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Multidimensional Poverty in Kenya: Analysis of Maternal and Child Wellbeing

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Abstract

This paper generates multidimensional poverty profiles for women and children over a ten-year period from 1993 to 2003.Data from the national Demographic and Health Survey are used to improve measurement of poverty in Kenya in four ways: First, the paper constructs a composite wealth index (CWI). Second, it applies the Alkire and Foster (2007) approach to the measurement of multidimensional poverty based on the CWI and health status. Third, stochastic dominance approaches are used to make poverty orderings across groups. Fourth, the probability of being poor in assets, health or both is explored using a bivariate probit model. The results show that the distribution of poor women and children differs across groups, space and time. We also find that the CWI and residence in a rural area respectively contribute more to multidimensional poverty than health and residence in an urban area. The results further suggest that understanding the correlates of wellbeing in a multidimensional context can generate policy insights for improving human capital investments.

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

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1. Introduction

According to Sen (1985), poverty should be viewed in relation to a lack of basic needs or basic capabilities. This means that poverty is a multidimensional phenomenon and should be measured using multiple indicators of wellbeing. In his seminal work, Sen (1976) pointed to a two-stage process of measuring poverty that involves identification and aggregation. The first of these stages focuses on identifying the poor. Traditional welfare studies measure poverty in terms of deprivation of means, which leads to analyses of monetary indicators (incomes and expenditures). The logic and rationale behind the money-metric approach to studying poverty is that, in principle, an individual who is above the monetary poverty line is presumed to have sufficient purchasing power to acquire a consumption bundle that yields a functional level of wellbeing.

Money-metric approaches to poverty measurement have a number of drawbacks. The main drawback is that this approach presupposes an existing market for all factors that contribute positively to welfare and that prices reflect weighted utility across all households in a given context. However, some attributes (public goods) may be impossible or difficult to purchase because markets do not exist or are imperfect where they do exist. Income is thus a limited reflection of wellbeing because it does not incorporate key dimensions of poverty relating to quality of life. Another drawback of the income approach is that households with income at or even above the poverty line may not actually use their income to buy the minimum bundle of basic needs. This means that some household members may remain deprived of some basic needs even when the household is non-poor in monetary terms (Thorbecke, 2008).Another approach to measuring poverty is the non-monetary approach. Sen (1985) and others have argued that poverty should be viewed as a deprivation of capabilities and functionings rather than of means. It is these capabilities and functionings that are vital to one's wellbeing. Sen's approach also suggests that policies should not necessarily be evaluated by their ability to satisfy utility or to increase income. Rather, they should be evaluated by their ability to enhance the individuals' capabilities and their ability to achieve a socially acceptable level of functioning.[1]Non-monetary approaches therefore consider wellbeing in terms of freedoms and achievements, and assess wellbeing in terms of basic capabilities such as the ability to be well fed, educated, healthy and decent, without being overly concerned about utility per se. Capabilities range from "absolute deprivation of goods" for approaches which focus on nutrition

[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 a particular type life (Sen, 1985).

or other “basic needs”, to the “relative deprivation of goods” (Townsend, 1979). This means that poverty indices must capture the inability of individuals to attain some minimal level of capabilities required to function.

The aggregation stage involves the use of indices to aggregate individual-level information, often at the level of population subgroups or regions. A number of approaches extend unidimensional poverty indices to cover multiple dimensions, but most approaches aggregate individual-level information into a single measure (see Tsui (2002), and Bourguignon and Chakravarty (2003), for example). Emerging literature that analyzes poverty as a multidimensional issue uses dominance approaches as per Atkinson (1987) and Foster and Shorrocks (1988). For unidimensional cases, the works of Duclos *et al*. (2006a, 2006b, 2008) or Sahn and Stifel (2002) can be referred to. Duclos, Sahn and Younger, (2006a, 2006b, and 2008) extend the partial poverty ordering methods to multidimensional settings. Another alternative is Alkire and Foster (2007), who propose what they call a counting approach to measuring multidimensional poverty. Their approach is appealing for three reasons: First, the identification procedure uses two cut-offs, one of which involves dimension-specific thresholds to identify individuals who are deprived for the respective dimensions and the other of which is the number of dimensions an individual must be deprived of to be considered as poor. A second reason why this approach is appealing is that it satisfies several desirable properties including decomposability, which makes it particularly suitable for policy targeting. Third, as is the case for several other measures of multidimensional poverty, the researcher is free to assign different weights to each dimension.

This study analyses multidimensional poverty among women and children in Kenya. We focus on women and children because they comprise the largest share of the poor and vulnerable in Kenya. In addition, maternal and child poverty has potentially debilitating long-term effects on the long term child growth and development. Nutritional status and a household composite wealth indicator (CWI) are the basis of comparison between groups. Following Sen’s definition of wellbeing, child anthropometric measures and body mass index, both of which are indicators of food and health deprivation, are considered as more direct measures of capability deprivation than income and expenditures. This allows us to directly observe individual wellbeing. Furthermore, poor nutritional status implies that people suffer from inadequate caloric intake and/or health problems, both of which are important dimensions of wellbeing. Nutrition can also be used as a quality-of-life indicator for the poor because it is fairly responsive to socio-economic conditions. Unlike incomes and expenditures, these measures of wellbeing are also easily assessed at the individual rather than household level.

A child or woman is considered as poor if she comes from a household whose CWI is below some pre-determined poverty line and/or if her nutritional status is below a certain threshold. Stochastic dominance analysis is also performed. A bivariate probit model of multidimensional poverty is also estimated. The study suggests policies for improving maternal and child nutritional status in Kenya on the basis of these findings. The study contributes to the literature in three ways. First, it constructs a CWI to rank maternal and child health. This CWI is similar to the deprivation index proposed under the Bristol approach (Gordon *et al*. 2003). Second, the study fills a gap in research on multidimensional poverty studies in Kenya. Previous studies have concentrated on unidimensional poverty analysis Multidimensional poverty analysis can reveal complexities and ambiguities in the distribution of wellbeing that cannot be captured in a unidimensional analysis of poverty[2]. Third, women tend to be relatively disadvantaged in human capital investments in Kenya. However, research on women's nutritional status in Kenya remains scarce. Given the long term and intergenerational consequences of poor maternal nutrition (Meyerhoefer and Sahn, 2007), this is a serious research gap.

The rest of the paper is structured as follows: Section 2 provides background on maternal and child poverty in Kenya. Section 3 describes the data used. Section 4 presents the analytical frameworks and methodology, and section 5 reports the results. Section 6 summarizes and concludes the report then offers policy recommendations and suggestions for further research.

2. Background and Context

Kenya is a low-income country with a food deficit, a population of about 37 million and an estimated gross national per capita income of about US$1,470 in 2010 (PPP). The Human Development Index was 0.47 in 1975 and rose to 0.52 by 2005. The Human Poverty Index was 37.5% in 2002 and 38.5% in 2005. Over 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 estimated HIV prevalence among adults aged 15 to 49 years was 5% and 7% between 2000 and 2009 (WHO, 2010).

[2] There is a dearth of multidimensional poverty studies in developing countries, particularly in Africa.

Stagnating food production, an unfavourable economic environment and poverty are the major causes of food insecurity in the country. The national caloric supply has barely met population energy requirements for years, resulting in undernourishment of a third of the population (Republic of Kenya, 2005). After independence in 1963, the government of Kenya identified poverty, ignorance and disease as some of the major problems facing Kenya (Republic of Kenya, 1965). Since then, the country's development agenda has emphasized income growth, job creation and the provision of basic social services. Poverty and food insecurity nevertheless remain widespread. The earliest estimates of the incidence of poverty in Kenya date back to the early 1970s. Food poverty was estimated to afflict about 30% of the population in 1972. The incidence of rural poverty was estimated at 38.5% in 1974/75 (UNDP, 1999), but is estimated to have risen to 46.3% by 1992. The incidence of poverty then remained fairly constant between 1992 and 1994, when the estimated share of Kenyans living in poverty ranged from 46.3% to 47% of the population. The percentage of the poor rose to 52.3% in 1997 and 56% by 2000. It then declined to 47% in 2005/6 (KNBS, 2007). The proportion of people living in poverty is projected to 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 are food and subsistence farmers in rural areas and workers in the informal sector in cities. About a third of rural households are female-headed, two-thirds of which have no male support. The incidence of severe poverty is significantly higher among such households (estimated at 44 percent as opposed to 20 percent for male-headed households in 1997). It is estimated that 69% of the active female population work in subsistence farming as opposed to 43% of men (Republic of Kenya, 2007). Children from such households and orphans face higher risks of falling into poverty and vulnerability than their counterparts from male-headed households.

Poor nutrition is one of the major problems affecting the most vulnerable – children and women in Kenya. Available evidence indicates that a large share of the population cannot satisfy their caloric requirements. Malnutrition remains a significant contributing factor to deaths among children under the age of five. Nutritional deficiencies contribute to stunted growth and high rates of disability, illness and death, particularly during the first two years of life. These deficiencies 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. The nutritional status of women and children has seen little or no progress in recent decades: Child malnutrition declined between 1960 and the late 1980s, only to stagnate in the late 1980s. In the 1990s, an estimated 33% of children under the age of five in Kenya suffered from chronic malnutrition. Although this dropped

to about 30% by 2003, estimates from the 2008/09 demographic and health survey (KNBS and ICF Macro, 2010) indicate that the percentage of stunted children in 2005/06 had risen to 35%. Other measures of child nutrition remained fairly constant (appendix A, table A1) over this period.

Causes of child malnutrition in Kenya include a lack of food, a diet without necessary nutrients, common and preventable infections or illnesses which rob the body of nutrients, inadequate personal care and unsafe water that may cause diarrhoea or other illnesses. Short birth spacing also negatively affects child nutrition because early weaning of children may result in insufficient care during the first two to three years of life (Kabubo-Mariara, Nd'enge and Kirii, 2009). Meanwhile, only 13% of mothers exclusively use breastfeeding. HIV/AIDS and related complications are a heavy burden on poor women, their children and orphans. Other major challenges include low prioritization, poor funding and limited understanding of nutrition issues across multiple sectors (UNICEF, 2009).

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

3. Data

This study uses three rounds of DHS data (1993, 1998 and 2003). The DHS collects information on nationally representative samples of women aged 15 to 49 and their children. The 1993 and 1998 data covered all regions of Kenya except the North Eastern province. The 2003 data covered all provinces. The DHS data contains a wealth of information on demographics, nutrition and health (including BMI and child anthropometrics) for women and

children and is thus well-suited to answering this study's research questions. The DHS used a two-stage sample design. The first stage involved selecting sample points (clusters) from a national master sample maintained by the Central Bureau of Statistics (CBS, now the Kenya National Bureau of Statistics). This sample comes from the fourth National Sample Survey and Evaluation Program (NASSEP IV). The 1993 and 1998 Kenya DHS selected 536 clusters, 444 rural and 92 urban, from seven of the eight provinces in Kenya. The 1993 survey collected data from 34 districts, while the 1998 survey collected data 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. The desired sample of households was selected among these clusters using systematic sampling methods.

The three surveys are fairly comparable but differ in a number of ways. The 1993DHS collected information on 7,540 women aged 15-49, and 6,115 children aged less than 60 months from 7950 households from February to August 1993. The 1998 DHS collected information on 7,881 women aged 15-49 and 5,672 children under the age of 60 months from 8,380 households from February to July 1998. The 2003 DHS in Kenya covered 8,195 women aged 15-49 and 5,949 children aged less than 60 months from 8,561 households in the months of April to August, 2003. After pooling the three rounds of DHS data and cleaning the data to make the samples comparable, we obtained a sample of about 12,500 children aged between 0 and 60 months and about 15,000 women aged 15 to 49 years.[3] All surveys collected information relating to demographic and socio-economic characteristics for all respondents along with more extensive information on pre-school children.

4. Analytical framework and methodology

4.1. Constructing a composite wealth indicator: Methodological choices

Studies of multidimensional poverty first focus on constructing a composite measure of poverty/wealth. In order to achieve the study's first objective, we construct a composite wealth indicator (CWI) that captures multiple aspects of household wealth as recorded in the DHS survey. This CWI is one of the dimensions of the multidimensional poverty index used for the

[3] To make the samples comparable, it was necessary to recode some variables and to omit the North Eastern province which was not covered in the first 2 years of the survey.

comparisons made in subsequent sections of the study. The challenges involved in constructing a CWI should not be underestimated. A prominent difficulty involves aggregation of 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 CWI that stems from static mechanisms and is mainly based on multidimensional analysis techniques (Asselin, 2009). The inertia approaches are factorial techniques, namely factor analysis (FA), 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, the definition of the functional form of the CWI is less arbitrary. Second, it allows the poverty dimensions to be chosen optimally.[4] Having settled on the inertia approach, the choice remains between different inertia approaches given the structure of the data available and the assumptions with respect to each indicator being studied (Asselin, 2009; Ki, *et al*., 2005).

There are three main alternative approaches to constructing a CWI: principal components analysis (PCA), factor analysis (FA) and multiple correspondence analysis (MCA).[5] In this study, a two-stage procedure is used to construct the CWI. In the first stage, we use an MCA to estimate the individual scores for each dimension. In the second stage we use the continuous dimensional scores estimated during the first stage to perform a PCA of the individual CWI. The combination of MCA and PCA is appropriate for two reasons. First, it ensures that the estimated CWI captures the optimal scaling property of the MCA in the first step. Second, it avoids the disadvantages of the PCA, which is only applied to continuous variables during the second stage. Using the normalized score (the MCA score for each dimension divided by the square root of the first eigenvalue) before using the PCA data reduction procedure allows this two-stage approach to avoid overestimating the contribution of any dimension that have higher variability (Ki *et al*. 2005). It also allows us to derive uncorrelated linear combinations of wellbeing indicators.

[4]The main limitation of the entropy approach is the arbitrary choice of parameters and weights used in the functional form. Inertia approaches use a methodology that constructs a CWI with a minimum of arbitrariness in the definition of the functional form. The nominal weighting involves non-linear quantification of each qualitative primary indicator, which implies that there is no constraint on functional forms. It also allows for an optimal choice of the pertinent dimensions of poverty and discards redundant information (Asselin, 2009).

[5] The PCA and MCA approaches are discussed in Appendix C1. More information on FA is available in a technical appendix to this report that is available from the authors upon request.

4.2. Multidimensional poverty comparisons

Most of the literature on the measurement of poverty follows the one-dimensional approach, which uses a monetary indicator to identify a person as poor. 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 thus leads to the question of how aggregation should be carried out. The multidimensional poverty comparisons in this paper account for both the identification and aggregation problems using two approaches: the stochastic dominance approach (Duclos, Sahn and Younger, 2006a), and the dual cut-off and counting approach (Alkire and Foster, 2007).

Duclos, Sahn and Younger extend partial poverty ordering approaches to multidimensional settings. The approach is based on Chakravarty *et al*. (1998), Tsui (2002) and Bourguignon and Chakravarty (2003).[6] These authors develop desirable axioms for measures of multidimensional poverty by viewing a multidimensional poverty index as an aggregation of individual shortfalls relative to some minimum level of basic needs for each dimension (see appendix C2.1 for details). This approach is used to generate bi-dimensional poverty dominance surfaces using the CWI and health dimensions of child poverty. We further extend the analysis to test for statistical significance of the poverty dominance tests. We use the DASP software package (Araar and Duclos, 2007) to derive dominance curves and surfaces. The package is also used for the Alkire and Foster multidimensional poverty analysis.

Alkire and Foster (2007) proposed a new approach to measuring multidimensional poverty which accommodates the union and intersection approaches as well as more intermediate options. In contrast to earlier approaches, the new approach uses a dual cut-off identification method. It also proposes a counting approach similar to the aggregation method in the Foster *et al*. (1984) family of poverty indices (see appendix C2.2 for details). The Alkire and Foster approach is used in this paper to consider whether a child is poor in terms of a wealth dimension measured by the CWI and in at least three health-related dimensions: nutritional status as measured by standardized anthropometric measures of *height for age* (*haz*), *weight for age* (*waz*) and *weight for height* (*whz*).

[6] These studies have been criticized for aggregating multiple measures of wellbeing into a one-dimensional index, which amounts to returning to a univariate analysis. Duclos et al. (2006) look to avoid this problem by expanding poverty comparisons based on dominance criteria to cover multidimensional settings.

The deprivation thresholds for nutritional status follow the United States National Centre for Health Statistics median reference where a cut-off of minus two standard deviations for *haz, waz* and *whz* are respectively taken as measures of previous/chronic malnutrition, wasting and current/acute malnutrition. Since the multidimensional poverty indices can only be computed for positive values, we standardize the z-scores as recommended by the WHO and the Centre for Disease Control (CDC) (Kuczmarski *et al*., 2002; see appendix C3 for details). For women, we consider whether a woman is poor in two dimensions: the CWI and body mass index (BMI). We use the WHO recommendation of a BMI under 18.5 as the poverty threshold. The BMI is conventionally calculated as weight in kilograms divided by the square of height in metres.

Selecting variable weights is an important challenge when constructing a measure of multidimensional poverty. The main methods of weighting proposed in the literature include equal weights, frequency-based weights, most favourable weights, multivariate statistical weights, regression-based weights and normative weights (Decancq and Lugo, 2008). None of the weighting methods has been found to be strictly superior, and most approaches to measuring poverty do not suitably address the weighting issue. Instead, they give the researcher latitude to normatively assign weights to each dimension (Batana, 2008). The use of equal weights is the most common but also the most controversial approach (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 situations. In this study, we use equal weights for child nutrition and the CWI, but the nutrition-specific weightings are divided equally between the three nested dimensions of child nutrition. For women, equal weights are assigned to the CWI and BMI.

5. Results

5.1 Construction of the composite wealth indicator

5.1.1 Introduction

We compute the CWI using a set of six poverty domains. The choice of domains is based on the need to capture multiple aspects of welfare following the universal definition of child poverty adopted by the UN general assembly in 2007 and the Bristol indicators of child deprivation[7] (UNICEF, 2007; Gordon *et al*. 2003). The selected domains have been modified to

[7] According to the UN assembly, 'Children living in poverty are deprived of nutrition, water and sanitation facilities, access to basic health-care services, shelter, education, participation and protection, and while a severe lack of goods and services hurts every human being, it is most threatening and harmful to children, leaving them unable to enjoy their rights, to reach their full potential and to participate as full

capture various forms of wellbeing given the available data and the need to ensure comparability between survey years. The first domain measures assets owned by households at the time of the survey. While possession of these assets may reflect different needs (for instance: a radio and TV for communication and entertainment; a bicycle for transportation or recreation; a refrigerator for comfort), all are expected to have positive scores which imply positive contributions to the CWI, i.e., improved wellbeing. The second domain captures the household's main source of drinking water. Poor households are more likely to rely on surface water (rivers, springs, wells and other surface sources), while richer households are more likely to have access to piped water, whether in their own residence or from public taps.

The third domain is sanitation, which we select to capture the environment a household operates within. Ownership of a modern toilet such as a flush toilet positively impacts the CWI. The impact of a pit latrine on the CWI depends on whether it is an improved or a traditional pit latrine. No toilet and other types of toilets (such as bush and flying toilets) indicate poverty and thus contributes negatively to the CWI. The fourth domain measures housing materials. Low quality flooring indicates unhygienic conditions, while a modern roof positively impacts the CWI. The fifth and sixth domains – health and education – capture the human capital dimensions of wellbeing. These can be expected to have differing impacts on the CWI depending on accessibility and the initial endowment. The health indicators reflect good access to health care at the cluster level. Completion of higher education is expected to help households escape poverty and thus positively impacts our measure of the CWI.

5.1.2 The two-step MCA/PCA composite wealth indicator

The CWI results are presented in table1. The results are obtained by first using an MCA to estimate individual scores for each dimension and then applying a PCA to the continuous dimensional scores in order to calculate the CWI. The results show that household assets and the source of drinking water should yield the heaviest weights. The lowest weight is attributed to housing materials. Poor sanitation and rudimentary housing materials have a welfare-reducing impact. The two-step approach gave a more conservative estimate of the CWI than individual approaches (these results are not presented). Application of the PCA to the continuous variables (scores) derived from the MCA in the first step moderates the weights used to construct the final CWI. This is because the MCA scores for each dimension are divided by the square root of the first eigenvalue before performing the PCA reduction. The computed CWI

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members of the society (UNICEF 2007). The Bristol indicators include food, water, sanitation facilities, health, shelter, education and information (Gordon *et al*. 2003).

was normalized to positive values.[8]Although this approach has been contentious in the literature, it does not affect the distribution of poor and non-poor children or women in our sample.

Table 1: Contribution of each group of indicators to CWI

Indicator	*Contribution (%)*	*Weight*
Household assets	9.07	0.543
Source of drinking water	29.14	0.404
Sanitation	19.62	-0.278
Housing material	16.44	-0.606
Access to health care	12.28	0.331
Educational attainment	13.46	0.245

Source: Authors' computations from DHS data

5.2 Incidence of multidimensional poverty

In this subsection, we discuss the incidence of poverty based on the composite wealth indicator derived above, the standardized scores for children and the BMI among women. We begin by standardizing the anthropometric measurements then define poverty thresholds for each poverty indicator. The latter allows us to compare poor vs. non-poor groups. The cut-off for the CWI is based on a relative poverty line set at the 40th percentile. The dimensional cut-off for our CWI is 2.3692.[9] That means that a child is poor if he/she comes from a household whose CWI is under 2.4. The poverty thresholds for standardized health indicators are computed, as usual, as two z-scores below the average for the WHO reference population.The poverty 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. The cut-off for BMI is 18.5. The sample statistics are presented in table A2. The results show that about 32% of all children are height-for-age poor (stunted) or suffer from long-term or chronic malnutrition, 9% are weight-for-age poor (underweight) while

[8] Normalization involves adding the absolute value ($C_{\min}$) of the average of the minimum nominal weight ($w^k_{\min}$) of each CWI indicator for each household so that all CWI scores are positive. Asselin (2009) expresses the average minimum weight as $C_{\min} = \sum_{k=1}^{k} w^k_{\min} \Big/ K$

[9] The alternative thresholds for the 25th and 60th percentiles are respectively 1.87 and 3.04. The results using these thresholds are omitted from this report for the sake of brevity.

11% are weight-for-height poor (wasted). The average BMI is 22 for rural areas and the full sample and is 24 for urban areas.

The results suggest that multidimensional poverty is a rural phenomenon. The largest rural-urban differential is observed in the CWI dimension of poverty: 84% of households who are poor in this respect are found in rural areas and the rest are urban. Table 2 shows the incidence of poverty by region and poverty dimension. In both wealth and health dimensions of poverty, Nairobi and Central are least poor. Nyanza is the poorest province in terms of wealth, followed by the Western and Coast provinces. The Eastern and Coast provinces are poorest in all child health measures. The highest incidence of BMI poverty occurs among women located in the Rift Valley, Coast and Eastern provinces.

Table 2: Incidence of poverty in Kenya by region and poverty dimension (%)

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

Source: Authors' calculations using DHS data

Map 1 (appendix B) presents the CWI and health-based FGT headcount indices for children by district. First, it is important to point out that the estimates for Garissa, Wajir, Mandera, Marsabit and Turkana districts are interpolated from neighbouring districts and should thus be interpreted with caution. The map suggests that correlation between the CWI and health poverty is low. Poverty in terms of wealth dimension is concentrated in the Western and Nyanza regions, parts of the Rift Valley, Coast province and parts of Eastern province (Kitui district). Health poverty is concentrated in the north of Kenya and the Coast and Rift Valley provinces. Map 2 shows that the distributions of poor women and poor children across regions in Kenya are similar. However, there is a higher concentration of poor children in the Coast and lower Eastern province and there are more poor women in parts of the Rift Valley province.

5.3. Multidimensional poverty analysis: Alkire and Foster (2007) approach

5.3.1 Child poverty

Poverty estimates

This section presents selected child poverty results based on the Alkire and Foster (2007) dual cut-off and counting approach to measuring multidimensional poverty. The multidimensional poverty estimates are based on two dimensions (wealth and child health) and four indicators. The first indicator is the wealth indicator (CWI). Three child health indicators are considered: standardized *height for age*, standardized *weight for age* and standardized *weight for height*. The CWI and child health are assigned equal weights (each a weight of 2), but each child health indicator is assigned nested weights (0.667).The analysis is based on the poverty thresholds defined above. Table 3 presents the multidimensional poverty indices for selected cut-offs. First, it is clear from the table that the estimated index depends on the cut-off (k). That is, the estimated poverty index will depend on the sum of weights of the deprivations a child is expected to experience. Second, the measures of poverty decrease with the cut-off (see Batana, 2008). For instance, when looking at the head count ratio (H), 41% of the children are multidimensionally poor when the weighted sum of the deprivations (k) experienced by the children equals 1, compared to 5% when k=3. No child is poor when k=4. The adjusted head count ratio (M0) however suggests that for the same cut offs, 24% and 4% of the children are respectively poor. The corresponding adjusted poverty gap (M1) and adjusted gap squared (M2) are quite low.

Table 3: Alkire and Foster child multidimensional poverty indices

	Full Sample				*Rural*				*Urban*			
Cut-off k	H	M0	M1	M2	H	M0	M1	M2	H	M0	M1	M2
1	0.412	0.242	0.055	0.021	0.463	0.273	0.063	0.025	0.105	0.055	0.007	0.002
2	0.144	0.111	0.023	0.009	0.164	0.127	0.027	0.01	0.022	0.017	0.003	0.001
3	0.051	0.049	0.009	0.003	0.059	0.056	0.01	0.004	0.007	0.007	0	0

Source: Authors' calculations from DHS data

Decomposing poverty: Location, dimension and other subgroups

In this section, we decompose the Alkire and Foster (2007) M classes of indices to assess the contribution of various subgroups to overall multidimensional poverty. The last two

column panels of table 3 present the Alkire and Foster (2007) multidimensional poverty indices by area of residence.

Consistent with monetary measures of poverty in Kenya, poverty rates are highest in rural areas where 46% of children are multidimensionally poor when k=1compared to 11% in urban areas. When k=3, 6% and 1% of children in rural and urban areas are respectively considered as multidimensionally poor. The trend in poverty indices observed in the full sample is reflected in the indices for area of residence. We further decompose the Alkire and Foster indices by district. The results presented in map 3 show that when k=1, child multidimensional poverty is concentrated in the Nyanza, Western and Coast provinces of Kenya, with the highest incidence observed in West Pokot (54%) and Lamu districts (44%). For k=3, fewer children are poor in Nyanza and parts of the Coast province. Looking at the district maps that we generated from the available district-level FGT head counts (map 4), we can see that there is low correlation between dimensions of wellbeing. However, CWI and income/expenditure-based poverty seem to rank regions fairly similarly, with large concentrations of poverty in the lower Eastern, Coast, Western and Nyanza provinces.

Further investigation into the relative contribution of location (region of residence and urban versus rural residence) to the Alkire and Foster multidimensional poverty indices (these results are not included for brevity's sake) shows that rural areas account for more than 95% of total multidimensional poverty. The results also suggest that the Rift Valley province contributes the most to multidimensional poverty, the Central contributes the least, while the contribution of Nairobi province is almost zero. However, actual poverty indices indicate that Nyanza province reported the highest incidence of child poverty for cut-off (k) value between 1 and 2, while Coast province reported the highest incidence for values of k greater than 3.

One issue with the Alkire and Foster class of poverty indices is that they are not additively decomposable. This makes it controversial to decompose the indices across dimensions. The adjusted headcount and poverty gaps can, however, be decomposed by taking into account the number of poor adjusted by the number of dimensions. The relative contributions of various dimensions of poverty to overall multidimensional poverty are reported in table 4. The results suggest that the highest contribution to the poverty indices is from the CWI, ranging from 50% to 99% for each M-class indicator at different dimensional cut-offs. The contribution of health indicators is fairly modest and is most pronounced for M0. *Height for age* (*haz*) contributes the most to health deprivation (except for M0 when k>2.5), followed by *weight for height* (*whz*).

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

	M0				*M1*				*M2*			
Cut-off k	CWI	Haz	Whz	Waz	CWI	Haz	whz	waz	CWI	haz	whz	waz
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
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
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

Source: Authors' computations from DHS data

We also explored gender differentials in multidimensional poverty. Decomposition of child poverty by gender (results not presented for brevity) suggests that boys contribute more to multidimensional poverty than girls for all possible poverty cut-offs, although the difference is marginal. Looking at the survey results over time shows that multidimensional poverty among children dropped marginally between 1993 and 1998, and declined substantially between 1998 and 2003 (results omitted to save space).

Robustness checks and sensitivity analysis

To check for robustness of the results, we assess the sensitivity of the poverty indices to changes in the CWI poverty line. Two alternative poverty lines are considered: the 25th percentile, with a CWI of 1.86 and the 60th percentile, which yields a poverty line of 3.04. We only present and discuss results for decomposition of poverty indices into various subgroups for the 25th percentile to save on space. The results for the 60th percentile are consistent with the results for the other two alternative poverty lines. The results suggest that Rift Valley contributed most to child poverty, while the Nairobi and Central provinces contributed the least. We also observe that rural areas contributed between 96% and 100% to overall multidimensional poverty. The wealth (CWI) dimension contributed the most ((52% to 98%) to overall poverty. Except for M0 when k=3, haz contributed the most among health indicators to multidimensional poverty. The results for the 25th percentile (including multidimensional poverty indices) are consistent with the results using the 40th percentile of the CWI as the poverty line. The results suggest that the Alkire and Foster (2007) multidimensional poverty rankings are robust to the choice of poverty lines.

5.3.2 Multidimensional Poverty among women

Poverty estimates

The Alkire and Foster (2007) approach applied to women's poverty is based on two main indicators of poverty: the CWI and BMI. These two dimensions are each assigned an equal weight of 1. We set poverty cut-offs for each dimension, below which a woman is deemed poor. As for children, the CWI cut-off is based on a relative poverty line set at the 40th percentile, with a dimensional cut-off equal to 2.37. For the BMI, the poverty line is set at 18.5. Thus a woman who has a BMI lower than 18.5 or who is from a household with a CWI of less than 2.4 is considered to be poor. The indices generated are presented in table 5. The results show that 44% of all women are poor in at least one dimension, i.e. when k=1, as opposed to just 5% of women when k=2. As for children, the proportion of multidimensionally poor women is relatively higher in rural areas, respectively at 50% and 6% for 1 and 2 dimensional cut-offs.

Table 5: Alkire and Foster multidimensional poverty indices (women)

Group	*K=1*				*K=2*			
	H0	M0	M1	M2	H0	M0	M1	M2
Urban	0.138	0.074	0.011	0.003	0.01	0.01	0.002	0.001
Rural	0.492	0.274	0.071	0.029	0.057	0.057	0.011	0.004
Full Sample	0.44	0.245	0.062	0.025	0.05	0.05	0.01	0.004

Source: Authors' computations from DHS data

Decomposing poverty: Location, dimension and other subgroups

Decomposition of women's multidimensional poverty into various subgroups suggests that Rift Valley contributed most to women's poverty, while Central province contributed the least among rural provinces. The results further show that 95% of multidimensionally poor women live in rural areas. Among women, the CWI contributed more than other dimensions to the Alkire and Foster multidimensional index. Comparing the district maps for women (not presented to save space) with map 3 (child poverty map) suggests that the Alkire and Foster multidimensional poverty indices for women rank provinces differently for the two dimensions (health and wealth) of wellbeing in terms of the province's concentration of poor women and children. While the poorest children are from the Coast and Western provinces, the poorest

women are from districts located in the Rift Valley and North Eastern provinces. Multidimensional poverty indices among women, as indicated by the omitted survey results, show that poverty declined between 1993 and 2003. As was the case for children, the decline was more pronounced between 1998 and 2003.

Robustness checks and sensitivity analysis

A sensitivity test of the poverty lines for women is carried out with respect to the CWI poverty line. Based on the 25th percentile CWI poverty line defined above, the results for women are consistent with those for the 40th percentile CWI threshold (and also with the results for children). Rift Valley contributed the most to multidimensional poverty (which ranges from 30% to 42% for the two cut-offs k=1 and k=3), while Nairobi and Central contributed the least. The results for contribution by area of residence and dimensions are also consistent with the results presented above. These results support earlier findings that the Alkire and Foster multidimensional poverty orderings are robust to the choice of the poverty line for children.

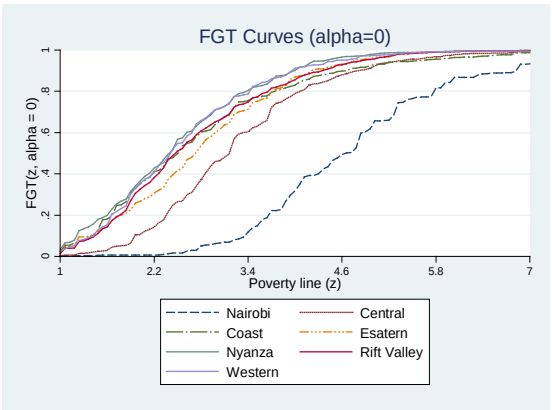
5.4 Stochastic dominance analysis

In this paper, stochastic dominance analysis is based on Duclos, Sahn and Younger (2006a). We test for dominance of the CWI and health poverty between rural and urban areas and also between regions. The dominance results for women are similar to those for children, but only the latter are presented.

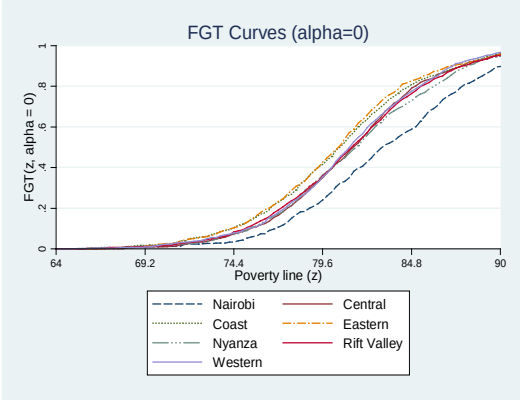
5.4.1 Unidimensional stochastic dominance

The first order dominance tests for children are presented in figure 1. The results in figure 1(i) show that Nairobi clearly dominates all regions for CWI poverty. We do not observe dominance between the other provinces except for the Central province which clearly dominates all other provinces for a CWI range of 1.5 to 4.6 points. Figure 1(i) also suggests that Nairobi dominates other provinces in child health except at very low nutritional thresholds. Eastern province seems to be dominated by all other regions for nutrition threshold scores between 72 and 86 (see appendix C for details on the derivation of these scores). There is no clear pattern of dominance between other provinces. The dominance results by area of residence and gender (not presented) show that urban areas clearly dominate rural areas in CWI poverty, but only dominate rural areas for nutritional poverty beyond a standardized *height-for-age* of 72. The results also suggest that the difference in poverty across all thresholds is less pronounced for nutrition than for the CWI. Furthermore, there is no dominance of wealth poverty between girls and boys, but girls dominate boys in nutritional wellbeing.

Figure 1: FGT curves for CWI and nutrition by region



i). CWI by region

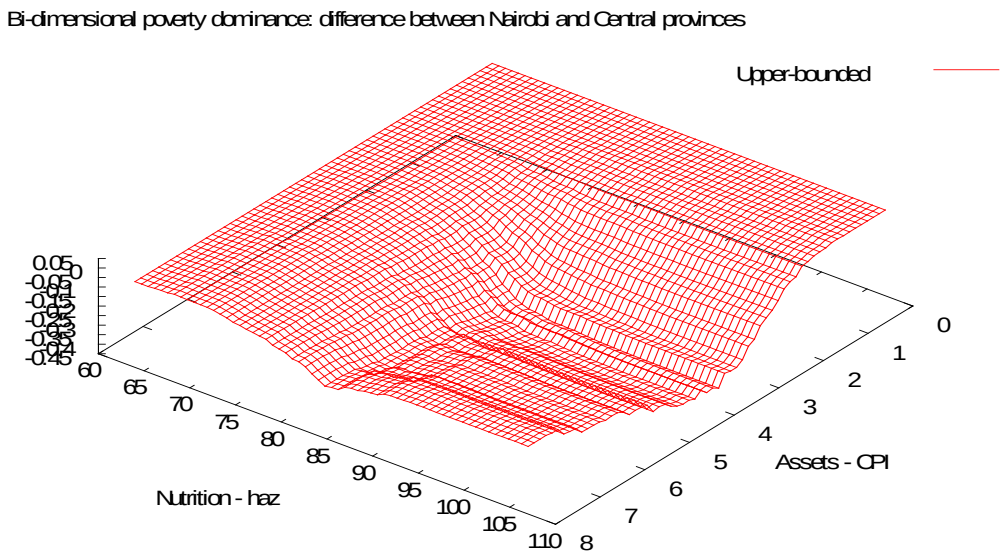


ii). Nutrition by region

5.4.2 Bi-dimensional stochastic dominance with statistical significance

We test for bivariate poverty dominance across different groups by using bi-dimensional dominance surfaces to compare the zero surface and the upper bound surface of the confidence interval of the difference in poverty between the two distributions. If the upper bounds are less than zero at all points, we can conclude that poverty in one region is lower than poverty in another region. The results in figure 2 show the upper bound of the confidence intervals for the difference between the poverty dominance surfaces for Nairobi and Central provinces. In this case, the upper bound surface is below zero across the entire range, which means that there is less poverty in Nairobi than in Central province. We say also that Nairobi dominates the Central region in welfare.

Figure 2. Bi-dimensional poverty dominance for children: Three dimensional surface diagram

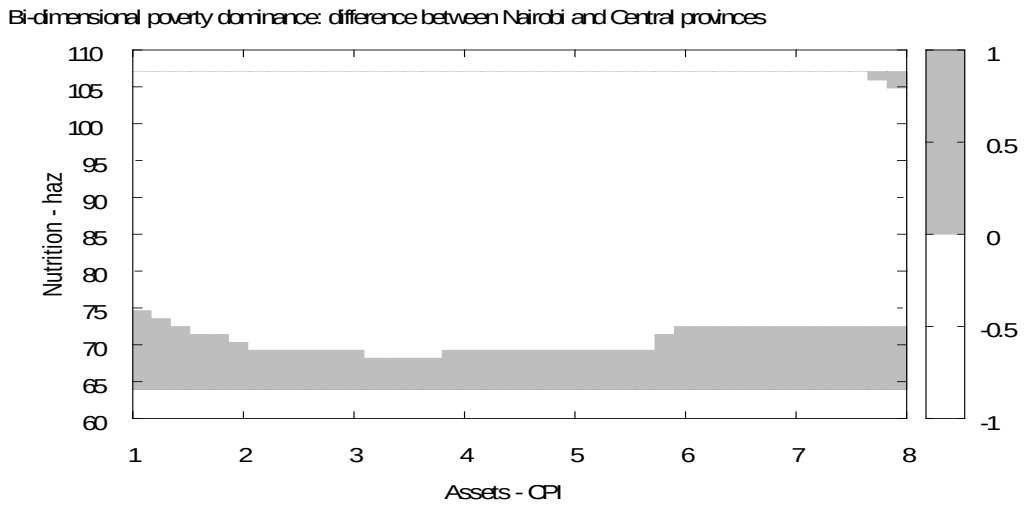


Source:Developed by the authors using DHS data

This type of graph does not allow us to test for statistical significance of dominance across groups. This test is instead carried out using the map view two-dimensional graphs, as presented in table A3 in appendix A. To facilitate interpretation of the graphs we present an enlarged graph with Nairobi in the row and Central province in the column in figure 3. The vertical y-axis of the graph presents health (standardized nutrition scores), while the horizontal x-axis presents CWI scores. A white colour indicates that for a particular x-y combination of poverty lines, (such as 5, 75), the difference in poverty between Nairobi and Central province is below 0 (the upper bound of the confidence interval of this difference is below 0). That is, the condition that Nairobi is less poor than Central province is satisfied with statistical robustness.

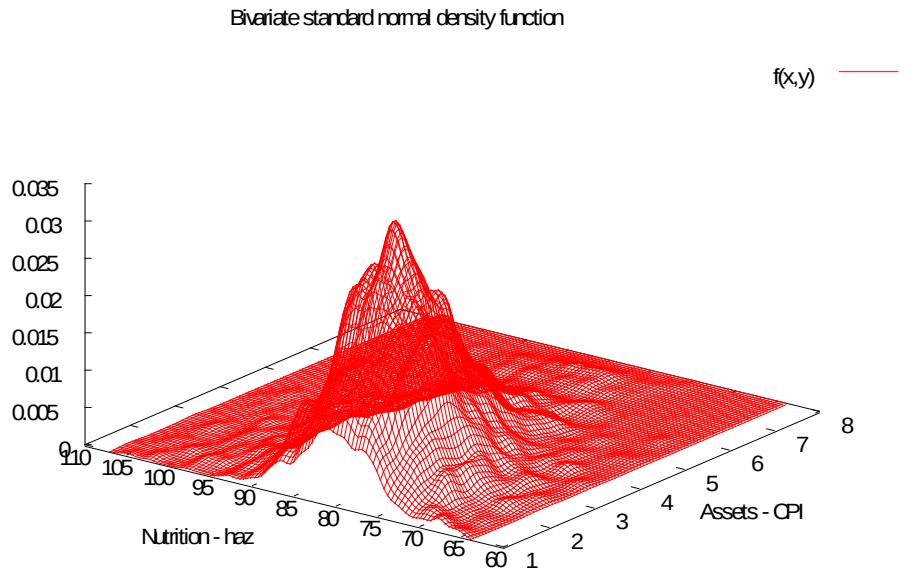
The use of grey indicates that Nairobi is less poor than Central province, but that statistical robustness is not satisfied.

Figure 3. Bi-dimensional poverty dominance for children: two-dimensional map view diagram



Source: Developed by the authors using DHS data

Figure 4: Bi-variate standard normal density function



Source: Authors' construction using DHS data.

5.5.3 Econometric results

Introduction

Since the CWI and health poverty are determined by different factors, we estimate the seemingly unrelated bivariate model of multidimensional poverty. The estimation results are presented in table 6. The Wald χ^2(2.d.f) test shows that the bivariate model fits the data better than the individual probit models. This is supported by results of the Wald χ^2 (1.d.f) test of significance of ρ. The computed χ^2=21.668, which shows that ρ is statistically significant even though it is quite small (0.06). Another goodness-of-fit test is the classification test. We usually assume with logit or probit models that the predicted probability of a zero outcome is equal to the predicted probability of the variable taking a value of less than one half. The predicted successful outcome is thus one where the predicted probability is higher than half. It is not easy to specify the cut-offs for the bivariate probit model. The classification test that we propose specifies the predicted outcome as the one with the highest predicted probability. Using this proposed classification test we find that the bivariate probit estimate predicted about half of observed real cases.

The last column of table 6 presents the marginal impacts of the explanatory variables on the probability of being poor for *both* CWI and health. Interpretation of marginal effects will be illustrated for the education variable. The estimated marginal effect implies that completing secondary education reduces the likelihood of being multidimensionally poor by 0.11 points, while completing post-secondary education reduces this probability by 0.098 points. Where a variable only explains one dimension of poverty, the marginal impact is the variable's effect 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 poor in the wealth dimension by 0.002 points. Other marginal effects can be interpreted similarly. The results show that educational attainment and access to electricity have relatively high marginal impacts on the probability of being multidimensionally poor. We also observe region-specific impacts on the probability of being poor in the wealth dimension. . Nyanza, Western and Rift Valley provinces exhibit higher marginal impacts than Nairobi. Individual factors for health poverty, for their part, have low marginal impacts.

Probability of being CWI poor

We investigate the impact of household characteristics, mother's education, access to electricity and regional characteristics. To avoid potential econometric problems such as reverse causality, we omit all variables used to calculate the CWI index. The results show that households with more children under the age of 5 have a greater probability of 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 (particularly for women) from productive economic activities which lowers incomes and consumption.

Education and skill acquisition at the household level are captured by the mother's education. The results show that, compared to having no education or just primary education, secondary and post-secondary education both have a significant and negative impact on the probability of being CWI 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 is used to capture two factors in this model: community-level infrastructural development and households' standard of living. The results show that households with access to electricity are less likely to be poor than their counterparts without electricity. This suggests that infrastructure is a major factor for escaping poverty at the community level. The results also suggest that poor households are less likely to have access to electricity than the less poor.

Provincial dummies are included to capture regional characteristics. Poverty is expected to be high in regions characterized by geographical isolation, a low resource base, low rainfall and other inhospitable climatic conditions. Regional differences in poverty could also be due to the governance system, supporting policies (environmental, economic, and political) and social capital investments. The results show that all provinces are much poorer in terms of wealth than Nairobi. The results also suggest that children from Nyanza province face the highest likelihood of being CWI poor, while children in Central province face the lowest probability. Children from the Western, Rift Valley and Coast provinces are also more likely to be poor. These results suggest a need for further investigation into the regional determinants of poverty in Kenya.

Table 6: Bivariate probit model of multidimensional poverty: Estimated marginaleffects

Variable	*Pr(CWI poor)*	*Pr(Health poor)*	Pr(CWI poor,
Child characteristics			
Male child dummy	-0.0182***	0.0306***	0.0130***
Number of children <5 years	-0.0039**		-0.0015**
Age of child (months)		0.0026***	0.0013***
Child is of multiple birth		0.0706***	0.0351***
Household characteristics			
Mothers' height		-0.0064***	-0.0032***
Mother has secondary education	-0.2900***	0.0695***	-0.1575***
Mother has post-secondary	-0.4147***	0.0825***	-0.2389***
Log household size		0.0120***	0.0060***
Housing & environmental			
Household has electricity	-0.4292***	0.1240***	-0.2146***
House has rudimentary floor		0.0003***	0.0001***
Unsafe drinking water		0.0133**	
Unsanitary toilet conditions		0.0267***	0.0133***
Regional dummies			
Central province	0.1403***		0.0564***
Coast province	0.3141***		0.1262***
Eastern province	0.2469***		0.0992***
Nyanza province	0.3867***		0.1554***
Rift valley province	0.3417***		0.1373***
Western province	0.3566***		0.1433***
Survey year dummy			
1998 survey year	-0.0372***	0.0451***	-0.0112***
2003 survey year	-0.1170***	0.0499***	-0.0445***
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
Source: Authors' computations from DHS data

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

Probability of being health poor

We investigate the impact of child, household and environmental characteristics on the probability of a child being health poor (stunted). The results of the male child dummy variable show that boys are more likely to be stunted than girls. This corroborates studies that have shown that male children are vulnerable 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. Children are more vulnerable to malnutrition during the process of weaning. Children who are completely weaned are likely to get adequate nutrients from regular food intake, however, which improves their nutritional status (Shrimpton *et al*. 2001; Kabubo-Mariara, Nd'enge and Kirii, 2009). Shrimpton *et al*. (2001) have shown that although the score for children's height for age falls sharply from birth to 24 months, the process of stunting continues at a much slower rate after the 24th month. Our results also show that children of multiple births are likely to be more health poor than singletons, with the former scoring 0.04 points higher in terms of health poverty. Twins are more likely to be born with lower birth weight, are more likely to get inadequate breastfeeding and must compete with their sibling(s) for nutritional intake.

Household characteristics include household size and the mothers' characteristics (education and height). Mother's height has a small but significant negative correlation with the probability of being health poor. Height captures genetic effects and the effects of family background characteristics. Maternal education is inversely correlated to the likelihood of being health poor. Children's nutrition is also better for mothers with more than primary education. Maternal education improves nutrition via the household preference function and also through better childcare practices. This result suggests that human capital investment is important for improved child nutritional status. As for household size, there is an inverse correlation with children's health status. This could be due to competition for food among siblings, which implies a need to encourage family planning and promote smaller family sizes.

Housing standards are measured by two factors: access to electricity and the flooring material of the main dwelling house, both of which are also indicators of living standards. The literature suggests that the poor have little or no access to electricity and live in precarious and relatively unsanitary dwellings, which contribute to poor health and lower productivity of household members. For example, in our sample, children who live in households with access to electricity tend to be less health poor than those without access to electricity, and children who live in dwellings with unsanitary/rudimentary floors are more likely to be health poor than

other children. Children who have no access to electricity and live in unsanitary housing conditions are likely to reside in rural areas and urban slums.

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

The results by year of survey show that poverty with respect to health increased between 1993 and 1998 then declined in the following five years, altogether resulting in a lower poverty rate in 2003 than in 1993.

6. Discussion

6.1 Summary and conclusion

Previous research on poverty in Kenya has mainly focused on unidimensional measures of poverty based on either income or expenditure data. However, previous studies have shown that poverty and deprivation rates differ substantially, that the factors which underlie poverty and deprivation do not always correspond, and that the relationship between monetary poverty and deprivation is positive but not very strong (Notten, 2009). Many children who are severely deprived in physical dimensions (e.g. water and sanitation, housing, transportation and communication) are not considered as poor in monetary terms. Consequently, a monetary poverty indicator would underestimate the severity of material deprivation. A few studies do examine non-monetary poverty in Kenya, but focus on just one measure of deprivation/capabilities such as nutrition, health and education. However, none of these indicators can capture all dimensions of poverty. To address this void, an emerging literature considers multidimensional poverty measures across several dimensions of deprivation experienced by the poor. Such poverty measures complement unidimensional measures, and together offer a more complete picture of poverty and better information for anti- poverty policy.

This paper contributes to the literature on non-monetary multidimensional poverty. We measure multidimensional poverty among women and children in Kenya using two dimensions of welfare: a composite wealth indicator (a measure of household wealth) and nutritional status (a measure of health). We also carry out dominance tests for multidimensional poverty to identify its determinants. The analyses used three rounds (1993, 1998 and 2003) of the Demographic and Health Survey (DHS).

The methodological approaches applied in this paper are complementary. The results generated give a comprehensive picture of the extent, distribution and ordering of poverty among women and children in Kenya, and the determinants of multidimensional poverty among Kenyan children. First, a two-step inertia approach (multiple correspondence analysis and principal components analysis) is used to construct a composite wealth indicator (CWI) for the purpose of welfare comparisons. The CWI is used as an alternative measure of wealth because income data is not available in the DHS. Some previous studies have also used the CWI to analyze the extent of poverty, but we go beyond this and use the CWI to rank women and children for multiple dimensions of wellbeing. The Alkire and Foster (2007) counting approach is then used to measure multidimensional poverty in the two dimensions and four indicators of wellbeing. The approach enables us to generate poverty indices and determine the relative contribution of indicators of welfare dimensions and population subgroups to multidimensional poverty among women and children. In order to compare welfare across population subgroups we apply stochastic dominance approaches. As opposed to other approaches, a major advantage of this approach is that we are able to test for statistical significance of differences in poverty orderings. Finally, we specify a bivariate probit model to explain the incidence of multidimensional poverty among children. Most multivariate studies of poverty focus on explaining unidimensional poverty such as income poverty or poverty based on a composite indicator. Our approach allows us to go beyond exploring the determinants of an individual being poor in one dimension and non-poor in the other as well as the probability of being poor in several dimensions. This approach helps us to analyze factors that are likely to be relevant for policies that may address multiple dimensions of poverty in Kenya.

Several results emerge concerning multidimensional poverty measurement in Kenya. First, the CWI constructed in this paper weights household assets and source of drinking water most heavily. In absolute terms, the source of drinking water and the type of sanitation contribute most to the CWI. Households who are deprived of assets, safe drinking water and good sanitation are therefore most likely to be poor. Second, we find that the estimated Alkire and Foster poverty indices depend on the number of dimensions considered and that measured poverty decreases with the number of dimensional cut-offs, i.e., the weighted sum of the deprivations(k). The highest contributions to multidimensional poverty are from the health component of the CWI, rural rather than urban residence and being a boy rather than a girl. Welfare ranking among provinces is sensitive to the choice of poverty cut-offs. Although Nyanza province has the largest proportion of poor children at low cut-offs, Coast province has the largest proportion at higher cut-offs. Rift Valley contributes the largest share to national poverty

at all cut-offs. We also find that multidimensional poverty declined somewhat between 1993 and 1998, but fell much more between 1998 and 2003.The results for women are consistent with those for children. A sensitivity analysis shows that the Alkire and Foster multidimensional poverty orderings are robust to the choice of poverty line, but not to the choice of dimensional cut-off. Third, district poverty maps show that women and children are poorer in rural districts, mostly in the Coast, Eastern and Nyanza provinces, than women and children in other regions. The maps also show large disparities in multidimensional poverty, but suggest that there is weak correlation between dimensions of wellbeing.

Fourth, unidimensional stochastic dominance tests show that urban areas dominate rural areas, while Nairobi dominates all other regions for both indicators of wellbeing. Bi-dimensional stochastic dominance with statistical significance tests also suggests this order of dominance. Moreover, it shows that it is difficult to give a complete ranking of areas of residence, regions and gender groups for each of the two welfare measures. Fifth, the econometric results show that child, household, environmental and geographical characteristics are important correlates of multidimensional poverty. Education attainment and access to electricity have relatively high impacts on the probability of being multidimensionally poor. The results also reveal a high probability of being asset poor in rural provinces, particularly in Nyanza, Western and Rift Valley.

6.2 Policy Implications

This study focuses on multiple dimensions of deprivation, a key focus of the Millennium Development Goals (MDGs). The paper directly addresses three key MDGs for Kenya: First, high levels of malnutrition are often addressed through poverty reduction efforts (MDG1). Second, we use a number of strategies to study maternal health including maternal nutrition which is crucial for lowering maternal mortality (MDG5). Third, it addresses the MDG7 targets, which are to halve the proportion of people without sustainable access to safe drinking water and basic sanitation by 2015 and to achieve a significant improvement in the lives of slum dwellers by 2020. Slum dwellers are often deprived of good shelter and access to water, sanitation and health care. The study also indirectly addresses two other MDGs. There is the battle against child mortality, MDG4,which is most likely to be lost if children are poor and deprived of basic necessities. MDG6 is also at stake because poor women and children are more susceptible to HIV/AIDS, malaria and other diseases, and this is all the more so in Sub-Saharan Africa. The study results point to several policy implications to improve the welfare of poor women and children as per the MDG targets in Kenya.

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

Second, the results suggest that interventions geared toward poverty alleviation need to be geographically targeted to reach the poor. Social budgeting and other targeting schemes require availability of information on vulnerable groups disaggregated by region, gender and other relevant socioeconomic variables to reveal existing disparities. This study contributes to this process by providing information on existing measures of poverty disparities among these disaggregated groups. The results provide an excellent basis for the design of multidimensional targeting programs. The results can be useful for rethinking existing social protection programs such as unconditional cash transfers and to ensure that these transfers actually reach the most vulnerable households, who care for orphaned and vulnerable children. At present, there are local poverty reduction initiatives such as the Local Authority Transfer Fund and the Constituency Development Fund. These initiatives do not take into account the geographic distribution of poor children in Kenya. It is important to redesign these interventions carefully to target children living in poverty because child poverty is often different from poverty at the household level. Also, as the country embraces devolution in the implementation of the new

constitution promulgated on 27th August 2010, multidimensional poverty indicators for children and women will be essential for policy formulation at the local county level.

Third, the results also show that the poorest women and children are from households which are most deprived in terms of household assets and access to water, sanitation and shelter. These children are often predisposed to water- and sanitation-related health problems such as diarrhoea and other diseases. These forms of deprivation are therefore likely to have long-term implications for child growth and development. The results also suggest that improving poor household's access to electricity is crucial in the fight against poverty. It is important that both public and private providers step up efforts to provide the necessary infrastructure (such as piped water, sewage systems and pit latrines, among others) to areas that the poor live in: rural areas and urban slums. The bivariate probit model results also suggest that programmes and policies which aim to improve women's access to education will reduce child poverty. This has implications for long-term human capital investment and intergenerational effects on child welfare.

Fourth, fighting poverty calls for a collaborative approach that ensures the availability and actual use of strategic information on the needs of the most vulnerable children. This information should be availed to all who are involved in the fight against child poverty including: community-based organizations, civil society, local non-governmental organizations and other stakeholders. Such information would ensure active and informed participation of local communities in the design, implementation and monitoring of development programs. These stakeholders can surely benefit from information on the incidence, dimensions, distribution, dominance and determinants of multidimensional poverty among children in Kenya. This paper provides precisely that information. Further strengthening of capacity among local stakeholders will ensure comprehensive identification of local needs, alternative mechanisms for service delivery and appropriate targeting mechanisms for development programmes. This would increase the impact of such interventions on the most vulnerable women and children and also boost the sustainability of the programs. The government and development partners have an important role to play in strengthening and mobilizing local stakeholders to this end.

Fifth, the health indicators used in this paper are nutritional measures for women and children. Although the household CWI contributes more than health to multidimensional poverty, the nutritional status of the most vulnerable women and children must be targeted by well-designed programs. These could be implemented under the auspices of current programs involving cash transfers, school feeding programmes, vitamin A supplements and promotion of

social and behavioural change with respect to the use of contraception by women and infant feeding practices.

Finally, the results of the bivariate probit model show the importance of improving living standards to ensure long-term physical growth and development among children. This reinforces the importance of a multidimensional approach to analyzing the fight against poverty. Improving living standards would require lifting households with vulnerable women and children out of deprivation in terms of household assets and access to water, sanitation, shelter, health and education. Policies which boost the country's economic growth but which also ensure pro-poor growth are necessary. A policy that addresses just one form of deprivation is unlikely to bear much fruit. As the country implements the long term blue print, which includes Vision 2030 (Republic of Kenya, 2007) and a new constitution that gives priority to rights of women and children, multidimensional poverty indicators are presumably going to be crucial for informing policy.

6.3 Suggestions for further research

To win the battle against maternal and child poverty in Kenya, it is important to extend multidimensional poverty research to cover issues for which there is relatively little information. These issues should include, but not be limited to, those which affect the most deprived and marginalized children. For example, child labour is an ongoing issue, while the nature, extent and causes of violence, exploitation, abuse and child trafficking certainly warrant further investigation. It is also important to include monetary indicators of poverty in the multidimensional poverty measure so as to get a more complete picture of the nature, extent and distribution of child poverty in Kenya. Although this study has focused on poverty among both women and children, data limitations have prevented us from looking at complementarities between poverty for the two subgroups. There would be additional value in studying the relationship between poverty among women and poverty among children, as well as the intergenerational transmission of poverty from women to their children.

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APPENDICES

Appendix A: Tables

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

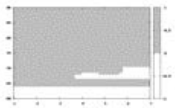
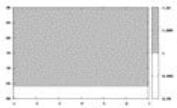
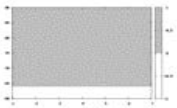
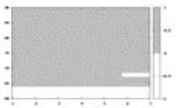
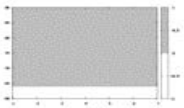
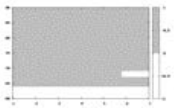
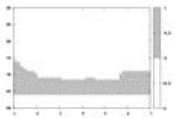
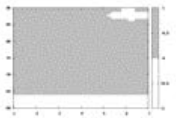
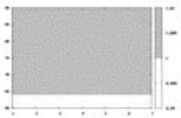
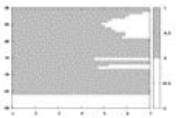
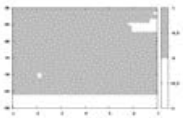
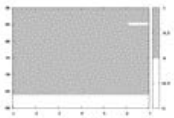
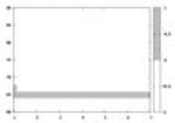
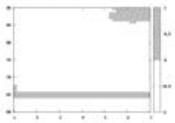
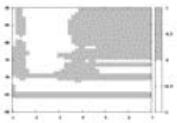
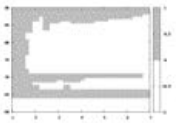
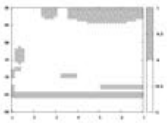
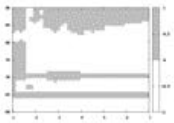
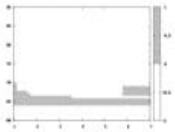
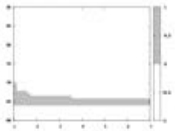
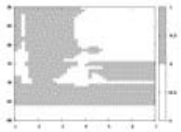
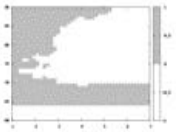
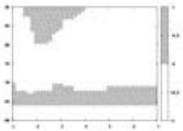
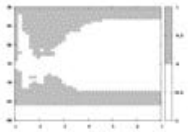
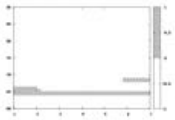
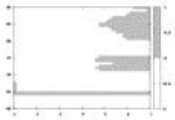
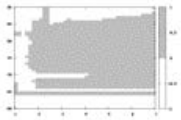
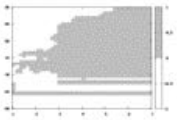
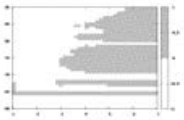
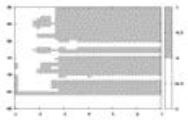
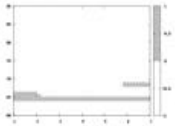
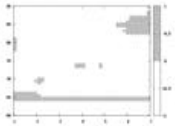
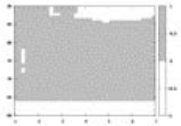
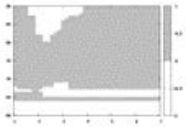
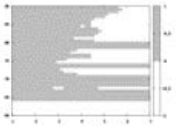
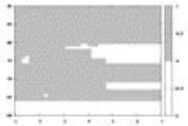
Year\indicator	*1993*	*1998*	*2003*	*2005/6*	*2008/9*	*2000-7*
Children (%)						
Height for age (stunting)	32.7	33	30.3	34.5	35.3	30
Weight for height (wasting)	5.9	6.1	5.6	6.3	6.7	6
Weight for age (underweight)	22.3	22.1	19.9	20.9	16.1	20
Women						
Body mass index	22	21.9	22.7	-	-	-
% with low body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

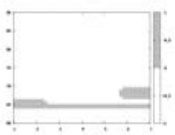
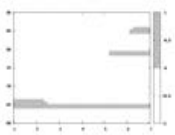
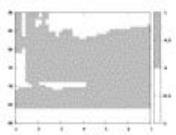
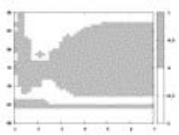
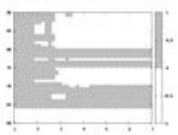
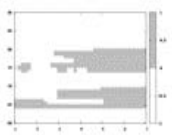
Source: CBS, MOH & ORC Macro, 1994, 1999, 2004;KNBS and ICF Macro, 2010; UNICEF, 2009.

Table A2: Sample statistics

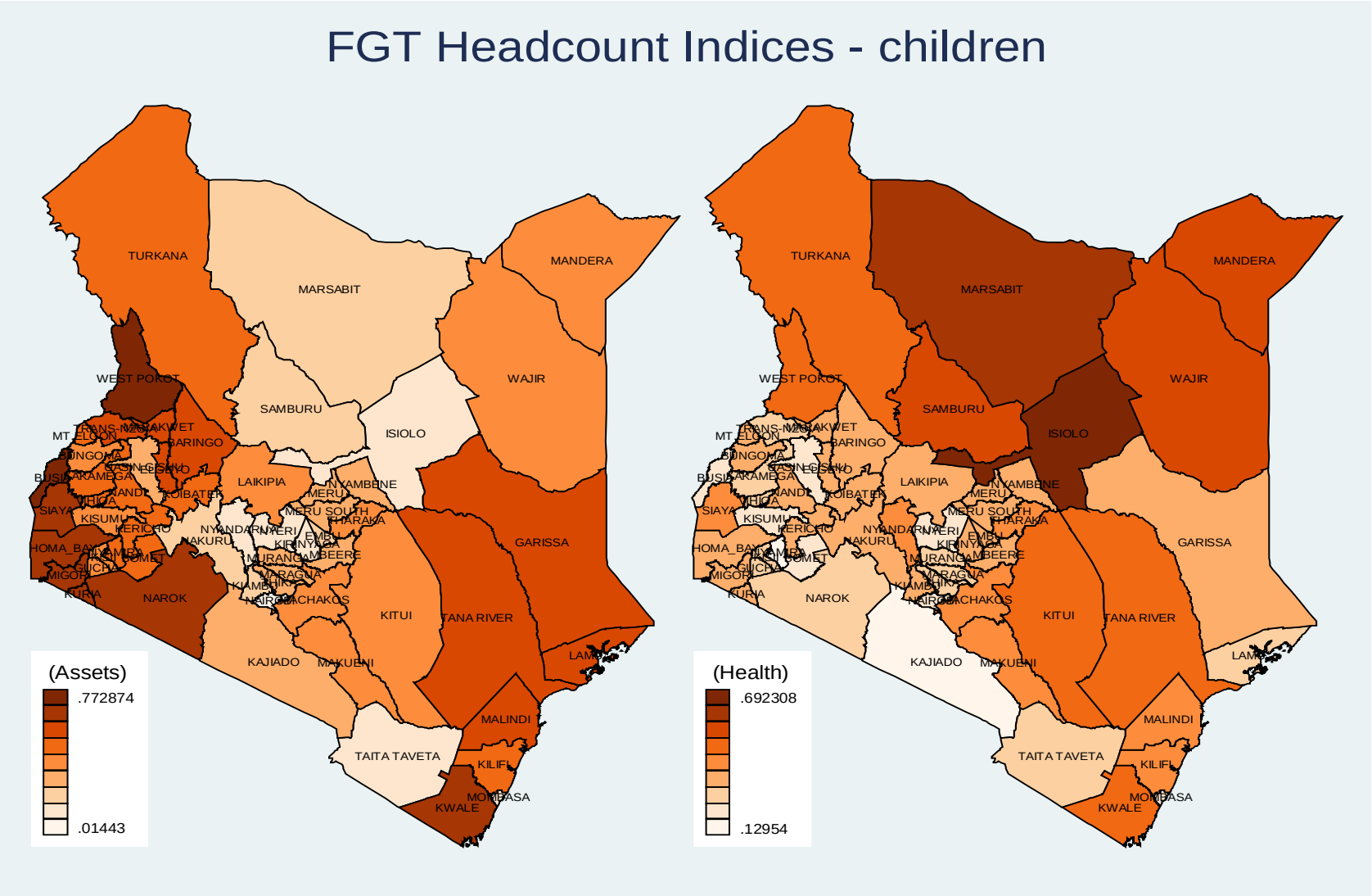
Variable	*Rural*		*Urban*		*Full sample*	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev
standardized *haz*	81.21	5.19	82.74	5.35	81.43	5.24
standardized *waz*	11.02	1.54	11.68	1.93	11.12	1.62
standardized *whz*	11.18	1.11	11.65	1.34	11.25	1.16
Composite wealth indicator	2.67	1.09	4.38	1.35	2.92	1.28
CWI poor	0.45	0.50	0.10	0.29	0.39	0.49
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
Sample size (%)	84		16		100	

Table A3: Dominance tests across provinces with statistical significance

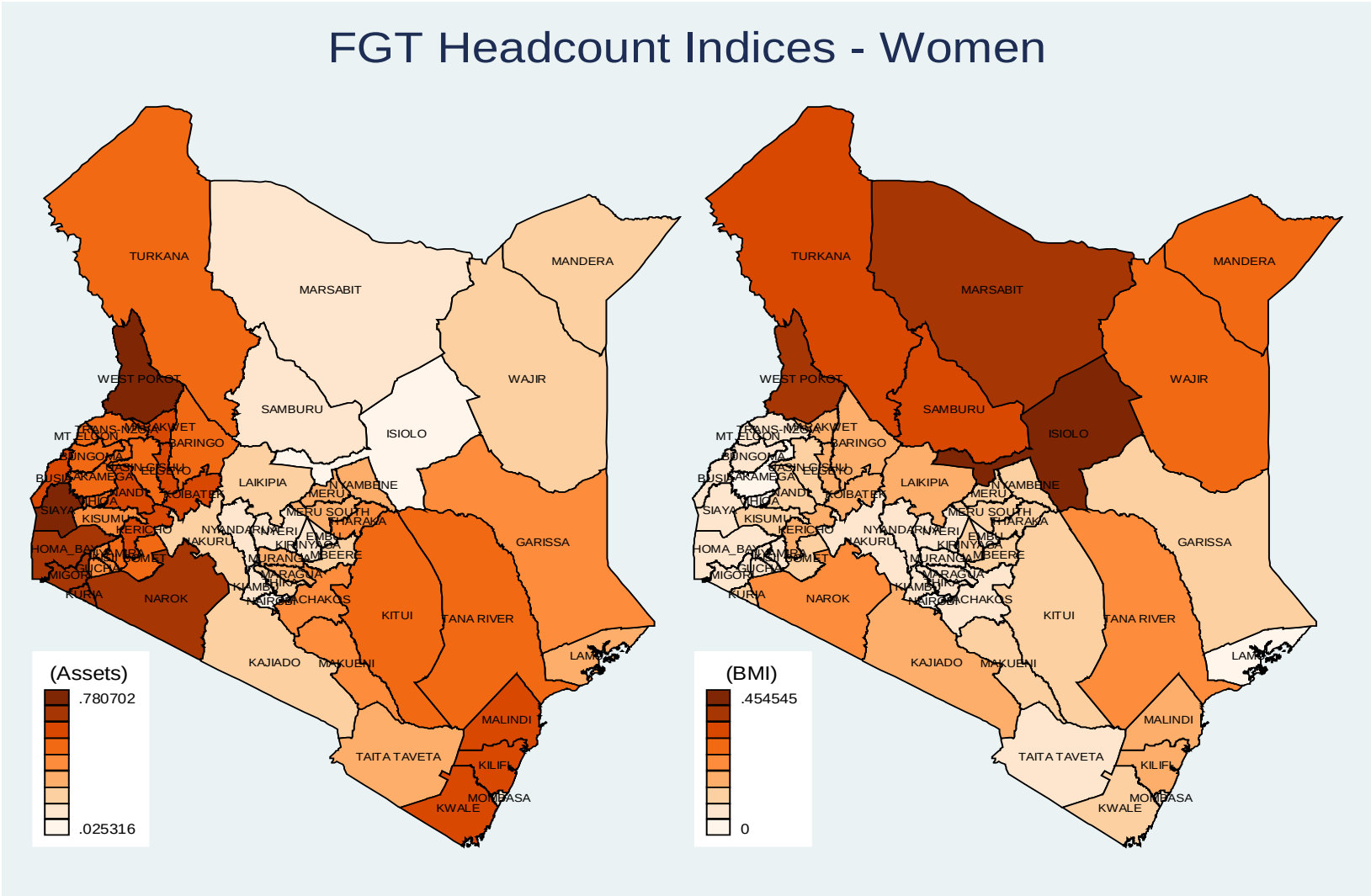
	Nairobi	Central	Coast	Eastern	Nyanza	Rift Valley	Western
Nairobi							
Central							
Coast							
Eastern							
Nyanza							
Rift Valley							

Western							

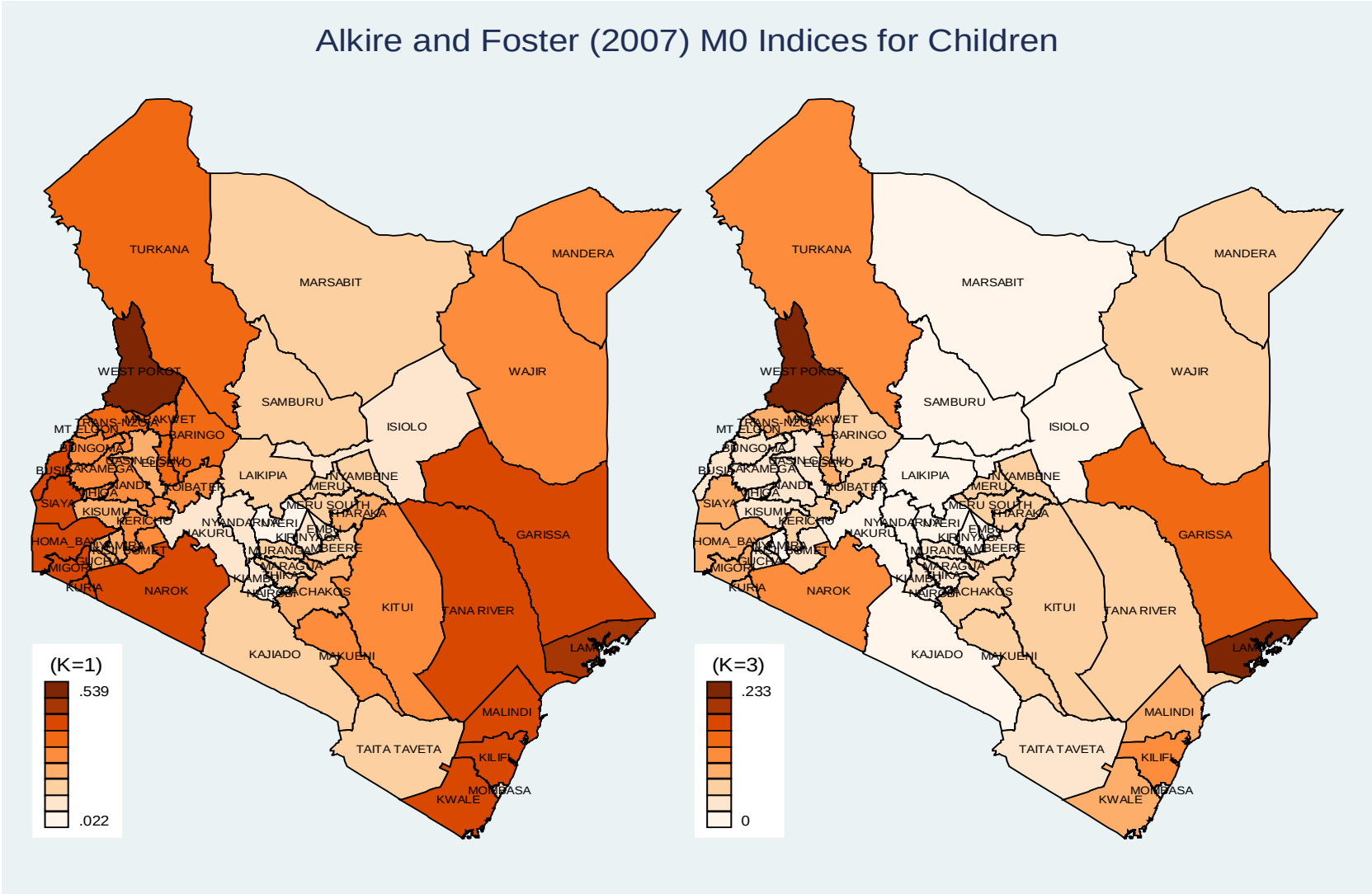
Appendix B: District poverty maps



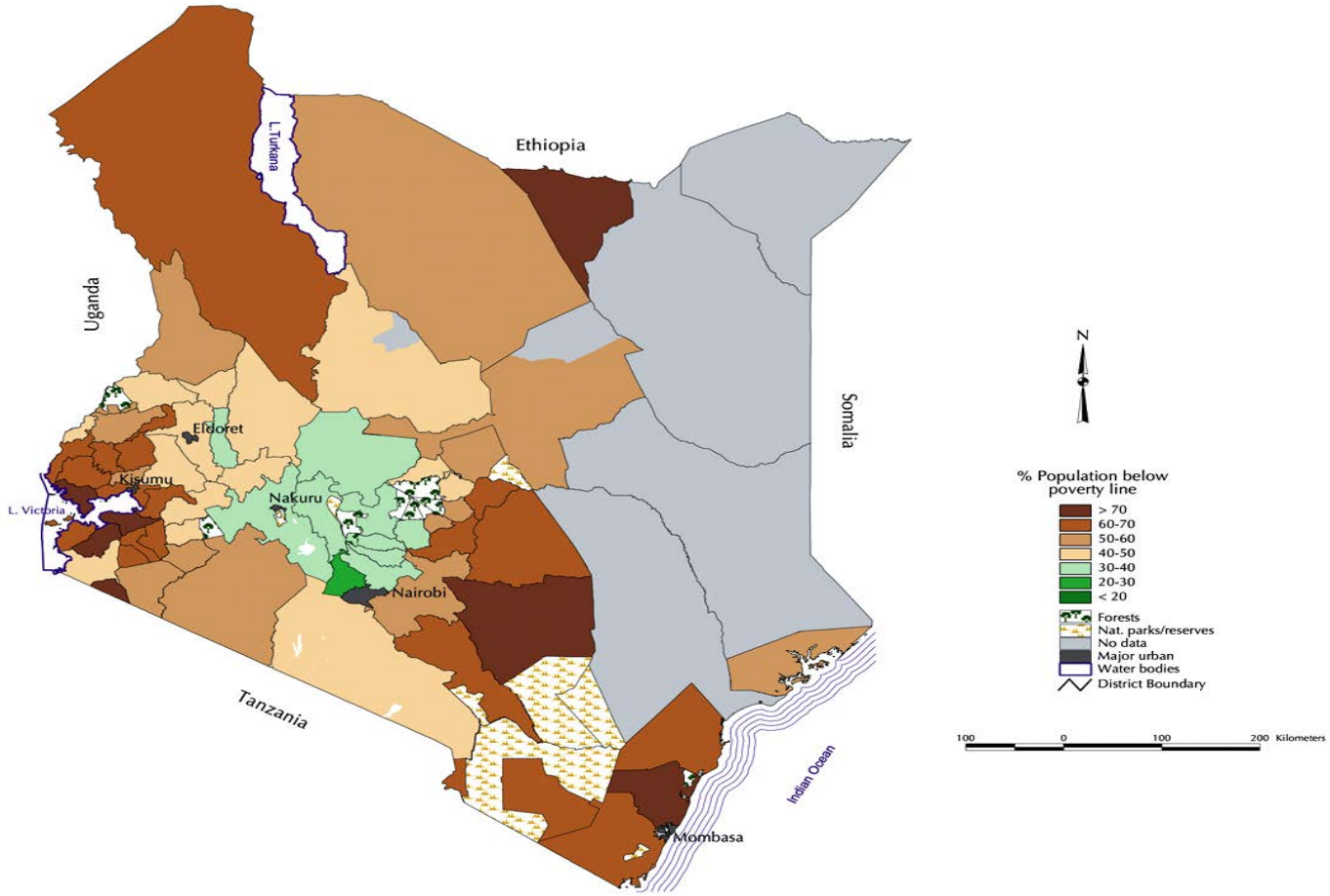
Map 1: District level poverty indices (FGT α=0) for children



Map 2: District level poverty indices (FGT α=0) for women



Map 3: District level Alkire and Foster (2007) M0 indices for



children
Source: Kenya National Bureau of Statistics

Map 4: District level income poverty incidence (FGT, α=0) - 1997

Appendix C– Methodology and Relevant Literature

C1 Constructing a composite wealth indicator

C1.1 Principal Component Analysis (PCA)

Like other factorial analysis techniques, PCA is a data reduction method used to summarize several variables into one factor (Asselin, 2009). PCA consists of building a sequence of uncorrelated (orthogonal) and normalized linear combinations of the original input variables such that the entire variability of the set of input variables (total variance), defined as the trace of the covariance matrix, is exhausted. Optimality arises because the first component (an uncorrelated linear combination) captures the largest proportion of the total variance and ensures that all of the variance is explained when all possible components have been extracted (Asselin, 2009).

To construct a CWI, most studies use the standardized first principal component of the variance-covariance matrix of observed household assets and allow the data to weight each asset based on its correlation with the other assets (Filmer and Pritchett, 2001). This procedure first standardizes the CWI variables by calculating z-scores, then calculates the factor coefficient scores (factor loadings) and multiplies the indicators' values by their loading for each household. This last set of numbers is then summed to produce the household's index value. Only the first of the factors produced from this process 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).

We define the CWI (C_i) derived from the PCA as:

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

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 CWI defined in (1) is the latent variable regressed on the *k* primary poverty indicators that are most informative in terms of explained variance. The PCA procedure has two major limitations (Asselin 2009): First, PCA is designed for quantitative variables measured in standardized units. The optimal sampling properties for parameter estimation depend on the multivariate normal distribution. In other words, PCA is appropriate for normally distributed continuous variables. The assumption of a multivariate normal distribution does not hold for nominal variables. Since ordinal variables do not have an origin or a unit of measurement, the lack of any obvious interpretation for means, variances and co-variances derived from the PCA makes the procedure inappropriate. A second

limitation of PCA pertains to operationalization of the composite indicator, which is unappealing outside the sampled population because the weights derived using PCA are only applicable to standardized primary indicators. Due to these limitations of PCA, alternative factorial techniques have been proposed. These include factor analysis (Sahn and Stifel, 2000) and multiple correspondence analysis (Asselin, 2009) among others.

C1.2 Multiple Correspondence Analysis

MCA is the application of a simple correspondence analysis (CA) algorithm on multivariate nominal data coded in the form of an indicator matrix (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 is designed to improve on the PCA procedure when the latter approach loses its optimal parametric estimation properties and also to provide a more powerful tool to describe the hidden structure in a set of qualitative variables (Asselin, 2009). MCA is thus appropriate for analysis of nominal assets data. While the MCA uses a chi-square metric, the PCA uses a Euclidean metric to measure distances between two columns of the data matrix under analysis. MCA also has two desirable properties that PCA does not: First, it satisfies the distributional equivalence property, i.e., marginalization preference. For our purposes, this property means that MCA places too much weight on the smaller categories within each primary indicator: the poorest groups would receive a higher weight in the CWI. Second, MCA satisfies the duality property, which stipulates (i) that the composite poverty score of a population subgroup is the simple average of the standardized factorial weights for the poverty categories to which it belongs and (ii)that the weight of a given poverty category is the simple average of the standardized composite poverty scores of the population subgroups belonging to the corresponding poverty gaps (Asselin, 2009). Asselin further shows that the MCA-based CWI 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 CWI and reduce poverty. Second, it must satisfy composite poverty ordering consistency, such that the population ordering for a primary indicator is preserved with the composite indicator. That is to say that a population group with a category of indicators inferior to those of another group will be poorer than the latter group.

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

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

where j_k are the number of categories for indicator *k*, $W_{jk}^{*I,k}$ is the score of category *j* and $I_{I,jk}^{k}$ is a binary variable which takes a value of 1 when the unit *I* has a category j_k .

The 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 gives eigenvalues which better approximate the inertia explained by the factors than the eigenvalues from the indicator matrix. The scoring coefficients from the MCA are applied to each household to estimate its asset index and rank households on a scale from -1 to 1. Arbitrariness in weighting is avoided by using the results from the factor loadings as weights.

In the absence of expenditure or income data, poverty studies construct a composite wealth indicator based on asset information (Sahn and Stifel, 2003). The last three decades have seen the emergence of a substantial body of research that uses CWI-based alternatives rather than the conventional expenditure-based approach to defining poverty. An influential study on the use of asset indices was carried out by Filmer and Pritchett (2001). They construct a linear index of wealth using Indian data. They use the PCA approach and conclude that applying PCA to a set of asset indicators is a consistent and stable alternative to studying poverty when there is no consumption expenditure data. Macro International has also employed the Filmer and Pritchett PCA approach to compute asset indices from 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 rather than principal component analysis to construct an index based on household assets. The study concludes that, in the absence of expenditure data, the asset index can be used as a measure of economic welfare. Booysen *et al*. (2007) diverge from this approach and use an MCA to construct asset-based composite wealth indicators. They clearly present the advantages of using MCA over PCA, pointing to attractive statistical properties of MCA. Other researchers compare CWIs that have been built using a number of different approaches. Njong and Ningaye (2008) use PCA and MCA approaches to estimate multidimensional poverty indices. The authors suggest that policy makers should pay more attention to MCA-based asset indices because they reveal a greater incidence of poverty. Ki *et al*. (2005) construct a CWI for Senegal based on the MCA and inertia approach, citing advantages of an MCA over other approaches. Lawson *et al*. (2007) also use an MCA to derive a CWI for Togo.

C2 Approaches to multidimensional poverty comparisons

C2.1 The stochastic dominance (SD) approach

To illustrate the stochastic dominance approach, let us assume that $z = (z_1,...,z_k)$ is vector of the minimum levels of the *k* basic needs, $x = (x_1,...,x_k)$ is a vector of the *i*th person's k basic needs and X is a matrix summarizing the distribution of the k attributes among *n* persons. The general form of measures of multidimensional poverty is:

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

where π is an individual poverty function that indicates how many aspects of poverty must be aggregated at the individual level, and x_i and z are as defined above. The function *F(.)* reflects the way in which individual poverty measures are aggregated into an overall poverty index. The properties of *F(.)* and π (.) depend on the axioms that the poverty measures must satisfy. Typical axioms include symmetry, continuity, focus, scale invariance, principle of population, monotonicity, subgroup consistency, subgroup decomposability, factor decomposability, Pigou-Dalton transfer, non decreasing poverty under correlation increasing arrangement and normality.[10]

This paper considers two welfare indicators: CWI (x) and nutritional status (y). Assuming differentiability, each indicator can contribute to a measure of overall welfare (see Duclos *et al*. 2006a) as denoted by:

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

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

$$\Lambda(\lambda) = \left\{(x,y)\middle|\lambda(x,y) \leq 0\right\}. \quad \text{..... (5)}$$

Denoting the joint cumulative distribution function (CDF) of x and y as F(x, y) and assuming that the indices are additive across individuals, we can define a multidimensional poverty index that combines the CWI and nutritional status as:

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

[10] To establish conditions for robustness of poverty measures, some studies assume that the poverty measure does not have to satisfy all the above axioms (see for instance Bourguignon and Chakravarty, 2003; Bibi, 2005; Deutsch and Silber, 2005; Duclos and Araar, 2006). However, Duclos *et al*. (2006a) generalize the stochastic dominance approach to be applied in the multidimensional context.

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

$$\pi\left(x,y;\lambda\right)\begin{cases}\geq 0 & \text{if } \lambda(\text{x,y}) \leq 0\\ =0 & \text{otherwise.}\end{cases} \quad \text{……………………………………………………..…………… (7)}$$

In equations (6) and (7), π is the weight that the poverty measure attaches to a child/woman inside the poverty frontier. The poverty focus axiom dictates thatπ =0 for any child/woman above the poverty frontier. The multidimensional headcount is obtained when π=1 (Duclos *et al*., 2006a).

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

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

for integers $\alpha_x \geq 0$ and $\alpha_y \geq 0$. The SD surface can be generated by allowing z_x and z_y, the poverty lines, to vary over an appropriately chosen domain, with the height of the surface determined by (8). $F\left(x,y\right)$ is the joint CDF for the CWI and nutritional status. $P^{1,1}\left(z_x,z_y\right)$ generates a cumulative density surface that is analogous to a poverty incidence curve in a one-dimensional poverty analysis, while $P^{2,2}\left(z_x,z_y\right)$ is the two-dimensional average poverty gap index (Duclos *et al*. 2006a).

The bi-dimensional form is a special case due to the complexity of expanding the unidimensional analysis. In particular, there is the distinction between being poor in just one dimension or two (and at the limit, in all dimensions. In our two-dimensional case, an individual is deemed to be poor if they have either a low CWI or poor nutritional status. In such cases,πis:

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

Where x_i and z are as defined above. An intersection approach would consider those with low CWI and poor nutritional status as poor, in which case we have

$$\pi\left(x_i,z\right)\begin{cases}>0, & \text{if } \text{x}_{\text{i,j}} \leq z_j, \forall j=1,2,...,k,\\ =0, & \text{otherwise,}\end{cases} \quad \text{……………………………………………………(10)}$$

We check for bi-dimensional poverty dominance by comparing surfaces of distributions defined by equation (9), considering the order of dominance. These comparisons are valid for broad classes of poverty functions (which are generated according to the order of dominance) except for the FGT. Distributions are also influenced by covariance between the CWI and

nutritional status because the integrand is multiplicative. The higher the correlation between these two poverty indicators, the higher the dominance surfaces, all else equal.

The surfaces defined by equation (8) can be used to compare multidimensional poverty distributions using a class of poverty indices which implicitly define the order of dominance. Using equations (6) and (7), a class of bi-dimensional poverty indices $(\pi(\lambda^*))$ is defined. These poverty indices are additively separable, anonymous, continuous at the poverty frontier, non-increasing in welfare indicators and are substitutes for welfare indicators. Substitutability means that an increase in the CWI has the greatest impact on welfare when the increase occurs among less healthy children/women and vice versa. This class of poverty indices also assumes that the marginal poverty benefit of an increase in either CWI or nutritional status decreases with the value of the other variable. In other words, the lower the initial value of a person's CWI, the greater their increase in deprivation if they suddenly face lower nutrition. Such an assumption can be understood as one of "substitutability" of dimensions: the higher a child's CWI, the lower the decline in poverty associated with a given improvement in nutrition.

Formally, this also assumes that poverty is non-decreasing under a correlation-increasing switch. A correlation-increasing switch leaves the marginal distributions of both the CWI and nutritional status unaffected, but increases the correlation between both welfare indicators by increasing the incidence of multiple deprivations (Bourguignon and Chakravarty, 2003). Duclos *et al*. (2006a) demonstrated that further assumptions about general poverty indices allow definition of a general form for bi-dimensional poverty indices as well as extensions to comparisons of higher-ordered poverty dominance.

While a substantial literature on the use of stochastic dominance analysis does exist, empirical literature that examines stochastic dominance in a multidimensional poverty setting is very much in short supply. An emerging body of literature on stochastic dominance and multidimensional poverty, following the works of Duclos *et al*. (2006a, 2006b, 2008), is filling this void. Kabubo-Mariara, Araar and Duclos (2010) use the approach to test for multidimensional poverty dominance among Kenyan children. They find results that are robust to the choice of the poverty line and to the choice of aggregation procedures across dimensions and across children. Batana and Duclos (2010) examine multidimensional stochastic dominance when one of the indicators of wellbeing is discrete. Their findings suggest that tests based on the likelihood ratio can be useful for analyzing multidimensional poverty and welfare dominance when one of the dimensions of welfare is qualitative.

C2.2 Dual cut-off and counting approach

To illustrate the Alkire and Foster (2007) approach, we start by assuming a population of *n* persons and *d > 2* dimensions or capabilities. Let $x=[x_{ij}]$ be the *n x d* matrix of achievements in the various dimensions. For example, $x_{ij} > 0$ is the outcome for person *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 permitted to vary in order to facilitate comparisons of poverty across populations of differing sizes. The domain of the matrices considered is given by $X = \{x \in R_{+}^{nd} : n \geq 1\}$ and the dimension-specific deprivation cut-off is denoted by z_j (Alkire and Foster, 2007).

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

$$\text{for all i and j, } x_{ij}^0 = \begin{cases} 1 \text{ if } x_{ij} < z_j \\ 0 \text{ otherwise} \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(11)}$$

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

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

With a cut-off k, $(k = 1, ..., d)$, we can compare the number of deprivations per person. The identification function relating to cut-off *k* is such that $\rho_k(x_i, z) = 1$ when $c_i \geq k$, and $\rho_k(x_i, z) = 0$ when $c_i < k$. In other words, the multidimensionally poor are deprived in at least *k* dimensions.

Given ρ in equation (12), the aggregation rule brings together the matrix *x* and the cut-off vector *z* to generate a class of multidimensional poverty measures $M(x; z)$, with $M : X \ x \ R_{++}^{d} \rightarrow R$ as the multidimensional poverty index. We can thus define the multidimensional headcount ratio as:

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

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 cut-off *k* in set z_k. As with most FGT measures, the share of possible deprivations suffered by a poor

person and the average share of deprivation among the poor can be derived from equation (13) by normalizing across 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 both the monotonicity and transfer axioms. The poverty headcount H also violates dimensional monotonicity: if a poor person becomes deprived in an additional dimension (in which he/she was not previously deprived), H does not change (Alkire and Foster, 2007). To deal with this shortcoming, Alkire and Foster propose an adjusted headcount which combines H and the average deprivation share across the poor (A) and thus satisfies dimensional monotonicity. The adjusted headcount is the number of deprivations experienced by the poor divided by the maximum number of deprivations that could be experienced by all people (nd) and is defined as:

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

If the variables in *x* are cardinal, the associated matrix of (normalized) gaps or shortfalls can also be useful when investigating poverty. 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 the power of α is $g_{ij}^{\alpha} = (g_{ij}^1)^{\alpha}$. G^{α} can be expressed as

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

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

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

When $\alpha = 0$, M_{α} is the adjusted headcount ratio (M_0). When $\alpha = 1$, we get the adjusted poverty gap (M_1 = HAG), the sum of normalized gaps among the poor divided by the largest possible sum of normalized gaps. M_1 summarizes the incidence of poverty, the average range of deprivations and the average depth of deprivation. It obeys the axioms of dimensional monotonicity and monotonicity. Hence, if a person becomes more deprived in a particular dimension, M_1 will increase. When $\alpha = 2$, M_{α} is the adjusted squared poverty gap (M_2). It summarizes the incidence of poverty, the average range and the severity of deprivations among

the poor. If a poor person becomes more deprived in some particular dimension, the increase in M_2 will be greater for a higher initial level of deprivation in that dimension. The measure obeys the monotonicity and transfer axioms, being sensitive to inequality of deprivations among the poor.

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

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

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

The M_α family of poverty measures presented above assumes that all dimensions receive the same weight, an assumption that may be relaxed at times (Alkire and Foster, 2007). Let *w* be a *d*-dimensional row vector, where w_j is the weight associated with dimension *j*. We then define the $n \times d$ matrix $g^\alpha = [g_{ij}^\alpha]$ where $g_{ij}^\alpha = w_j((z_j - x_{ij})/z_j)^\alpha$ when $x_{ij} < z_j$, and $g_{ij}^\alpha = 0$ otherwise. As shown above, the deprivation column vector's i^{th} entry, $c_i = |g_i^0|$, represents the weighted sum of the dimensions for which person *i* is deprived. c_i varies between 1 and *d*, so the cut-off to identify the multidimensionally poor can be any real number *k* such that $0 < k \le d$. When equal weights are used for each dimension, $k = \min\{w_j\}$, and the identification criterion also corresponds to the union approach to poverty measurement. In the case where $k = d$, the intersection approach is used as the identification criterion. Alkire and Foster (2007) also consider the case where $1 < k < d$. With two dimensions, this criterion combines the dimensions as proposed by Duclos, Sahn, and Younger (2006a).

A number of studies have applied the Alkire and Foster (2007) approach to the study of multidimensional poverty in developing countries. These include Batana (2008) in a study of fourteen Sub-Sahara Africa countries. Another application of the approach is a study by Santos and Ura (2008), whose data from Bhutan. Alkire and Suman (2008) also use the dual cut-off approach to study multidimensional poverty in India. Other studies that have used the Alkire and Foster approach to study multidimensional poverty among children include: Roche (2009), in a study of child deprivation in Bangladesh; Roelen, Gassman and de Neubourg (2009) for Vietnam; Beggeri *et al*. (2009) in an analysis of deprivation of Afghan children; Battiston *et al*. (2009) in Latin America; and Azevedo and Robles (2009) in a Mexican pilot study. Some of the

studies illustrate the value of multidimensional poverty measurement over unidimensional approaches when designing policy. For instance, Batana finds that ranking countries on the basis of the Alkire and Foster (2007) multidimensional measures of poverty differs from ranking based on standard welfare measures (poverty as measured by income and the human development index). The studies also show that Alkire and Foster (2007) poverty orderings are robust to different poverty cut-offs. They also illustrate the value that decomposable Alkire and Foster multidimensional poverty measures can have in terms of informing multisectoral planning.

C3 Standardization of z-scores

The standardized anthropometric measure is constructed such that a child's position in the distribution relative to the percentiles in the WHO reference population is the same for his/her actual and standardized z-scores. The procedure to standardize 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* be the distribution function of z-scores in the WHO population for age/sex group defined by *a* (age) and *g* (gender), *z* as the actual z-score, $\bar{a}$ = 24 months and $\bar{g}$ =female, the standardized z-score (Z) can be expressed as

$$Z = F^{-1}_{\bar{a},\bar{g}}(F_{a,g}(z)) \quad \text{(18)}$$

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

$$\text{Std\_Z} = \text{M}(1+\text{LSZ})^{1/\text{L}}\text{L} \quad \text{(19)}$$

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

C4 Econometric model of multidimensional child poverty

[11] In this paper, we use 24-month-old girls as per Sahn and Younger (2006). It can, however, be shown that the standardization is robust to the choice of age and gender. 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. Also see Kuczmarski *et al*. (2002).

In the bivariate probit model of multidimensional poverty, we consider two related outcomes. Y_{1i}^* is the first latent variable (the CWI) and Y_{2i}^* is the second latent variable (the health index) such that:

$$Y_{1i}^* = X_{1i}\beta_1 + \mu_{1i} \quad \text{.....} \quad (20)$$

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

$$Y_{2i}^* = X_{2i}\beta_2 + \mu_{2i} \quad \text{.....} \quad (21)$$

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

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

$$\phi(\mu_1, \mu_2) = \frac{1}{2\pi\sigma_{\mu 1}\sigma_{\mu 2}\sqrt{1-\rho^2}} \exp\left[-\frac{1}{2}\left(\frac{\mu_1^2 + \mu_2^2 - 2\rho\mu_1\mu_2}{1-\rho^2}\right)\right] \text{.....}(22)$$

where ρ is a correlation parameter denoting the extent to which the two covary. The bivariate normal cumulative density function (Φ_2) that can be obtained from (22) is defined as:

$$\int_{\mu 1}\int_{\mu 2} \phi_2(\mu_1, \mu_2, \rho) d\mu_1 d\mu_2 \text{.....} \quad (23)$$