivation index proposed under the Bristol approach (Gordon et al. 2003). Second, the study addresses a research gap on multidimensional poverty studies in Kenya. Previous studies have concentrated on unidimensional poverty comparisons, leading to partial understanding of poverty. Multidimensional poverty analysis can reveal complexities and ambiguities in the distribution of wellbeing that unidimensional poverty analysis cannot capture. Third, though women tend to be relatively more disadvantaged in human capital investments in Kenya, there is a dearth of studies on women’s nutritional status in Kenya. Yet the consequences of poor maternal nutrition are both long term and intergenerational (Meyerhoefer and Sahn, 2007).

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3 There is a dearth of multidimensional poverty studies in developing countries, more so in Africa, though the literature is growing. See the literature review section for relevant studies.
The rest of the paper is structured as follows: Section 2 provides background on maternal and child poverty in Kenya. Section 3 describes the data used. Section 4 presents the analytical frameworks and methodology. Section 5 reports the results and section 6 summarizes and concludes the report and also offers policy recommendations.

2. **Background and Context**

Kenya is a low-income, food-deficit country with a population of about 37 million and an estimated gross national income per capita of about US$1,470 in 2010 (PPP international). The Human development index was estimated at 0.47 in 1975 and rose to 0.52 in 2005. The Human poverty index was estimated to range between 37.5% in 2002 to 38.5% in 2005. For the same period, the gender related-development index is estimated to have increased from 0.49 to 0.52. The UNDP Human Development Index ranked Kenya 134th out of the 173 countries assessed in 2002, and 144th out of the 179 countries assessed in 2006 (UNDP, 2008). Life expectancy at birth stood at 54 years in 2007, down from 61 years in 1990, while HIV prevalence among adults aged 15 to 49 years was estimated to range between 5% and 7% between 2000 and 2009 (WHO, 2010).

Stagnation of food production, an unfavorable economic environment and poverty are the major causes of food insecurity in the country. The national dietary energy supply has for many years barely met population energy requirements, resulting in undernourishment for a third of the population (Republic of Kenya 2005. After independence in 1963, the Government of Kenya identified poverty, ignorance and disease as some of the major problems facing Kenya (Republic of Kenya, 1965). Since then, the development agenda of the country has placed emphasis on income growth, job creation and provision of basic social services. However, poverty and food insecurity remain widespread. The first national estimates of the incidence of poverty available for the country date back to early 1970s. In 1972 food poverty was estimated to afflict about 30% of the population. Thereafter, the incidence of rural poverty was estimated to be 38.5 % in 1974/75 (UNDP, 1999). The incidence of poverty is estimated to have risen to 46.8% in 1981/82. Thereafter, the incidence of poverty remained fairly constant between 1992 and 1994, when the percentage of the poor were estimated to range between 46.3% and 47% of the total population in the country. The percentage of the poor however rose to 52.3% in 1997 and to about 56% by the year 2000. The incidence of poverty thereafter declined to 47% in 2005/6 (KNBS, 2007). It is projected that the number of people living in poverty will increase to 65.9% by 2015 unless economic growth is accelerated to about 7% (UNDP, 2005; GoK, 2005 and GOF, 2005).

The majority of the poor and most vulnerable in rural areas are food and subsistence farmers and those who derive the bulk of their income from the urban informal sector. About a third of rural households are female-headed, and two-thirds of them have no male support. The incidence of severe poverty is significantly higher among such households (estimated at 44 percent compared to 20 percent for male-headed households in 1997). It is estimated that 69% of the active female population work as subsistence farmers compared to 43% of men (Republic of Kenya, 2007). Children from such households (and orphans) face higher risks of falling into poverty and vulnerability than their counterparts from male headed households.
Poor nutrition is one of the major problems affecting the most vulnerable—children and women in Kenya. Available evidence indicates that a large part of the population cannot satisfy their energy requirements. Malnutrition remains a significant contributing factor to deaths among under-five year old children. Nutritional deficiencies contribute to growth faltering, high rates of disability, illness and death particularly during the first two years of life. 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. There has been little or no progress in the nutritional status of women and children. In the period between 1960 and the late 1980s, child malnutrition declined, eventually stagnating in the late 1980s. In the 1990s, about 33% of children under five years in Kenya were estimated to suffer from chronic malnutrition. Though this dropped to about 30% by 2003, estimates from the 2008-9 demographic and health survey (CBS, MOH & ORC Macro, 2009) indicate that the percentage of stunted children in 2005/06 had risen to 35%. In the same period, other measures of child nutrition remained fairly constant (Appendix A, Table A1).

Multiple causes of malnutrition in children in Kenya include the lack of food, a diet that does not include necessary nutrients, common and preventable infections or illnesses that rob the body of nutrients, inadequate caretaking, and unsafe water that may cause diarrhoea or other illnesses. Others include short birth spacing, which may lead to early weaning of children such that they do not receive sufficient care during the first two to three years of life (Kabubo-Mariara, Nd’enge and Kirii, 2009). Exclusive breastfeeding rates are extremely low, estimated at about 13%. HIV/AIDS and related complications are a heavy burden on poor women, their children and orphans. Other major challenges include low prioritization, poor funding and limited understanding of nutrition issues across multiple sectors (UNICEF, 2009).

Our focus on women’s nutritional status is be motivated by the observation that women's nutrition affects a wide range of health and social issues, including pregnancy outcomes, family care, household food security, and local and national economic development. Nutritional deficiencies can have serious consequences, especially for child bearing women and is leading factor for maternal and infant mortality. Though statistics are scanty, iron deficiency anemia is the most common form of malnutrition, and afflicted about 56% of women in 1999 (CBS, MOH & ORC Macro, 2004). This is one of the leading causes of maternal death among pregnant women. Chronic energy deficiency among women leads to low birth weights and neonatal mortality. Vitamin A deficiency in pregnant and lactating mothers, and also in children is also a major challenge in Kenya. Iodine deficiency disorder is also prevalent in women and children. The average body mass index (BMI) for women in Kenya remained fairly constant between 1993 and 2003, but the proportion of women with low BMI increased by 2% (Appendix A, Table A1).

3. Data
This study uses three rounds of DHS data (1993, 1998 and 2003). The DHS collects information on nationally representative samples of women aged 15 to 49 and their children. The 1993 and 1998 data covered all regions of Kenya except North Eastern province. The 2003 data covered all provinces. The DHS data contains rich information on demographic, nutrition and health (including BMI and child anthropometrics) information about women and children and is therefore suitable to answer the research questions of this study. The DHS utilized a two-stage
The first stage involved selecting sample points (clusters) from a national master sample maintained by Central Bureau of Statistics (CBS, now Kenya National Bureau of Statistics) - 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.

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 7,950 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. After pooling the three rounds of DHS data and cleaning the data to make the samples comparable, we obtained a sample of about 12,500 children aged between 0 and 60 months and about 15,000 women aged 15 to 49 years. 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.

4. Analytical Framework and Methodology

4.1. Constructing a Composite Poverty Indicator: Methodological choices

Studies of multidimensional poverty begin by focusing on construction of a composite measure of poverty/wealth. To achieve objective one of this study, we construct a composite poverty indicator (CPI) that captures multiple aspects of household wealth recorded in the DHS survey. This CPI forms the basis of one of the dimensions of the multidimensional poverty comparisons in subsequent sections of the study. There are however major challenges in constructing a composite poverty indicator. Most prominent is the difficulty involved in the aggregation of the various types of assets into a single number that represents the total value of household 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 poverty indicator that stems from static mechanisms and is mainly based on multidimensional analysis techniques (Asselin, 2009). 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 preferred to the entropy approach for two reasons. First, it is less arbitrary in the definition of the functional form for the composite

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4 To make the samples comparable, it was necessary to recode some variables and also to omit North Eastern province which was not covered in the first 2 years of the survey.
indicator. Second, it enables an optimal choice among the relevant poverty dimensions to be made. Having settled on the inertia approach, the task that remains is the choice between different inertia approaches given the structure of the data available and the assumptions formulated on the indicators under study (Asselin, 2009; see also Ki, et al. 2005).

There are three main alternative approaches to construct a composite poverty indicator: the principal components analysis (PCA), factor analysis (FA) and multiple correspondence analysis (MCA). In this study, we use a two stage procedure to construction of the CPI. In the first stage, we use the MCA approach to estimate the individual scores for each dimension. In the second stage, using the continuous dimensional scores (estimated at the first stage), we perform a PCA estimation to compute the individual composite indicator of wellbeing, the CPI. The combination of MCA and PCA is appropriate because it ensures that estimation of the CPI captures the advantages of the MCA in the first step, the property of optimal scaling and avoids the disadvantages of the PCA in that PCA is applied only to continuous variables at the second stage. By using the normalized score (MCA score for each dimension divided by the square root of the first eigen value) before using the PCA data reduction procedure, this two-stage approach avoids overestimation of the contribution of dimensions with higher variability (Ki et al. 2005) and uncorrelated linear combinations of indicators of wellbeing are derived. The CPI derived is thus superior to those that can be derived from any single approach such as the factor analysis, the MCA or PCA.

4.2. Multidimensional Poverty Comparisons

Most literature on poverty measurement follows the one-dimensional approach, identifying a person as poor by means 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. The multidimensional poverty comparisons in this paper take into account both the identification and aggregation problems using two approaches: the stochastic dominance approach (Duclos, Sahn and Younger, 2006a) and the dual cutoff and counting approach (Alkire and Foster, 2007).

Duclos, Sahn and Younger extend approaches of partial poverty orderings to multidimensional settings. The approach can be illustrated based on the work of Chakravarty et al. (1998) and Tsui

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5 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, 2009).

6 The PCA and MCA approaches are discussed in Appendix C1. More information on the FA is available in a technical appendix to this report available from the authors upon request. Though FA has certain statistical advantages, it is not applied in this paper due to its limitations over the PCA and some technical difficulties associated with the approach (Asselin, 2009).
These authors developed desirable axioms for multidimensional poverty measures, viewing a multidimensional poverty index 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 the minimum level of basic needs (see Appendix C2.1 for details). This approach is applied to generate bi-dimensional poverty dominance surfaces using CPI and health dimensions of child poverty. We further extend the analysis to test for statistical significance of the dominance of poverty. We used DASP software (Araar and Duclos, 2007) to derive dominance curves and surfaces. The package is also used for the Alkire and Foster multidimensional poverty analysis.

Alkire and Foster (2007) proposed a new approach to multi-dimensional poverty measurement, which accommodates the extreme approaches (union and intersection) as well as intermediate options. In contrast to earlier approaches, the new approach uses a dual cutoff identification method. It also proposes a counting approach similar to the aggregation method in the Foster et al. (1984) family of poverty indices (see Appendix C2.2 for details). The application of the Alkire and Foster approach in this paper considers whether a child is poor in a wealth dimension measured by the CPI and in at least three 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. Since the multidimensional poverty indices can only be computed for positive values, we standardize the z-scores, as recommended by WHO and the Centre for Disease Control (Kuczmarski et al. 2002 (see Appendix C3)). For women, we consider whether a woman is poor in two dimensions, the CPI and the body mass index (BMI). We use the WHO recommendation of a BMI less than 18.5 as the poverty threshold. The BMI is conventionally computed as weight in kilograms divided by square of height in metres.

The choice of weights in multidimensional poverty analysis presents a challenge for construction of multidimensional poverty. The main methods of weighting proposed in the literature include equal weights, frequency-based weights, most favorable weights, multivariate statistical weights, regression based weights and normative weights (Decancq and Lugo, 2008). None of the weighting methods has been shown 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). The use of equal weights is the most common but controversial (Decancq and Lugo, 2008; Alkire and Foster, 2007). According to Atkinson (2003), equal weights is an arbitrary normative weighting system that is appropriate in some but not in all situations. In this paper, we use equal weights for child nutrition and CPI, but the nutrition specific weights are then divided equally between each of the three nested dimensions of child nutrition. For women, equal weights are assigned to the CPI and BMI.

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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.
5. Results
5.1 Construction of the Composite Poverty Indicator

5.1.1 Introduction
We compute the CPI based on a set of six domains. The choice of domains is informed by the need to capture multiple aspects of poverty based on first the universal definition of child poverty adopted by the UN general assembly in 2007 and the Bristol indicators of child deprivation\(^8\) (UNICEF, 2007; Gordon et al. 2003). The selected domains have been modified to capture various forms of wellbeing given the available data, and the need to ensure comparability from one survey year to another. The first domain reflects possession of assets by households at the time of the survey. While possession of these assets may reflect different needs (for instance: radio and TV for communication and entertainment; bicycle for transportation or recreation; refrigerator for comfort), all are expected to have positive scores and therefore a welfare improving effect reflected by a positive contribution to the CPI. The second domain captures the main source of drinking water in a household. Poor households are more likely to rely on surface water (rivers, springs, wells and other surface sources), while richer households are more likely to access piped water, either in own residence or from public taps.

The third domain we selected is sanitation to capture the environment within which a household operates. Ownership of a modern toilet such as a flush toilet would be expected to positively impact on the CPI. Pit latrine could also have a positive impact depending on whether it is an improved or a traditional pit latrine. No toilet and other forms of toilet (such as bush and flying toilets) reflect poverty and will have a negative contribution to the CPI. The fourth domain captures housing material. Low quality floor reflects unhygienic conditions, while a modern roof is expected to have a positive impact on CPI. The fifth and sixth domains- health and education capture the human capital dimensions of wellbeing. These would be expected to have differing impact on the CPI depending on accessibility and endowment. The health indicators reflect good access to health care at a cluster level. Higher education, attainment is expected to help households to escape poverty and thus a positive impact on the CPI.

5.1.2 The two step MCA/PCA composite poverty indicator
The CPI results are presented in Tables 1. The results are obtained by first using the MCA approach to estimate the individual scores for each dimension, then applying the PCA method to the continuous dimensional scores to compute the CPI. The results show that the largest weights are from household assets and source of drinking water. The lowest weight is from housing material. The two step approach yielded a more conservative estimate of the CPI than individual approaches (results not presented). Application of the PCA to the continuous variables (scores) derived from the first step MCA moderates the weights that enter into construction of the final CPI. This is because the MCA scores for each dimension are divided by the square root of the first eigen value before performing the PCA reduction. The computed CPI was normalized to

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\(^8\) According to the UN assembly, ‘Children living in poverty are deprived of nutrition, water and sanitation facilities, access to basic health-care services, shelter, education, participation and protection, and while a severe lack of goods and services hurts every human being, it is most threatening and harmful to children, leaving them unable to enjoy their rights, to reach their full potential and to participate as full members of the society’ (UNICEF 2007). The Bristol indicators include: food, water, sanitation facilities, health, shelter, education and information (Gordon et al. 2003).
positive values\(^9\). Though this has been contended in the literature, it does not affect the distribution of poor and non-poor children/women in our sample.

<table>
<thead>
<tr>
<th>Indicators</th>
<th>Contribution (%)</th>
<th>Weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household assets</td>
<td>9.07</td>
<td>0.543</td>
</tr>
<tr>
<td>Source of drinking water</td>
<td>29.14</td>
<td>0.404</td>
</tr>
<tr>
<td>Sanitation</td>
<td>19.62</td>
<td>-0.278</td>
</tr>
<tr>
<td>Housing material</td>
<td>16.44</td>
<td>-0.606</td>
</tr>
<tr>
<td>Access to health care</td>
<td>12.28</td>
<td>0.331</td>
</tr>
<tr>
<td>Education attainment</td>
<td>13.46</td>
<td>0.245</td>
</tr>
</tbody>
</table>

*Source: Authors’ computations from DHS data*

### 5.2 Incidence of Multi-dimensional Poverty

In this subsection, we discuss the incidence of poverty based on the composite poverty indicator derived above, the standardized scores for children and BMI for women. First we standardize the anthropometric measures and then define the poverty thresholds for each poverty indicator. The later enables us to compare poor vs. non-poor groups. For the CPI, the cutoff is based on a relative poverty line set at the 40\(^{th}\) percentile. The dimensional cutoff for CPI is 2.3692\(^{10}\). That is, a child is poor if he/she comes from a household whose CPI is less than 2.4. The poverty thresholds for standardized health indicators are based on the usual -2 z-scores. The dimension cutoff for standardized height for age is 79.10, the cutoff for weight for height is 9.36 and the cutoff for weight for age is 10.03. The cut off for BMI is 18.5. The sample statistics are presented in Table A2. The results show that about 32\% of all children are found to be height for age poor (stunted) or suffering from long term or chronic malnutrition, 9\% are weight for age poor (underweight) while 11\% are weight for height poor (wasted). The average BMI is 22 for rural areas and the full sample, but 24 for urban areas. The results in the table suggest that poverty is basically a rural phenomenon. The largest rural-urban differential is observed in the CPI dimension of poverty. 84\% of the households are found in rural areas, and the rest are urban.

Table 2 shows the incidence of poverty by region and poverty dimension. In all dimensions of poverty, Nairobi and Central are least poor in terms of the composite poverty indicator. Nyanza is the wealth poorest province followed by Western and Coast provinces. Eastern and Coast provinces are poorest in all child health measures.

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\(^9\) Normalization involves adding the absolute value (\(C_{\text{min}}\)) of the average of the minimum categorical weight (\(w_{\text{min}}^{k}\)) of each indicator to the CPI of each household to obtain a positive CPI score. Asselin (2009) expresses the average minimum weight as: 

\[
C_{\text{min}} = \frac{\sum_{k=1}^{K} w_{\text{min}}^{k}}{K}
\]

\(^{10}\) The alternative thresholds are 1.87 and 3.04 for 25\(^{th}\) and 60\(^{th}\) percentiles respectively. The results using these thresholds are not presented in this report to save on space.
The highest incidence of body mass index poverty is within women located in Rift Valley, Coast and Eastern provinces.

Table 2: Incidence of Multi-dimensional Poverty in Kenya by Region and poverty dimension (%)

<table>
<thead>
<tr>
<th>Region</th>
<th>CPI poor</th>
<th>HAZ poor</th>
<th>WAZ poor</th>
<th>WHZ poor</th>
<th>BMI poor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nairobi</td>
<td>2.06</td>
<td>13.94</td>
<td>1.71</td>
<td>1.89</td>
<td>4.04</td>
</tr>
<tr>
<td>Central</td>
<td>15.59</td>
<td>23.09</td>
<td>5.60</td>
<td>6.18</td>
<td>6.38</td>
</tr>
<tr>
<td>Coast</td>
<td>43.67</td>
<td>27.82</td>
<td>9.34</td>
<td>11.12</td>
<td>12.88</td>
</tr>
<tr>
<td>Eastern</td>
<td>32.21</td>
<td>30.17</td>
<td>8.49</td>
<td>10.74</td>
<td>10.04</td>
</tr>
<tr>
<td>Nyanza</td>
<td>47.07</td>
<td>25.73</td>
<td>5.63</td>
<td>7.95</td>
<td>8.33</td>
</tr>
<tr>
<td>Rift Valley</td>
<td>42.00</td>
<td>24.27</td>
<td>7.25</td>
<td>9.92</td>
<td>14.93</td>
</tr>
<tr>
<td>Western</td>
<td>45.47</td>
<td>24.83</td>
<td>6.36</td>
<td>7.88</td>
<td>6.55</td>
</tr>
<tr>
<td>Urban</td>
<td>5.61</td>
<td>16.41</td>
<td>3.44</td>
<td>4.28</td>
<td>4.97</td>
</tr>
<tr>
<td>Rural</td>
<td>42.28</td>
<td>26.78</td>
<td>7.37</td>
<td>9.42</td>
<td>10.86</td>
</tr>
<tr>
<td>National</td>
<td>36.52</td>
<td>25.15</td>
<td>6.76</td>
<td>8.61</td>
<td>9.94</td>
</tr>
</tbody>
</table>

*Source: Authors’ computations from DHS data*

Map 1 (Appendix B) presents the CPI and health based FGT head count indices for children by district. First it is important to note that the estimates for Garissa, Wajir, Mandera, Marsabit and Turkana districts are interpolated from neighbouring districts and should therefore be interpreted with caution. The map suggests that there is low correlation between the CPI and health poverty. CPI poverty is concentrated in the Western and Nyanza, some parts of the Rift Valley regions, Coast province and some parts of Eastern province (Kitui district). Health poverty is more concentrated in the Northern part of Kenya, Coast and Rift Valley provinces. Map 2 shows that the distribution of poor women across regions in Kenya is similar to the distribution of poor children, but there is a higher concentration of poor children in the Coast and lower Eastern province, but more poor women in some parts of the Rift Valley province.


5.3.1 Child poverty

*Poverty estimates*

This section presents selected child poverty results based on the Alkire and Foster (2007) dual cutoff and counting approach to multidimensional poverty measurement. Our multidimensional poverty estimates are based on two dimensions: the CPI and child health. Three child health indicators were considered: standardized height for age, standardized weight for age and standardized weight for height. CPI and child health are assigned equal weights (each a weight of 2), but each child health indicator is assigned nested weights (0.667). The analysis is based on the poverty lines/thresholds defined earlier. Table 3 presents the multidimensional poverty indices for selected cutoffs. We can see from the table that the estimated index depends on the cutoff (k). In other words, the estimated poverty index will depend on the sum of weights of the deprivations a child experiences. It can also be observed from the table that the poverty measure decreases with the level of k (Batana, 2008). For instance, taking the head count ratio (H), 41% of the children are multidimensionally poor when the sum of weights of the deprivations (k)
experienced by the children equal 1, compared to 5% for k=3. No child is poor when k=4. The adjusted head count ratio (M0) however suggests that for the same cut offs, 24% and 4% (respectively) of the children are poor. The corresponding adjusted poverty gap (M1) and adjusted gap squared (M2) are quite low.

### Table 3: Alkire and Foster Child Multidimensional Poverty Indices

<table>
<thead>
<tr>
<th>Cutoff k</th>
<th>H</th>
<th>M0</th>
<th>M1</th>
<th>M2</th>
<th>H</th>
<th>M0</th>
<th>M1</th>
<th>M2</th>
<th>H</th>
<th>M0</th>
<th>M1</th>
<th>M2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.412</td>
<td>0.242</td>
<td>0.055</td>
<td>0.021</td>
<td>0.463</td>
<td>0.273</td>
<td>0.063</td>
<td>0.025</td>
<td>0.105</td>
<td>0.055</td>
<td>0.007</td>
<td>0.002</td>
</tr>
<tr>
<td>2</td>
<td>0.144</td>
<td>0.111</td>
<td>0.023</td>
<td>0.009</td>
<td>0.164</td>
<td>0.127</td>
<td>0.027</td>
<td>0.01</td>
<td>0.022</td>
<td>0.017</td>
<td>0.003</td>
<td>0.001</td>
</tr>
<tr>
<td>3</td>
<td>0.051</td>
<td>0.049</td>
<td>0.009</td>
<td>0.003</td>
<td>0.059</td>
<td>0.056</td>
<td>0.01</td>
<td>0.004</td>
<td>0.007</td>
<td>0.007</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

**Source:** Authors’ computations from DHS data

### Decomposing poverty: Location, dimension and other sub groups

In this section, we decompose the Alkire and Foster (2007) M’s class of indices to assess the contribution of various subgroups to overall multidimensional poverty. The last two column panels of Table 3 present the Alkire and Foster (2007) multidimensional poverty indices by area of residence. Consistent with monetary measures of poverty in Kenya, poverty rates are highest in rural areas, with 46% of children multidimensionally poor when \( k=1 \), compared to 11% in urban areas. 6% and 1% of the kids are multidimensionally poor in rural and urban areas respectively when \( k=3 \). The trend in poverty indices observed in the full sample is reflected in the indices for area of residence. We further decompose the Alkire and Foster indices by district. The results presented in Map 3 show that for \( k=1 \), child multidimensional poverty is concentrated in Nyanza, Western and Coast provinces of Kenya, with the highest incidence observed in West Pokot (54%) and Lamu districts (44%). For \( k=3 \), less children are poor in Nyanza, and some parts of Coast province. Comparing the district maps that we have generated with available district level poverty incidence (FGT head count) map (Map 4), we can see that there is low correlation between dimensions of wellbeing. However, CPI and income/expenditure based poverty seem to rank regions fairly closely, with large concentration of poverty in lower Eastern, Coast, Western and Nyanza provinces.

We further investigate the relative contribution of location (residence and region) to the Alkire and Foster multidimensional poverty indices (results not presented). We find that rural areas account for more than 95% of overall multidimensional poverty. The results for contribution of regions suggest that Rift Valley province contributes the highest to all multidimensional poverty indices. The lowest contribution from rural provinces is from Central province. The contribution of Nairobi province is almost zero. However, actual poverty indices indicate that Nyanza province reported the highest incidence of child poverty for value of \( k \) between 1 and 2, while Coast province reported the highest incidence for values of \( k>3 \).

One issue with the Alkire and Foster class of poverty indices is that they are not additively decomposable and thus it is controversial to decompose the indices across dimensions. The adjusted head count and poverty gaps can however be decomposed by taking into account the number of poor adjusted by the number of dimensions. The relative contributions of various dimensions of poverty to overall multidimensional poverty are reported in Table 4. The results suggest that the highest contribution to the poverty indices is from the CPI, ranging from 50% to 99% for different M’s at different dimensional cutoffs. The contribution from health indicators is
quite modest and is most pronounce for M0. Height for age (haz) constitutes the largest contribution towards health deprivation (except for M0 for k>2.5), followed by weight for height (whz).

Table 4: The relative contribution of dimensions to the Alkire and Foster child MDP indices

<table>
<thead>
<tr>
<th>Cutoff k</th>
<th>CPI</th>
<th>haz</th>
<th>whz</th>
<th>waz</th>
<th>CPI</th>
<th>haz</th>
<th>whz</th>
<th>waz</th>
<th>CPI</th>
<th>haz</th>
<th>whz</th>
<th>waz</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>74.33</td>
<td>12.48</td>
<td>7.31</td>
<td>5.88</td>
<td>94.99</td>
<td>2.68</td>
<td>1.15</td>
<td>1.18</td>
<td>99.04</td>
<td>0.54</td>
<td>0.18</td>
<td>0.24</td>
</tr>
<tr>
<td>2</td>
<td>64.82</td>
<td>20.46</td>
<td>8.13</td>
<td>6.59</td>
<td>92.72</td>
<td>4.28</td>
<td>1.46</td>
<td>1.54</td>
<td>98.66</td>
<td>0.79</td>
<td>0.24</td>
<td>0.32</td>
</tr>
<tr>
<td>3</td>
<td>52.08</td>
<td>15.72</td>
<td>17.36</td>
<td>14.83</td>
<td>86.5</td>
<td>5.66</td>
<td>3.82</td>
<td>4.02</td>
<td>97.11</td>
<td>1.36</td>
<td>0.66</td>
<td>0.87</td>
</tr>
</tbody>
</table>

Source: Authors’ computations from DHS data

We also explored for gender differentials in multi-dimensional poverty. Decomposition of poverty by gender of child (results not presented) suggested that for all possible poverty cutoffs, boys contribute more to multidimensional poverty than girls, but the difference is marginal. Results by year of survey further suggest that multidimensional poverty dropped marginally between 1993 and 1998, but significantly between 1998 and 2003 (results not presented to save on space).

Robustness checks and sensitivity analysis
To check for robustness of the results, we assess the sensitivity of the poverty indices presented above to changes in the CPI poverty line. Two alternative poverty lines are considered: the 25th percentile, with a CPI of 1.8626 and a 60th percentile, with a poverty line of 3.04. To save on space, we only present and discuss results for decomposition of poverty indices into various subgroups based on the 25th percentile. The results for the 60th percentile are actually consistent with results for the other two alternative poverty lines. The results for suggest that Rift Valley made the largest contribution to child poverty, while Nairobi and Central provinces contributed the least. We also observe that rural areas contributed between 96% and 100% to overall poverty. The largest contribution of dimensions was from the CPI, ranging from 52% to 98%. Except for M0 when k=3, haz marked the largest contribution among health indicators to multidimensional poverty. The results (including multidimensional poverty indices) are consistent with the results using the 40th percentile of the CPI as the poverty line. The results suggest that the Alkire and Foster (2007) multidimensional poverty orderings are robust to the choice of the poverty line.

5.3.2 Women’s Poverty
Poverty estimates
The Alkire and Foster (2007) approach applied to women’s poverty is based on two main indicators of poverty: CPI and BMI. These two dimensions are assigned equal weights (each a weight of 1) and for each dimensions, we set poverty lines/cutoffs below which a woman is deemed poor. Like for children, the CPI cutoff is based a relative poverty line of 40th percentile, with a dimensional cutoff equal to 2.3692. For the BMI, the poverty line is set at 18.5. Thus a woman who has a BMI lower than 18.5 or is from a household with a CPI less than 2.4 is considered poor.
The Alkire and Foster (2007) women multidimensional poverty indices are presented in Table 5. The results show that 44% of all women are poor at \( k=1 \) or in at least one dimension, compared to only 5% who are poor when \( k=2 \). Like for children, the proportion of multidimensionally poor women is higher in rural (compared to urban) areas at 50% and 6% for 1 and 2 dimensional cut offs respectively.

<table>
<thead>
<tr>
<th>Group</th>
<th>( K=1 )</th>
<th>( K=2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>H0  M0  M1  M2</td>
<td>H0  M0  M1  M2</td>
</tr>
<tr>
<td>Urban</td>
<td>0.138 0.074 0.011 0.003</td>
<td>0.01 0.01 0.002 0.001</td>
</tr>
<tr>
<td>Rural</td>
<td>0.492 0.274 0.071 0.029</td>
<td>0.057 0.057 0.011 0.004</td>
</tr>
<tr>
<td>Full Sample</td>
<td>0.44 0.245 0.062 0.025</td>
<td>0.05 0.05 0.01 0.004</td>
</tr>
</tbody>
</table>

Decomposing poverty: Location, dimension and other sub groups
Decomposition of women’s multidimensional poverty into various subgroups suggests that Rift Valley leads in the contribution to women poverty, while Central province makes the lowest contribution from rural provinces. The results further show that rural areas contributed more than 95% of women’s multidimensional poverty. For dimensions, the CPI contributed the largest proportion to Alkire and Foster multidimensional poverty among women. Comparing district maps for the Alkire and Foster multidimensional poverty indices for women (not presented to save on space) with Map 3 suggests that this approach ranks provinces differently in terms of concentration of poor women and children by the two dimensions of wellbeing. While the poorest children are from coast and western provinces, the poorest women are from districts located in the Rift Valley and North Eastern provinces. Multidimensional poverty indices for women by year of survey (results not presented) show that poverty declined between 1993 and 2003. Like for children, the decline was more pronounced between 1998 and 2003.

Robustness checks and sensitivity analysis
We further test the sensitivity of the poverty indices for women to changes in the CPI poverty line. Based on the 25\(^{th}\) percentile CPI poverty line defined earlier, the results for women are consistent with those for the 40\(^{th}\) percentile CPI threshold, (and also results for children). Rift Valley province contributed the most to multidimensional poverty (ranging from 30% to 42% for two cut offs, \( k=1 \) and \( k=3 \)), while Nairobi and Central contributed the least. The results for contribution by area of residence and dimensions are also consistent with results presented earlier. These results support earlier findings for children that the Alkire and Foster multidimensional poverty orderings are robust to the choice of the poverty line.

5.4 Stochastic Dominance Analysis
In this paper, stochastic dominance analysis is based on Duclos, Sahn and Younger (2006a). We test for dominance of the CPI and health poverty between rural and urban areas, and between regions. The dominance results for women are fairly close to those for children. To save on space, the results for women are not presented.
5.4.1 Unidimensional stochastic dominance
The first order dominance tests for children are presented in Figure 1. The results in figure 1(i) show that Nairobi clearly dominates all regions in CPI poverty. We however observe no dominance between the other provinces, except for Central province, which clearly dominates all other provinces for a CPI range of 1.5 to 4.6 points. Figure 1(i) also suggests that Nairobi province dominates other provinces in child health except at very low nutrition thresholds. Eastern province seems to be dominated by all other regions for nutrition thresholds between 72 and 86 scores. There is no clear pattern of dominance between other provinces. The dominance results by area of residence and gender (not presented) suggests show that urban areas clearly dominate rural areas in CPI poverty, but dominate rural areas in nutrition poverty only beyond a standardized height for age of 72 scores. The results further suggest that the difference in poverty over all thresholds is less pronounced for nutrition than for the CPI. Results further suggest that there is no dominance of wealth poverty between girls and boys, but that girls dominate boys in nutritional wellbeing.

![FGT Curves (alpha=0)](image)

i). CPI by region

ii). Nutrition by region

Figure 1: FGT curves for CPI and nutrition by region

5.4.2 Bi-dimensional stochastic dominance with statistical significance
We test for bi-variate poverty dominance across different groups using bi-dimensional dominance surfaces by comparing between the zero surface and the upper bound surface of the confidence interval of the difference in poverty between two distributions. If the upper bounds are everywhere below zero, then we can conclude that poverty in one region is lower than poverty in another region. The results in figure 2 show the upper bound of the confidence intervals of the difference between poverty dominance surfaces for Nairobi and Central provinces. In this case, the upper bound surface is everywhere below zero, thus poverty in Nairobi is lower than poverty in Central province. We say also that Nairobi dominates Central region in welfare.
This type of graph however does not allow us to test for statistical significance of dominance across groups. To do so, we instead use the map view two dimensional graphs presented in Appendix A, Table A3. To interpret the graphs, we magnify the Nairobi-Central provinces graph in figure 3, where Nairobi in the row and Central in the column position. The vertical y-axis of the graph presents health (standardized nutrition scores), while the horizontal x-axis presents CPI scores. A white color indicates that for a particular combination of poverty lines (x,y) values, for instance (5, 75), the difference in poverty between Nairobi and Central province is below 0 (the upper bound of the confidence interval of this difference is below 0). That is, the condition that Nairobi is less poor than Central province is satisfied with statistical robustness. A gray color indicates that the condition that Nairobi is less poor than Central province is not satisfied considering statistical robustness.
Looking at the corresponding graph for the difference between Central and Nairobi (graph 1,2) in Table A3, it is apparent that the dominance condition is not satisfied in most instances, except for a few observations for standardized nutrition scores between 67 and 70 and CPI scores between 4 and 7. This shows that it is difficult to give a complete ranking of provinces by the two measures of wellbeing. In other words, the statistical robustness is not 2 way: the ranking of (x,y – say difference between Nairobi and Central provinces) is completely different from the ranking of (y,x - difference between Central and Nairobi). The other graphs show that for nutrition thresholds above 72, Nairobi province dominates all other provinces in well being. Central province also dominates all provinces (except Nairobi) beyond some threshold of the two measures of wellbeing. The results further suggest that Coast and Eastern provinces fared worst when welfare is evaluated in the two measures of wellbeing.

5.5 Multidimensional Child Poverty: an Econometric Analysis

5.5.1 Introduction
In this section, we explore the correlates of multidimensional poverty in Kenya. Within the monetary approach to poverty measurement, many empirical studies have used the Logit model to show the factors that contribute significantly to the probability of being poor. Because we have two dimensions (CPI and health) of wellbeing, we propose a more appropriate econometric model - the bi-variate Probit model (see Appendix C4 for specification). This choice is justified by the following two reasons: First, an individual may experience any of the two dimensions of poverty or the two together. Second, it is expected that the two indicators of wellbeing, which form the latent variables under the proposed econometric specification, may be partially correlated.

5.5.2 Descriptive results
Figure 4 shows the partial correlation between the two dimensions of wellbeing (latent variables). A positive correlation is portrayed by the direction that we observe for the pick-mountain of the joint density function and that of the 45° diagonal line. This justifies use of the bi-variate Probit model.
5.5.3 Econometric Results

Introduction

Since CPI and health poverty are not determined by the same factors, we estimate the seemingly unrelated bi-variate model of multidimensional poverty. The estimation results are presented in Table 6. The Wald Chi(2) test shows that the bi-variate model fits the data better than the individual Probit models. This is also supported by Wald chi2(1) test for significance of rho { (Chi2(1)= 21.668)}, which shows that although rho is quite small (0.06), it is statistically significant. Among the goodness of fit tests is the classification test. Usually, with the Logit or Probit models, we assume that the predicted zero outcome is that where the predicted probability is lower than half, and the predicted successful outcome is one where the predicted probability is higher than half. With the bi-Probit model, it is not easy to specify the cutoffs. The classification test, that we propose, is by assigning the predicted outcome to the concordant highest predicted probability. Using this proposed test of classification, we find that about half of observed real cases were predicted with the estimated bi-variate Probit model.

The last column of Table 6 presents the marginal impacts of the explanatory variables on the probability of being poor in both CPIs and health. The interpretation of the marginal effects can be illustrated with the effect of education. The estimated marginal effect shows that attainment of secondary education reduces the likelihood of being multidimensional poor by 0.11 points, while attainment of post secondary education reduces this probability by 0.098 points. Where a variable only explains one dimension of poverty, the marginal impact is the effect of that variable on the likelihood of being poor in that dimension, given that the child is also poor in the other dimension. For instance, the presence of small children increases the probability of being CPI poor by 0.002 points. Other marginal effects can be interpreted in the same way. The results show that education attainment and access to electricity exert relatively high marginal impacts on the probability of being multidimensional poor. We also observe high marginal impacts on the

Figure 4: Bi-variate standard normal density function

\[ f(x,y) \]

\[
\begin{align*}
\text{Nutrition - haz} & \quad \text{Assets - CPI} \\
10 & \quad 105 \\
95 & \quad 100 \\
90 & \quad 95 \\
85 & \quad 90 \\
80 & \quad 85 \\
75 & \quad 80 \\
70 & \quad 75 \\
65 & \quad 70 \\
60 & \quad 65 \\
55 & \quad 60 \\
50 & \quad 55 \\
45 & \quad 50 \\
40 & \quad 45 \\
35 & \quad 40 \\
30 & \quad 35 \\
25 & \quad 30 \\
20 & \quad 25 \\
15 & \quad 20 \\
10 & \quad 15 \\
5 & \quad 10 \\
0 & \quad 5 \\
0.005 & \quad 0.05 \\
0.01 & \quad 0.1 \\
0.015 & \quad 0.15 \\
0.02 & \quad 0.2 \\
0.025 & \quad 0.25 \\
0.03 & \quad 0.3 \\
0.035 & \quad 0.35
\end{align*}
\]
probability of being CPI poor from geographical location. Nyanza, Western and Rift valley provinces exert higher marginal impacts relative to Nairobi province. Individual factors for health poverty have low marginal impacts.

**Probability of being CPI poor**

We investigate the impact of household characteristics, mother’s education, access to electricity and regional characteristics. To avoid potential econometric problems such as reverse causality, we omit all variables that entered into the calculation of the CPI index. The results show that the number of children less than 5 years old in a household increases the probability of a household being poor. There are two possible explanations for this: first specialized consumption requirements for young children are likely to strain household consumption patterns. Second, more children will divert labour (especially women’s time) from productive economic activities and therefore lower incomes and consumption.

Education and skill acquisition at the household level are captured by mother’s education. The results show that relative to no and primary education, secondary and post secondary education exert a significant and decreasing impact on the probability of being CPI poor. Education contributes to the process of moulding attitudinal skills and developing technical skills, and also facilitates the adoption and modification of technology. Limited access to education also affects the ability of the population to get non-farm employment and to obtain information that would improve the quality of their lives.

Electricity in this model is used to capture two factors: community level infrastructure development and household standards of living. The results show that households with access to electricity have a lower likelihood of being poor than their counterparts without electricity. This suggests that at the community level, infrastructure is a major factor for escaping poverty. The result also suggests that poor households are less likely to have access to electricity than the less poor.

Provincial dummies are included to capture regional level characteristics. Poverty is expected to be high in regions characterized by geographical isolation, a low resource base, low rainfall, and other inhospitable climatic conditions. Differences in poverty by regions could also be due to the governance system, supporting policies (environmental, economic, and political) and social capital investments. The results show that relative to Nairobi, all other provinces are much poorer in wealth. The marginal effects suggest that children from Nyanza province face the highest likelihood of being CPI poor, while children in Central province face the lowest probability. Children from Western, Rift valley and Coast province also face relatively high probabilities of being poor. These results suggest the need to investigate further the regional determinants of poverty in Kenya.
Table 6: Bi-Probit model of Multidimensional Poverty: Estimated Marginal Effects

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pr(CPI poor)</th>
<th>Pr(Health poor)</th>
<th>Pr (CPI poor, health poor)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Child characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male child dummy</td>
<td>-0.0182***</td>
<td>0.0306***</td>
<td>0.0130***</td>
</tr>
<tr>
<td>Number of children &lt;5 years</td>
<td>0.0039**</td>
<td>0.0026***</td>
<td>0.0013***</td>
</tr>
<tr>
<td>Age of child (months)</td>
<td></td>
<td>0.0706***</td>
<td></td>
</tr>
<tr>
<td>Child is of multiple birth</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Household characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mothers height</td>
<td>-0.0064***</td>
<td>-0.0032***</td>
<td></td>
</tr>
<tr>
<td>Mother has secondary education</td>
<td>-0.2900***</td>
<td>-0.0695***</td>
<td>-0.1575***</td>
</tr>
<tr>
<td>Mother has post secondary</td>
<td>-0.4147***</td>
<td>-0.0835***</td>
<td>-0.2389***</td>
</tr>
<tr>
<td>Log household size</td>
<td>0.0120***</td>
<td></td>
<td>0.0060***</td>
</tr>
<tr>
<td><strong>Housing &amp; environmental</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Household has electricity</td>
<td>-0.4292***</td>
<td>-0.1240***</td>
<td>-0.2146***</td>
</tr>
<tr>
<td>House has rudimentary floor</td>
<td>0.0003***</td>
<td>0.0001***</td>
<td>0.0001***</td>
</tr>
<tr>
<td>Unsafe drinking water</td>
<td>0.0133**</td>
<td>0.0066**</td>
<td></td>
</tr>
<tr>
<td>Unsanitary toilet conditions</td>
<td>0.0267***</td>
<td>0.0133**</td>
<td></td>
</tr>
<tr>
<td><strong>Regional dummies</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Central province</td>
<td>0.1403***</td>
<td></td>
<td>0.0564***</td>
</tr>
<tr>
<td>Coast province</td>
<td>0.3141***</td>
<td></td>
<td>0.1262***</td>
</tr>
<tr>
<td>Eastern province</td>
<td>0.2469***</td>
<td></td>
<td>0.0992***</td>
</tr>
<tr>
<td>Nyanza province</td>
<td>0.3867***</td>
<td></td>
<td>0.1554***</td>
</tr>
<tr>
<td>Rift valley province</td>
<td>0.3417***</td>
<td></td>
<td>0.1373***</td>
</tr>
<tr>
<td>Western province</td>
<td>0.3566***</td>
<td></td>
<td>0.1433***</td>
</tr>
<tr>
<td><strong>Survey year dummy</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1998 survey year</td>
<td>-0.0373***</td>
<td>0.0451***</td>
<td>0.0112***</td>
</tr>
<tr>
<td>2003 survey year</td>
<td>-0.1170***</td>
<td>0.0499***</td>
<td>-0.0445***</td>
</tr>
<tr>
<td>Athrho</td>
<td>0.0604***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>25984</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wald chi2(26)</td>
<td>4525***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log pseudo likelihood</td>
<td>-29068.975</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1

We control for the year of survey by introducing dummy variables for 1998 and 2003 survey periods. This captures the trend in poverty over the three DHS periods. The results suggest that wealth based poverty decreased over the survey period. This suggests a growth in the CPI, which can be explained by improvements in the domains constituting the CPI: household assets, access to safe drinking water, sanitation, housing material, access to health care and education. These could in turn have resulted from growth in per capita incomes and development of infrastructure over the 10 year period. However, the marginal effects suggest that the decline in wealth based poverty over this period was quite modest.

**Probability of being health poor**

We investigate the impact of child, household and environmental characteristics on the probability of a child being health poor (stunted). The male child dummy results show that boys are more likely to be stunted than girls. This supports studies that have shown vulnerability of the boy child to health poverty in developing countries. The age of the child is inversely
correlated with the probability of being health poor. This finding can be explained by changes in feeding patterns as a child grows older. With cessation of breastfeeding and weaning, children become more vulnerable to malnutrition. However, children who are completely weaned are likely to get adequate nutrients from regular food intake, thereby improving their nutritional status (Shrimpton et al. 2001, (Kabubo-Mariara, Nd’enge and Kirii, 2009). Shrimpton et al. 2001 have shown that although children’s height fall sharply from birth to 24 months, the process of stunting continues at a much slower rate after the 24th month. Our results further show that children of multiple births are likely to be more health poor than singletons. The marginal effects suggest that health poverty increases by 0.04 points if a child is of a multiple birth compared to those of single births. Compared to singletons, twins are likely to be born with relatively lower birth weight, are likely to get inadequate breast feeding and to compete for nutritional intake with the sibling.

Household characteristics include household size and mothers’ characteristics (education and height). Mother’s height is negatively correlated with the probability of being health poor. The marginal effect is highly significant, but low. Height captures the genetic effects and the effects resulting from family background characteristics. Maternal education is inversely correlated to the likelihood of being health poor. Children’s nutrition also improves with an increase in the level of mother’s education relative to no or primary education. Maternal education improves nutrition through altering the household preference function and also through better child care practices. This result suggests the importance of human capital investments in improving children’s nutritional status. Household size is inversely correlated to children’s health status. This could be due to competition for food among siblings and implies the need to encourage family planning and increase advocacy for smaller families.

Housing standards are measured by two factors: access to electricity and the material of the floor of the main dwelling house, both indicators of living standards. Literature suggests that the poor have little or no access to electricity and live in precarious, less sanitary dwellings, which contribute to poor health and lower productivity of household members. The results show that children who live in households with access to electricity are likely to be less health poor than their counterparts with access to electricity. Children who live in dwellings that have unsanitary/rudimentary floors face a higher probability of being health poor than other children. Children without access to electricity and living in unsanitary housing conditions are likely to reside in rural areas and urban slums.

Two variables are included to capture the environment in which a child lives: quality of water and sanitation. The results show that children from households that use water from low quality (unprotected) sources are likely to be 0.007 points more vulnerable to health poverty than children who have access to better quality water. A child from a household that either has no toilet or has a traditional pit latrine is 0.013 times more likely to be health poor, compared to a child with better toilet facilities.

The results for year of survey show that relative to 1993, health poverty was higher in 1998 and 2003. However, we do not observe a significant difference between 1993 and 2003. The marginal effects show that multidimensional poverty increased between 1993 and 1998, but declined between 1993 and 2003.
7. Discussion

7.1 Summary and Conclusion
Most of the previous research on poverty in Kenya has focused on unidimensional measures of poverty based on either income or expenditure measures. Previous studies have however shown that the incidence rates of poverty and deprivation differ substantially in terms of magnitude; that high-risk poverty characteristics do not necessarily correspond to high-risk deprivation characteristics; and that the relation between monetary poverty and deprivation is positive but not very strong (Notten, 2009). Many children who qualify as severely deprived in physical dimensions (e.g. water and sanitation, housing, transportation and communication) would not qualify as poor in monetary terms. A monetary poverty indicator would thus substantially underestimate the severity of material deprivation. Studies of non-monetary poverty in Kenya have focused on single measures of deprivation/capabilities such as nutrition, health and education. However, no single poverty indicator can capture the multiple dimensions that constitute poverty. To address this gap multi-dimensional poverty measures are based on several dimensions along which poor people experience deprivation. Such poverty measures complement unidimensional based measures to obtain a more complete picture of poverty and better inform policy for addressing poverty.

This paper adds to an emerging body of literature that examines non-monetary multiple dimensions of poverty. We determine the extent of multidimensional poverty among women and children in Kenya based on two dimensions of welfare: a composite poverty indicator (a measure of household wealth) and nutritional status (a measure of health). We further test for multidimensional poverty dominance and identify the determinants of multidimensional poverty. The analyses utilized three rounds (1993, 1998 and 2003) of Demographic and Health Survey (DHS).

The various methodological approaches used in this paper, though distinct, are intended to be complementary. They generate results which give a comprehensive picture of the extent, distribution and ordering of poverty among women and children in Kenya, together with the determinants of multidimensional poverty among Kenyan children. A two step inertia approach (multiple correspondence analysis and principal components analysis) is used to construct a composite poverty indicator (CPI) for making poverty comparisons. The CPI is used as an alternative measure of wealth to income which is not available in DHS data. Though some studies have used the CPI to analyze the extent of poverty, this study goes beyond this to use the CPI to rank women and children in multiple dimensions of wellbeing. The Alkire and Foster (2007) counting approach is applied to measure multidimensional poverty in the two dimensions of wellbeing. With this approach we can not only generate poverty indices, but also determine the relative contribution of dimensions and sub-groups to multidimensional poverty among women and children. Stochastic dominance approaches are used to compare welfare across population subgroups, but most important to test for statistical significance of differences in poverty orderings which is not possible under the other approaches. We specify a bi-Probit model to explain the incidence of multidimensional poverty. Most multivariate studies of poverty focus on explaining unidimensional poverty, or poverty based on a composite indicator. Our approach enables us to not only explore the determinants of an individual being poor in one dimension, while non-poor in the other, but also the probability of being poor in several
dimensions. This approach also helps us to analyze factors that are likely to be of policy relevance in addressing multiple dimensions of poverty in Kenya. Several results emerge concerning multidimensional poverty measurement in Kenya. First, the largest weights for the CPI constructed in this paper are from household assets holding and sources of drinking water. However, in absolute terms, sources of drinking water and sanitation make the largest contribution to the CPI. Thus households deprived of assets; safe drinking water and good sanitation are likely to be poorest, relative to all other households. Second, we see that the estimated Alkire and Foster poverty indices depend on the number of dimensions considered and that the poverty measure decreases with the number of dimensional cutoffs or sum of weights \((k)\). The highest contribution to multidimensional poverty is from the CPI relative to health indicators, rural areas relative to urban areas and boys relative to girls. Welfare ranking of provinces is sensitive to the choice of poverty cutoffs. As a result, although Nyanza province has the largest proportion of poor children at low cutoffs, Coast province has the largest proportion at higher cutoffs and Rift valley province contributes the largest proportion to poverty at all cutoffs. We further find that multidimensional poverty declined marginally between 1993 and 1998, but significantly between 1998 and 2003 and that the results for women are consistent with those for children. In addition, sensitivity analysis shows that the Alkire and Foster multidimensional poverty orderings are robust to choice of poverty line, but not to the choice of dimensional cutoff. Third, district poverty further maps show that women and children located in rural districts, mostly in the Coast, Eastern and Nyanza provinces are poorer than women and children in other regions. The maps further show large disparities in multidimensional poverty, but suggest that there is weak correlation between dimensions of wellbeing.

Fourth, one-dimensional stochastic dominance tests show that urban areas dominate rural areas, while Nairobi province dominates all other regions in the two indicators of wellbeing. Bi-dimensional stochastic dominance with statistical significance tests also suggests this order of dominance. It also illustrates that it is difficult to give a complete ranking of areas of residence, regions and gender groups by the two welfare measures. Fifth, the econometric results show that child, household, environmental and geographical characteristics are important correlates of multidimensional poverty. The results show that education attainment and access to electricity exert relatively high marginal impacts on the probability of being multidimensional poor. We also observe high marginal impacts on the probability of being asset poor from rural provinces, more so from Nyanza, Western and Rift valley provinces. Individual factors for health poverty have low marginal impacts.

### 7.2 Policy Implications

This study focuses on multiple dimensions of deprivation, a key focus of Millennium Development Goals (MDGs). The paper addresses directly three key MDGs for Kenya: first high levels of malnutrition are often addressed through poverty reduction efforts (MDG 1). Second, maternal health is addressed through a number of strategies and good maternal nutrition is crucial for lowering maternal mortality (MDG 5). Third, MDG 7 targets: to halve, by 2015, the proportion of people without sustainable access to safe drinking water and basic sanitation; and to achieve, by 2020, a significant improvement in the lives of slum dwellers. Slum dwellers are often deprived of good shelter, access to water and sanitation, and health care. The study also addresses indirectly two other MDGs: MDG4 as the battle against child mortality is most likely
to be lost if children are poor and deprived of basic necessities; MDG6, as poor women and children are more susceptible to HIV/AIDS, malaria and other diseases, more so in sub Saharan Africa. The study results point at several policy implications for improving the welfare of poor women and children along the MDG targets in Kenya.

First, monetary poverty analyses constitute an important evidence base for determining poverty reduction strategies in Kenya and play an important role in the formulation of national development strategies and the resulting allocation of resources. Understanding the deprivations of the most vulnerable women and children, the factors predisposing them to multidimensional poverty, and then targeting initiatives towards these groups should also be an integral part of national planning. Towards this end, in June 2010, the Government of Kenya launched the social budgeting initiative. Started on a pilot basis in three districts in 2005, the social budgeting initiative seeks to address some of the causes of the insufficiency and ineffectiveness of social investments. It aims to improve the current budgeting processes by increasing budgetary allocations for children and improving the effectiveness of expenditures in these areas (UNICEF, 2007). As the country rolls out the initiative to the rest of the country, it is important to consider the distribution of multidimensional poor and vulnerable women and children and ensure specific targeting of such groups in provision of social services. Though the move towards social budgeting in Kenya is a step forward towards addressing the rights of children and other vulnerable groups, macro economic and social budgeting processes including allocation and methods of tracking expenditures should be designed in a manner that ensures equitable allocation of available resources and sufficient investment for the most vulnerable children and households. The political will to prioritize children’s needs and allocate expenditures accordingly is a very essential part of the requisite policy intervention.

Second, the results suggest that interventions geared toward poverty alleviation need to be geographically targeted to reach out to the poor groups. Social budgeting and other targeting schemes require availability of information on vulnerable groups, disaggregated by region, gender and other relevant socio economic variables to show existing disparities. This study makes a contribution towards this process by providing information on existing disparities in poverty measures disaggregated by area and region of residence, gender and social economic groups. The results provide a rich base on which to design multidimensional targeting programs. The results can be useful for re-thinking the existing social protection programmes, such as the unconditional cash transfers and to ensure that these effectively reach the most vulnerable households caring for orphaned and vulnerable children. At present, there are local poverty reduction initiatives such as the Local Authority Transfer Fund and the Constituency Development Fund. These initiatives do not take into account the distribution of poor children across districts in Kenya. It is important to re-design these interventions carefully to target children living in poverty, because child poverty is often different from poverty affecting the whole household. In addition, as the country embraces devolution in the implementation of the new constitution promulgated on 27th August 2010, multidimensional poverty indicators for children and women will be essential for policy formulation at the local County level.

Third, the results also suggest that the poorest women and children are from households most deprived of various measures of household assets, water, sanitation, and shelter. Such children
are often predisposed to water and sanitation related health problems such as diarrheal and other diseases. These forms of deprivation are therefore likely to have long terms implications for growth and development of children. The results also suggest that improving access to electricity by poor households is a crucial strategy to fight poverty. It is important that governments and private providers step up efforts to provide the necessary infrastructure (such as piped water, sewerage systems, and pit latrines among others) to areas in which the poor live: rural areas and urban slums. The bi-Probit model results further suggest that programmes and policies aimed at improving access to education by women will reduce child poverty. This has implications for long term human capital investment and intergenerational effects on child welfare.

Fourth, fighting poverty calls for a collaborative approach that ensures that strategic information on the needs of the most vulnerable children is made available to and used by all those involved in the fight against childhood poverty including: community based organizations; civil society; local non-governmental organizations; and other stakeholders. Such information would ensure active and informed participation of local communities in the design, implementation and monitoring of development programmes. There is clearly need among these stakeholders for information on the incidence, dimensions, distribution, dominance and determinants of multidimensional poverty among children in Kenya. This paper offers this information. It is however important to strengthen the capacity of these local stakeholders in order to ensure: comprehensive identification of local needs; alternative mechanisms for service delivery; and appropriate targeting mechanisms for development programmes. This would increase the impact of such interventions on the most vulnerable women and children and also boost their sustainability. The government and development partners have an important role to play in strengthening and mobilizing local stakeholders toward this end.

Fifth, the health indicators used in this paper are nutritional measures for women and children. Consequently, although relative to the health dimension, the household wealth status index makes a larger contribution to multidimensional poverty, it is essential that mechanisms that specifically address the nutritional status of the most vulnerable women and children are designed. These could be done as part of the cash transfer programmes, school feeding programmes, vitamin A supplementation, promotion of social and behaviour change towards use of contraception by women and infant feeding practices.

Finally, the bi-Probit model results point at the importance of improving the standards of living in order to ensure long term physical growth and development of children. This reinforces the importance of a multidimensional approach to the fight against poverty. Improvement in the standards of living would require lifting households in which vulnerable women and children live in from various forms of deprivation: household asset holding, water, sanitation, shelter, health and education. Policies that boost the country’s economic growth, but also ensure pro-poor growth are necessary. A lone policy addressing only one specific form of deprivation is unlikely to bear much fruit. As the country implements the long term blue print - Vision 2030 (Republic of Kenya, 2007) and the new constitution (that gives priority to rights of women and children), multidimensional poverty indicators are presumably going to be crucial for informing policy.
Suggestions for further research

To win the battle against maternal and child poverty in Kenya, it is important to extend multidimensional research to cover issues for which there is relatively little information. These should include, but are not limited to: the most deprived and marginalized children, including child labour, the nature, extent and causes of violence, exploitation, abuse and trafficking of children. It is also important to include monetary indicators of poverty in the multidimensional measure in order to get a complete picture of the nature, extent, and distribution of child poverty in Kenya. Though this study has focused on both women and childhood poverty, it fails to look at the complementarities between poverties for the two subgroups due to data limitations. There would be value added by studying the relationship between poverties for women and children and also the intergeneration transmission of poverty from women to their children.

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APPENDICES

Appendix A  Tables

Table A1: Nutritional Indicators in Kenya (1993-2007)

<table>
<thead>
<tr>
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<tbody>
<tr>
<td></td>
<td>Children (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Height for age (stunting)</td>
<td>32.7</td>
<td>33</td>
<td>30.3</td>
<td>34.5</td>
<td>35.3</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>Weight for height (wasting)</td>
<td>5.9</td>
<td>6.1</td>
<td>5.6</td>
<td>6.3</td>
<td>6.7</td>
<td>6</td>
</tr>
<tr>
<td></td>
<td>Weight for age (underweight)</td>
<td>22.3</td>
<td>22.1</td>
<td>19.9</td>
<td>20.9</td>
<td>16.1</td>
<td>20</td>
</tr>
<tr>
<td>Women</td>
<td>Body mass index</td>
<td>22</td>
<td>21.9</td>
<td>22.7</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>% with low Body mass index</td>
<td>10</td>
<td>11.9</td>
<td>12</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>


Table A2: Sample Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Rural</th>
<th>Urban</th>
<th>Full sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std. Dev.</td>
<td>Mean</td>
</tr>
<tr>
<td>standardized haz</td>
<td>81.21</td>
<td>5.19</td>
<td>82.74</td>
</tr>
<tr>
<td>standardized waz</td>
<td>11.02</td>
<td>1.54</td>
<td>11.68</td>
</tr>
<tr>
<td>standardized whz</td>
<td>11.18</td>
<td>1.11</td>
<td>11.65</td>
</tr>
<tr>
<td>Composite Poverty Indicator</td>
<td>2.67</td>
<td>1.09</td>
<td>4.38</td>
</tr>
<tr>
<td>CPI poor</td>
<td>0.45</td>
<td>0.50</td>
<td>0.10</td>
</tr>
<tr>
<td>haz poor</td>
<td>0.33</td>
<td>0.47</td>
<td>0.23</td>
</tr>
<tr>
<td>waz poor</td>
<td>0.09</td>
<td>0.29</td>
<td>0.05</td>
</tr>
<tr>
<td>whz poor</td>
<td>0.12</td>
<td>0.32</td>
<td>0.06</td>
</tr>
<tr>
<td>Body mass index (BMI)</td>
<td>21.74</td>
<td>3.23</td>
<td>23.71</td>
</tr>
<tr>
<td>BMI poor</td>
<td>0.11</td>
<td>0.32</td>
<td>0.06</td>
</tr>
<tr>
<td>Sample size (%)</td>
<td>84</td>
<td></td>
<td>16</td>
</tr>
<tr>
<td></td>
<td>Nairobi</td>
<td>Central</td>
<td>Coast</td>
</tr>
<tr>
<td>----------</td>
<td>---------</td>
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</tr>
<tr>
<td>Nairobi</td>
<td></td>
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<tr>
<td>Central</td>
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<td></td>
</tr>
<tr>
<td>Coast</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eastern</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nyanza</td>
<td></td>
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<td></td>
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<tr>
<td>Rift Valley</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Western</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix B  District Poverty Maps

Map 1: District Level Poverty Indices (FGT $\alpha=0$) for children
Map 2: District Level Poverty Indices (FGT α=0) for Women
Alkire and Foster (2007) M0 Indices for Children
Map 3: District Level Alkire and Foster (2007) M0 Indices for children

Source: Kenya National Bureau of Statistics

Map 4: District level Income Poverty Incidence (FGT, α=0) - 1997
Appendix C  Methodology and Relevant Literature

C1  Constructing a Composite Poverty Indicator

C1.1  Principal Components Analysis

Like other factorial analysis techniques, PCA is a data reduction method for summarizing several variables into one factor (Asselin, 2009). The PCA consists of building a sequence of uncorrelated (orthogonal) and normalized linear combinations of the original input variables, exhausting the whole variability of the set of input variables (total variance) defined as the trace of the covariance matrix. The optimality comes from the fact that the first component (uncorrelated linear combination) captures the largest proportion of the total variance and ensures that when all possible components have been extracted, the whole variance is explained (Asselin, 2009).

To construct a CPI, 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, 2001). This procedure first standardizes the indicator variables (calculating z-scores); then the factor coefficient scores (factor loadings) are calculated; and finally, for each household, the indicator values are multiplied by the loadings and summed to produce the household’s index value. In this process, only the first of the factors produced is used to represent the wealth index. The resulting sum is itself a standardized score with a mean of zero and a standard deviation of one (Rutstein and Johnson, 2004).

The CPI ($C_i$) derived from the PCA can be defined as:

$$C_i = \sum_{k=1}^{K} W^{1,k} I^{*k}$$  \hspace{1cm} \text{...(1)}

Where K is the number of primary indicators, $W^{1,k}$ are the weights (factor score coefficients) and $I^{*k}$ are the standardized primary indicators. The first component of the CPI defined in (1) is the best regressed latent variable on the K primary poverty indicators and is most informative in terms of the explained variance. The PCA procedure has two major limitations (Asselin 2009): First, PCA is designed for quantitative variables measured in the same units. The optimal sampling properties for parameter estimation depend on the multivariate normal distribution. In other words PCA is appropriate for use with continuous normally distributed variables. The assumption of multivariate normal distribution does not hold with categorical variables. Since ordinal variables do not have an origin or a unit of measurement, means, variances and covariances obtained using PCA would have no real meaning and the procedure would be inappropriate; Second, the operationalization of the composite indicator, outside the sampled population is not appealing because the weights derived using PCA are only applicable to standardized primary indicators. Due to these limitations of PCA, alternative factorial techniques have been proposed. These include factor analysis (Sahn and Stifel, 2000) and Multiple Correspondence Analysis (Asselin, 2009) among others.
## C1.2 Multiple Correspondence Analysis

MCA is the application of the simple correspondence analysis (CA) algorithm to multivariate categorical data coded in the form of an indicator matrix or a Burt matrix. It consists of exploring the internal structure of a covariance matrix while producing an additive decreasing disaggregation of the total variance (inertia) of the matrix. MCA was designed to improve on the PCA procedure when the latter loses its parametric estimation optimal properties and to provide more powerful tools for describing the hidden structure in a set of qualitative variables (Asselin, 2009). It is therefore appropriate for the analysis of categorical assets data. While the MCA uses the chi-square metric, the PCA uses the Euclidean metric to measure distances between two columns of the data matrix under analysis. In addition, MCA satisfies two desirable properties that PCA does not: First, MCA satisfies the distributional equivalence property or marginalization preference. This property ensures that MCA overweights the smaller categories within each primary indicator – for our purpose assets of the poorest groups would receive a higher weight in construction of the CPI. Second, MCA satisfies the reciprocal bi-additivity or duality property, which stipulates that (i) the composite poverty score of a population unit is the simple average of the standardized factorial weights or the poverty categories to which it belongs. (ii), the weight of a given poverty category is the simple average of the standardized composite poverty scores of the population units belonging to the corresponding poverty gaps (Asselin, 2009). Asselin further shows that the MCA-based CPI must satisfy two important properties: first, it must be monotonically increasing in each of its primary indicators, such that an improvement in any indicator will increase the CPI and reduce poverty; second, it must satisfy the composite poverty ordering consistency, such that the population ordering for a primary indicator is preserved with the composite indicator. That is, a population group with a category of indicators that are inferior to those of another group will be poorer than the latter group.

Following Asselin (2009), the functional form of the MCA-based CPI can be written as:

$$C_i = \frac{1}{K} \left( \sum_{k=1}^{K} \sum_{j=1}^{J_k} W_{jk}^* I_{I_k}^* \right)$$

Where $j_k$ are the number of categories for indicator $k$, $W_{jk}^*$ is the score of category $j$ in $I_k$ is the binary variable 0/1 taking the value 1 when the unit I has the category $j_k$.

MCA in this paper is based on the Burt matrix calculated from the data. The Burt matrix is the indicator matrix transposed and post-multiplied by itself. This matrix yields eigen values which give a better approximation of the inertia explained by the factors than the eigen values of the indicator matrix. The scoring coefficients from MCA are 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 rely on the factor loadings results for weights.

In the absence of expenditure or income data, poverty studies construct a composite indicator of wealth based on asset information (Sahn and Stifel, 2003). A substantial literature that uses a CPI based alternative to the conventional use of expenditures in defining poverty has developed in the past three decades. An influential study on the use of an asset index is Filmer and Pritchett (2001). They construct a linear index of wealth based on data from India. They use the PCA
approach and concluded that in the absence of data on consumption expenditures, applying PCA to a set of asset indicators is a coherent and stable alternative. Macro International has also employed the Filmer and Pritchett PCA approach to compute asset indices from the DHS data for several countries (Rutstein and Johnson, 2004). Sahn and Stifel (2003) evaluate the potential of an asset-based index as an indicator of household economic welfare. Unlike Filmer and Pritchett (2001), they use factor analysis on household assets instead of principal component analysis to construct the asset index. The study concludes that in the absence of expenditure data there is no reason not to use the asset index as a measure of economic welfare. Deviating from these studies Booysen et al. (2007) use MCA to construct asset-based composite poverty indicators. They clearly delineate the advantages of using MCA over PCA, citing attractive statistical properties possessed by MCA. Other researchers compare CPIs constructed using alternative approaches. Njong and Ningaye (2008) use PCA and MCA approaches to estimate multidimensional poverty indices. The authors suggest that policy makers should give more attention to asset indices based on MCA since they show greater incidence of poverty. Ki et al. (2005) construct a CPI for Senegal based on the MCA and inertia approach, citing advantages of MCA over other approaches. Lawson Body et al. (2007) also use the MCA to derive a CPI for Togo.

**C2 Approaches to Multidimensional Poverty Comparisons**

**C2.1 Stochastic Dominance (SD) Approach**

To illustrate the stochastic dominance approach, let us assume $z = (z_1,\ldots,z_k)$ is a k-vector of the minimum levels of the k basic needs; $x = (x_1,\ldots,x_k)$ the vector of k basic needs of the i\textsuperscript{th} person; and $X$ is a matrix summarizing the distribution of k attributes among n persons. A general form of multidimensional poverty measures is:

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

where $\pi$ is an individual poverty function that indicates how many aspects of poverty must be aggregated at the individual level, $x_i$ and $z$ are as defined above. 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, Pigou-Dalton transfer, nondecreasing poverty under correlation increasing arrangement and normality\textsuperscript{11}.

\textsuperscript{11} To establish conditions for robustness of 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; Duclos and Araar, 2006). However, Duclos et al. (2006a) generalize the stochastic dominance approach to be applied under the multidimensional context of wellbeing.
This paper considers two welfare indicators; CPI ($x$) and nutritional status ($y$). Assuming differentiability, each indicator can contribute to overall welfare measure denoted as (see Duclos et al. 2006a):

$$\lambda(x, y) : \mathbb{R}^2 \rightarrow \mathbb{R} \quad \frac{\partial \lambda(x, y)}{\partial x} \geq 0, \quad \frac{\partial \lambda(x, y)}{\partial y} \geq 0$$  \hspace{1cm} (4)

We assume, as Duclos, et al. (2006a), that an unknown poverty frontier, defined implicitly by $\lambda(x, y) = 0$, separates the poor children/women from the non-poor. The frontier is analogous to the usual downward sloping indifference curves. The set of poor children/women can then be given as:

$$\Lambda(\lambda) = \{(x, y) | \lambda(x, y) \leq 0\}.$$  \hspace{1cm} (5)

Denoting the joint CDF of $x$ and $y$ by $F(x, y)$ and assuming additivity of such indices across persons, a multidimensional poverty index that combines the CPI and nutritional status is defined as:

$$P(\lambda) = \int_{\Lambda(\lambda)} \pi(x, y; \lambda) dF(x, y)$$  \hspace{1cm} (6)

where $\pi(x, y; \lambda)$ is the contribution to multidimensional poverty of an individual with welfare indicators $x$ and $y$ such that:

$$\pi(x, y; \lambda) = \begin{cases} 
\geq 0 & \text{if } \lambda(x, y) \leq 0 \\
= 0 & \text{otherwise.} \end{cases} \hspace{1cm} (7)$$

In equations (6) and (7), $\pi$ 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 et al, 2006a).

Modifying the usual one-dimensional SD curve or FGT poverty index (Foster, Greer and Thorbecke, 1984), a bi-dimensional SD surface can be defined as

$$P^{\alpha_x, \alpha_y}(z_x, z_y) = \int_0^{z_x} \int_0^{z_y} (z_x - x)^{\alpha_x} (z_y - y)^{\alpha_y} dF(x, y)$$  \hspace{1cm} (8)

for integers $\alpha_x \geq 0$ and $\alpha_y \geq 0$. The SD 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 (8). $F(x, y)$ is the joint CDF for CPI and nutritional status. $P^{1,1}(z_x, z_y)$ generates a cumulative density surface analogous to a poverty incidence curve in one-dimensional poverty analysis while $P^{2,2}(z_x, z_y)$ is the bi-dimensional average poverty gap index (Duclos et al. 2006a).
The bi-dimensional formulation is a special case, since there are complexities in expanding the one-dimensional analysis. In particular, 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 CPI or poor nutritional status, he/she is poor by a union definition and \( \pi \) will be:

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

(9)

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

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

(10)

We check for bi-dimensional poverty dominance by comparing between surfaces of distributions defined by equation (9), considering the order of dominance. The comparisons made from (9) are valid for broad classes of poverty functions (which are generated considering the order of dominance) other than the FGT. Further, the surface will be influenced by the covariance between the CPI 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.

Comparing surfaces defined by equation (8), we compare distributions for the multidimensional poverty using a class of poverty indices which define implicitly the dominance order. Using equations (6) and (7), a class of bi-dimensional poverty indices \( \pi(x^*) \) is defined. These poverty indices are additively separable, anonymous, continuous at the poverty frontier, non-increasing in welfare indicators, and for which welfare indicators are substitutes. Substitutability means that an increase in CPI has the greatest impact on welfare when it occurs for the less healthy children/women and vice versa. Further, this class of poverty indices assumes that the marginal poverty benefit of an increase in either CPI or nutritional status decreases with the value of the other variable. That is, the lower the initial value of a person’s CPI, the greater the increase in deprivation if the person suddenly faces lower nutrition. Such an assumption can be understood as one of “substitutability” of dimensions: the higher a child’s CPI, the less is overall poverty deemed to be reduced if nutrition is increased.

Formally, this also assumes non-decreasing poverty under a correlation-increasing switch. A correlation-increasing switch leaves the marginal distributions of both CPI and nutritional status unaffected but increases in the correlation of both welfare indicators by making the incidence of multiple deprivations higher after than before the switch (Bourguignon and Chakravarty, 2003). Duclos et al. (2006a) demonstrated that with further assumptions about the general poverty indices, a general form of bi-dimensional poverty indices can be defined and extended to higher order dominance poverty comparisons.
While there is substantial literature on the use of stochastic dominance analysis, there is a dearth of empirical literature that examines stochastic dominance in a multidimensional poverty setting. However, there is now emerging literature on the latter following the works of Duclos et al. (2006a, 2006b, 2006c). Kabubo-Mariara, Araar and Duclos (2010) use the approach to test for multidimensional poverty dominance among Kenyan children. They find results that are robust to the choice of the poverty line and to the choice of aggregation procedures across dimensions and across children. Batana and Duclos (2010) examine multidimensional stochastic dominance when one of the indicators of wellbeing is discrete. Their findings suggest that tests based on the likelihood ratio can be useful for analyzing multidimensional poverty and welfare dominance when one of the dimensions of welfare is qualitative.

**C2.2 Dual Cutoff and Counting approach**

To illustrate the Alkire and Foster (2007) approach, we start by assuming a population of \( n \) persons and \( d > 2 \) dimensions or capabilities. Letting \( x = [x_{ij}] \) be the \( n \times d \) matrix of achievements in the various dimensions. The typical entry \( x_{ij} > 0 \) is the achievement of person \( i = 1, 2, \ldots, n \) in dimension \( j = 1, 2, \ldots, d \). We assume that the number of dimensions are fixed and given. The size of the population, \( n \) is allowed to vary to allow poverty comparisons across populations of different sizes. The domain of matrices considered is given by \( X = \{ x \in \mathbb{R}^{nd} : n \geq 1 \} \) and the dimension-specific deprivation cutoff is denoted by \( z_j \) (Alkire and Foster, 2007).

To identify the poor, we assume that all dimensions are equally weighted. The matrix of deprivations can be represented by \( x^0 = [x^0_{ij}] \) where:

\[
\text{for all } i \text{ and } j, \quad x^0_{ij} = \begin{cases} 
1 & \text{if } x_{ij} < z_j \\
0 & \text{otherwise}
\end{cases}
\]

(11)

The sum of each row of \( x^0 \) gives a column vector \( c \) of deprivation counts, the number of deprivations \( (c_i) \) suffered by person \( i \). To identify the poor, the identification function is:

\[
\rho(x, z) = \begin{cases} 
1 & \text{if individual is multidimensionally poor} \\
0 & \text{otherwise}
\end{cases}
\]

(12)

With a cutoff \( k, (k = 1, \ldots, d) \), we can compare the number of deprivations per person. The identification function relating to cutoff \( k \) is such that \( \rho_k(x, z) = 1 \) when \( c_i \geq k \), and \( \rho_k(x, z) = 0 \) when \( c_i < k \). A multidimensional poor person is deprived in at least \( k \) dimensions.

Given \( \rho \) in equation (12) the aggregation rule associates the matrix \( x \) and the cutoff vector \( z \) to generate a class of multidimensional poverty measures \( M(x; z) \), with \( M : X \times R^d_+ \rightarrow R \) as the multidimensional poverty index. We can define the multidimensional headcount ratio as:
\[ H = \frac{q_k}{n} \] 

(13)

where \( q_k = \sum_{i=1}^{n} \rho_k (x_i, z) \) i.e. the number of people identified as poor based on \( z \) and cutoff \( k \), in set \( z_k \). As with the usual FGT measures, the share of possible deprivations suffered by a poor person and the average deprivation share across the poor can be derived from equation (13) by normalizing over the number of dimensions and the number of poor in \( z_k \).

Like the usual FGT headcount ratio, \( H \) is insensitive to the depth and severity of poverty and violates monotonicity and transfer axioms. The headcount, \( H \) 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, 2007). To deal with this shortcoming, Alkire and Foster propose an adjusted headcount which combines \( H \) and the average deprivation share across the poor (\( A \)) and thus satisfies dimensional monotonicity. The adjusted headcount is the number of deprivations experienced by the poor, divided by the maximum number of deprivations that could be experienced by all people (\( nd \)) and is defined as:

\[ M_0 = HA = \frac{1}{nd} \sum_{i=1}^{n} c_i \rho_k (x_i; z) \] 

(14)

If the variables in \( x \) are cardinal, the associated matrix of (normalized) gaps or shortfalls can provide additional information for poverty evaluation. For any \( x \), we let \( g^1 \) be the matrix of normalized gaps, with the typical element: \( g^1_{ij} = (z_j - x_j) / z_j \) when \( x_j < z_j \), and \( g^1_{ij} = 0 \) otherwise. \( g^1 \) is an \( n \times d \) matrix with elements between 0 and 1. Each nonzero element measures the extent to which person \( i \) is deprived in dimension \( j \). In general, for any value of \( \alpha > 0 \) the normalized poverty gap raised to power \( \alpha \) is \( g^\alpha_{ij} = (g^1_{ij})^\alpha \) and \( G^\alpha \) can be expressed as:

\[ G^\alpha = \frac{1}{\sum_{i=1}^{n} c_i \rho_k (x_i; z)} \sum_{j=1}^{d} \sum_{i=1}^{n} g^\alpha_{ij} \rho_k (x_i; z) \] 

(15)

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

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

(16)

When \( \alpha = 0 \), \( M_\alpha \) is the adjusted headcount ratio (\( M_0 \)). When \( \alpha = 1 \), we get the adjusted poverty gap (\( M_1 = HAG \)), the sum of normalized gaps of the poor divided by the largest possible sum of normalized gaps. \( M_1 \) summarizes the incidence of poverty, the average range of deprivations and the average depth of deprivations of the poor. It obeys the axioms of dimensional monotonicity and monotonicity. Hence, if a person becomes more deprived in a particular dimension, \( M_1 \) will increase. When \( \alpha = 2 \), \( M_\alpha \) is the adjusted squared poverty gap (\( M_2 \)). It summarizes the incidence
of poverty, the average range and severity of deprivations of the poor. If a poor person becomes more deprived in a particular dimension, \( M_2 \) will increase more the larger the initial level of deprivation for this person in this dimension. The measure obeys the axioms of monotonicity and transfer, being sensitive to the inequality of deprivations among the poor.

The family of poverty measures described above is decomposable by population subgroups. For example with subgroups, \( n_1 \) and \( n_2 \) (say rural and urban), the overall poverty level is decomposed into two as follows:

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

This indicates that overall poverty is the weighted average of subgroup poverty levels (with population shares as weights).

The \( M_\alpha \) family of poverty measures presented assumes that all dimensions receive the same weight, an assumption that could at times be relaxed (Alkire and Foster, 2007). Let \( w \) be a \( d \) dimensional row vector, where \( w_j \) is the weight associated with dimension \( j \). We then define the \( n \times d \) matrix \( g^\alpha = [g^\alpha_{ij}] \) where \( g^\alpha_{ij} = w_j((z_j - x_{ij})/z_j)^\alpha \) when \( x_{ij} < z_j \), and \( g^\alpha_{ij} = 0 \) otherwise. As illustrated before, a column vector of deprivation counts whose \( i \)th entry \( c_i = |g^0_{i*}| \) 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 of the multidimensionally poor is 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 to poverty measurement, whereas when \( k = d \), the identification criterion corresponds to the intersection approach. Alkire and Foster (2007) also define an intermediate approach when \( 1 < k < d \). With two dimensions, this criterion combines the dimensions as proposed by Duclos, Sahn, and Younger (2006a).

A number of studies have applied the Alkire and Foster (2007) approach to study multidimensional poverty in developing countries. These include Batana (2008) in a study of fourteen Sub-Saharan Africa countries. Another application of the approach is a study by Santos and Ura (2008) using Bhutan data. Alkire and Suman (2008) also apply the dual cutoff approach to study multidimensional poverty in India. Other studies that have used the Alkire and Foster approach to study multidimensional poverty among children include: Roche (2009), in a study of child deprivation in Bangladesh; Roelen, Gassman and de Neubourg (2009) for Vietnam; Beggeri et al. (2009) in an analysis of deprivation of Afghan children; Battiston et al. (2009) in Latin America; Azevedo and Robles (2009) in a pilot in Mexico. Some of the studies illustrate the value to policy design of multidimensional poverty measurement over unidimensional approaches. For instance, Batana finds that ranking of countries based on the Alkire and Foster (2007) multi-dimensional poverty measure differs from ranking based on standard welfare measures (HDI and income poverty). The studies also illustrate that Alkire and Foster (2007) poverty orderings are robust to different poverty cutoffs. They also illustrate the policy value of the decomposable Alkire and Foster multidimensional poverty measures to inform multisectoral planning.
C3 Standardization of z-scores

The standardized anthropometric measure is constructed such that a child’s position in the distribution, in terms of the WHO reference population percentiles, is the same for his/her actual z-score and standardized z-score. The procedure for standardization of the z-scores is as follows: first find each child’s percentile in the reference population distribution for his/her age and gender. Then convert that percentile to the z-score associated with that percentile for an arbitrarily chosen age and gender\(^{12}\). If we let \( F \) to be the distribution function of z-scores in the WHO population for age/sex group defined by \( a \) (age) and \( g \) (gender); \( z \) be the actual z-score, \( \bar{a} = 24 \) months and \( \bar{g} = \text{female} \). The standardized z-score (\( Z \)) can be expressed as:

\[
Z = F_{\bar{a},\bar{g}}^{-1}(F_{a,g}(z))
\]

To arrive at the final standardized values, we use the CDC recommended lambda, mu, and sigma (LMS) procedure and associated parameter\(^{13}\):

\[
\text{Std}_Z = M(1+ L S Z)^{1/L} \]

where \( M \) is the median; \( L \) is the power in the Box-Cox transformation (for detecting skewness); \( S \) is the generalized coefficient of variation; and \( Z \) is the z-score that corresponds to the percentile.

C4 Econometric Model of Multidimensional Child Poverty

In the bi-variate Probit model of multidimensional poverty, we consider two interrelated outcomes, \( Y_{1i}^* \) the first latent variable (CPI) and \( Y_{2i}^* \) the second latent variable (health index) such that:

\[
Y_{1i}^* = X_{1i} \beta_1 + \mu_{1i}
\]

\( Y_{1i} = 1 \) if \( Y_{1i}^* \leq Z_{CPI}^* \), \( Y_{1i} = 0 \) otherwise

\[
Y_{2i}^* = X_{2i} \beta_2 + \mu_{2i}
\]

\( Y_{2i} = 1 \) if \( Y_{2i}^* \leq Z_{nat}^* \), \( Y_{2i} = 0 \) otherwise

If the two outcomes are partially correlated, the two models’ errors are correlated such that \( \text{Cov}(\mu_{1i}, \mu_{2i}) \neq 0 \). In this case the probability of being poor in CPI will depend on the probability of being poor in health. The bi-variate joint probability distribution for the two standard normally distributed error terms is defined as:

---

\(^{12}\) In this paper, we use 24-month-old girls as in Sahn and Younger (2006). It can be however shown that the standardization is robust to the choice of age and gender. Moreover, since the transformation is monotonic, it preserves the rank order of the children of a given age and gender.

\(^{13}\) The values of parameters and percentiles for standardization are available online at: [http://www.cdc.gov/growthcharts/percentile_data_files.htm](http://www.cdc.gov/growthcharts/percentile_data_files.htm). See also Kuczmarski et al. (2002).
where \( \rho \) is a correlated parameter denoting the extent to which the two co-vary. The bi-variate normal cumulative density function \( (\Phi_2) \) that can be obtained from (22) is defined as:

\[
\int_{\mu_1}^{\mu_2} \int_{\mu_2}^{\mu_2} \phi_2(\mu_1, \mu_2, \rho) d\mu_1 d\mu_2 \]