Multdimensional Poverty in Kenya: Analysis of Maternal and Child Wellbeing

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Abstract

This paper utilizes Demographic and Health Survey (DHS) data to generate multidimensional poverty profiles for women and children in Kenya during the period 1993 to 2003.We measure wellbeing in two dimensions: assets and health status. A child/woman is considered poor if she comes from a household whose asset index is below an asset poverty line and/or if nutritional status is below a set threshold. We use different inertia approaches to compute a composite poverty indicator. The Alkire and Foster (AK) dual cutoff and counting approach is applied to measure and order multidimensional poverty analysis using the two indicators of wellbeing. Stochastic dominance approaches are used to compare multidimensional poverty orderings over health and assets across regions and areas of residence. A bi-Probit model is employed to explore the determinants of multidimensional poverty. The AK results show that the highest contribution to multidimensional poverty is from the composite poverty indicator. Rural areas also contribute more than urban areas, while boys make a larger contribution than girls. The results further show that poverty increased between 1993 and 1998, but thereafter decline in 2003. The stochastic dominance analysis results suggest slightly different orderings of poverty from the AK approach, especially for regions. The bi-Probit model results suggest that understanding the determinants of wellbeing in a multidimensional context can generate useful policy insights for improving human capital investments in Kenya.

Key words: *Multidimensional poverty, Composite poverty indicator, factorial analysis, 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.

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[1]. 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 and Bourguignon and Chakravarty, 2003). Emerging literature that analyzes poverty as a

[1] 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).

multidimensional issue uses dominance approaches following Atkinson (1987) and Foster and Shorrocks (1988) in the unidimensional context. Duclos, Sahn and Younger, (2006a, 2006a, 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 focuses on multidimensional poverty analysis for women and children in Kenya. Poverty comparisons are based on nutritional status and a household composite poverty indicator 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.

This study carries out multidimensional poverty comparisons for women and children health in Kenya, based on nutritional indicators and a composite indicator of wellbeing. 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 several aspects. First, it constructs a composite poverty indicator, which allows the ranking of maternal and child health. Second, it addresses a research gap on multidimensional poverty studies in Kenya. Previous studies have concentrated on unidimensional poverty comparisons, which only lead to partial understanding of poverty, and often to unfocused or ineffective poverty reduction programs[2]. Multidimensional poverty analysis helps to reveal complexities and ambiguities in the distribution of wellbeing that income based poverty analysis cannot capture. Third, 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).

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 provides a brief literature review on multi-dimensional poverty measurement. Section 5 presents the analytical frameworks and methodology. Section 6 reports the results. Section 7 summarizes and concludes.

[2] There is a dearth of multidimensional poverty studies in developing countries, more so Africa, though the literature is growing. See the literature review section for relevant studies.

2. Background and Context

Kenya is a low-income, food-deficit country with a population of about 37 million and an estimated per capita gross domestic product of about US$1540 in 2007. 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, 2009).

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 barely meets population energy requirements, resulting in undernourishment for a third of the population. 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. Poverty and food insecurity however remain widespread especially in rural areas, but in recent years both have increased in urban areas, frustrating the country's development agenda.

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 (Republic of Kenya 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, GOK 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, 2001). 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 (Table A1).

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 a 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. 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% (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 (Whyte and Kariuki, 1991). 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).

3. Literature Review

This section presents a brief review of literature. It concentrates on three strands of literature: Multidimensional poverty analysis based on the composite poverty indicator (CPI); the Alkire and Foster (2007) approach and the stochastic dominance approach.

3.1 Composite Poverty Indicator

In the absence of expenditure or income data, poverty studies construct an index of household welfare based on asset information (Sahn and Stifel, 2003). One of the challenges in this approach is aggregation of the asset information. 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 less arbitrary than the entropy approach in the definition of the functional form for the composite indicator. The approach also enables an optimal choice among the relevant poverty dimensions[3]. 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).

A substantial literature that uses an asset-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 asset ownership indicator variables using data from India. The weights for the asset indicators were derived using PCA. In this case, the weights are the standardized first principal component of the variance-covariance matrix of the observed household assets. The results from sensitivity analysis showed that the wealth index was robust to assets included. In addition, results from multivariate analysis show that the composite wealth indicator is a significant predictor of school enrolment. On average, children from richer households were more likely to be enrolled in school. They conclude 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 employed the Filmer and Pritchett, (2000), 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 data are drawn from multi-purpose surveys in several developing countries. Direct comparison of the composite poverty indicator and predicted expenditures to report expenditure indicates that the ranking of household poverty according to the asset index is more consistent with predicted expenditures than reported expenditure. However, the asset index is a valid predictor of child nutrition (measured by height-for-age), a key indicator of child welfare. 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.

Unlike Filmer and Pritchet (2001) and Sahn and Stifel (2003), 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.

They used data from DHS surveys in seven African countries with at least three DHS surveys between the late 1980s and early 2000s. In addition to constructing a composite poverty index, they compute and compare measures of inequality. They argue that PCA was developed for the

[3]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).

analysis of continuous variables and not categorical variables. Since they have categorical data, they prefer MCA. In addition, their results indicate that trends in poverty and inequality are not uniform across the sample of countries. Overall poverty declined in Ghana, Kenya, Mali, Senegal and Zimbabwe. Inequality consistently declined in Tanzania while inequality increased in Zambia. However, although the aggregate asset index suggests improvement in welfare, decomposition of this improvement indicates that it is accumulation of private assets (e.g. television and fridges) that improved the asset poverty index while access to public services that are critical for poverty alleviation deteriorated. The policy lesson is that tracking changes in the overall index is not adequate without decomposition to identify what is driving it. The results also bring out a major deficiency of the asset index that the household asset indicators underlying the index change slowly over-time. This means that the index may fail to pick up important short-term and medium-term changes in the economic situation of households.

Other researchers compare asset indices constructed using alternative approaches. For example, Njong and Ningaye (2008) use PCA, MCA, and fuzzy set approaches to estimate multidimensional poverty indices. The data used are drawn from a household survey mounted in Cameroon in 2001. The results of stochastic dominance tests indicate that the PCA-based index dominates the MCA-based index and fuzzy set index. The meaning that can be deduced from the result is that overall poverty (headcount) index based on PCA-based asset index shows less poverty than the other two indices. The authors suggest that policy makers should give more attention to asset indices based on MCA and fuzzy set approaches since they show greater incidence of poverty.

Ki et al. (2005) construct a composite poverty indicator for Senegal based on a broad range of non-monetary variables that capture basic needs. The CPI is based on the MCA and inertia approach. The results indicate that for households in Senegal the most prevalent forms of poverty relate to (i) inadequacy of human capital and unpleasant living conditions (ii) shortage or absence of basic infrastructure and (iii) lack of goods of comfort and household equipment. Rural households, farmers, polygamists, large families, male managed household are the most affected by multi-dimensional poverty. Lawson Body et al. (2007) also use the MCA to derive a CPI for Togo. Their results suggest that except for the bicycle, the ownership of durable goods reflects a relatively high standard of living, and positively contributes towards the household asset index. Safe drinking water, electricity, modern toilet facilities, terraces, and ceilings and walls also have a positive contribution to the CPI. Some other goods and services such as unprotected water and the lack of toilet facilities are found to have a negative effect on the asset index.

3.2 Alkire and Foster (2007) dual cutoff approach

Alkire and Foster (2007) propose a dual cut-off method to identify the poor and measures of poverty similar to those in the Foster et al (1984) family of poverty measures. The method is illustrated using data from the USA and Indonesia. For the US they consider the following variables (all assumed ordinal): fifteen income groups measured in poverty line increments, self-reported health status, health insurance, and years of schooling. For Indonesia, five dimensions are considered: expenditure, health (body mass index), years of schooling, access to clean drinking water and access to sanitation facilities. The results indicate that the dual cut-off identification method and the adjusted headcount poverty measure are appropriate to use with capabilities and functionings that are ordinal.

Batana (2008) uses the Alkire and Foster (2007) method to estimate multi-dimensional poverty in fourteen Sub-Sahara Africa countries. Identification of who is poor and who is not poor is based on four dimensions-assets, health, schooling and empowerment. Four main results include: Firstly, there are important cross-country differences in multi-dimensional poverty. Secondly, 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). Thirdly, decomposition of multi-dimensional poverty by location, indicates that multi-dimensional poverty is more prevalent in rural than urban areas. Finally, decomposition of poverty by dimensions indicates that lack of schooling is the key contributor to multi-dimensional poverty.

Another application of the Alkire and Foster (2007) approach to multidimensional poverty measurement is in a recent paper by Santos and Ura (2008). They use data from Bhutan and consider five dimensions: income, education, and room availability, access to electricity and access to drinking water. For rural Bhutan, they also consider access to roads and land ownership. In contrast to the other applications that use equal weights, two alternative weighting systems are used. Decomposition of multi-dimensional poverty estimates into rural and urban indicate that poverty is more prevalent in rural than urban areas. The results in this paper also indicate that the weighting system can make a difference in terms of identifying the forms of deprivation that make the highest contribution to multi-dimensional poverty. The results also indicate that district poverty ranking was robust to different poverty cutoffs.

Alkire and Suman (2008) apply the dual cutoff approach to study multidimensional poverty in India. They find that 60 percent of the poor households identified under the AF multidimensional poverty measurement were not included in India's social assistance program that targets the poor households as identified by comparing their income with the official income poverty line. Alkire and Suman (2008) also illustrate the policy value of the decomposable Alkire and Foster multidimensional poverty measures: to inform multisectoral planning by identifying local priorities for public investment. Based on the results, they conclude that the Alkire and Foster (2007) approach can be used to assess the dimensions that drive multidimensional poverty in different contexts.

3.3 Stochastic dominance in a multi-dimensional setting

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. Duclos et al. (2006a) use multidimensional poverty analysis to obtain evidence on the sensitivity of spatial poverty orderings to choice of multidimensional poverty lines and indices. The analysis is carried out for Uganda, Ghana and Madagascar based on two measures of wellbeing: logarithm of household per capita expenditure and children's height-for-age scores. Unlike previous dominance literature, the authors compute sampling distributions of the poverty estimators to permit statistical tests of differences in poverty measures. The approach used applies to "union", "intersection" and "intermediate" definitions. It is found that bi-variate multidimensional poverty orderings differ from uni-variate poverty orderings and that the poverty orderings are robust to the choice of the poverty threshold.

Kabubo-Mariara, Araar and Duclos (2009) use the Duclos, Sahn and younger (2006) approach to test for multidimensional poverty dominance among Kenyan children. Two important dimensions of wellbeing are considered: child survival and the ownership of assets. They use bi-dimensional dominance analysis to demonstrate that urban areas dominate rural areas by the two indicators of wellbeing taken jointly, but that there is no clear dominance of poverty between rural provinces. They also 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. They use sequential dominance techniques using statistical inference methods based on the empirical likelihood ratio to test for strict dominance. This approach permits test of a null hypothesis of non-dominance versus an alternative hypothesis of dominance. The results based on DHSs for several West African countries shows the existence of multidimensional dominance relationships between most of these countries. In particular, Côte d'Ivoire dominates all the other countries, followed by Mali and Togo. The findings also 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.

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. We use an index of household assets as the CPI. However, like any other composite indicator of wealth, there are major challenges in constructing a household asset index. 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 indicator. Second, it enables an optimal choice among the relevant poverty dimensions to be made[4]. Having settled on the inertia approach, the task that remains is the choice between

[4]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

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). In this section, we explore the main alternative approaches to construct a composite poverty indicator.

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, 2000). 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:

$$C_i = \sum_{k=1}^{K} W^{I,k} I_i^{*k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where K is the number of primary indicators, $W^{I,k}$ 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 co-

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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).

variances 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.

Factor Analysis

Factor analysis (FA) is the reverse approach of exploring multidimensionality compared to the PCA. It identifies a vector (K) of linear combinations (m<K) latent variables called factors or communalities), able to predict the K observed indicators with as small an error as possible. The FA has statistical advantages over the PCA that make it more appropriate: First, the PCA forces all of the components to accurately and completely explain the correlation structure between the assets. FA, on the other hand, accounts for the covariance of the assets in terms of a much smaller number of hypothetical common factors (Sahn and Stifel, 2000). Second, FA allows for asset-specific influences to explain the variances such that all of the common factors are not forced to explain the entire covariance matrix. In many cases, it is assumed that the one common factor that explains the variance in the ownership of the set of assets is a measure of economic status, or welfare. Third, the assumptions necessary to identify the model using FA are stated explicitly and provide guidance in determining which assets should or should not be included in the index (Sahn and Stifel 2000, 2003). A limitation of FA over PCA is that for most forms of FA, singularity or extreme multicollineraity is a serious problem because of the need to obtain the inverse covariance matrix. Another issue is that though it is also developed for numerical variables as the PCA, FA is an unnecessary detour with technical difficulties (Asselin, 2009).

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 overweighs 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:

$$C_i = \frac{1}{K}\left(\sum_{k=1}^{K}\sum_{j_k=1}^{J_k} W_{j_k}^{*I,k} I_{i,j_k}^{k}\right) \quad \text{...} (2)$$

Where j_k are the number of categories for indicator k, $W_{jk}^{*I,k}$ is the score of category j, $I_{I,jk}^{k}$ 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 this paper, we use four alternative approaches to construct the CPI: A first approach is to apply MCA to the entire dataset (all sets of indicators) to estimate the weight and relative contribution of each indicator rather than a set of indicators. The second and third approaches are FA and PCA respectively. The fourth is a two stage procedure. In the first stage, we use the MCA approach to compute a score for each group of indicators/dimension. In the second stage, we use the PCA approach to estimate weights for each group of indicators and finally the composite poverty index. 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 all others and is later used for poverty orderings and comparisons in this paper.

4.2. Multidimensional Poverty Comparisons

In most literature, poverty measurement follows the unidimensional 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 developed by Duclos, Sahn and

Younger (2006) and the dual cut off and counting approach developed by Alkire and Foster, (2007). We now turn to a discussion of these approaches.

4.2.1 Stochastic Dominance Approach

Duclos, Sahn and Younger (2006) 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 (2002) and Bourguignon and Chakravarty (2003) [5]. 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. Let $z = (z_1,...,z_k)$ be a k-vector of the minimum levels of the k basic need; $x = (x_1,...,x_k)$ the vector of k basic needs of the i[th] person; and X is a matrix summarizing the distribution of k attributes among n persons. The most general form of multidimensional poverty measures can be given by:

$$P(X, z) = F\left[\pi(x_i, z)\right] \quad \text{...(3)}$$

where π 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. To establish conditions for the robustness of a poverty measures, some studies assume that the poverty measure does not have to satisfy all the above axioms (see for instance Bourguignon and Chakravarty, 2003; Bibi, 2005; Deutsch and Silber, 2005; Duclos and Araar, 2006).

However, Duclos et al. (2006a) generalize the stochastic dominance approach to be applied under the multidimensional context of wellbeing.

We consider two measures of wellbeing; assets (x) and nutritional status (y). Assuming differentiability, each of the indicators can contribute to overall measure of wellbeing denoted as (see Duclos et al., 2006a):

$$\lambda(x, y): \Re^2 \to \Re \left| \frac{\partial \lambda(x, y)}{\partial x} \geq 0, \frac{\partial \lambda(x, y)}{\partial y} \geq 0 \right. \quad \text{...(4)}$$

[5] In this study we use the Duclos et al. (2006) and the Alkire and Foster (2008) approaches. We also compare these multidimensional poverty indices with alternative indices based on the approaches in Tsui (2002); Bourguignon and Chakravarty (2003); and Chakravarty, Murkerjee and Ranade (1998) - (see technical appendix for methodology).

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

$$\Lambda(\lambda) = \{(x, y) | \lambda(x, y) \le 0\}. \quad (5)$$

To define the multidimensional poverty indices let the joint cumulative distribution of x and y be denoted by F(x, y). Assuming additivity of such indices across persons, a multidimensional poverty index that combines the asset index and nutritional status is defined as:

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

where π(x, y;λ) is the contribution to multidimensional poverty of an individual with wellbeing indicators x and y such that:

$$\pi(x, y; \lambda) \begin{cases} \ge 0 & \text{if } \lambda(\text{x,y}) \le 0 \\ = 0 & \text{otherwise.} \end{cases} \quad (7)$$

In equations (6) and (7), π is the weight that the poverty measure attaches to a child/woman inside the poverty frontier. By the poverty focus axiom, π =0 for a child/woman outside the poverty frontier. The multidimensional headcount is obtained when π=1 (Duclos et al, 2006a). Modifying the usual one-dimensional stochastic dominance curve or FGT poverty index (Foster, Greer and Thorbecke, 1984), a bi-dimensional stochastic dominance surface can be defined as

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

for integers $\alpha_x \ge 0$ and $\alpha_y \ge 0$. The dominance surface can be generated by varying the poverty lines z_x and z_y over an appropriately chosen domain, with the height of the surface determined by (8). $F(x, y)$ is the joint distribution function for assets and nutritional status. $P^{1,1}(z_x, z_y)$ generates a cumulative density surface analogous to a poverty incidence curve in a unidimensional analysis. $P^{2,2}(z_x, z_y)$ can be thought of as a bi-dimensional average poverty gap index (Duclos et al. 2006a).

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

$$\pi(x_i, z) \begin{cases} = 0, & \text{if } \mathrm{x}_{\mathrm{i,j}} \ge z_j, \forall j = 1, 2, ..., k, \\ > 0, & \text{otherwise,} \end{cases} \quad (9)$$

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

$$\pi\left(x_i, z\right)\begin{cases} >0, & \text{if } x_{i,j} \le z_j, \forall j = 1,2,...,k, \\ =0, & \text{otherwise,} \end{cases} \qquad (10)$$

We check for bi-dimensional poverty dominance by comparing between surfaces of distributions defined by equation (9) considering the order of dominance. The comparisons that can be 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 assets and the nutritional status, because the integrand is multiplicative. The higher the correlation between these two poverty indicators, the higher the dominance surfaces, other things equal.

By comparing between surfaces, defined by (8), we compare between distributions for the multidimensional poverty using a class of poverty indices which define implicitly the dominance order. From (6) and (7), we can define a class of bi-dimensional poverty indices $(\pi(\lambda^*))$ that are additively separable, anonymous, continuous at the poverty frontier, non-increasing in both assets and nutrition, and for which assets and nutrition are substitutes. This substitutability means that an increase in assets has the greatest impact on wellbeing when it occurs for the less healthy children/women and vice versa. This class of bi-dimensional poverty indices assumes that the marginal poverty benefit of an increase in either assets or nutrition decreases with the value of the other variable. That is, the lower the initial value of an individual's asset index, the greater the increase in his deprivation if he suddenly faces lower nutrition. Such an assumption can be understood as one of "substitutability" of dimensions: the more a child has of assets, the less is overall poverty deemed to be reduced if nutrition is increased. More formally, this also assumes non-decreasing poverty under a correlation-increasing switch. A correlation-increasing switch leaves the marginal distributions of both assets and nutrition unaffected but increases the correlation of both dimensions of wellbeing 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. To derive poverty indices and corresponding dominance surfaces, DASP software (Araar and Duclos, 2007) was used.

4.2.2 Dual Cutoff and Counting approach

Recently, 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[6]. In addition, it proposes a counting approach that follows the aggregation method in the Foster et al. (1984) family of poverty indices.

[6] The approach is said to be a dual cutoff method because it defines some within dimension cutoffs to determine whether an individual is deprived or not in each dimension, and the across dimensions cutoff k to determine who is

Let us assume a population of *n* persons and *d > 2* dimensions or capabilities. Let $\mathrm{x}=[\mathrm{x}_{\mathrm{ij}}]$ denote the *n x d* matrix of achievements in the various dimensions, where the typical entry $x_{ij} > 0$ is the achievement of individual *i = 1,2,…, n* in dimension *j = 1,2,…, 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 under consideration is given by $X = \{x \in R_{+}^{nd} : n \geq 1\}$ and the dimension-specific deprivation cutoff is denoted by z_j (Alkire and Foster 2007).

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

$$\text{for all i and j, } \mathrm{x}_{\mathrm{ij}}^{0} = \begin{cases} 1 \text{ if } \mathrm{x}_{\mathrm{ij}} < \mathrm{z}_{\mathrm{j}} \\ 0 \text{ otherwise} \end{cases} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{(11)}$$

We can sum each row of x^0 to obtain a column vector *c* of deprivation counts containing the number of deprivations (c_i) suffered by individual *i*. To identify the poor, we consider the identification function written as:

$$\rho(x_i, z) = \begin{cases} 1 \text{ if individual is multidimensionally poor} \\ 0 \text{ otherwise} \end{cases} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{(12)}$$

With a cutoff *k,* we are able to compare the number of deprivations per individual. Since we have assumed that each selected dimension has the same weight, the cutoff $k = 1,....,d$. The identification function relating to cutoff k is such that $\rho_k(x_i, z) = 1$ when $c_i \geq k$, and $\rho_k(x_i, z) = 0$ when $c_i < k$. A person is multidimensionally poor if he/she is deprived in at least *k* dimensions.

Given ρ in equation (12) the aggregation associates the matrix *x* and the cutoff vector *z* to generate $M(x;z)$ a class of multidimensional poverty measures with $M : X \ x \ R_{++}^{d} \rightarrow R$ as an index of multidimensional poverty. The first multidimensional poverty measures that we can define is the headcount ratio defined as:

$$H = \frac{q_k}{n} \quad \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \text{(13)}$$

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

to be considered multidimensionally poor. It is also presented as a counting approach, since it identifies the poor based on the number of dimensions in which they are deprived (Alkire and Foster, 2007).

individual 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. In the multidimensional context, it also violates dimensional monotonicity: if a poor person becomes deprived in an additional dimension (in which he/she was not previously deprived), H does not change (Alkire and Foster, 2007). To deal with this shortcoming, Alkire and Foster propose an adjusted headcount which combines the head count and the average deprivation share across the poor (A) and thus satisfies dimensional monotonicity. 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:

$$M_0 = HA = \frac{1}{nd}\sum_{i=1}^{n} c_i \rho_k(x_i; z) \quad \ldots\ldots\ldots \quad (14)$$

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: $g_{ij}^1 = (z_j - x_{ij})/z_j$ when $x_{ij} < z_j$, and $g_{ij}^1 = 0$ otherwise. g^1 is an *n x 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 α is $g_{ij}^{\alpha} = (g_{ij}^1)^{\alpha}$ and G^{α} can be expressed as:

$$G^{\alpha} = \frac{1}{\sum_{i=1}^{n} c_i \rho_k(x_i; z)} \sum_{j=1}^{d}\sum_{i=1}^{n} g_{ij}^{\alpha} \rho_k(x_i; z) \quad \ldots\ldots\ldots \quad (15)$$

The dimension adjusted FGT measure $M_{\alpha} = HAG^{\alpha}$ is defined as

$$M^{\alpha} = \frac{1}{nd}\sum_{j=1}^{d}\sum_{i=1}^{n} g_{ij}^{\alpha} \rho_k(x_i; z) \quad \ldots\ldots\ldots \quad (16)$$

When $\alpha = 0$, M_{α} is the adjusted headcount ratio (M_0). When $\alpha = 1$, we get the adjusted poverty gap (M_1 = HAG), which is the sum of the normalized gaps of the poor divided by the highest possible sum of normalized gaps. M_1 is a summary of 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. This means that if an individual becomes more deprived in a particular dimension, M_1 will increase. When $\alpha = 2$, the measure is the adjusted squared poverty gap (M_2). This is a summary of 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 individual in this dimension. This measure obeys the axioms of monotonicity and transfer, being sensitive to the inequality of deprivations among the poor.

The measures of poverty in the $M_{\alpha}(x;z)$ family are decomposable by population subgroups. The decomposition can be conducted for any number of subgroups. For illustration purposes we assume that a population is divided into n_1 and n_2 subgroups (say rural and urban). The weighted average of the sum of the subgroup poverty levels (using population shares as weights) equals the overall poverty level obtained when the whole group is considered:

$$M(x;z) = \frac{n_1}{n} M(x_1;z) + \frac{n_2}{n} M(x_2;z) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (17)$$

The $M_{\alpha}(x;z)$ family of multidimensional poverty measures presented above assumes that all dimensions receive the same weight. However, it is possible to extend into a more general form, to allow different weighting systems. Following Alkire and Foster (2007), we let *w* be a *d* dimensional row vector, whose typical element w_j is the weight associated with dimension *j*. We then define the $n \times d$ matrix $g^{\alpha} = [g_{ij}^{\alpha}]$ whose typical element is $g_{ij}^{\alpha} = w_j((z_j - x_{ij})/z_j)^{\alpha}$ when $x_{ij} < z_j$, and $g_{ij}^{\alpha} = 0$ otherwise. As illustrated before, a column vector of deprivation counts can be defined, whose i^{th} entry $c_i = | g_i^0 |$ represents the sum of weights for the dimensions in which person *i* is deprived. c_i varies between 1 and *d*, and so the dimensional cutoff for the identification step of the multidimensionally poor will be a real number *k*, such that $0 < k \le d$. When equal weights are used, $k = \min\{w_j\}$, the identification criterion corresponds to the union approach, whereas when $k = d$, the identification criterion corresponds to the intersection approach. Alkire and Foster (2007) also define an intermediate approach when $1 < k < d$. In the case of only two dimensions, this criterion will be a combination of these dimensions as proposed by Duclos, Sahn, and Younger (2006a).

The above approach is applied to measure multidimensional poverty among children and women in Kenya. We consider whether a child is poor in a wealth dimension measured by the asset index and in at least 3 health related dimensions: nutritional status measured by standardized anthropometric measures of height for age (*haz*), weight for age (*waz*) and weight for height (*whz*). The deprivation thresholds for nutritional status follow the United States National Centre for Health Statistics (NCHS) median reference where a cut-off of minus two (-2) standard deviations for *haz, waz and whz* are taken as measures of past/chronic malnutrition, wasting and current/acute malnutrition respectively. Since the multidimensional poverty indices can only be computed for positive values, we use standardize the z-scores, as recommended by WHO and the Centre for Disease Control (Kuczmarski et al.2002). For women, we consider multidimensional poverty based on 2 dimensions, the CPI, which in itself is a multidimensional measure of poverty, and the body mass index. For BMI, we use the WHO recommendation of a BMI less than 18.5 as the poverty line.

Choice of Weights

One challenge with construction of multidimensional poverty indices is the choice of weights, yet the ordering of wellbeing bundles can be very sensitive to the choice of weights (Decancq and Lugo, 2008). 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 these methods has been proved to be the best, and most approaches to poverty measurement do not provide suitable methods to address the weighting issue. Instead, they give the latitude to assign weights to each dimension in a normative way (Batana, 2008). Caution is however advanced on the trade-offs that arise from using different weighting methods and the need for robustness tests to determine the impact of specific value of weights on poverty indices (Decancq and Lugo, 2008). The most commonly used approach to weighting is equal weighting. Though convenient, equal weighting is far from uncontroversial (Decancq and Lugo, 2008; Alkire and Foster, 2007). According to Atkinson (2003), equal weights is an arbitrary normative weighting system that is appropriate in some but not in all situations. This paper assigns equal weights to the CPI and nutrition. For child nutrition, we use nested weights, where nutrition is assigned equal weight with asset index, but the nutrition specific weight are then divided equally between each of the three nested dimensions of child nutrition (Batana, 2008; Alkire and Foster 2007). For women, equal weights are applied to the asset index and body mass index.

5. Data

In this study we examine 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 information about women and children and is therefore suitable to answer the research questions of this study. The DHS utilized a two-stage sample design. The first stage involved selecting sample points (clusters) from a national master sample maintained by Central Bureau of Statistics (CBS)[7]- 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 7950 households in the months of February to August 1993. The 1998 KDHS collected information on 7,881 women aged 15-49, and 5,672 children aged less than 60 months from 8,380 households in the months of February to July 1998. The 2003 KDHS covered 8,195 women aged 15-49 and 5,949 children aged less than 60 months from 8,561 households in the

[7] The name has since changed to Kenya National Bureau of Statistics (KNBS)

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.

6. Results

6.1 Construction of the Composite Poverty Indicator

6.1.1 Introduction

In this study we compute the CPI based on a set of six domains and twenty-nine indicators (see Table 1). The selected domains capture various forms of wellbeing given the available data, and ensuring comparability from one survey year to another. The first domain reflects possession of four 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 a public tap. Other forms of water include bottled water.

***** Table 1 Here *****

The second 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 and thus a positive weight. 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. Similarly, low quality floor reflects unhygienic conditions, while a modern roof is expected to have a positive impact on CPI. The third and fourth 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 three health indicators reflect good access to health care at a cluster level and are therefore expected to have a positive impact on the CPI. For education, no education is expected to have a negative contribution to the CPI, while attainment of primary and post primary education could help households to escape poverty and are therefore expect to have a positive impact on the CPI.

Our asset-based alternative to the expenditure-based poverty indicator is constructed using the methodology presented in the previous section. This section presents the results of the CPI derived using the four alternative approaches: MCA, two-step MCA/PCA, PCA and FA.

6.1.2 Alternative approaches

Two step MCA/PCA

The results from the two-step approach are presented in Tables 2 and 3. Table 2 presents the weights, contribution of each variable, the squared correlations, the distance to the centre of the axis and the relative frequencies. Any variable with a negative score reduces welfare and vice-versa. The results suggest that ownership of household assets (namely fridge and TV) have the largest weights. This suggests that households with such assets are likely to have a higher CPI. This finding is similar to that of Ki, et al. (2005) for Senegal. The authors argue that this result reflects an important property of MCA: separating the poor from the rich households by the way weights are computed. The relative frequencies also show that for each domain, indicators that are likely to contribute more to poverty have higher frequencies (for instance, for household assets, lack of a fridge and TV have highest frequencies, other indicators with large weights include some forms of sanitation and access to health care). For each set of indicators we also assessed the contribution of the first dimension to the total inertia. Sanitation had the lowest share of inertia (41.37%). This was followed by household assets, whose share of inertia for the first dimension was only 43.86%. The set of indicator with the largest share was the source of drinking water (60.73%) followed by access to health (60.25%). The MCA coordinate plots for each set of wealth indicators are presented in figure 1.

***** Table 2 Here *****

Table 3 presents the second stage results whereby PCA is applied to the continuous variables (scores) obtained from the various MCA estimates in Table 2. The largest contribution and weights are from household assets and source of drinking water. The lowest contribution is from housing material, which also has the lowest weight. From the PCA, it would seem that only sanitation and housing materials are associated with overall negative impact on welfare.

***** Table 3 Here *****

Multiple correspondence analysis

The results for MCA applied to all sets of indicators in one set are presented in Table 4. Comparing the results in Tables 2 and 4, it is observable that applying MCA on indicators in all domains yields different results from the partial application of MCA to each set of indicators in a domain. For instance, in Table 3, the largest weights are from ownership of TV and refrigerator. Although this is also the case for the results in Table 4, all other indicators with relatively higher weights in Table 2 have much lower weights in Table 4 (see for instance sanitation and access to health). The signs of the weights in Table 4 are however consistent with those in Table 2. That is, indicators that reflect a higher standard of living (such as having a TV, a radio, a flush toilet) contribute positively to the CPI, while indicators that reflect a lower standard of living contribute negatively to the CPI. The results from MCA suggest that the first dimension explained a relatively small share of inertia (19.19%)

***** Table 4 Here *****

Factor analysis

Table 5 shows that the ranking of indicators based on the results of principal factorial analysis differs from that based on results of other approaches presented earlier. Nevertheless, the largest weights are from indicators that reflect relatively high living standards, namely possession of piped water, flush toilet and TV. The lower and negative weights reflect low standards of living. The ranking of indicators by weight is however inconsistent with usual standards of living. For instance, possession of a pit latrine is ranked lower than having no toilet and other toilet, both more unhygienic sanitary conditions.

***** Table 5 Here *****

Principal components analysis

The indicator weights derived from the PCA approach are presented in the last column of Table 5. The ranking of indicators using the PCA approach is close to the ranking using FA, but it is not entirely consistent for indicators that reflect relatively low standards of living. Like for FA, possession of piped water, flush toilet and TV have the highest weights, but the lowest weights are assigned to low quality floor and use of surface water.

6.1.3 Estimated Composite Poverty Indicators

Table 6 presents the various composite poverty indicators based on the alternative statistical approaches above. The results suggest that the different approaches yield different CPIs. The two step approach reports a more conservative estimate of the CPI with a mean of -0.056. Comparing the CPIs computed from two step approach and the ordinary MCA, we can conclude that as expected, 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 CPIs estimated from FA and PCA are on average both positive, but the CPI from PCA is twice as large as that constructed from factor analysis. Overall, the largest CPI is from the PCA approach. This reflects the limitations of the PCA approach mentioned earlier and also widely discussed in the literature (Asselin, 2009; Sahn and Stifel, 2003). In this study, multidimensional poverty analysis is based on the CPI constructed from the two step (MCA and PCA) approach. To analyze multidimensional poverty, we normalize this index to positive values[8]. Though this is contentious in the literature, it does not affect the distribution of poor and non-poor children/women in our sample.

***** Table 6 Here *****

6.2 Incidence of Poverty

6.2.1 Child deprivation

In this section, we examine the extent of deprivation experienced by children in the sample based on the composite poverty indicator. Table 7 shows the incidence of poverty by region and area of residence for different poverty groups. The results show that by all definitions of the poverty

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[8] The normalization is done by adding the absolute value ($C_{\min}$) of the average of the minimum categorical weight ($w_{\min}^{k}$) of each indicator to the CPI of each household to obtain a positive CPI score. Asselin (2009) expresses the average minimum weight as: $C_{\min} = \sum_{k=1}^{k} w_{\min}^{k} \Big/ K$.

line, Nairobi is least poor in terms of assets, followed by Central and Coast provinces. Nyanza is the poorest province followed by Rift valley and Western provinces.

***** Table 7 Here *****

In Table 8a, we investigate the degree of overlap of poor children from various definitions of poverty. The results indicate lack of overlap in children falling into poverty (Laderchi et al. 2003; Booysen et al. 2007). To illustrate this absence of overlap, consider children who are poor in terms of low height for age and also by a 25 percentile CPI poverty line. We can see from the table that only 9% (1,181 out of 12,455 children) can be considered poor by both dimensions. 15% (1,933) are poor by the 25 percentile CPI poverty line, but are non-poor height wise. 21% are height for age poor, but not poor by this CPI definition. 31% are height for age poor irrespective of their 25 percentile CPI status, compared to 25% who are poor by this definition of CPI irrespective of their height for age. This lack of overlap is observed for the other two indicators of health status and alternative CPI poverty lines. Overall, the data suggests that 84% of these children are found in rural areas, while the rest 16% are urban. 32% of all children are found to be height for age poor (stunted) or suffering from long term or chronic malnutrition (Table A2). 9% are weight for age poor (underweight) while 11% are weight for height poor (wasted). About 36% of all children are CPI poor.

***** Table 8 Here *****

6.2.2 Women's deprivation

The patterns of deprivation and incidence of poverty among women are close to those of children. For instance, the percentage of women who are deprived of various assets by the CPI quintile show that the extent of deprivation falls with increase in CPI. The results (not presented) also suggest that women's health status improves as we move to higher wealth quintiles. Further, although only about 23% of the women have no education, more than 90% are deprived of higher education. The last column panel in table 7 presents the incidence of poverty among women by province and area of residence for different poverty line groups. The results show that the distribution of poor women by regions follows closely the respective distribution of poor children.

Table 8b investigates the degree of overlap of poor women for various definitions of poverty. The results support earlier results on children which portray lack of overlaps in women falling into poverty. For instance, assuming a CPI poverty line covering 25 percentile, 22% of the women are poor by this definition of poverty, but are non-poor by low BMI definition. Only 4% of the women are both BMI and 25th CPI percentile poor. Other figures in the table can be interpreted in a similar manner. 45% of rural women are CPI poor, compared to only 11% of urban women. On the other hand, 11% of rural women are BMI poor, compared to only 8% in urban areas. The data further reveals that 38% of all women are CPI poor, but only 11% have a low body mass index (BMI). 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 asset dimension of poverty (Table A2).

6.3. Multidimensional Poverty Analysis: Dual Cut off Approach

6.3.1 Child poverty

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 reported in previous section and child health. Three child health indicators were considered: standardized height for age, standardized weight for age and standardized weight for height. As indicated earlier, both CPI and child health are assigned equal weights (each a weight of 2), but each child health indicator is assigned nested weights (0.667). For each of the dimensions, we set poverty lines/dimensional cut offs below which a child is deemed poor. For the CPI, the cut off is based on a relative poverty line set at the 40th percentile. The dimensional cut off for CPI is 2.3692[9]. That is, a child is poor if she comes from a household whose asset index is less than 2.4. The poverty lines for standardized health indicators are based on the usual -2 z-scores. The dimension cut off for standardized height for age is 79.10, the cut off for weight for height is 9.36 and the cut off for weight for age is 10.03. Table 9 presents the multidimensional poverty indices for the full sample. We can see from the table that the estimated index depends on the cut off (*k*). 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 poverty is evaluated at *k=1*, compared to 5% for *k=3,* and *0%* 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 9 Here *****

Table 10a presents 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 in rural areas 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. Table 10b presents the relative contribution of rural and urban areas to the Alkire and Foster multidimensional poverty indices. The trend in the results differs by area of residence. For rural areas, the contribution rises with *k,* but for urban areas, the contribution falls with *k*. Rural areas account for more than 95% of overall multidimensional poverty except for *k=0.5*. The contribution of rural areas is even higher for M0, M1 and M2.

***** Table 10 Here *****

The relative contributions of various indicators of poverty to overall multidimensional poverty are reported in Table 11a. The results suggest that the highest contribution to the poverty indices is from the CPI, ranging from 50% to 76% for M0, 84% to 95% for M1, and 96 to 99% for M2 for different dimensional cutoffs. The contribution from health indicators is quite modest and is

[9] The alternative thresholds are 1.87 and 3.04 for 25th and 60th percentiles respectively. The results using these thresholds are discussed in section 6.4.

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 11 Here *****

Regional differences in multidimensional poverty are apparent from Table 12a. For $k=1$ and $k=3$, Nyanza province reported the highest incidence of child poverty with 50% of the children poor in at least 1 dimension, while Nairobi reported the lowest incidence of child poverty at only 5%. The results for M1, and M2 are consistent with those of H0. For k=3, no child is poor in Nairobi, while the highest percentage of the poor were found in Coast province. The relative contribution of regions to the Alkire and Foster indices are presented in table 12b. The results show 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 nil.

***** Table 12 Here *****

We also explored for gender differentials in multi-dimensional poverty. The results in Table 13a suggest that for k=1, no gender differentials in child poverty are detected. However, for k=3, 6% of the boys are multidimensionally poor, compared to only 4% of the girls. For all possible poverty cutoffs, boys contribute more to multidimensional poverty than girls (table 13b). Tables 14a and 14b present poverty indices by survey year and area of residence for k=1 and k=3. The results show that for urban areas, multidimensional poverty increased between 1993 and 1998, but thereafter dropped in 2003. This is observed for all indices for the two cutoff points.

***** Table 13 Here *****
***** Table 14 Here *****

Figure 2 illustrate multidimensional poverty incidence curves. To save on space we concentrate on the head count ratio curves only. The shapes of the curves for other measures of poverty (M0, M1 and M2) are consistent with respective head count curves. Figure 2(a) shows that urban areas dominate rural areas in poverty. Figure 2(b) shows Nairobi clearly dominates other regions in multidimensional poverty. Central also dominates other all other regions except Nairobi. It is however difficult to order other provinces at all possible cut offs.

***** Figure 2 Here *****

6.3.2 Women poverty

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 cut off is based a relative poverty line of 40^{th} percentile, with a dimensional cut off equal to 2.3692 (main results). 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 poor.

The Alkire and Foster (2007) women multidimensional poverty indices are presented in Table 15a. The results show that 44% of all women are poor in at least one dimension (either low CPI or low BMI), compared to only 5% who are poor when both dimensions are taken into consideration. The proportion of multidimensionally poor women is slightly higher in rural areas at 50% and 6% for 1 and 2 dimensional cut offs respectively. In urban area, only 14% and 1% are poor for the two cutoffs respectively. There are regional differences also. At *k*= 1, Nyanza province has the largest proportion of multidimensionally poor women (54%), while Nairobi recorded the lowest (4%). The same is observed for M1 and M2. The adjusted head count (M0) is however highest for Rift Valley, followed by Nyanza. At *k*=2, Rift Valley has the largest proportion (8%) of poor women, while Nyanza province ranked fourth. The poverty ranking of provinces by other indices is consistent with those of H0.

***** Table 15 Here *****

Table 15b presents the relative contribution of regions, area of residence and poverty dimension to the Alkire and Foster multidimensional poverty indices for women. The results show that Nyanza province leads in the contribution to women poverty, at about 30% for *k*=1 and 40% for *k*=2. The lowest contribution is from Nairobi province. The results further suggest that rural areas contribute more than 95% of women's multidimensional poverty. This is consistent with earlier results for child poverty. For dimensions, the CPI contributes the largest proportion to Alkire and Foster multidimensional poverty. The contribution ranges from a 50% contribution to the adjusted head count ratio (M0) for *k*=2 to a 99% contribution to poverty gap squared (M2) for *k*=1. The Alkire and Foster multidimensional poverty incidence curves are presented in figure 2. To save on save, we only present the head count ratio curves.

Tables 16a and 16b present multidimensional poverty indices for women by survey year for the two different cut offs. The results for all indices suggest that poverty declined between 1993 and 2003. For k=1, the proportion of multidimensionally poor women fell from 51% in 1993 to 37% in 2003. For *k*=2, the proportion declined from 6% to 5%.

***** Table 16 Here *****

6.3.3 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 based on the 25th percentile[10]. Tables 17a and 17b present results for children, while tables 18a and 18b present results for women. For children, we only present results for selected cut offs. The results show that 29% and 4% of all children are poor when *k*=1 and *k*=3 respectively. The results further show that 46% (5%) of the rural children are poor in at least one (three) dimension(s), compared to only 11%(0%) in urban areas. Coast province has the largest proportion of poor children at 36%(6%) for *k*=1(k=3), while Nairobi has the lowest at 4%(0%). Nyanza is the second poorest region. Though Nyanza ranked first using the 40th percentile, the difference for *k*=1 for the two percentiles is insignificant. The

[10] The results for the 60th percentile are actually consistent with results for the other two alternative poverty lines.

results for the relative contribution of regions to overall poverty show that consistent with the results for the 40th percentile, Rift Valley makes the largest contribution to child poverty, while Nairobi contributes the least. We also observe that rural areas contributed between 96% and 1% to overall poverty. The largest contribution of dimensions is from the CPI, ranging from 52% to 98%. Except for Mo when *k*=3, *haz* makes the largest contribution among health indicators to multidimensional poverty.

***** Table 17 Here *****

The results in table 18a suggest that 32% of women are multidimensionally poor for *k*=1, compared to only 4% for *k*=2. In rural areas, 36% and 4% of the women are poor for *k*=1 and *k*=2 respectively. For urban areas, 10% and 1% are poor for *k*=1 and *k*=2 respectively. The ranking of provinces by poverty indices is consistent with the ranking using the 40th percentile. Nyanza province recorded the highest proportion of poor women for *k*=1 (40%), and Rift Valley topped for *k*=2 (6%). Nairobi recorded the lowest poverty rates. Table 18b presents the contribution of region, residence and dimension to multidimensional poverty indices. Consistent with the results for 40th percentile, Rift Valley province contributed the most to multidimensional poverty (ranging from 30% to 42% for both cut offs), while Nairobi contributed the least. The results for contribution by area of residence and dimensions are also consistent with results presented earlier. The results suggest that the Alkire and Foster multidimensional poverty orderings are robust to the choice of the poverty line.

***** Table 18 Here *****

6.3.4 Alternative Multidimensional Poverty Measures

Table 19a present multidimensional child poverty indices computed using other approaches. The union head count index suggests that at least 59% of the children are multidimensionally poor. That is, poor in at least one dimension - assets or health. The intersection definition however suggests that only 16% are multidimensionally poor (deprived of both assets and nutrition). Compared to urban areas, rural areas take the largest share of these poor children. Tsui's (2002) index gives the lowest estimates of poverty, with only 0.5% of the children being estimated to be poor. Chakravarty et al. (1998) and Bourguignon and Chakravarty (2003) approaches estimate that about 15% of the children are (bi-dimensionally) poor.

The multidimensional poverty indices for women derived from alternative approaches are presented in table 19b. The largest estimates are from Chakravarty et al (1998), which suggest that 55% of all women are multidimensionally poor, 48% of whom are rural and 13% urban dwellers. The results further show that the Alkire and Foster (2007) head count index (H0) for *k=1* is equivalent to the union head count index and estimates that 44% of all women (49% of rural women and 12% of urban women) are multidimensionally poor. The intersection head count index is synonymous to the Alkire and Foster (2007) head count index (H0) for *k=2, (or k=d)* or all dimensions in this case. Only 5%, 1% and 6% of the women in rural, urban and the full sample respectively are multidimensionally poor in both CPI and BMI.

***** Table 19 Here *****

6.4 Stochastic Dominance Analysis

6.4.1 First order stochastic dominance

In this paper, stochastic dominance analysis is based on Duclos, Sahn and Younger (2006). We test for dominance of asset 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, these results are presented in a technical appendix to this report. The first order dominance tests for children are presented in Figure 3. The results in figure(a) show that Nairobi clearly dominates all regions in asset poverty. We however observe no dominance between the other provinces, except for Central province, which clearly dominates all other provinces for an asset range 1.5 to 4.6 points. Figure (b) shows the dominance curves by area of residence. The results show that urban areas clearly dominate rural areas in assets poverty. Figure (c) shows that there is no dominance of asset poverty between girls and boys. Figures (d) to (f) present the dominance curves for nutrition based poverty. Figure (d) 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 27 and 86 scores. There is no other clear pattern of dominance between other provinces. Figure (e) suggests that urban areas dominate rural areas in nutrition poverty beyond a standardized height for age of 72 scores. Comparing the results with those in figure (e), we note that the difference in poverty over all thresholds is less pronounced for nutrition than for assets. The last figure (f) presents dominance curves by gender of child. Unlike for assets, girls dominate boys in nutritional wellbeing.

6.4.2 Bi-dimensional stochastic dominance with statistical significance

We test for bi-variate poverty dominance across different groups using bi-dimensional dominance surfaces. The results in figure 4(a) show the upper bound of the confidence intervals of the difference between poverty dominance surfaces. If the upper bounds are everywhere below zero, then we can conclude that poverty in one region is lower than poverty in another region. This holds true for the difference between Nairobi and Central provinces. 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 2 dimensional graphs presented in appendix table A3. To interpret the graphs, we magnify the Nairobi-Central provinces graph in figure 4(b), where Nairobi in the row and Central in the column position. The vertical y-axis of the graph presents nutrition (standardized scores), while the horizontal x-axis presents assets (scores). A white color indicates that for a particular combination of (x,y) values, for instance (6, 68) – 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). A gray color indicates that the condition that the row region is less poor than the column region is not satisfied. Looking at the corresponding graph for the difference between Central and Nairobi (graph 2,1) in appendix table A3, it is apparent that the dominance condition is satisfied in most instances, except for standardized nutrition scores between 64 and 72. This shows that it is difficult to give a complete ranking of provinces by the two measures of wellbeing. Further, 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 (x,y - 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.

6.5 Multidimensional Poverty: an Econometric Analysis

6.5.1 Preliminaries

In this section, we try to show the main determinants of multidimensional poverty in Kenya. Recall that, with the monetary approach, many empirical studies have extensively used the Logit model to show the factors that contribute significantly to the probability of being poor. With more than one dimension of wellbeing, we are confronted to propose more appropriate specification of the econometric model. In our case with the two dimensions of wellbeing (assets and health), we propose the use of bi-variate Probit model. This choice is justified by the following two reasons: First, it is trivial that the individual may experience any of the two alternatives (being poor in assets or in health) or the two together. Second, it is expected that the two indicators of wellbeing, which form the latent variables under the proposed econometric specification, are expected to be partially correlated.

The bi-variate Probit model of multidimensional poverty can be illustrated by considering the two interrelated outcomes. Let Y_{1i}^* be the first latent variable (asset index) and Y_{2i}^* the second latent variable (haz index) such that:

$$Y_{1i}^* = X_{1i}\beta_1 + \mu_{1i} \qquad (18)$$

Y_{1i} =1 if $\mathrm{Y}_{1i}^* \leq Z_{CPI}$, Y_{1i} =0 otherwise

$$Y_{2i}^* = X_{2i}\beta_2 + \mu_{2i} \qquad (19)$$

Y_{2i} =1 if $\mathrm{Y}_{2i}^* \leq Z_{haz}$, Y_{2i} =0 otherwise

If the two outcomes are interrelated, the two models' errors are correlated such that $Cov(\mu_{1i}, \mu_{21}) \neq 0$. In this case the probability of being poor in assets will depend on the probability of being poor in health. The bi-variate joint distribution for the two standard-normally distributed error terms is defined as:

$$\phi(\mu_1, \mu_2) = \frac{1}{2\pi\sigma_{\mu 1}\sigma_{\mu 2}\sqrt{1-\rho^2}} \exp\left[-\frac{1}{2}\left(\frac{\mu_1^2 + \mu_2^2 - 2\rho\mu_1\mu_2}{1-\rho^2} \right) \right] \qquad (20)$$

where ρ is a correlated parameter denoting the extent to which the two co-vary. The bi-variate normal cumulative density function (Φ_2) that can be obtained from (3) is defined as:

$$\int_{\mu 1}\int_{\mu 2}\phi_2(\mu_1,\mu_2,\rho)d\mu_1 d\mu_2 \qquad (21)$$

6.5.2 Descriptive results

Figure 5 shows the partial correlation between the two retained dimensions of wellbeing (latent variables). A positive correlation is portrayed by direction that we observe for the pick-mountain of the joint density function and that of the 45^{o} diagonal line.

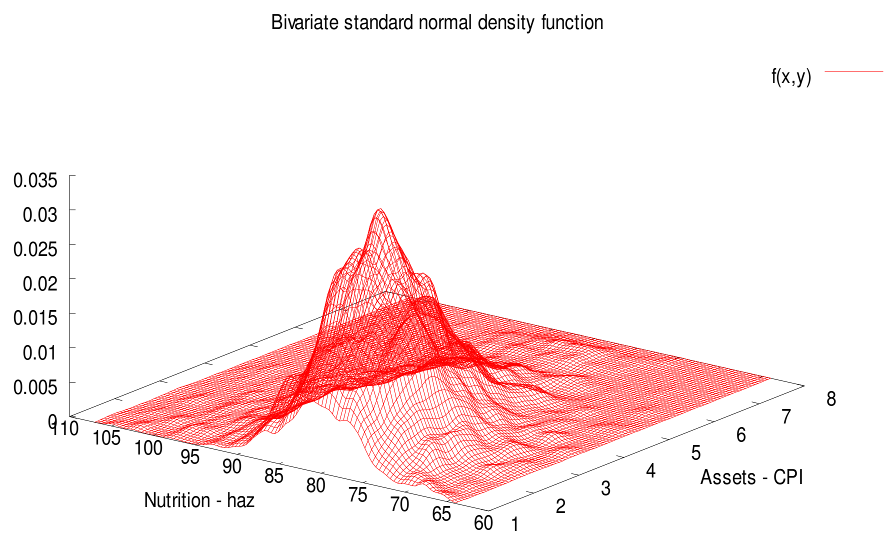

Figure 5: Bi-variate standard normal density function

6.5.3 Econometric Results

Introduction

Since asset and health poverty are not determined by the same factors, we estimate the seemingly unrelated bi-variate model of multidimensional poverty. The results of estimation of the bi-Probit model are presented in table 20. 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 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 predicated 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 20 presents the marginal impacts of the explanatory variables on the probability of being poor in both assets and health. The interpretation of the marginal effects can be illustrated with the effect of education. The estimated marginal effect shows that attainment of primary education reduces the likelihood of being multidimensional poor by 0.11 points, while attainment of 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 asset poor by 0.002 points. Other marginal effects can be interpreted in the same way. The results suggest that the highest marginal impacts on the probability of being multidimensional poor are from education attainment and access to electricity. The highest marginal impacts on the probability of being asset poor are from geographical location. Nyanza, Western and Rift valley provinces exert the highest marginal impacts relative to Nairobi province. Individual factors for health poverty have low conditional marginal impacts.

Probability of being asset poor

We investigate the impact of household characteristics, mother's education, access to electricity and regional characteristics. 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 education, primary and post primary education exert a significant and decreasing impact on the probability of being asset 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 assets. The marginal effects suggest that children from Nyanza province face the highest likelihood of being asset 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.

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 asset poverty decreased over the survey period. This suggests a growth in assets, which can be explained by growth in per capita incomes and development of infrastructure over the 10 year period. The marginal effects however suggest that the decline in asset poverty with year of survey 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 et al. 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 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 of 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. Conclusion

This paper performs multidimensional poverty analysis for women and children in Kenya using two dimensions of wellbeing: assets and health. The paper also tests for multidimensional poverty dominance and investigates the determinants of multidimensional poverty. Three rounds of Demographic and Health Survey (DHS) data for the period 1993, 1998 and 2003 is utilized.

Four inertia approaches are used to compute a composite poverty indicator (CPI): factor analysis (FA); principal components analysis (PCA); multiple correspondence analysis (MCA); and a two step approach (MCA/PCA). The two step CPI is then used to make poverty comparisons. The choice of thresholds for the CPI is based on percentiles of the distribution of households. For health, anthropometric measures (child nutrition) and the body mass index (BMI) for women are used. Nutritional deprivation thresholds for children are based on the United States National Centre for Health Statistics (NCHS) median reference where a cut-off of minus two (-2) standard deviations for anthropometric z-scores. The z-scores are then standardized following recommendations by WHO and the Centre for Disease Control. For women, the WHO recommendation of a BMI less than 18.5 poverty threshold is used.

The Alkire and Foster (AF) dual cut off and counting approach is applied to measure multidimensional poverty in the two dimensions of wellbeing. The results suggest that the estimated poverty index depends on the number of dimensions considered and that the poverty measure decreases with the number of dimensions. The results further suggest that the highest contribution to multidimensional poverty is from the assets relative to health, rural areas relative to urban areas and boys relative to girls. The welfare ranking of provinces depends on the choice of poverty cutoffs. Although Nyanza province has the largest proportion of poor children at low cutoffs, Coast province has the largest proportion at higher cutoffs. Rift valley province contributes the largest proportion to poverty at all cutoffs. We further find that poverty increased between 1993 and 1998, but declined between 1998 and 2003. The results for women are consistent with those for children. The results suggest that the AF multidimensional poverty orderings are robust to the choice of the poverty line, but not to the choice of the poverty cutoff.
The first order stochastic dominance analysis shows that urban areas dominate rural areas, while Nairobi province dominates all other regions in the two indicators of wellbeing. This order of dominance is also observed for the AF multidimensional poverty. Bi-dimensional stochastic dominance with statistical significance also suggest this order of dominance, but show that it is difficult to give a complete ranking of areas of residence, regions and gender groups by the two measures of wellbeing.

The econometric results for multidimensional poverty show that child, household, environmental and geographical characteristics are important correlates of poverty. Mother's education attainment and access to electricity exert the highest joint marginal impacts on the probability of being multidimensional poor. The highest marginal impacts on the probability of being asset poor are from geographical location, with Nyanza, Western and Rift valley provinces exerting the highest marginal impacts relative to Nairobi province. Individual factors for health poverty have low conditional marginal impacts.

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APPENDICES

Appendix I: Tables

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

Year\indicator	*1993*	*1998*	*2003*	*2005/6*	*2008/9*	*2000-7*
Children (%)						
Height for age (stunting)	32.7	33	30.3	34.5	35.3	30
Weight for height (wasting)	5.9	6.1	5.6	6.3	6.7	6
Weight for age (underweight)	22.3	22.1	19.9	20.9	16.1	20
Women						
Body mass index	22	21.9	22.7	-		-
% with low Body mass index	10	11.9	12	-		-

Source: CBS, MOH & ORC Macro, 1994, 1999 ,2004, 2009; UNICEF, 2009.

Table 1: List of variables and indicators for construction of CPI.

Variables	**Indicators (Binary categories)**
Household assets	Owns a radio Owns a TV Owns a fridge owns a bicycle
Source of drinking water	Piped water Surface water other sources of water
Sanitation	Household has a pit latrine Household has a flush toilet Household has a other type of toilet Household has a no toilet
Housing	House has low quality of floor House has modern roof
Access to health care	Women in household accessed prenatal care Women in household accessed modern birthing care Women in household accessed modern contraception
Education attainment	Head has no education Head attained primary education Head attained post primary education

Table 2: Stage One Results for MCA Applied on Different Sets of Indicators of Wealth

Indicators	Weights	Squared correlation	Contribution (%)	Distance to the centre	Relative Frequencies
Household assets					
Owns a radio	0.521	0.418	0.062	0.805	0.152
No radio	-0.803	0.418	0.096	1.242	0.098
Owns a TV	1.931	0.671	0.215	2.357	0.038
No TV	-0.348	0.671	0.039	0.424	0.212
Owns a fridge	3.124	0.539	0.193	4.254	0.013
No Fridge	-0.173	0.539	0.011	0.235	0.237
No bicycle	0.609	0.126	0.035	1.716	0.063
Owns a bicycle	-0.207	0.126	0.012	0.583	0.187
Source of drinking water					
Piped water	1.424	0.855	0.257	1.54	0.099
No piped water	-0.601	0.855	0.109	0.65	0.234
Surface water	0.789	0.761	0.146	0.90	0.183
No surface water	-0.965	0.761	0.179	1.11	0.150
Other sources of water	1.004	0.206	0.073	2.21	0.057
No other sources	-0.205	0.206	0.015	0.45	0.277
Sanitation: Household has					
Flush toilet	1.574	0.289	0.101	2.93	0.026
No flush toilet	-0.184	0.289	0.012	0.34	0.224
Pit latrine	-0.699	0.911	0.124	0.73	0.163
No pit latrine	1.304	0.911	0.231	1.37	0.087
Other type of toilet	-0.018	0.024	0	0.12	0.247
No other type	1.321	0.024	0.009	8.53	0.003
No toilet	-0.256	0.43	0.022	0.39	0.217
Toilet	1.683	0.43	0.145	2.57	0.033
Housing material					
High quality of floor	0.823	0.512	0.204	1.15	0.215
Low quality of floor	-0.622	0.512	0.154	0.87	0.285
Rudimentary roof	-1.328	0.512	0.277	1.86	0.112
Modern roof	0.385	0.512	0.08	0.54	0.388
Health care: women accessing					
Prenatal care	1.653	0.679	0.234	2.006	0.066
No prenatal care	-0.411	0.679	0.058	0.499	0.267
Modern birthing care	1.956	0.645	0.237	2.436	0.048
No modern birthing care	-0.33	0.645	0.04	0.411	0.285
Modern contraception	0.638	0.484	0.095	0.917	0.181
No modern contraception	-0.758	0.484	0.113	1.090	0.152
Education attainment (Head)					
No education	-0.02	0.002	0.00	0.49	0.269
Some education	0.08	0.002	0.001	2.05	0.064
Primary education	0.78	0.86	0.159	0.84	0.195
No primary education	-1.10	0.86	0.224	1.19	0.139
Post primary education	1.12	0.817	0.221	1.24	0.131
No post primary education	-0.73	0.817	0.143	0.80	0.203

Table 3: Contribution of Each Group of Indicators to CPI.

Indicators	*Contribution (%)*	*Weights*
Household assets	9.07	0.543
Source of drinking water	29.14	0.404
Sanitation	19.62	0.078
Housing material	16.44	-0.606
Access to health care	12.28	0.331
Education attainment	13.46	0.245

Table 4: Results for MCA Applied to all Indicators of Wealth

Indicators	Weights	Squared correlation	Contribution (%)	Distance to the centre	Relative Frequencies
Household assets					
Owns a radio	0.252	0.135	0.005	0.685	0.033
No radio	-0.537	0.135	0.011	1.461	0.020
Owns a TV	1.582	0.516	0.051	2.201	0.005
No TV	-0.326	0.516	0.011	0.454	0.047
Owns a fridge	2.524	0.398	0.045	3.999	0.001
No Fridge	-0.158	0.398	0.003	0.250	0.051
No bicycle	0.012	0.000	0.000	1.588	0.015
Owns a bicycle	-0.005	0.000	0.000	0.630	0.038
Source of drinking water					
Piped water	1.069	0.570	0.046	1.416	0.012
No piped water	-0.533	0.570	0.023	0.706	0.041
Surface water	0.588	0.556	0.026	0.788	0.027
No surface water	-0.946	0.556	0.041	1.269	0.026
Other sources of water	0.358	0.028	0.003	2.149	0.012
No other sources	-0.078	0.028	0.001	0.465	0.041
Sanitation: Household has					
Flush toilet	-0.222	0.134	0.004	0.608	0.038
No flush toilet	0.601	0.134	0.012	1.645	0.015
Pit latrine	-0.596	0.001	0.000	18.128	0.001
No pit latrine	0.002	0.001	0.000	0.552	0.052
Other type of toilet	2.142	0.609	0.065	2.744	0.004
No other type	-0.284	0.609	0.009	0.364	0.049
No toilet	-0.107	0.065	0.001	0.417	0.012
Toilet	0.614	0.065	0.007	2.400	0.010
Housing material					
High quality of floor	0.949	0.508	0.039	1.330	0.015
Low quality of floor	-0.536	0.508	0.022	0.752	0.035
Rudimentary roof	-0.385	0.040	0.004	1.921	0.020
Modern roof	0.104	0.040	0.001	0.521	0.033
Health care: women accessing					
Prenatal care	0.062	0.021	0.000	0.425	0.043
No prenatal care	-0.343	0.021	0.002	2.355	0.010
Modern birthing care	0.159	0.020	0.001	1.138	0.013
No modern birthing care	-0.123	0.020	0.001	0.879	0.040
Modern contraception	0.310	0.025	0.002	1.968	0.013
No modern contraception	-0.080	0.025	0.001	0.508	0.040
Education attainment (Head)					
No education	-0.015	0.000	0.000	0.872	0.032
Some education	0.020	0.000	0.000	1.147	0.021
Primary education	0.151	0.013	0.001	1.325	0.011
No primary education	-0.086	0.013	0.001	0.755	0.041
Post primary education	0.016	0.000	0.000	1.820	0.033
No post primary education	-0.005	0.000	0.000	0.549	0.035

Table 5: Factor and Principal Components Analysis Weights

Indicator	*Factor Analysis*	*Principal Components Analysis*
Household assets		
Radio	0.049	0.223
TV	0.096	0.332
Fridge	0.047	0.2422
Bicycle	0.021	0.0278
Source of drinking water		
Piped water	0.169	0.3401
Surface water	-0.213	-0.2411
Other sources of water	-0.084	-0.0547
Sanitation: Household has		
Flush toilet	0.192	0.0273
Pit latrine	-0.151	0.0193
Other toilet	-0.022	0.3325
No toilet	-0.357	-0.2521
Housing material		
Low quality of floor	-0.097	-0.3749
Modern roof	0.077	0.3058
Health care: women accessing		
Prenatal care	0.007	0.071
Modern birthing care	0.014	0.0946
Modern contraception	0.030	0.2075
Education attainment (Head)		
No education	-0.350	-0.1589
Primary education	-0.395	-0.1402
Post primary education	0.000	0.3042

Table 6: Summary Statistics for Alternative Composite Poverty Indicators

Approach	*Mean*	*Std. Dev.*	*Min*	*Max*
MCA & PCA	0.0055	1.344	-4.825	2.865
MCA	-0.0007	0.431	-1.590	0.717
Factor analysis	0.0013	0.982	-1.442	3.283
PCA	-0.0006	1.933	-3.035	7.052

Table 7: Children and Women Poverty Incidence by Region and Poverty Group

Region	*% below Poverty Line based on CPI Percentiles:*					
	Children			***Women***		
	25th	***40th***	***60th***	***25th***	***40th***	***60th***
Nairobi	1.11	2.22	7.46	1.52	3.27	9.67
Central	5.29	15.24	40.29	5.89	15.45	41.31
Coast	22.98	38.51	57.80	26.93	42.16	60.90
Eastern	21.03	31.98	57.01	22.90	33.48	58.60
Nyanza	36.15	50.36	71.94	35.20	49.72	71.71
Rift Valley	29.17	44.74	66.82	27.30	42.59	63.14
Western	28.63	44.36	69.63	30.23	47.00	71.23
Urban	4.88	9.52	18.98	3.64	7.44	16.90
Rural	28.87	43.81	67.87	29.25	44.18	68.12
National	25.00	38.28	59.99	25.17	38.33	59.96

Table 8a: Poverty comparisons: Overlaps in Child poverty by alternative indicators

		CPI Poverty Line					
		25th percentile		***40th percentile***		***60th percentile***	
Health indicator		Non-poor	Poor	Non-poor	Poor	Non-poor	Poor
Height for age	Non-poor	6,665	1,933	5,597	3,001	3,768	4,830
	Poor	2,676	1,181	2,090	1,767	1,215	2,642
Weight for age	Non-poor	7,592	2,213	6,360	3,445	4,240	5,565
	Poor	1,749	901	1,327	1,323	743	1,907
Weight for height	Non-poor	8,833	2,823	7,303	4,353	4,760	6,896
	Poor	508	291	384	415	223	576

Table 8b: Poverty comparisons: Overlaps in Women poverty by alternative indicators

	CPI Poverty Line					
	25th percentile		***40th percentile***		***60th percentile***	
BMI status	Non-poor	Poor	Non-poor	Poor	Non-poor	Poor
Non-poor	10077 (67%)	3321 (22%)	8343 (56%)	5055 (34%)	5520 (37%)	7878 (52%)
Poor	1030 (7%)	582 (4%)	800 (5%)	812 (5%)	437 (3%)	1175 (8%)

Table A2: Sample Statistics

Variable	*Rural*		*Urban*		*Full sample*	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev
standardized *haz*	81.21	5.19	82.74	5.35	81.43	5.24
standardized *waz*	11.02	1.54	11.68	1.93	11.12	1.62
standardized *whz*	11.18	1.11	11.65	1.34	11.25	1.16
Composite Poverty Indicator	2.67	1.09	4.38	1.35	2.92	1.28
CPI poor	0.41	0.49	0.06	0.23	0.36	0.48
haz poor	0.33	0.47	0.23	0.42	0.32	0.47
waz poor	0.09	0.29	0.05	0.21	0.09	0.28
whz poor	0.12	0.32	0.06	0.24	0.11	0.31
Body mass index (BMI)	21.74	3.23	23.71	4.29	22.05	3.50
BMI poor	0.11	0.32	0.06	0.24	0.11	0.31
CPI poor	0.44	0.50	0.07	0.26	0.38	0.49

Table 9: Alkire and Foster Child Multidimensional Poverty Indices (Full Sample)

	H	M0	M1	M2
0.5	0.551	0.265	0.055	0.021
1	0.412	0.242	0.055	0.021
1.5	0.394	0.236	0.055	0.021
2	0.144	0.111	0.023	0.009
2.5	0.144	0.111	0.023	0.009
3	0.051	0.049	0.009	0.003
3.5	0.039	0.039	0.007	0.003

Table 10a: Alkire and Foster Child Multidimensional Poverty Indices (Area of Residence)

	Rural				*Urban*			
Cutoff k	H	M0	M1	M2	H	M0	M1	M2
0.5	0.597	0.296	0.063	0.025	0.277	0.084	0.008	0.002
1	0.463	0.273	0.063	0.025	0.105	0.055	0.007	0.002
1.5	0.446	0.267	0.063	0.025	0.088	0.05	0.007	0.002
2	0.164	0.127	0.027	0.01	0.022	0.017	0.003	0.001
2.5	0.164	0.127	0.027	0.01	0.022	0.017	0.003	0.001
3	0.059	0.056	0.01	0.004	0.007	0.007	0	0
3.5	0.045	0.045	0.008	0.003	0.006	0.006	0	0

Table 10b: The relative contribution to the Alkire and Foster child MDP indices (Residence)

	Rural				*Urban*			
	H	M0	M1	M2	H	M0	M1	M2
0.5	0.928	0.955	0.98	0.987	0.027	0.045	0.02	0.013
1	0.963	0.967	0.982	0.988	0.037	0.033	0.018	0.012
1.5	0.968	0.97	0.983	0.988	0.032	0.03	0.017	0.012
2	0.978	0.978	0.984	0.987	0.022	0.022	0.016	0.013
2.5	0.978	0.978	0.984	0.987	0.022	0.022	0.016	0.013
3	0.981	0.98	0.992	0.998	0.019	0.02	0.008	0.002
3.5	0.978	0.978	0.992	0.998	0.022	0.022	0.008	0.002

Table 11a: The relative contribution of dimensions to the Alkire and Foster child MDP indices

	M0				*M1*				*M2*			
Cutoff k	Assets	haz	whz	waz	Assets	haz	whz	waz	Assets	haz	whz	waz
0.5	67.82	19.97	6.84	5.37	93.73	3.97	1.14	1.17	98.85	0.73	0.18	0.24
1	74.33	12.48	7.31	5.88	94.99	2.68	1.15	1.18	99.04	0.54	0.18	0.24
1.5	76.15	12.06	6.26	5.53	95.27	2.54	1.07	1.12	99.08	0.51	0.17	0.23
2	64.82	20.46	8.13	6.59	92.72	4.28	1.46	1.54	98.66	0.79	0.24	0.32
2.5	64.82	20.46	8.13	6.59	92.72	4.28	1.46	1.54	98.66	0.79	0.24	0.32
3	52.08	15.72	17.36	14.83	86.5	5.66	3.82	4.02	97.11	1.36	0.66	0.87
3.5	50.00	16.67	16.67	16.67	84.41	6.5	4.38	4.72	96.53	1.62	0.79	1.06

Table 12a: Alkire and Foster Child Multidimensional Poverty Indices by Region

		K=1				*K=3*			
Group	Pop Share	H0	M0	M1	M2	H0	M0	M1	M2
Nairobi	0.050	0.042	0.021	0.003	0.001	0	0	0	0
Central	0.121	0.209	0.122	0.019	0.006	0.026	0.026	0.003	0.001
Coast	0.081	0.496	0.307	0.063	0.024	0.082	0.08	0.012	0.004
Eastern	0.188	0.388	0.231	0.054	0.022	0.057	0.055	0.011	0.004
Nyanza	0.16	0.498	0.292	0.076	0.032	0.052	0.05	0.01	0.004
Rift Valley	0.245	0.469	0.274	0.059	0.022	0.062	0.058	0.01	0.004
Western	0.155	0.493	0.284	0.067	0.026	0.046	0.045	0.009	0.004

Table 12b: Relative Contribution to the Alkire and Foster MDP Indices for Children (Region)

	K=1				*K=3*			
Group	H0	M0	M1	M2	H0	M0	M1	M2
Nairobi	0.005	0.004	0.003	0.002	0	0	0	0
Central	0.061	0.061	0.041	0.032	0.063	0.063	0.047	0.039
Coast	0.098	0.104	0.094	0.090	0.131	0.132	0.114	0.095
Eastern	0.177	0.180	0.185	0.192	0.209	0.210	0.226	0.238
Nyanza	0.193	0.192	0.221	0.242	0.163	0.163	0.174	0.186
Rift Valley	0.280	0.277	0.265	0.252	0.296	0.291	0.284	0.269
Western	0.185	0.182	0.190	0.189	0.140	0.142	0.155	0.173

Table 13a: Alkire and Foster Child Multidimensional Poverty Indices by Gender

Indices		*K=1*				*K=3*			
Group	Pop. share	H0	M0	M1	M2	H0	M0	M1	M2
Male	0.502	0.413	0.246	0.055	0.021	0.058	0.056	0.01	0.004
Female	0.498	0.41	0.238	0.055	0.021	0.044	0.043	0.008	0.003

Table 13b: Relative Contribution to the Alkire and Foster MDP Indices for Children (Gender)

Contribution	*K=1*				*K=3*			
Group	H0	M0	M1	M2	H0	M0	M1	M2
Male	0.504	0.51	0.502	0.503	0.569	0.569	0.567	0.569
Female	0.496	0.49	0.498	0.497	0.431	0.431	0.433	0.431

Table 14a: Alkire and Foster Child Multidimensional Poverty Indices by Year (K=1)

	H0			***M0***			***M1***			***M2***		
Group	1993	1998	2003	1993	1998	2003	1993	1998	2003	1993	1998	2003
Urban	0.108	0.154	0.118	0.055	0.083	0.063	0.006	0.013	0.009	0.001	0.004	0.003
Rural	0.547	0.499	0.374	0.324	0.302	0.216	0.086	0.082	0.038	0.036	0.036	0.013
Full Sample	0.505	0.449	0.313	0.298	0.27	0.18	0.078	0.072	0.031	0.033	0.032	0.01

Table 14b: Alkire and Foster Child Multidimensional Poverty Indices by Year (K=3)

	H0			***M0***			***M1***			***M2***		
Group	1993	1998	2003	1993	1998	2003	1993	1998	2003	1993	1998	2003
Urban	0.007	0.012	0.007	0.006	0.011	0.006	0	0.001	0	0	0	0
Rural	0.072	0.074	0.04	0.069	0.071	0.039	0.014	0.015	0.005	0.006	0.006	0.002
Full Sample	0.066	0.065	0.032	0.063	0.062	0.031	0.013	0.013	0.004	0.005	0.005	0.001

Table 15a: Alkire and Foster Multidimensional Poverty Indices (Women)

Group		*K=1*				*K=2*			
	Pop. share	H0	M0	M1	M2	H0	M0	M1	M2
Region									
Nairobi	0.043	0.075	0.038	0.004	0.001	0.001	0.001	0	0
Central	0.099	0.229	0.122	0.02	0.006	0.016	0.016	0.002	0.001
Coast	0.155	0.474	0.27	0.061	0.024	0.065	0.065	0.012	0.004
Eastern	0.145	0.393	0.22	0.054	0.022	0.048	0.048	0.009	0.004
Nyanza	0.162	0.539	0.291	0.088	0.04	0.043	0.043	0.009	0.004
Rift Valley	0.248	0.507	0.294	0.074	0.03	0.082	0.082	0.016	0.006
Western	0.149	0.474	0.251	0.067	0.027	0.028	0.028	0.006	0.003
Residence									
Urban	0.146	0.138	0.074	0.011	0.003	0.01	0.01	0.002	0.001
Rural	0.854	0.492	0.274	0.071	0.029	0.057	0.057	0.011	0.004
Full Sample	1	0.44	0.245	0.062	0.025	0.05	0.05	0.01	0.004

Table 15b: The relative contribution to the Alkire and Foster MDP indices (Women)

		K=1				*K=2*			
Group	Pop. share	H0	M0	M1	M2	H0	M0	M1	M2
Region									
Nairobi	0.043	0.007	0.007	0.003	0.002	0.001	0.001	0	0
Central	0.099	0.051	0.049	0.032	0.023	0.032	0.032	0.022	0.018
Coast	0.155	0.168	0.171	0.153	0.144	0.203	0.203	0.194	0.181
Eastern	0.145	0.129	0.13	0.127	0.127	0.137	0.137	0.141	0.149
Nyanza	0.162	0.198	0.192	0.231	0.254	0.139	0.139	0.148	0.157
Rift Valley	0.248	0.286	0.298	0.294	0.289	0.404	0.404	0.405	0.393
Western	0.149	0.161	0.153	0.161	0.159	0.084	0.084	0.088	0.102
Residence									
Urban	0.146	0.046	0.044	0.026	0.02	0.03	0.03	0.025	0.026
Rural	0.854	0.954	0.956	0.974	0.98	0.97	0.97	0.975	0.974
Dimension									
Assets			78.27	95.30	98.86		50	84.29	95.55
BMI			21.73	4.70	1.14		50	15.71	4.45

Table 16a: Alkire and Foster Multidimensional Poverty Indices for Women by Year for K=1

Index	*H0*			*M0*			*M1*			*M2*		
Year	1993	1998	2003	1993	1998	2003	1993	1998	2003	1993	1998	2003
Urban	0.13	0.16	0.19	0.07	0.09	0.11	0.01	0.02	0.02	0	0.01	0.01
Rural	0.55	0.51	0.43	0.3	0.28	0.25	0.09	0.08	0.05	0.04	0.04	0.02
Full sample	0.51	0.47	0.37	0.28	0.26	0.22	0.08	0.07	0.04	0.03	0.03	0.02

Table 16b: Alkire and Foster Multidimensional Poverty Indices for Women by Year for K=2

Index	*H0*			*M0*			*M1*			*M2*		
Year	1993	1998	2003	1993	1998	2003	1993	1998	2003	1993	1998	2003
Urban	0.029	0.01	0.012	0.029	0.01	0.012	0.006	0	0.003	0.003	0	0.001
Rural	0.068	0.059	0.056	0.068	0.059	0.056	0.011	0.012	0.012	0.004	0.005	0.005
Full sample	0.059	0.054	0.050	0.059	0.054	0.050	0.01	0.011	0.011	0.003	0.004	0.005

Sensitivity Analysis: A&F Indices for CPI Poverty line set at 25th percentile

Table 17a: Alkire and Foster Multidimensional Poverty Indices (Children)

	K=1				*K=3*			
Group	H0	M0	M1	M2	H0	M0	M1	M2
Region								
Nairobi	0.035	0.017	0.002	0.001	0.000	0.000	0.000	0.000
Central	0.123	0.066	0.008	0.002	0.009	0.009	0.001	0.000
Coast	0.364	0.217	0.033	0.011	0.051	0.049	0.006	0.002
Eastern	0.294	0.169	0.031	0.011	0.036	0.035	0.006	0.002
Nyanza	0.356	0.205	0.043	0.017	0.035	0.034	0.006	0.002
Rift Valley	0.322	0.184	0.029	0.01	0.041	0.039	0.005	0.002
Western	0.346	0.197	0.034	0.012	0.031	0.030	0.005	0.002
Residence								
Urban	0.078	0.037	0.003	0.001	0.032	0.031	0.005	0.002
Rural	0.326	0.188	0.033	0.012	0.000	0.000	0.000	0.000
Full Sample	0.291	0.166	0.029	0.01	0.038	0.036	0.006	0.002

Table 17b: The relative contribution to the Alkire and Foster MDP indices (Children)

	K=1				*K=3*			
Group	H0	M0	M1	M2	H0	M0	M1	M2
Region								
Nairobi	0.006	0.005	0.003	0.002	0	0	0	0
Central	0.051	0.048	0.033	0.026	0.035	0.035	0.034	0.033
Coast	0.102	0.106	0.093	0.085	0.128	0.128	0.097	0.076
Eastern	0.19	0.19	0.199	0.202	0.211	0.21	0.239	0.253
Nyanza	0.195	0.197	0.238	0.266	0.172	0.173	0.188	0.195
Rift Valley	0.272	0.271	0.249	0.235	0.307	0.305	0.271	0.247
Western	0.184	0.184	0.185	0.183	0.147	0.15	0.172	0.196
Residence								
Urban	0.038	0.032	0.016	0.009	0	0.00	0.00	0.00
Rural	0.962	0.968	0.984	0.991	1	1.00	1.00	1.00
Dimension								
Assets		66.09	91.10	98.08		52.07	83.70	96.03
haz_std		14.81	4.48	1.04		15.89	6.86	1.88
whz_std		10.55	2.17	0.38		17.36	4.58	0.89
waz_std		8.55	2.25	0.50		14.68	4.86	1.20

Table 18a: Alkire and Foster Multidimensional Poverty Indices (Women)

		K=1				K=2			
Group	Pop. share	H0	M0	M1	M2	H0	M0	M1	M2
Region									
Nairobi	0.043	0.052	0.026	0.002	0	0	0	0	0
Central	0.099	0.128	0.068	0.008	0.002	0.007	0.007	0.001	0
Coast	0.155	0.346	0.194	0.033	0.011	0.042	0.042	0.007	0.002
Eastern	0.145	0.306	0.17	0.031	0.011	0.034	0.034	0.006	0.002
Nyanza	0.162	0.403	0.218	0.052	0.022	0.034	0.034	0.005	0.002
Rift Valley	0.248	0.374	0.217	0.041	0.015	0.059	0.059	0.009	0.003
Western	0.149	0.324	0.173	0.035	0.013	0.021	0.021	0.004	0.001
Residence									
Urban	0.146	0.096	0.051	0.005	0.002	0.005	0.005	0.001	0
Rural	0.854	0.357	0.199	0.039	0.015	0.041	0.041	0.006	0.002
Full Sample	1	0.319	0.177	0.034	0.013	0.035	0.035	0.006	0.002

Table 18b: The relative contribution to the Alkire and Foster MDP indices (Women)

	K=1				K=2			
Group	H0	M0	M1	M2	H0	M0	M1	M2
Region								
Nairobi	0.007	0.006	0.002	0.001	0	0	0	0
Central	0.04	0.038	0.024	0.019	0.019	0.019	0.016	0.014
Coast	0.169	0.17	0.149	0.139	0.184	0.184	0.184	0.173
Eastern	0.138	0.139	0.13	0.127	0.14	0.14	0.147	0.155
Nyanza	0.204	0.199	0.247	0.277	0.154	0.154	0.154	0.161
Rift Valley	0.29	0.303	0.295	0.286	0.417	0.417	0.4	0.381
Western	0.152	0.145	0.152	0.152	0.087	0.087	0.099	0.116
Residence								
Urban	0.044	0.042	0.023	0.018	0.023	0.023	0.026	0.029
Rural	0.956	0.958	0.977	0.982	0.977	0.977	0.974	0.971
Dimension								
Assets		69.98	91.49	97.72		50	81.65	94.4
BMI		30.02	8.51	2.28		50	18.35	5.6

Alternative multidimensional poverty indicators

Table 19a: Comparison of alternative multidimensional (child) poverty indicators

Poverty Index	*Rural*	*Urban*	*Population*
Chakravarty et al. (1998)	0.146	0.0525	0.127
Bourguignon and Chakravarty (2003)	0.146	0.025	0.127
Multiplicative Extended FGT Index	0.016	0.025	0.139
Tsui (2002) Index	0.005	0.001	0.005
Intersection head count index	0.156	0.021	0.136
Union head count index	0.593	0.272	0.542
Extended Watts index	0.194	0.029	0.167
Alkire and Foster (2007) H0 for *k*=1	0.463	0.105	0.412
Alkire and Foster (2007) H0 for *k*=3	0.052	0.011	0.045

Table 20b: Comparison of alternative multidimensional (Women) poverty indicators

Poverty Index	*Rural*	*Urban*	*Population*
Chakravarty et al. (1998)	0.550	0.127	0.483
Bourguignon and Chakravarty (2003)	0.142	0.018	0.123
Multiplicative Extended FGT Index	0.058	0.008	0.050
Tsui (2002) Index	0.002	0.001	0.002
Intersection head count index	0.058	0.008	0.050
Union head count index	0.492	0.120	0.492
Extended Watts index	0.191	0.012	0.164
Alkire and Foster (2007) H0 for *k*=1	0.491	0.119	0.441
Alkire and Foster (2007) H0 for *k*=2	0.058	0.007	0.051

Table 20: Bi-Probit model of Multidimensional Poverty

Variable	*Asset poor*	*Health poor*	*Joint marginal effects*
	Coefficients	Coefficients	Pr (CPI_poor, haz_poor))
Child characteristics			
Male child dummy	-0.0146	0.1301***	0.0130***
Number of children <5 years	0.0151*		0.0015*
Age of child (months)		0.0117***	0.0013***
Child is of multiple birth		0.3153***	0.0373***
Household characteristics			
Mothers height		-0.0287***	-0.0032***
Mother has primary education	-1.2525***	-0.2625***	-0.1118***
Mother has post primary education	-1.8296***	-0.4639***	-0.0980***
Log household size		0.0535***	0.0060***
Housing & environmental characteristics			
Household has electricity	-1.8022***	-0.2704***	-0.1098***
House has rudimentary floor		0.0013***	0.0001***
Unsafe drinking water		0.0594**	0.0067**
Unsanitary toilet conditions		0.1192***	0.0129***
Regional dummies			
Central province	0.5506***		0.0593***
Coast province	1.2325***		0.1283***
Eastern province	0.9691***		0.1032***
Nyanza province	1.5175***		0.1522***
Rift valley province	1.3410***		0.1379***
Western province	1.3993***		0.1429***
Survey year dummy			
1998 survey year	-0.0732***	0.1678***	0.0108***
2003 survey year	-0.4520***	0.0161	-0.0430***
Constant	-1.0790***	3.3401***	
Athrho	0.0604***		
Observations	25984		
Wald chi2(26)	4525***		
Log pseudo likelihood	-29068.975		

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

Appendix II: Figures

Figure 1: MCA Coordinate Plots for various categories of Wealth indicators

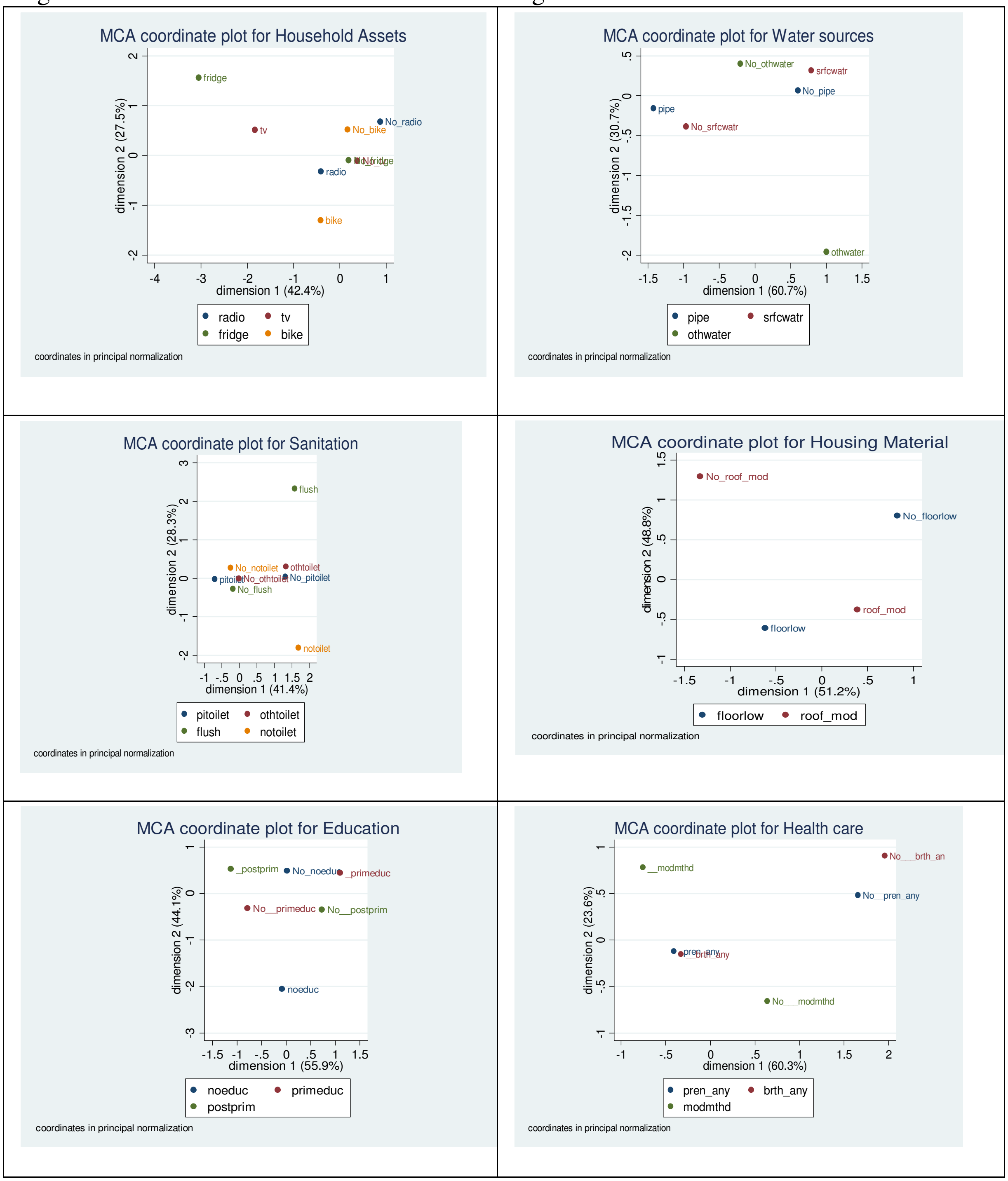
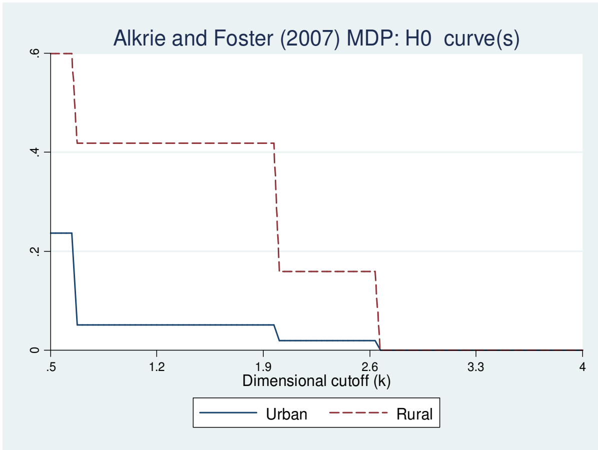
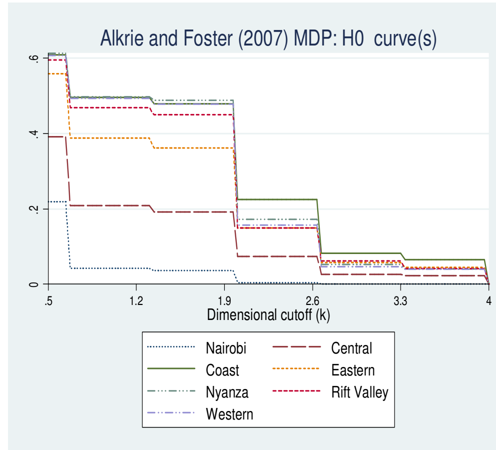


Figure 2: Alkire and Foster Multidimensional (Child) Poverty Incidence Curves

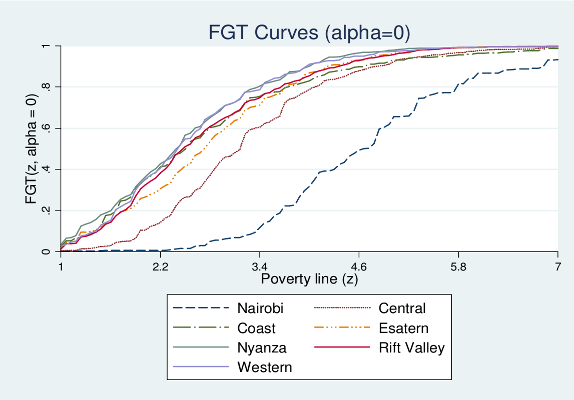


a). MDP curves for area of residence

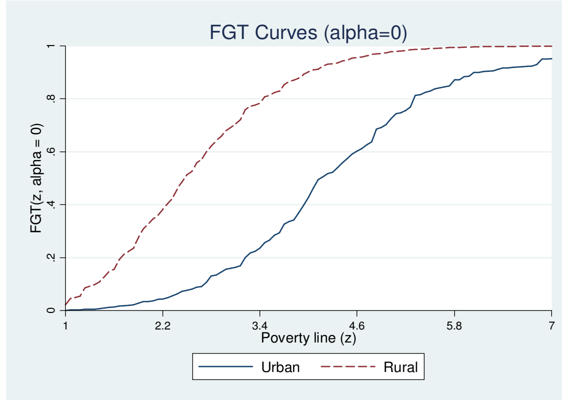


a). MDP curves for area of regions

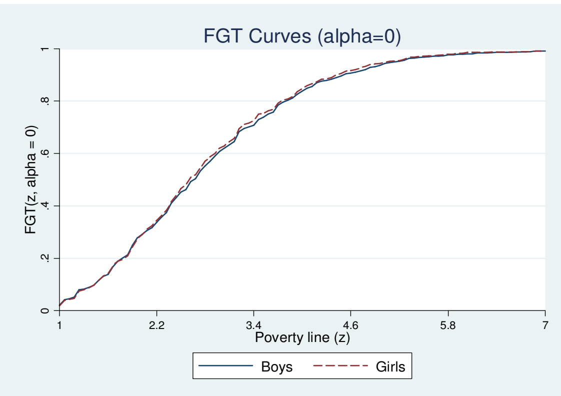
Figure 3: FGT curves for assets and nutrition by region, area of residence and gender of child.



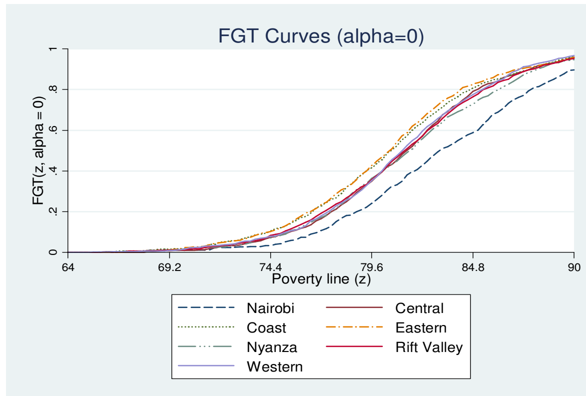
a). Assets by region



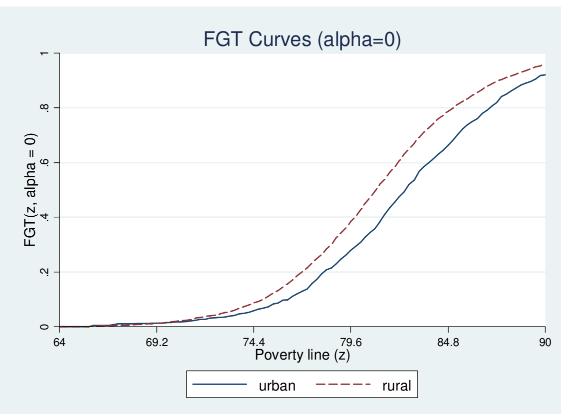
b). Assets by area of residence



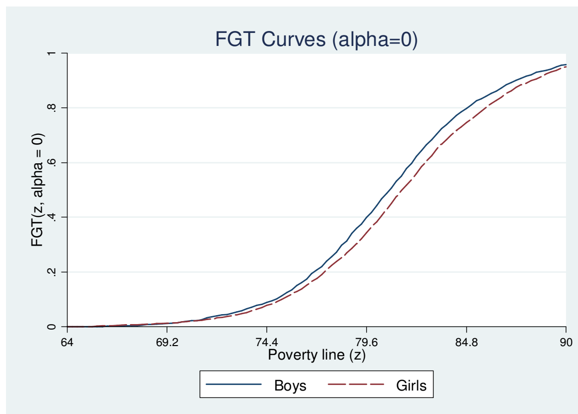
c). Assets by gender



d). Nutrition by region

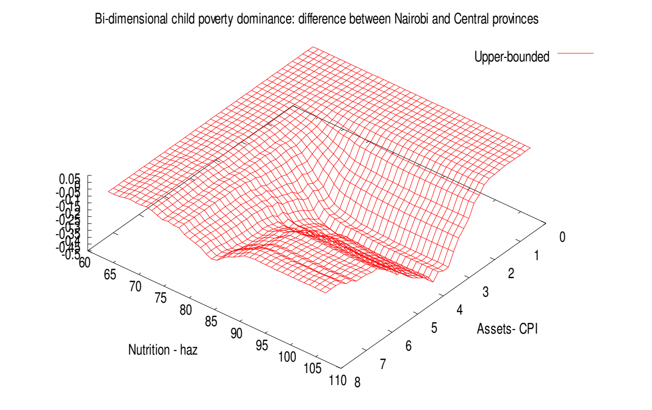


e).Nutrion by area of residence

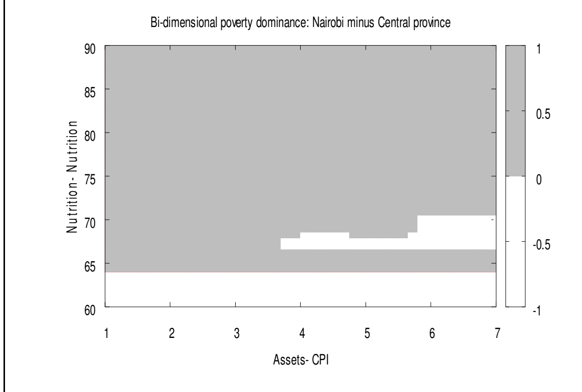


f). Nutrion by gender

Figure 4: Bi-dimensional poverty dominance for children

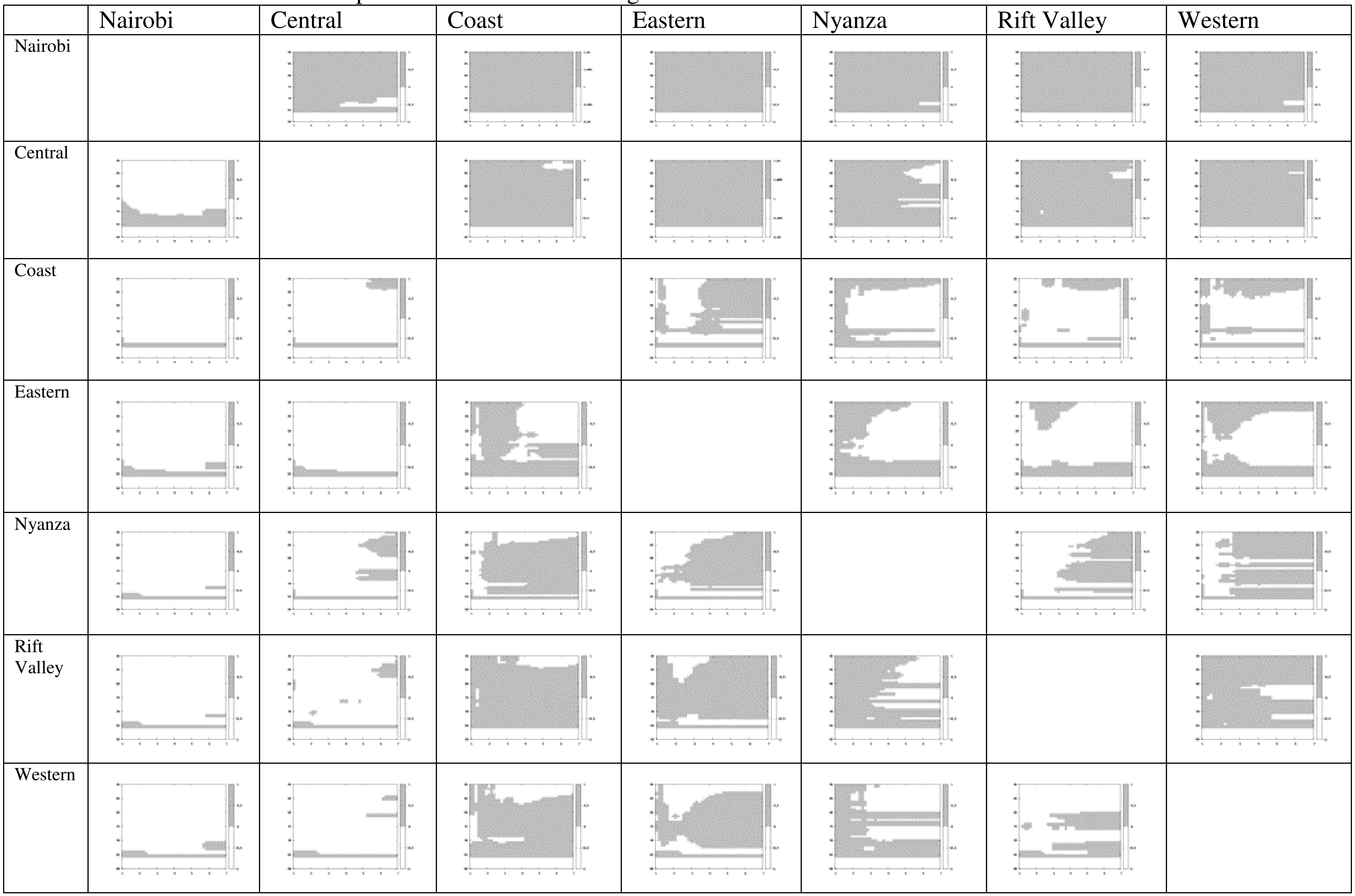


a). Three dimensional surface diagram



b): Map view two dimensional diagram

Table A3: Dominance tests across provinces with statistical Significance.



Appendix III 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[11]. 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 $\bar{g}$ =female. The standardized z-score (Z) can be expressed as:

$$Z = F^{-1}_{\bar{a},\bar{g}}(F_{a,g}(z)) \quad \text{(A1)}$$

To arrive at the final standardized values, we use the CDC recommended lambda, mu, and sigma (LMS) procedure and associated parameter[12]:

$$\text{Std\_Z} = M(1 + LSZ)^{1/L}L \quad \text{(A2)}$$

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.

[11] 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.

[12] The values *of* parameters and percentiles for standardization are available online at: http://www.cdc.gov/growthcharts/percentile_data_files.htm. See also Kuczmarski et al. (2002).