CONSTRUCTION OF MULTIDIMENSIONAL POVERTY INDEX OF KENYA USING THE ALKIRE-FOSTER METHOD

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Declaration

I declare that this work has not been previously submitted and approved for the award of a degree by this or any other University. To the best of my knowledge and belief, the Research Proposal contains no material previously published or written by another person except where due reference is made in the Research Proposal itself.

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ABSTRACT

In this paper, we use one specification of the Alkire-Foster approach, which is referred to as the Multidimensional Poverty Index (MPI), to calculate the poverty index of Kenya. This index was computed for 104 countries in Alkire and Santos (2010)and launched as a prominent feature of the annual United Nations Development Program(UNDP). Human Development Report, replacing the previous Human Poverty Index of the United Nations Development Program.

The novelty of this paper is that it seeks to reconstruct the poverty index which is used in Kenya's Revenue Allocation formula. Currently, the country is using a modification of Human Development Index as used by UNDP which gives weights to different aspects of deprivation, a method that has been dubbed as 'Lucy's model', named after the person who developed it in December 2015, and was approved for use by the Commission for Revenue Allocation to distribute funds from the National government to county governments, by the National Assembly of Kenya on 10th March 2016.

The paper compares the allocations arrived at by both Lucy's Model and Alkire-Foster method in terms of equality of means, variances, correlations and other statistical tests of significance in differences between two or more data sets.

Keywords: Multidimensional poverty, unidimensional poverty, deprivations, AF method.

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1. INTRODUCTION

1.1 Background

Defining poverty as a phenomenon of multiple dimensions goes back to the seminal work of Amartya Sen. In practice, however, the vast majority of empirical work on poverty uses a one-dimension measure of well-being, usually household income or expenditure. This is also the case in Kenya, although the conceptualization of poverty in the country has steadily evolved since 2003. In terms of defining multidimensional poverty measure, several possibilities have been proposed in theoretical and empirical literature

Poverty is a multifaceted concept which includes social, economic and political elements. Generally, poverty is viewed in three dimensions which are standards of living, health and level of education. The Human Development Index is commonly used by the United Nations Development Program to calculate the poverty index of countries and rank them in order of the most developed country to the least developed country. In 2010, a new method was used to calculate the poverty index of 104 countries. This method is known as the Alkire-Foster (AF) method. This method is used to measure acute poverty by calculating the proportion of people who experience multiple deprivations and also by calculating the intensity of those deprivations. The deprivations are based on indicators that explain the three dimensions stated.The approach also satisfies several desirable properties, or axioms, including decomposability, which makes it particularly suitable for policy analysis and targeting

The Alkire-Foster Method is an accurate method for calculating the poverty index and it helps in making policies that are used to target the poor people in a country. This paper seeks to construct the multidimensional poverty index of Kenya by calculating the poverty index of Kenya's 47 counties then ranking from the 'wealthiest' to the poorest county.

1.2 Motivation for the study

The motivation of this study is to reconstruct the poverty index of Kenya which will guide the national government on how to share revenues among counties for the purpose of poverty reduction in the country. Poverty index is one of the factors that are considered in the Kenya's Revenue Allocation Formula and it is calculated as a modification of HDI index. The modified formula is termed as Lucy's model, and is expressed as follows:

$$CA_i = 0.46PN_i + 0.27ES_i + 0.17PI_i + 0.07LA_i + 0.02FE_i + 0.01DF_i$$

Where; CA_i is the revenue allocation for the i^{th} county; PN_i is the Population Factor; ES_i is Equal Share Factor; PI_i is the Poverty Index; LA_i is the Land Area Factor; FE_i is the Fiscal Effort Factor and DF_i is the Development Factor(Muthoni, 2016).

In the model above, it is worth noting that the Poverty Index bears one of the largest weights. The Poverty Index above was calculated using the Human Development Index that is used by the United Nations to calculate the poverty levels and development standards of a country or a particular region UNDP (2010).The Human Development Index is a welfare index that combines the aggregate dimensional achievements of all people into one overall score; Alkire (2011). This means that this method identifies the poor and ignores the data of the non-poor.

The Alkire-Foster (AF) method is a new approach that actually determines the number of people who are poor and the number of deprivations they have. This is important for economic policies since governments can use this information to plan and cater for the poor in the economy. With the AF method, policymakers can identify the poorest people and the aspects in which they are most deprived. This information is also vital in investing resources where they are likely to be most effective at reducing poverty. Policymakers can identify which deprivations constitute poverty and which are most common among and within a group, so that policies can be designed to address particular needs. The AF method integrates many different aspects of poverty into a single measure, reflecting interconnections among deprivations and helping to identify poverty traps.

The AF method isalso quicker in showing the effects in changes in policy than income alone. For example, if a new social program aimed at increasing good education is introduced to an area, it will be a long time before any positive benefit in returns from education are reflected in an income measure. In contrast, a multidimensional poverty measure that includes child enrolment and achievement could reflect a reduction in this aspect of poverty relatively quickly, because it is measuring it directly; OPHI (2016).Different dimensions, measures and cutoffs can be used to create measures tailored to specific uses, situations and societies. This method can be used to create poverty measures to target poor people as beneficiaries of Conditional Cash Transfers or services, and for the monitoring and evaluation of the programs; OPHI (2016).The AF methodology also shows the intensity of poverty and the measure creates using the AF method are transparent. This means they can be broken down quickly and easily by region or by social group; OPHI (2016).

1.3 Problem Statement

Lucy's Modelis perceived to be the 'best' model for revenue sharing formula for Kenya according to Muthoni(2016). However, the multidimensional poverty index used in this model is not complete. The Multidimensional Poverty Index (MPI) used in this model has three main dimensions namely health, education and standards of living, and used the approach outlined in the Human Development Report(2010). These dimensions have certain indicators. In the normal calculation of the MPI using this approach, some of the indicators may be left out. Also, in the construction of Lucy's poverty index, weights were assigned to the different dimensions of poverty. The weights used are derived from other countries whose economy and poverty level is similar to that of Kenya. This method of calculating the poverty index may not be able to determine the people who are actually poor in Kenya. It may lead to over-representation or under-representation of poor people in Kenya. As a result, the revenue allocation formula may be inaccurate since the poverty index is a factor that bears a lot of weight in the revenue allocation formula.

To remedy this, the Alkire-Foster method shall be applied in this paper to reconstruct the poverty index. This is an accurate method for measuring poverty since it consists of deprivation cutoffs and a poverty cutoff (dual cutoff approach). This method helps to determine and give a headcount of all the poor people in the country depending on the cutoff of the different indicators in the dimensions of poverty.

1.4 Research Objectives

1. To reconstruct the poverty index using the Alkire-Foster method therefore improving the Poverty Index of Lucy's model.
2. To compare the difference between the AF method results and the Lucy's model, with particular attention given to the poverty allocations.

1.5 Research Questions

1. Are there any missing dimensions of the poverty index?
2. What is the difference between the Alkire-Foster method and the Human Development Index Method (a method on which Lucy's model is based)?
3. Does the change in recalculating the poverty index using the Alkire-Foster method result in changes in the poverty allocations calculated previously using Lucy's Model?

2. LITERATURE REVIEW

This chapter covers literature on the Multidimensional Poverty Index. Multidimensional measures provide an alternative lens through which poverty may be viewed and understood. How we measure poverty can influence how we come to understand it, how we analyze it and how we create policies to influence it. For this reason measurement methodologies can be of practical relevance, according to Alkire and Foster (2011).

Recently, Alkire and Foster (2011) attempted to offer a practical approach to identifying the poor and measuring aggregate poverty. The Alkire-Foster methodology is perhaps the best seen as a general framework for measuring multidimensional poverty since many decisions are left to the user. These include the selection of dimensions, dimensional cutoffs, dimensional weights and a poverty cutoff. This flexibility makes it particularly useful for measurement efforts at the country level even at the county level as for the case of Kenya. These decisions can fit the purpose of the measure and can embody normative judgments regarding what it means to be poor in the respective countries. As this is quite a departure from the traditional unidimensional and multidimensional poverty measurement, further elaboration may be warranted. The method delivers an aggregate poverty measure that reflects the prevalence of poverty and the joint distribution of deprivations. Useful partial indices are reported that reveal the intuition and layers of information embedded in the summary measure, according toAlkire(2011).

If on the other hand there is data on achievements in several dimensionsdistributed across a population, then followingSen(1976), it is important to ask: Who is poor and how should overall poverty be measured in this setting? If the underlying concept of poverty admits a natural way of aggregating the various dimensions into an overall variable, then a unidimensional methodology can be used. In a unidimensional approach, the poor are identified on a basis of a single cutoff and overall poverty is evaluated using a unidimensional measure such as a measure of the Foster, Greer and Thorbecke(FGT) class. FGT class of indices is a traditional measure of poverty that basically involves aggregating various dimensions into an overall variable and viewed through a unidimensional lens.

However, if an aggregate variable cannot be plausibly constructed and instead there are several important distinct dimensions, how can we identify the poor and measure poverty in this case? Bourguignon and Chakravarty(2003) propose the use of dimension-specific lines, which are called deprivation cutoffs in Alkire and Foster's work (2007), as the basis for determining who is deprived and in which dimension. Alkire and Foster then posit the existence of an identification function, which determines whether a person is deprived enough to be called poor, and a poverty measure, which evaluates how much poverty there is overall. Axioms analogous to the ones used in the unidimensional case can ensure that the measure properly reflects poverty and that it can be decomposed by subgroup. The axioms also ensure that the poverty measure is consistent with the identification function.

Much of the research in this area has been concerned with finding an appropriate poverty measure rather than devising new methods of identifying the poor. Two benchmark identification approaches are discussed by Atkinson (2003): the union and intersection approaches. Under union identification, a person who is deprived in any dimension is considered poor. Under intersection identification, only persons who are deprived in all dimensions are considered poor. Both approaches are easy to understand and have useful characteristics, such as being able to be applied to ordinal variables. However, they can be particularly ineffective at separating the poor from the non-poor. In a recent study by Sabina Alkire (2009) that uses ten dimensions to identify the poor in India, the union approach identifies 97 per cent of the population as poor, whereas the intersection approach identifies 1 per cent of the population as poor. Such a range of values is common in many studies.Bourguignon and Chakravarty's(2003)discussion on concernson identification functions show that tradeoffs are being made between continuous dimensional variables. However, this leads the discussion back to the original question of whether a coherent aggregate variable can be constructed from the individual dimensions. If the answer is no, as postulated above, then it may be somewhat difficult to justify the aggregation needed for a general identification function. If yes, then there may be good reason to explore a unidimensional method.

One important omission in this literature is proper discussion of the axiomatic structure for identification functions (or, more generally, for overall methodologies) that could help guide the construction of new identification techniques. Too little attention has been paid to developing practical alternatives to the union, intersection and unidimensional identification approaches. This is a key motivation behind Alkire and Fosters work in (2007) and (2011) .

3. GENERAL FRAMEWORK OF THE AF METHODOLOGY

3.1 AF Method compared to the Human Development Index (HDI)

The AF methodology is a general framework for multidimensional poverty measurement, which can be filled in different ways. The dimensions and cutoffs could vary, as could the weights and poverty cutoff. The measure could be applied at different level. For example, a poverty measure could be implemented at the village, state, or national levels. The specific choice of measures might vary: one institution might implement a measure with cardinal data to reflect the depth of poverty or inequality among the poor, whereas another could only have ordinal data available, and so would report the adjusted headcount ratio and the breadth of poverty. In sum, the AF method is a very flexible framework and can give rise to a number of concrete applications whose shapes depend upon the purpose for which they are designed; Alkire (2011).

There is a chance the AF method might be confused with the Human Development Index (HDI), which aggregates across achievements in health, education, and standard of living. In fact, the two measure very different things. The AF methodology (and its particular example of the MPI) measures poverty: it identifies who is poor and ignores the data of the non-poor. In contrast the HDI is a welfare index based on three marginal distributions that combines the aggregate dimensional achievements of all people (not just the poor) into one overall score. While the HDI may be limited in terms of data, dimensions and methodology, it has helped bring into view people's achievements in non-monetary spaces, and made it possible for other categories of multidimensional measures (such as poverty measures) to be envisioned; Alkire(2011).

3.2 Who chooses the parameters?

The AF methodology is a general framework for measuring multidimensional poverty; an open source technology that can be freely altered by the user to best match the measure's context and evaluative purpose. As with most measurement exercises, it will be the designers who will have to make and defend the specific decisions underlying the implementation, limited and guided by the purpose of the exercise and commonly held understandings of what that purpose entails. Traditional unidimensional measures require decisions that are qualitatively similar. For example should the variable be expenditure or income? What should the poverty cutoff be? Other implementation choices are less apparent but can likewise be important for final results. Robustness tests are crucial both for ensuring that results obtained are not unduly dependent upon the calibration choices and for allowing these choices to be made in the first place. The calibration of choices will depend upon the purpose of the measure, such as the space in which poverty is evaluated, the relevant comparisons across time or populations that the measure will inform, or the particular programs or institutions which will be evaluated. Calibration choices will also reflect data and resource constraints; Alkire (2011)

Enabling people to choose parameters according to a range of processes provides an essential flexibility and adaptability to allow the measures to be tailored to institutional, cultural and data-specific circumstances. In addition, the AF methodology is relatively transparent, and this feature can be helpful when parameters are set by (or at least opened to) public debate. It uses explicit indicators, weights and cutoffs, so that serious shortcomings in the choice of parameters could be debated and changed. To counterbalance and inform this flexibility, the use of dominance results and of robustness and sensitivity tests, which will show whether the key points of comparison are robust to a range of plausible parameter choices; Alkire(2011).

3.3 Missing Dimensions of Poverty in Data

Human Development is the process of expanding freedoms that people value and have reason to value according to Sen (1999). If we understand development to be the key process of expanding the freedoms that people value and have reason to value Sen(1990), then a key aspect of assessing these freedoms is to measure them in a manner that is consistent and comparable over time and space; Alkire(2007).There are a number of reasons why an initiative to identify and advocate a small set of indicators for important but non-standard dimensions of human development may be both useful and feasible.

First, more such data exist than in any previous generation, to such an extent that more data exists in some countries than are fully analyzed. The indicators are generated by household surveys and community-based surveys, as well as censuses and demographic and social surveys. Thus there is a wealth of experience with non-standard indicators which can inform the selection of technically accurate and cross-culturally comparable indicators.

Second, a number of initiatives are already exploring how to measure capabilities and how to structure national and regional assessments. Individual researchers working to advance capability measurement are developing surveys and undertaking studies using both micro and primary data. Finally, community based monitoring systems have incorporated and explored missing indicators related to capabilities and functions. This initiative to shortlist key missing indicators of human development for international data collection has drawn upon and endeavored to support such initiatives.

Third, these dimensions may be important triggers of human development in other dimensions (and oversight of them may also block or slow poverty reduction in other spaces), because each of these dimensions seem to be casually interconnected with other aspects of poverty in complex ways. The lowest ranking countries in terms of the HDI are countries in or emerging from violent conflict (UNDP, 2006). It has been argued repeatedly that empowerment is instrumentally significant for poverty reduction; and addressing social exclusion and disrespect by caste, religion, age, race or other categories seems an inescapable part of addressing poverty (Alkire, 2007).

Fourth, the missing dimensions are arguably intrinsically important-hence their selection. Multidimensional poverty measures can illuminate certain issues better, for example targeting, and distribution of acute poverty, if data are aggregated first across dimensions, and secondly across individuals. For the HDI, data are aggregated across all individuals for each domain. However a distinct advantage emerges if the data are all available from the same survey or from surveys that can be matched at the individual level.

3.4 Grounds for Indicator Selection

First, the indictors need to be internationally comparable. This is particularly important as there is a dearth of information available on comparative indicators of the missing dimensions. Second, the indicators seek to assess not only the instrumental but also the intrinsically valuable aspects of the dimensions. Third, it is essential to select indicators that would be able to identify changes in the dimension over time. Fourthly and crucially, the choice of the indicators draws on experience with particular indicators to date, that is, how frequently these indicators have been previously fielded and found to be adequate measures for research purposes (Alkire, 2007).

3.5 Missing Dimensions

Having pointed out the need for additional poverty data, there are specific dimensions that are valued by poor people and have policy relevance. The following describes the rationale behind the five dimensions that have been selected (Alkire, 2007)

3.5.1 Employment Quality

Employment is certainly not a new dimension of wellbeing, but it is sometimes forgotten in human development and poverty reduction policies, or at least, not considered in sufficient depth. Employment is the main source of income for most families in the world. Having a good and decent job is generally associated with being out of poverty, however poverty is defined. Additionally, employment can give a sense of self-respect and fulfillment. There is hence no question as to the importance of employment as a fundamental aspect of individual wellbeing. However, existing employment data generally focuses on formal employment and overlooks the kinds of employment open to poor people, as well as indications of the potential meaning of employment. Lugo,(2007), proposes five indicators of employment. These comprise informal employment; income from self-employment; occupational safety and health; and under and over employment. The final indicator relates to quantity; it seeks to determine the level of discouraged unemployment, that is, people who would like to be working but have stopped looking for a job; Alkire(2007).

3.5.2 Agency and Empowerment

Agency has been defined as ‘what a person is free to do and achieve in pursuit of whatever goals or values he or she regards as important Sen(1985b);more simply, as ‘someone who acts and brings about change; Sen (1999, p. 19). The opposite of a person with agency is someone who is coerced, oppressed or passive. Agency and its expansion (empowerment) recur as a variable that is intrinsic and instrumental importance to impoverished communities. Building on a growing body of empirical research Ibrahim and Alkire (2007), propose a 'short-list' of indicators aimed at capturing the individual and collective facts of agency. In brief, they use decision-making questions to identify perceptions of control. Who makes decisions about different areas of household life and whether the respondent could if he or she chose. To measure the extent to which people feel themselves to be coerced, and/or acting on their own initiative, the article proposes , uniquely, autonomy measure from psychology that have been tested across cultures and recently in poor communities. Other questions explore the extent to which individuals feel empowered to bring change at both the individual and communal levels; Alkire (2007).

3.5.3 Physical Safety

One of the greatest impediments to human security in the post-Cold War era is not war fought by the armed forces of nation states, but violence perpetrated by individuals, groups and state actors within nations' internal borders. Violence undoes the development gains achieved in area such as education, health, employment, income generation and infrastructure provision. Further, it impedes human freedom to live safely and security, and can sustain poverty traps in many communities. However, violence is not inevitable to human interaction. Most multi-ethnic, multi-religious and poor people live in peace. There is need for reliable and comparable data of violence against both person and property to greater inform our understanding of these conceptsAlkire(2007).

3.5.4 The Ability to go about without shame

Shame and humiliation are essential to the understanding of poverty yet internationally comparable data on these dimensions are missing. Based on existing indicators from related fields, Zavaleta(2007) proposes eight indicators to measure specific aspects of shame and humiliation. Indicators for measuring shame have been selected from the HIV/AIDS-related stigma literature, from literature on discrimination, and from instruments used in psychology. The first indicator relates to the shame of being associated with poverty, or the stigma of poverty. The second indicator relates to shame proneness, which refers to the 'tendency to experience the emotion of shame in response to specific negative events' Tangney (2002, p. 2003).Shame proneness is particularly relevant because it affects social relationships, self-respect and the ability to go about without shame; which are all aspects of capability poverty. Indicators of humiliation refer to that experienced in response to external events and to the internal experience of humiliation. The questions on external humiliation center on respectful treatment, unfair treatment, discrimination and perceptions that one's background impedes mobility; the question on internal humiliation seeks to gauge levels of accumulated humiliation at the individual level; Alkire (2007).

3.5.5 Psychological Wellbeing

The final aspect pertains to psychological and subjective states of wellbeing, which have clear intrinsic and instrumental value. They are a key component of the other dimensions proposed here, as well as an end result of their attainment. Moreover, they stand to contribute a richer perspective to the understanding of human experience and values, and particularly the importance of its non-material components. There are two approaches: perceptions of the meaning of life and the ability to strive towards excellence in fulfilling this idea; Alkire (2007).

In conclusion, it is important to recognize the limitations of this exercise of attaining missing data. The eventual goal is not merely to measure poverty but to create a framework for research and policy that will lead to lasting poverty reduction; Alkire (2007).

4. METHODOLOGY

This chapter outlines the research methodology the study will adopt. It looks at the research design, population of the study, sampling methods used, data collection techniques and data analysis techniques.

4.1 Research Design

This study will adopt a descriptive approach of poverty indices in Kenya. The main reason for this selective descriptive research design is because it provides a knowledge base when little is known. It also allows one to establish a relationship between variables.

4.2 Data

Secondary data will be employed in this study. The data used for this analysis is from the census, conducted by the Kenya National Bureau of Statistics in 2009. As noted, our choice of data is guided by the objective of establishing comparability with the global MPI estimates presented in Alkire and Santos (2010) and UNDP (2010). A key advantage of the MPI methodology is that it is based on a consistent methodology that seeks to use comparable data that facilitates international comparison. This data is also available at the Commission for Revenue Collection, Kenya

4.3 Population Sampling

The study focuses on all the 47 counties of Kenya. Data from the 2009 population census will be used. The 47 counties are heterogeneous in terms of their population sizes.

4.4 Alkire Foster Method

This is the method that will be used to calculate the poverty index:

Step 1: Choose the unit of analysis. In this case the unit of analysis will be at the county level.

Step 2: Choose dimensions. In this case it will be the level of schooling, level of healthcare and standard of living.

Step 3: Choose Indicators. These are chosen for each dimension on the principles of accuracy (using as many indicators as necessary so that the analysis can properly guide policy) and parsimony (using as few indicators as possible to ensure ease of analysis for policy purposes and transparency.

Level of education is indicated by the number of people who are completely illiterate, the number of people who have been educated up to the primary level and the number of people who have been educated up to the secondary school level.

Healthcare is indicated by the number of people not immunized and the number of people who go through home deliveries.

Standard of living is indicated by the number of people living in poor sanitation, the number of people who cannot access clean water (clean water is as far as a 30-minute walk) and the number of people who use inferior fuel.

Step 4: Set poverty lines. A poverty cutoff is set for each dimension. This step establishes the first cutoff in the methodology. Every person can be identified as deprived or non-deprived with respect to each dimension.

Step 5: Apply poverty lines. This step replaces the person's achievement with his or her status with respect to each cutoff.

Step 6: Count the number of deprivations for all the dimensions.

Step 7: Set the second cutoff. Assuming equal weights for simplicity, set a second cutoff 'k' with which gives the number of dimensions in which a person must be deprived in order to be considered mutidimensionally poor. Robustness tests can be performed across all values of 'k'.

Step 8: Apply Cutoff 'k' to obtain the set of poor persons and censor all non-poor data. This focus is now on the profile of the poor and the dimensions in which they are deprived.

Step 9: Calculate the headcount, H. Divide the number of poor people by the total number of people.

Step 10: Calculate the average poverty gap, A. A is the average number of deprivations a poor person suffers. It is calculated by adding the proportion of total deprivations each person suffers and dividing by the total number of poor persons.

Step 11: Calculate the Adjusted Headcount, M. If the data are binary or ordinal, multidimensional poverty is measured by the adjusted headcount, M, which is calculated as H times A. Headcount poverty is multiplied by the 'average' number of dimensions in which all poor people are deprived to reflect the breadth of dimensions.

A systematic overview of the multidimensional methodology of Alkire and Foster's work in (2007) and (2011) is used to describe the poor people using a 'dual cutoff' method. In this work, there is construction of poverty measures and each measure is drilled down to unfold distinctive partial indices that can illuminate policy questions. Decompositions are exhibited that explain and clarify the aggregate poverty level. In what follows will assume that the range of dimensional variables has been selected and data are available in the form of a $n \times d$ data matrix Y for n persons and $d \geq 2$ dimensions.

4.4.1 Identification

In unidimensional analysis, identification is normally accomplished by the use of a poverty line or threshold, with poor people being identified as those whose resource or achievement variable falls below the poverty line. In the multidimensional measurement setting, where there are multiple variables identification is a substantially more challenging exercise. This part of the AF method is most commonly overlooked or misunderstood. Therefore it is important to begin by understanding the basic elements of the AF method dual cutoff identification approach.

4.4.2 Deprivation Cutoffs

A vector $z = z_1, \dots, z_d$ of the deprivation cutoffs (one of each dimension) is used to determine whether a person is deprived. If the person's achievement level in a given dimension j falls short of the respective deprivation cutoff z_j, the person is said to be deprived in that dimension; if the person's level is at least as great as the deprivation cutoff, the person is not deprived in that dimension.

4.4.3 Weights

A vector $w = w_1, \dots, w_d$ of the weights or deprivation values is used to indicate the relative importance of the different deprivations. If each deprivation is viewed as having equal importance, then it leads to a benchmark case where all the weights are one and the sum to the number of dimensions d. If dimensions are viewed as having differential importance, this is reflected by a sum of vector whose entries sum to d but can vary from one, with higher weights indicating greater importance. Deprivation values affect identification as they determine the minimal contributions of deprivations that will identify a person as being poor; they also affect aggregation by altering the relative contributions of deprivation to overall poverty.

4.4.4 Deprivation Counts

A column vector $c = (c_1, \dots, c_n)'$ of deprivation counts reflects the breadth of each person's deprivation. The i^{th} person's deprivation count c_i is the number of deprivations experienced by i (in the case of equal weights) or the sum of the values of the deprivations experienced by i (in the general case).

4.4.5 Poverty Cutoff

A poverty cutoff k satisfying $0 < k \leq d$is used to determine whether a person has sufficient deprivations to be considered poor. If the i^{th} person's deprivation count c_i falls below k, the person is not considers to be poor; if the person's deprivation count is $k$or above, the person is identified as being poor. Note that when k is less than or equal to the minimum weight across all dimensions we have a union identification. When $k = d$, the intersection approach is being used. The deprivation count and poverty cutoff can also be expressed as percentages of d.

4.4.6 Identification Function

The identification function summarizes the outcome of the above process and indicates whether a person is poor in Y given deprivation cutoffs z, weights w and poverty cutoff k. If the person is poor, the identification function takes on a value of one; if the person is not poor, the identification function has a value of zero.

One of the interesting properties exhibited by the AF method approach is that it is applicable even one or more variable are ordinal. All cardinalizations of the ordinal variable (found by applying a monotonic transformation to the variable and its cutoff), yield identical conclusions regarding whether a person is deprived in the dimension and whether the person is poor. This expands the potential reach of the methodology by allowing it to be meaningfully applied to data with lower level measurement properties; Alkire (2011).

4.5 TheAlkire-Foster Multidimensional Poverty Index

The MPI is an extension of the one-dimensional class of decomposable poverty measures proposed by Foster, Greer and Thorbecke (1984) and emerged from the dimensional adjusted poverty headcount ratio proposed by Alkire and Foster (2007). The index is made up of two components: the poverty headcount, H, and an adjustment measure, A that represents the number of deprivations suffered, on average by the poor.

$$MPI = H \times A \quad (1)$$

Where;

$$H = \frac{q}{n} \quad (2)$$

This is simply the total number of poor, q, divided by the total population, n. Since this study is using data from a representative household survey, and since it wants to adjust for variations in household size (notably to ensure that the measurement takes into account that poorer households typically have more members) a weight $w_i = s_i \times h_i$ is applied where s_i is the sample weight and h_i the household size,$w_i$could be normalized so that $\sum_{i=1}^{n} \mathrm{w_i} = \mathrm{n}$

The total number of poor people is given by:

$$q = \sum_{i=1}^{n} w_i \, \rho_k \, (y_{i,} \, ; z) \quad (3)$$

This is the sum of individuals identified as poor using a dual cutoff approach represented by $\rho k(y; z)$ where $y_i = (y_{i1}, \dots, y_{ij} \dots \dots \dots, y_{id})$ represents the profile household $i's$ achievements across d 'dimensions'. The first cutoff is givenbyz_j, which is the deprivation threshold in each dimension, $j = 1, \dots, d$ of poverty that separates the deprived from the non-deprived. The second cutoff is representedby k, which is the number of deprivations required in order for the individual to be considered mutidimensionally poor. At one extreme when $k = 1$, the identification cutoff is equal to the union approach whereby poverty is defined as being deprived in just on dimension. At the other extreme, $k = d$ is equal to the intersection approach, where one is defined as mutidimensionally poor only if deprived in all dimensions. The poverty status of an individual is defined as a dichotomous variable equal to 1 if the number of deprivations countedc_i, for each individual $c_i \geq k$ and 0 if not.

It is useful to organize the multiple dimensions $d$according to T partitions with respective sizes. $d_1, d_2, \dots \dots \dots, d_t \dots \dots, d_T$, with$d = d_1 + d_2 + \cdots + d_T$. Each partition can be thought of as representing a domain containing d_t nested dimensions. Domains, or broad dimensions, considered in multidimensional welfare analysis vary in terms of how many are included and how these are defined, but the MPI uses three: health, education and material standard of living. Previously, the terms domains and dimensions have been used interchangeably, a practice that this paper seeks to depart from. Specifically, a formal distinction between domains and dimensions is introduced to extend the use of the MPI. This enables to differentiate between domains and deprivations that occur exclusively within one domain as opposed to deprivations that occur across several domains. This is particularly important, for the MPI, which has several indicators within a single domain, notably the one capturing material standard of living, that tend to be highly correlated. In the extended application of the MPI, the multidimensional poverty status first needs to be defined by the condition $ci \geq T$, where the multidimensional cutoff k is equal to the number of domains T, and we include an additional condition which the number of deprivations counted ci, includes non-zero values for each dimension. Formally, cican be composed by dimensions as $c_i^{d1} + c_i^{d2} + \cdots + c_i^{dT}$. The second condition holds if$c_i^{di} \geq 0\ \forall t$. This definition is more restrictive than the one based only on the first condition since it excludes individuals with T deprivations but without deprivation in at least one dimension indicator of any domain. The multidimensional cutoff for this alternative will be denoted by k^* and an individual is considered to be multidimensionally poor when$c_i \geq k^*$.

Since H is sensitive to the number of dimensions in which a poor person is deprived, as a poverty measure on its own it violates a principle that Alkire and Foster (2007) refer to as 'dimensional monotonicity', which states that if a poor person becomes newly deprived in an additional dimension, then overall poverty should increase. Therefore, H is adjusted by a measure of the number of deprivations that a poor person suffers, reflecting the intensity of A of poverty:

$$A = \frac{1}{qd} \sum_{i=1}^{n} w_i \, c_i^* \qquad (4)$$

Where c_i^* indicates that we are only counting deprivations for individuals for whom$c_i \geq k$. It is possible to assign different weights,ω^d to the dimensional deprivations in order to reflect differences in the importance attached to each of the multiple dimensions of poverty. In that case, c_i is the weighted number of deprivations in which the individual is deprived The MPI is automatically adjusted to reflect the weighting scheme.

$$c_i = \sum_{j=}^{d} P_{zj}\,(y_i\,, \omega_j^d\,) \qquad (5)$$

Where;

$$P_{zj}\big(y_i\,, \omega_j^d\big) = \begin{cases} \omega_j^d & if\, y_{ij} < z_j \\ 0 & \text{and 0 otherwise} \end{cases}$$

The MPI can be decomposed by sub-group:

$$MPI = \sum_{l=1}^{L} \varphi^l\, MPI^l \qquad (6)$$

Where φ^l is the population share of sub-group l (i.e.n^l/n) .This type of decomposition is useful for developing poverty profiles as it allows for identifying which subgroups have higher levels of poverty. In turn this is useful for purposes of targeting anti-poverty interventions. Equation (1) can also be used to evaluate the contribution,π_l of each sub-group to overall poverty:

$$\pi_l = \frac{\varphi^l MPI^l}{MPI} \qquad (7)$$

A useful complementary analysis is to decompose MPI by dimension and assess the contribution to overall poverty levels by each dimension:

$$\pi_j = \frac{\frac{1}{nd}\sum_{i-1}^{n} c_{i,j}^*}{MPI} \qquad (8)$$

Where $c_{i,j}^*$ is the same as $P_z(y_i, \omega_j^d)$ when $c_i \geq k$ and equals zero otherwise. While the MPI is sensitive to the number of deprivations of poverty, it is not sensitive to the depth of poverty. If a person becomes more deprived in one dimension the measure will not change. The depth and severity of poverty can be assessed using other members of the Alkire and Foster (2007) class of poverty measures or other such as those suggested by Bourguignon and Chakravarty(2003) and Tsui(2002). For purposes of this paper the incidence of poverty is focused on as represented by the MPI.

For purposes of the MPI, three domains or broad dimensions will be considered, namely, health, education and standard of living. Two dimensions or indicators will be retained in the health domain and the education domain, while six dimension indicators will be considered for the standard-of-living domain. Some of the indicators will be drawn from the individual sections of the surveys and other household sections. The MPI thus applies a unitary definition of the household whereby all members of a given household are afforded the same poverty status and intra-household inequality is not considered. The unitary household definition poses certain challenges when it comes to comparing two distributions of multidimensional poverty when household sizes are different.

The weights are set such that each broad dimension is weighted equally at 1/3 and, using nested weights, each indicator dimension also is weighted within each broad domain. The issue of which weights to apply is of considerable importance in compiling dimensional indices; Decanq(2010). For purposes of the MPI the Alkire and Santos (2010) of using equal weights across domains to ensure a methodology that enables international comparability.

4.6 Ranking Test: Mann-Whitney U Test

The Mann-Whitney U test is a non-parametric test that can be used in place of an unpaired t-test. It is used to test the null hypothesis that two samples come from the same population or alternatively, whether observations in one sample tend to be larger than observations in another. Although it is a non-parametric test it does not assume that the two distributions are similar in shape Shier (2004).

4.6.1 Carrying out the Mann-Whitney U Test

Suppose there is a sample of n_x observations $x_1, x_2, \dots\dots, x_n$ in one group (from one population) and a sample of n_y observations $y_1, y_2, \dots\dots, y_n$ in another group (from another population). The Mann-Whitney test is based on every observation y_j in another sample. The total number of pair wise comparisons that can be made is$n_x n_y$.

If the samples have the same median then each x_i has an equal chance (probability 0.5) of being greater or smaller than eachy_j. Therefore, the procedure is as follows:

1. Arrange all observations in order of magnitude.
2. Under each observation, write down X or Y (or some other relevant symbol) to indicate which sample they are from.
3. Under each x write down the number of ys which are left of it smaller than it); this indicates$x_i > y_j$. Under each y write down the number of xs which are to the left of it (smaller than it); this indicates$y_j > x_i$.
4. Add up the total number of times$x_i > y_j$, denote byU_x. Add up the total number of times$y_j > x_i$, denote byU_y. Check that$U_x + U_y = n_x n_y$.
5. Calculate$U = \min(U_x, U_y)$.
6. Use statistical tables for the Mann-Whitney U test to find the probability of observing a value of U or lower. If the test is one-sided, this is the p-value; if the test is a two-sided test, double this probability to obtain the p-value.

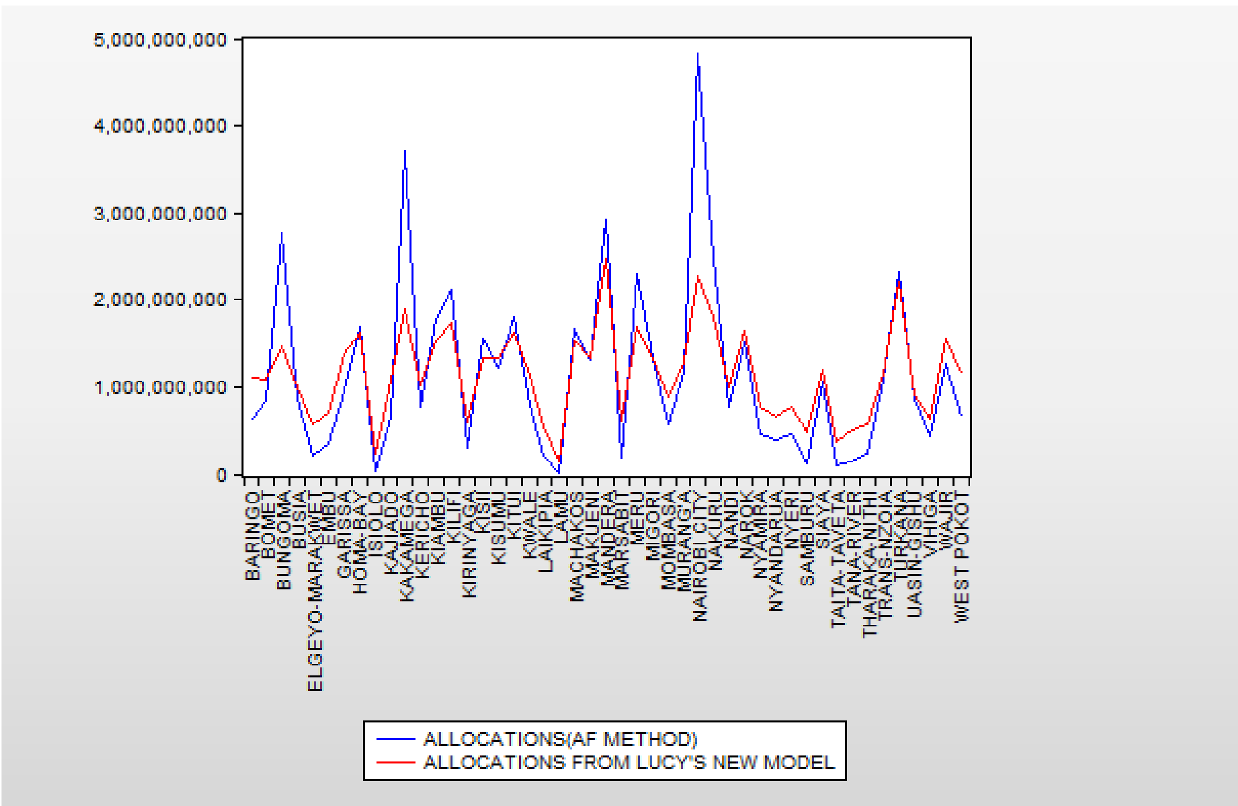
NOTE: If the number of observations is such that $n_x n_y$ is large enough (>20), a normal approximation can be used with$\mu_U = \frac{n_x n_y}{2}, \sigma_U = \sqrt{\frac{n_x n_y (N+1)}{12}}, where\ N = n_x + n_y$.

5. ANALYSIS AND DISCUSSION

5.1. Comparing the allocations

The money allocated towards counties by the Kenyan National government every fiscal year is roughly Kshs. 300,000,000,000 and 18% of this amount (Kshs. 54,000,000,000) is channeledtowards poverty alleviation and reduction in each of the 47 counties.

Figure 5.2: A line graph depicting Poverty Allocations by Alkire-Foster's method vs Lucy's Model



According to Lucy's model that uses the HDI to calculate the poverty index, the largest allocation towards poverty alleviation would go towards Turkana County. The largest allocation of money using the AF method would go towards Nairobi County.

5.1.1. Principal Component Analysis of the Allocations

Principal Components Analysis
Date: 10/25/16 Time: 07:00
Sample: 1 47
Included observations: 47
Computed using: Ordinary correlations
Extracting 2 of 2 possible components

Eigenvalues: (Sum = 2, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	1.894789	1.789577	0.9474	1.894789	0.9474
2	0.105211	---	0.0526	2.000000	1.0000

Eigenvectors (loadings):

Variable	PC 1	PC 2
ALLOCATIONS_AF...	0.707107	-0.707107
ALLOCATIONS_FR...	0.707107	0.707107

Ordinary correlations:

	ALLOCATIONS_AF_METHOD_	ALLOCATIO...
ALLOCATIONS_AF...	1.000000	
ALLOCATIONS_FR...	0.894789	1.000000

The correlation between the allocations derived from the AF method and the allocations derived from the HDI method is 0.894789. The variance between both sets of allocations is 0.707107 whereas the covariance is (-0.707107, 0.707107).

5.1.2. Test of equality of means between the allocations

Test for Equality of Means Between Series
Date: 10/25/16 Time: 07:01
Sample: 1 47
Included observations: 47

Method	df	Value	Probability
t-test	92	2.01E-15	1.0000
Satterthwaite-Welch t-test*	70.06504	1.61E-15	1.0000
Anova F-test	(1, 92)	4.05E-30	1.0000
Welch F-test*	(1, 70.065)	2.59E-30	1.0000

*Test allows for unequal cell variances

Analysis of Variance

Source of Variation	df	Sum of Sq.	Mean Sq.
Between	1	2.67E-12	2.67E-12
Within	92	6.07E+19	6.60E+17
Total	93	6.07E+19	6.53E+17

Category Statistics

Variable	Count	Mean	Std. Dev.	Std. Err. of Mean
ALLOCATI...	47	1.15E+09	1.01E+09	1.48E+08
ALLOCATI...	47	1.15E+09	5.39E+08	78664308
All	94	1.15E+09	8.08E+08	83359170

The mean of the allocations derived from the AF method and the allocations derived from the HDI is the same at 1.15. The standard deviations vary significantly as well as the standard error of the means. This may be due to the difference in the poverty indices according to both methods. For example, according to the AF method the county with the largest poverty index is Nairobi and the county with the largest poverty index according to the HDI is Turkana. Therefore the difference in allocations is significant and this can be explained by the difference in the standard deviation and the standard error of the mean.

5.1.3. Test of equality of variances between the allocations

Test for Equality of Variances Between Series
Date: 10/25/16 Time: 07:01
Sample: 1 47
Included observations: 47

Method	df	Value	Probability
F-test	(46, 46)	3.540529	0.0000
Siegel-Tukey		2.714722	0.0066
Bartlett	1	17.08802	0.0000
Levene	(1, 92)	9.653196	0.0025
Brown-Forsythe	(1, 92)	6.217628	0.0144

Category Statistics

Variable	Count	Std. Dev.	Mean Abs. Mean Diff.	Mean Abs. Median Diff.	Mean Tukey-Siegel Rank
ALLOCATI...	47	1.01E+09	7.63E+08	7.31E+08	39.85106
ALLOCATI...	47	5.39E+08	4.32E+08	4.32E+08	55.14894
All	94	8.08E+08	5.98E+08	5.81E+08	47.50000

Bartlett weighted standard deviation: 8.13e+08

The standard deviations of the HDI and the AF method varies significantly. The Bartlett weighted standard deviation is 8.13. This means that the variations are significant for the allocations that are generated for each county by using both the AF method and the HDI.

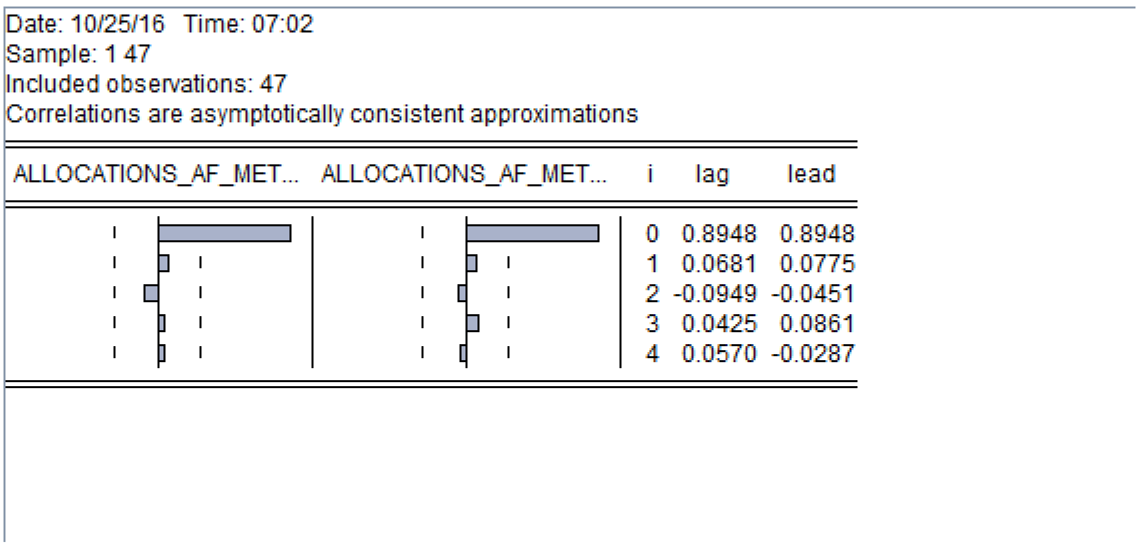
5.1.4. Correlogram of Allocations

Date: 10/25/16 Time: 07:01
Sample: 1 47
Included observations: 47

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.067	0.067	0.2255	0.635
		2	-0.077	-0.082	0.5327	0.766
		3	0.074	0.086	0.8204	0.845
		4	-0.002	-0.021	0.8206	0.936

The data in the analysis was lagged at 4. Autocorrelation is the highest at lag 3 with autocorrelation function (ACF) of 0.074, which alternates and becomes negative in the fourth lag. Partial autocorrelation is evident at lag 4 only with partial correlation function (PACF) of 0.8206. The probability that AF method and HDI are autocorrelated varies between 0.635 and 0.936, which is high. This is attributed to the fact that the same data was applied to both methods and the indicators used in both methods are the same.

5.1.5. Cross-correlogram of Allocations



Date: 10/25/16 Time: 07:02
Sample: 1 47
Included observations: 47
Correlations are asymptotically consistent approximations

ALLOCATIONS_AF_MET...	ALLOCATIONS_AF_MET...	i	lag	lead
		0	0.8948	0.8948
		1	0.0681	0.0775
		2	-0.0949	-0.0451
		3	0.0425	0.0861
		4	0.0570	-0.0287

The highest significant correlation is at lag zero which is 0.8948.

5.2. Ranking Test Results

To check if there is a difference in ranking between the Alkire-Foster method and the Human Development Index, the Mann-Whitney U test is applied. The null hypothesis states that there is no difference between the rankings of counties using both methods. The alternative hypothesis states that there is a difference in the rankings of counties using both methods. The results from the test show that$U_{test} = 949$. The test carried out is a two-tailed test has a 95% level of significance. Therefore, the$Z - score = 1.96$. The decision is to reject the null if

$U_{test} < U_{critical}$. In this case,$949 > 1.96$ therefore, in the decision is to fail to reject the null hypothesis. The test validates the null hypothesis which means that there is no difference between the rankings of counties using both methods.

5.3. Discussion of Results

From the results above, the county with the largest poverty index using the Alkire-Foster method is Nairobi County while the county with the largest poverty index using the Human Development Index is Mandera County. This can is because the Alkire-Foster method is a method that uses a dual-cutoff approach; it is biased towards the size of the population. This means that if the county population is large, then the poverty headcount and the poverty index tend to be large since there are a large number of households in a county with a large population.

The Human Development Index is a method based on weights assigned to the different indicators that characterize poverty. This means that if a county has a large number of people that lack in a certain aspect for example many people who are completely illiterate, then when multiplied by a certain weight then the county will be considered poor in that aspect.

The Human Development Index (HDI) fails to specify the number of people who are completely deprived in a particular aspect. The HDI 'generalizes' poverty and fails to identify the truly poor people in a particular aspect. This can be shown by the deviations in allocations in each county. The money allocated using poverty index derived from the Alkire-Foster method is less in most of the counties than the money allocated using the poverty index derived from the Human Development Index. This is a clear indication that the Alkire-Foster method is more objective since it targets the truly poor people in each county. It is worth noting that the total amount of money allocated to poverty alleviation is the same in both methods.

The results prove that the Alkire-Foster methodology identifies who is poor and ignores the data of the non-poor. The Human Development Index is a welfare based index based on marginal distributions that combine the aggregate dimensional achievements of all people into one overall score Alkire (2011).

The correlation of the allocations derived from the AF method and the allocations derived from the HDI method is 0.894789. This is a strong positive correlation between the allocations from both methods. The correlation of the AF method indices and HDI method indices is 0.471475 which is moderate. This means that the two indices have a moderate correlation, explaining the difference in the poorest counties from both methods.

6. CONCLUSION

The two main objectives of this study were to reconstruct Kenya's poverty index using the Alkire-Foster Method andcompare the difference between the poverty allocations arrived at by AF method and Lucy's model allocations. Based on the results of the study, we aimed to offer suggestions for improving the poverty index used in Lucy's model.

We constructed the Kenyan poverty index using the AF method using data from the Commission for Revenue Allocation. The cutoffs described in the methodology were used and from this we were able to come up with the indices shown in Appendix A.

The correlation between the allocations arrived at using both the AF method and the HDI in Lucy's model is 0.894789 which is quite high, indicating a strong positive correlation between the allocations from both methods. When we tested the significance of the difference in ranking the results from the test show that $U_{test} = 949$ with aZ score of1.96. The test validates the null hypothesis which means that there is no difference between the rankings of counties using both methods.

In conclusion, we find that though both methods indicate different counties as the neediest (Nairobi-AF method, Mandera-HDI; Lucy's model), there is no statistically significant difference between both the allocations arrived at by both models. We cannot offer suggestions for improvement of Lucy's model given the results of the study.

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APPENDICES

APPENDIX A:Poverty Indices by Alkire-Foster Method

COUNTY	PI (AF METHOD)
BARINGO	0.011795040
BOMET	0.015756143
BUNGOMA	0.051083904
BUSIA	0.015941833
ELGEYO-MARAKWET	0.004028614
EMBU	0.006594597
GARISSA	0.017788094
HOMA-BAY	0.031143334
ISIOLO	0.000664133
KAJIADO	0.012215570
KAKAMEGA	0.068857921
KERICHO	0.014117713
KIAMBU	0.033004206
KILIFI	0.039435142
KIRINYAGA	0.005577941
KISII	0.029046053
KISUMU	0.022540348
KITUI	0.033384776
KWALE	0.014870893
LAIKIPIA	0.003967731
LAMU	0.000285003
MACHAKOS	0.031021464
MAKUENI	0.024198070
MANDERA	0.054155499
MARSABIT	0.003725859
MERU	0.042395773
MIGORI	0.024611453
MOMBASA	0.010572368
MURANG'A	0.021764831
NAIROBI CITY	0.089287034
NAKURU	0.045913698
NANDI	0.014381295
NAROK	0.028158550
NYAMIRA	0.008637370
NYANDARUA	0.007345022
NYERI	0.008595484
SAMBURU	0.002266359

SIAYA	0.019689301
TAITA-TAVETA	0.001973413
TANA-RIVER	0.002521441
THARAKA-NITHI	0.004224201
TRANS-NZOIA	0.020162449
TURKANA	0.043079641
UASIN-GISHU	0.015785752
VIHIGA	0.007934874
WAJIR	0.023367883
WEST POKOT	0.012131929

APPENDIX B: Poverty Indices by Lucy's Model

COUNTY	PI (LNF)
BARINGO	0.0207376224
BOMET	0.0200914965
BUNGOMA	0.0270298910
BUSIA	0.0184203234
ELGEYO-MARAKWET	0.0103980195
EMBU	0.0130963157
GARISSA	0.0257039025
HOMA-BAY	0.0302572738
ISIOLO	0.0044140450
KAJIADO	0.0202085850
KAKAMEGA	0.0349231529
KERICHO	0.0189801493
KIAMBU	0.0282422752
KILIFI	0.0320465496
KIRINYAGA	0.0110786765
KISII	0.0245369095
KISUMU	0.0247058716
KITUI	0.0301530962
KWALE	0.0210968327
LAIKIPIA	0.0099663700
LAMU	0.0025889848
MACHAKOS	0.0284671227
MAKUENI	0.0248016747
MANDERA	0.0458866294
MARSABIT	0.0112521568
MERU	0.0315341078
MIGORI	0.0247011611

MOMBASA	0.0164538961
MURANG'A	0.0238309924
NAIROBI CITY	0.0421147467
NAKURU	0.0335683452
NANDI	0.0183739978
NAROK	0.0303429736
NYAMIRA	0.0143705917
NYANDARUA	0.0121814639
NYERI	0.0142100272
SAMBURU	0.0089179940
SIAYA	0.0221005326
TAITA-TAVETA	0.0069101391
TANA-RIVER	0.0094341149
THARAKA-NITHI	0.0106739335
TRANS-NZOIA	0.0213039003
TURKANA	0.0409373504
UASIN-GISHU	0.0168914782
VIHIGA	0.0118903015
WAJIR	0.0287610083
WEST POKOT	0.0214130171

APPENDIX C: Indices from The Richest To The Poorest

COUNTY	PI (AF METHOD)
LAMU	0.000285003
ISIOLO	0.000664133
TAITA-TAVETA	0.001973413
SAMBURU	0.002266359
TANA-RIVER	0.002521441
MARSABIT	0.003725859
LAIKIPIA	0.003967731
ELGEYO-MARAKWET	0.004028614
THARAKA-NITHI	0.004224201
KIRINYAGA	0.005577941
EMBU	0.006594597
NYANDARUA	0.007345022
VIHIGA	0.007934874
NYERI	0.008595484
NYAMIRA	0.008637370

COUNTY	PI (LNF)
LAMU	0.0025889848
ISIOLO	0.0044140450
TAITA-TAVETA	0.0069101391
SAMBURU	0.0089179940
TANA-RIVER	0.0094341149
LAIKIPIA	0.0099663700
ELGEYO-MARAKWET	0.0103980195
THARAKA-NITHI	0.0106739335
KIRINYAGA	0.0110786765
MARSABIT	0.0112521568
VIHIGA	0.0118903015
NYANDARUA	0.0121814639
EMBU	0.0130963157
NYERI	0.0142100272
NYAMIRA	0.0143705917

MOMBASA	0.010572368
BARINGO	0.011795040
WEST POKOT	0.012131929
KAJIADO	0.012215570
KERICHO	0.014117713
NANDI	0.014381295
KWALE	0.014870893
BOMET	0.015756143
UASIN-GISHU	0.015785752
BUSIA	0.015941833
GARISSA	0.017788094
SIAYA	0.019689301
TRANS-NZOIA	0.020162449
MURANG'A	0.021764831
KISUMU	0.022540348
WAJIR	0.023367883
MAKUENI	0.024198070
MIGORI	0.024611453
NAROK	0.028158550
KISII	0.029046053
MACHAKOS	0.031021464
HOMA-BAY	0.031143334
KIAMBU	0.033004206
KITUI	0.033384776
KILIFI	0.039435142
MERU	0.042395773
TURKANA	0.043079641
NAKURU	0.045913698
BUNGOMA	0.051083904
MANDERA	0.054155499
KAKAMEGA	0.068857921
NAIROBI CITY	0.089287034

MOMBASA	0.0164538961
UASIN-GISHU	0.0168914782
NANDI	0.0183739978
BUSIA	0.0184203234
KERICHO	0.0189801493
BOMET	0.0200914965
KAJIADO	0.0202085850
BARINGO	0.0207376224
KWALE	0.0210968327
TRANS-NZOIA	0.0213039003
WEST POKOT	0.0214130171
SIAYA	0.0221005326
MURANG'A	0.0238309924
KISII	0.0245369095
MIGORI	0.0247011611
KISUMU	0.0247058716
MAKUENI	0.0248016747
GARISSA	0.0257039025
BUNGOMA	0.0270298910
KIAMBU	0.0282422752
MACHAKOS	0.0284671227
WAJIR	0.0287610083
KITUI	0.0301530962
HOMA-BAY	0.0302572738
NAROK	0.0303429736
MERU	0.0315341078
KILIFI	0.0320465496
NAKURU	0.0335683452
KAKAMEGA	0.0349231529
TURKANA	0.0409373504
NAIROBI CITY	0.0421147467
MANDERA	0.0458866294

APPENDIX D: Allocations to Counties By Both Methods

	COUNTY	POVERTY INDEX	ALLOCATIONS(AF METHOD)	ALLOCATIONS FROM LUCY'S NEW MODEL	DEVIATION
1	BARINGO	0.01179504	636,932,182.72	1,119,831,607.52	(482,899,424.80)
2	BOMET	0.015756143	850,831,715.87	1,084,940,812.43	(234,109,096.55)
3	BUNGOMA	0.051083904	2,758,530,833.71	1,459,614,111.40	1,298,916,722.30
4	BUSIA	0.015941833	860,859,001.70	994,697,466.28	(133,838,464.58)
5	ELGEYO-MARAKWET	0.004028614	217,545,164.06	561,493,052.48	(343,947,888.43)
6	EMBU	0.006594597	356,108,250.52	707,201,047.84	(351,092,797.32)
7	GARISSA	0.017788094	960,557,079.68	1,388,010,736.83	(427,453,657.16)
8	HOMA-BAY	0.031143334	1,681,740,050.74	1,633,892,786.67	47,847,264.07
9	ISIOLO	0.000664133	35,863,206.39	238,358,427.39	(202,495,221.00)
10	KAJIADO	0.01221557	659,640,800.12	1,091,263,591.32	(431,622,791.19)
11	KAKAMEGA	0.068857921	3,718,327,722.44	1,885,850,254.80	1,832,477,467.64
12	KERICHO	0.014117713	762,356,476.55	1,024,928,060.74	(262,571,584.18)
13	KIAMBU	0.033004206	1,782,227,127.71	1,525,082,860.68	257,144,267.03
14	KILIFI	0.039435142	2,129,497,646.23	1,730,513,676.47	398,983,969.77
15	KIRINYAGA	0.005577941	301,208,838.17	598,248,528.56	(297,039,690.39)

16	KISII	0.029046053	1,568,486,837.65	1,324,993,114.47	243,493,723.18
17	KISUMU	0.022540348	1,217,178,788.01	1,334,117,065.74	(116,938,277.73)
18	KITUI	0.033384776	1,802,777,900.73	1,628,267,192.61	174,510,708.12
19	KWALE	0.014870893	803,028,201.63	1,139,228,967.68	(336,200,766.05)
20	LAIKIPIA	0.003967731	214,257,462.31	538,183,978.22	(323,926,515.91)
21	LAMU	0.000285003	15,390,149.17	139,805,181.66	(124,415,032.49)
22	MACHAKOS	0.031021464	1,675,159,038.89	1,537,224,623.51	137,934,415.38
23	MAKUENI	0.02419807	1,306,695,805.20	1,339,290,433.49	(32,594,628.28)
24	MANDERA	0.054155499	2,924,396,930.41	2,477,877,985.35	446,518,945.06
25	MARSABIT	0.003725859	201,196,368.65	607,616,466.56	(406,420,097.91)
26	MERU	0.042395773	2,289,371,741.40	1,702,841,818.83	586,529,922.57
27	MIGORI	0.024611453	1,329,018,451.58	1,333,862,700.97	(4,844,249.38)
28	MOMBASA	0.010572368	570,907,849.10	888,510,391.94	(317,602,542.84)
29	MURANG'A	0.021764831	1,175,300,871.93	1,286,873,588.63	(111,572,716.70)
30	NAIROBI CITY	0.089287034	4,821,499,856.16	2,274,196,322.12	2,547,303,534.04
31	NAKURU	0.045913698	2,479,339,678.58	1,812,690,641.01	666,649,037.57
32	NANDI	0.014381295	776,589,906.49	992,195,880.07	(215,605,973.58)
33	NAROK	0.02815855	1,520,561,689.47	1,638,520,576.03	(117,958,886.56)

34	NYAMIRA	0.00863737	466,417,984.61	776,011,952.59	(309,593,967.98)
35	NYANDARUA	0.007345022	396,631,174.75	657,799,053.05	(261,167,878.31)
36	NYERI	0.008595484	464,156,156.69	767,341,470.24	(303,185,313.55)
37	SAMBURU	0.002266359	122,383,383.79	481,571,674.42	(359,188,290.63)
38	SIAYA	0.019689301	1,063,222,258.07	1,193,428,762.73	(130,206,504.66)
39	TAITA-TAVETA	0.001973413	106,564,299.02	373,147,509.42	(266,583,210.40)
40	TANA-RIVER	0.002521441	136,157,803.15	509,442,206.57	(373,284,403.42)
41	THARAKA-NITHI	0.004224201	228,106,828.05	576,392,409.40	(348,285,581.35)
42	TRANS-NZOIA	0.020162449	1,088,772,252.98	1,150,410,616.74	(61,638,363.75)
43	TURKANA	0.043079641	2,326,300,597.67	2,210,616,920.90	115,683,676.76
44	UASIN-GISHU	0.015785752	852,430,584.79	912,139,825.29	(59,709,240.50)
45	VIHIGA	0.007934874	428,483,186.37	642,076,280.56	(213,593,094.19)
46	WAJIR	0.023367883	1,261,865,695.46	1,553,094,445.73	(291,228,750.28)
47	WEST POKOT	0.012131929	655,124,170.63	1,156,302,922.06	(501,178,751.44)
			54,000,000,000.00	54,000,000,000.00	

APPENDIX E:Results of Mann-Whitney Ranking Test

COUNTY	PI	Rank
BARINGO	0.000285003	1
BOMET	0.000664133	2
BUNGOMA	0.001973413	3
BUSIA	0.002266359	4
ELGEYO-MARAKWET	0.002521441	5
EMBU	0.002588985	6
GARISSA	0.003725859	7
HOMA-BAY	0.003967731	8
ISIOLO	0.004028614	9
KAJIADO	0.004224201	10
KAKAMEGA	0.004414045	11
KERICHO	0.005577941	12
KIAMBU	0.006594597	13
KILIFI	0.006910139	14
KIRINYAGA	0.007345022	15
KISII	0.007934874	16
KISUMU	0.008595484	17
KITUI	0.00863737	18
KWALE	0.008917994	19
LAIKIPIA	0.009434115	20
LAMU	0.009966370	21
MACHAKOS	0.010398019	22
MAKUENI	0.010572368	23
MANDERA	0.010673934	24
MARSABIT	0.011078676	25
MERU	0.011252157	26
MIGORI	0.01179504	27
MOMBASA	0.011890301	28
MURANG'A	0.012131929	29
NAIROBI CITY	0.012181464	30
NAKURU	0.01221557	31
NANDI	0.013096316	32
NAROK	0.014117713	33
NYAMIRA	0.014210027	34
NYANDARUA	0.014370592	35
NYERI	0.014381295	36
SAMBURU	0.014870893	37
SIAYA	0.015756143	38

TAITA-TAVETA	0.015785752	39
TANA-RIVER	0.015941833	40
THARAKA-NITHI	0.016453896	41
TRANS-NZOIA	0.016891478	42
TURKANA	0.017788094	43
UASIN-GISHU	0.018373998	44
VIHIGA	0.018420323	45
WAJIR	0.018980149	46
WEST POKOT	0.019689301	47
	0.020091497	48
	0.020162449	49
	0.020208585	50
	0.020737622	51
	0.021096833	52
	0.021303900	53
	0.021413017	54
	0.021764831	55
	0.022100533	56
	0.022540348	57
	0.023367883	58
	0.023830992	59
	0.02419807	60
	0.024536910	61
	0.024611453	62
	0.024701161	63
	0.024705872	64
	0.024801675	65
	0.025703903	66
	0.027029891	67
	0.02815855	68
	0.028242275	69
	0.028467123	70
	0.028761008	71
	0.029046053	72
	0.030153096	73
	0.030257274	74
	0.030342974	75
	0.031021464	76
	0.031143334	77
	0.031534108	78
	0.032046550	79
	0.033004206	80

0.033384776	81
0.033568345	82
0.034923153	83
0.039435142	84
0.040937350	85
0.042114747	86
0.042395773	87
0.043079641	88
0.045886629	89
0.045913698	90
0.051083904	91
0.054155499	92
0.068857921	93
0.089287034	94