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Regional Perspectives to the Multidimensional Poverty Index

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Regional Perspectives to the Multidimensional Poverty Index

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Abstract

The Multidimensional Poverty Index (MPI) is not the first attempt to examine poverty along multiple definitions. Vis-a-vis the existing work and other presently available measures, this method has greater advantage in terms of international comparability and reporting. However, the methodology of the Multidimensional Poverty Index (MPI) has been under strong scrutiny since its inception. One of the reasons for these critiques lies in the variation in the MPI country ranks and scores based on different indicators and a different weighing scheme. This paper analyzes the consequences of a different weighting scheme within the MPI, using a more data driven approach rather than a normative or equal weighting scheme. It attempts to assess this alternative weighting via its impact on the scores and relative ranking of various countries. Moreover, it attempts to resolve the differences in the definition of poverty that might emerge upon changing indicators, and thereby evaluate how this affects the construction of the MPI. An analysis covering 22 countries, using the Demographic and Health Survey data, is carried out to quantitatively evaluate the weights assigned to each of the indicators, using the technique of Principal Component Analysis (PCA) and Multiple Correspondence Analysis (MCA). A more detailed country-level analysis is carried out for India, wherein additional indicators based on the data are made available and therefore an alternative multidimensional construct is possible. The analysis shows that equal weighting of the three dimensions cannot be statistically justified and that in trying to capture a more multidimensional view of poverty and well-being, there might actually not be so much multidimensionality in the MPI.

Key words: Multidimensional poverty, weights, PCA, MCA, PLS

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Introduction

In 2010, Sabina Alkire and Marie Emma Santos first published a Human Development Research Paper which aimed at identifying a new index to measure acute multidimensional poverty across 104 developing nations (Alkire & Santos, 2014). It became popular as the AF methodology of measuring multidimensional poverty thereafter (names behind the researchers who developed the methodology), especially since the United Nations Development Programme took up the propagation of this method (Alkire & Foster, 2011).

The proposed Multidimensional Poverty Index (MPI) was not the first attempt to capture the multidimensional nature of wellbeing and deprivations. The Human Development Index (HDI) was already a step towards the creation of a composite index encompassing more than a single dimension of well-being, although it has also been criticized on account of its choice in indicators (Ravallion, 1997). Some of the early composite indicators that focused on human resource development were already introduced in the 1960's, however a larger focus came upon a more non-monetary/composite indicators of development later (Santos & Santos, 2014). Besides other examples like the IHDI, Gender Empowerment Measure (GEM), the Gender related Development Index (GDI) and the Human Poverty Index (which was supplanted by the MPI) to name a few, several developing countries have developed their own measures to capture poverty and other deprivations as a multidimensional concept (Alkire & Foster, 2011). But, nevertheless, the MPI was the first of its kind to compute multidimensional poverty for around 78% of the world's population using three types of datasets (DHS, MICS and WHS). It was able to provide a more holistic measure of the extent of deprivation that households living in poverty can experience, in comparison to the $1 a day poverty line proposed as a uni-dimensional measure of poverty. Although there are several non-income measures of poverty that are of prominence, this is the first that uses micro-level data with a household as the unit of measurement. Dotter & Klasen (2014) point out the utmost achievement of the MPI when they say that "…the main contribution of the MPI, vis-a-vis the existing work is its breadth of country-coverage and its international comparability…"

There are several strands of literature and analyses that discuss the weaknesses that are encountered when one creates a single measure to account for the multidimensional nature of poverty. This literature doesn't necessarily just focus on the weakness of this most recent attempt to understand the basic needs and capabilities that was suggested by Sen, way back in 1984 (Sen, 1984). Rather there has been a copious appraisal and a multitude of studies that deal with the challenges of using a dual cut-off method and the weighing scheme within the chosen dimensions (Ravallion, 2011; 2012a), the disregard towards the aspect of inequality within the dimensions and populations (Silber, 2011; Chakravarty & D'Ambrosio, 2006; Jayaraj & Subramanian, 2010; Rippin, 2012a; b), or the need to adjust the dimensions in line with average well-being, to reflect the weakly relative nature of well-being and income (Ravallion & Chen, 2011). When one chooses to, they can continue into a rather long discussion of the conceptual issues that a composite measure of multidimensional well-being can uncover. This however is not the aspiration of this paper.

The aim of this work is to calculate the MPI scores of countries but not as an end in itself. The paper seeks to address two concerns regarding the formulation of MPI. The first being: Can the use of seemingly arbitrary equal weighting assigned to the three dimensions be statistically justified? Should child mortality take a weight of 1/6 and the asset indicator assigned a weight of 1/18? This is a specific concern, especially in view of this measure's attempt to quantify multidimensional poverty while maintaining global comparability. Indeed, can all countries have uniform standardized weights for the indicators when the basic socioeconomic conditions underlying them are very different? If no, how far does weighing change with regions? Clark & McGillivray (2007), for example, suggest that amongst all the critiques concerning composite indices, it is better to allow the components and weights to vary across regions and countries, to take into account local and regional preferences. An example of this rather uncommon consensual approach to measuring poverty was the Breadline Britain survey, carried out in Britain in 1983 and 1990. This method sought to measure poverty in the UK by investigating what the public perceives as the minimum needs to be considered non-poor or alternatively, well off, and then identifying those who could not afford these necessities (Gordon & Pantazis, 1997).

Ravallion (2012b) and Decancq & Lugo (2013) examine indices of wellbeing and poverty critically in terms of the weights that are derived for each dimension. They raise the issue regarding the importance of tradeoffs between dimensions in such indices (wherein the MPI assumes that improvements in one dimension make up for the failings in another like other equal weighted indices) and conclude that the explicit tradeoffs between dimensions (and more so within dimensions) are important in terms of measuring what a poverty/ well being index claims to measure.

There are several methods that have already been discussed in the literature with respect to the creation of a multidimensional measure of well being and will be discussed in further detail. The main idea for this research follows the paper by Nguefack-Tsague, Klasen, & Zucchini (2011), wherein they perform a similar exercise for the Human Development Index and find that statistically, all three dimensions receive the same weight and therefore corroborate the story behind the equal weighing of the HDI.

The second part of the analysis intends to answer the question of how changing indicators affects the construction and weighting within the MPI? Alkire (2002) and later Ravallion (2012a) provide a veritable list of indicators that can be chosen to represent development or poverty as proposed by the World Bank and several other works that were based on empirical, economic or philosophical foundations. The Millennium Development Goals (MDGs) for instance are defined as a set of goals to achieve in terms of development targets. The Multidimensional Poverty Index is the first measure that aims to quantify acute poverty while simultaneously adhering to the minimum internationally comparable standards in terms of the millennium development goals (Alkire & Santos, 2014). Nonetheless, the current set of indicators included within the MPI and the decision behind their choice has also generated a lot of discussion. A large explanation for the selection of these indicators, apart from them being in close connection to the MDGs and their goals, is the unavailability of data on indicators that might be representative of well being in the 106 countries that are included in the initial analysis. Even within the dimensions, the choice of indicators was dictated to some extent by the lack of reliable data on the same for the mentioned countries. Several countries within the calculation of the MPI therefore only have 9 indicators since there is no reliable information available for the remaining indicator within the chosen dataset.

Although the MPI has evolved as a comparable method for poverty measurement for a large sample of countries, it is in part derived from indicators which may not be most suited for a particular region or country, but rather has been selected on the basis on data availability. This has meant that most policy applications incorporating a multiplicatively defined measure of poverty either change these indicators, insofar as even the dimensions, when they try to identify or measure multidimensional poverty in their specific contexts (Dhongde & Haveman, (2015) for USA; Santos, Villatoro, Mancero, & Gerstenfeld, (2015) for Latin American countries; Ura, Alkire, & Zangmo, (2012) for Bhutan; Rippin (2012b) for Germany; Coneval (2009) for Mexico etc.). The question that this analysis tries to address is whether these variables are enough and if not, are there other indicators that are better or equally good proxies for poverty and deprivation measurement? This aspect of the study specifically looks at the case of India to determine how the inclusion or exclusion of particular indicators will affect the construction and results of the MPI. Given the difference across regions, the author believes that a country, moreover even a region specific study might provide different and more applicable results.

In an attempt to answer the first question, a detailed analysis of 22 countries across four different regions is undertaken. These countries are primarily defined under the regions of South Asia, Africa, Northern Africa-Western Asia-Europe and Latin America, which is how the Demographic and Health Survey (DHS) has categorized them as well. Two techniques are used to construct the composite indices and quantitatively evaluate the weights assigned to each of the indicator. These are the Principal Component Analysis (PCA) and Multiple Correspondence Analysis (MCA) techniques, wherein each method eventually provides similar results. Due to the greater suitability as well as the general statistical preference of the MCA in creating indices using categorical and binary data, greater confidence is place upon the results from there rather than those of PCA. However, given the similarity in the results as well as the high correlation between the two indices that has also often been found in literature, the PCA is used for all further analyses within the paper.

The second question is addressed by constructing an alternative poverty index for India alone, involving two additional variables. The fact that we also have two waves of the dataset is used to run a more regional analysis on the country to get a more dynamic picture of poverty. This paper only looks at the most recent wave however, whereas a more dynamic study is left to be tackled in another study.

This paper is organized as follows: the first section would cover a brief introduction into the Multidimensional Poverty and the literature surrounding its shortcomings. The next section would talk about the method and the intended analyses. The third section details the results from the analyses and lastly this paper discusses the various conclusions that can be drawn from this work and how it can be applicable in general to understanding the nature of multidimensional poverty across countries.

The Multidimensional Poverty Index (MPI)

The MPI is not the first of its kind in an attempt to define the multidimensional nature of poverty. There have been closely related multidimensional poverty measures proposed in the literature before (Alkire & Foster, 2011) suggested their measure, like the Physical Quality of Life Index (Morris, 1979), the Human Development Index (HDI) or the Human Poverty Index (HPI), and other such indices which have undergone constant revision to account for their shortcomings. These are also based on the (weighted) aggregation of deprivations across dimensions, some using ordinal data and some based on original macro values (assumed continuous distribution) from each country. However the focus of this paper will not be examine the differences within these measures but rather to examine the relevance of the MPI in the global context.

The MPI uses 10 indicators, broadly categorized into 3 dimensions namely, health, education and standard of living. The weights are arbitrarily assigned to each dimension, to constitute an index with equally weighted dimensions, i.e. 1/3rd each; and the indicators within these dimensions also assume equal weights amongst themselves. Figure 1 gives the basic overview of the MPI as explained above. It also describes the threshold set within each indicator to determine whether a household is to be considered deprived in the particular basic functioning or not. Most of the standard of living indicators follow the MDG guidelines, and their cutoffs are set on that basis. Each household receives the apriori weight when it fails to pass the cutoff and is therefore considered to be 'poor' in terms of that particular indicator. In the end, the weights for each household are summed up to generate the weighted deprivations matrix for each household. A household has to be deprived in at least the equivalent of 33 percent, or equivalently, have a weighted deprivation score larger than .33, in order to be considered multidimensionally poor.

Figure 1. The Multidimensional Poverty Index

Indicator	Weight	Deprived
Health	1/3	
Child Mortality	1/6	If any child has died in the family
Nutrition	1/6	If any adult or child in the family is malnourished (BMI<18.5)
Education	1/3	
Years of Schooling	1/6	If no household member has completed 5 years of schooling
Child Enrolment	1/6	If any school-aged child is out of school in years 6-14 / 7-15/ 8-16
Standard of Living	1/3	
Electricity	1/18	If there is no electricity
Drinking Water	1/18	If MDG standards are not satisfied
Sanitation	1/18	If MDG standards are not satisfied including shared toilet
Flooring	1/18	If flooring is made of earth, sand or dung
Cooking Fuel	1/18	If wood, charcoal or dung is used
Assets	1/18	If household does not own more than one of radio, television, telephone or motorbike; and does not own a car/truck

Based on the dual cut-off method, a threshold of 30 percent applies for a country to be categorized as multidimensionally poor, and all those who have a higher score are considered multidimensionally poor. The MPI for a country is calculated as the product of Headcount (H), which is the percentage of households whose weighted deprivations lie above the 33% cut-off and are therefore considered multidimensionally poor, and the Intensity of Deprivation (A), which reflects the weighted sum of deprivation in which the poor households within each country data are considered deprived. Although the AF method does not specify dimensions, indicators, weights or cut-offs, it current global formula does set the aforementioned 10 indicators within the 3 dimensions and assigns equal weight within each dimension, and to each dimension as well (Alkire & Santos, 2014).

There has also been a considerable amount of discussion as well as a stream of literature that discusses the merits of this dual cut of approach adopted within the Alkire-Foster method (AF method from now on), functioning as an intermediary between the intersection and union approaches to multidimensional poverty (Ravallion, 2011; 2012; Rippin, 2012a; b; Dotter & Klasen, 2014)

An important concern that often comes up with the formulation of the MPI, and one that is the main focus of this paper, is the robustness of the currently arbitrary weighing scheme in the AF methodology. Following along the lines of Atkinson (2003), Alkire and Foster also decided to go for an equal weighting within their dimensions and indicators. Moreover they also follow up on the HDI convention and the consequent literature that discusses the merits and demerits of the equal weighting across and between dimensions. As the authors clarify, the "...OPHI workshops and meetings have been very active in discussing these topics and the conclusions derived were in no way unanimous or even concurrent on a single method of determining weights…"

Weights for any composite index of well being can be based on the tradeoffs they imply between the dimensions of well being, and these tradeoffs can be expressed on the basis of the Marginal Rate of Substitution (MRS) between the dimensions (Ravallion, 2012b). The marginal rate of substitution between two dimensions (indicators) is defined as the amount of one dimension (indicator) an individual is willing to give up for an extra unit of the other dimension (indicator), while maintaining the same level of well being. This MRS is composed of three different components which are easily affected within a given context. For example, one component depends on the ratio of the transformation between dimensions, raised to the power of a parameter that lies between 1 and 0. In principle this means that the scarcer the achievements are, the more valuable they become. Therefore, the amount of another dimension (indicator) needed in order to compensate for access to drinking water is much more in a desert or arid nation, in comparison to a tropical, water-abundant one. Likewise, in India, where there are high levels of malnourishment, the cost of improving this aspect of well being is much steeper in comparison to Cote d'Ivoire which has much lower levels of stunting but has a similar head count in poverty. These regional differences make it much more important to adequately measure this tradeoff between dimensions, especially when one accounts for the policy manoeuvres to tackle poverty and improve well being.

Likewise a second component of the MRS entails the ratio of the dimension specific weights between two dimensions. If dimension A is assigned larger weight than the dimension B, then naturally a person would be willing to give up more than a unit of dimension B in order to compensate for a unit of dimension A. In terms of the MPI, this can be loosely translated to the within dimension comparisons, or alternatively the comparisons between the standard of living indicators versus the education and health indicators, wherein the latter have higher weights. Thereby the weights within the MPI are important to determine the trade off that can exist between the indicators as well. Given that the MPI is a weighted linear aggregation and therefore imparts perfect substitutability between the dimensions (as well within the indicators), we assume a constant tradeoff between all levels of achievements. Moreover the Marginal Rate of Substitution is now assumed as exactly the ratio of the weights between the dimensions. Thereby we assume that each of these dimensions are equally important, however there is a large difference between the indicators within the dimension. A unit increase in three standard of living indictors, or equivalently a three unit increase in any of the standard of living indicators would be required to compensate for a unit decrease in a health or education indicator. Naturally this would mean that we are imposing a compensatory logic upon this index and implying that a unit increase in any of the health indicators would compensate for a unit decrease in three standard of living indicators. These are naturally value judgements which cause concern in the realm of different development levels across countries.

Decancq und Lugo (2013) also provide an overview of some of the popular and recent studies that have proposed multidimensional indices of wellbeing and poverty. They present a brief discussion about choices while generating weights in terms of creating composite indices, especially empirical applications of indices of well being, presenting three different methodologies which are also employed within the literature: equal weights, empirically derived or data driven weights and lastly, normative weights[2]. Within the category of data driven weights there are three kinds of weighting approaches analysed: frequency based weights, statistical weights and most favourable weights. Frequency based weights are determined as a function of the distribution of the achievements in a particular dimension, i.e. the more frequently there appears to be deprivation in a particular dimension, the more weight this dimension receives. Brandolini (2007) however empirically shows the weaknesses of the frequency weights in terms of their instability (while applied on Italian data) and moreover the relativity of this measure in terms of describing well being. Most favourable weights, in the same line, are also rather subjective, wherein an individual gets to select for each individual the most favourable weighting scheme. They therefore maximize individual well being, making it hard for comparison purposes. Moreover, it is also problematic in determining the tradeoffs between dimensions, as to how a particular individual determines their own well being. This method has also been used to assess macroeconomic performance (Melyn & Moesen,

[2] For a detailed comparison of these methods, refer to (Decancq & Lugo, 2013).

1991) and more recently also in the construction of composite indices of well being[3] (Mahlberg & Obersteiner, 2001; Despotis, 2004; 2005).

The third approach in weighting dimensions within indices, the statistical weights, can be further divided within two techniques: descriptive and explanatory model. The explanatory approach functions on the assumptions that some observed indicators are dependent on a set of unobserved underlying concept and manifests itself in the observed indicators, and that single indicators can thereby be used to measure, in part, this underlying concept (Krishnakumar & Nagar, 2008). These weights or latent concepts can be easiest assigned by factor analysis while more complicated methods like structural equation models (SEM), multiple indicator and multiple choice models (MIMIC) etc. are also used. On the other hand, Principal Component Analysis is a method used for purely descriptive weights, and thereby aggregating several dimensions into a single method of poverty measurement.

Another important conceptual issue that comes up within the current measure, and is intended to be tackled in this paper for a specific dataset, is the choice of indicators that have been included within the MPI. The global MPI created in 2010 relied on several means to determine the dimensions as well as the indicators within the dimensions (Alkire & Santos, 2014)[4]. The limitations in selecting the said indicators are heavily driven by data constraints, given that most of the data sources for the MPI, which range from country to country, do not even manage to capture all of the ten variables that are within the current MPI. Therefore not only the data but also the interpretability of the available data have both been main factors determining the dimensions and the indicators contained within the MPI. Nevertheless, there have been several policy applications of a multidimensional measure of well being, wherein additional indicators have been included to ensure a measure more specific to a given context. For example in the case of Nepal, they include 3 new indicators within the three dimensions, while in the Colombian case they capture 15 indicators within 5 different dimensions of multidimensional poverty. There have been many other such applications of the MPI in the other countries with different indicators to that capture other dimensions that are considered more context specific to each country, for example in Mexico, China etc.[5]. Alkire (2002) accounts the various 'dimensions' that are published by poverty studies, cross cultural psychology, moral philosophy, quality of life indicators, participatory development, and basic needs. Based on this list of indicators, one can add several other dimensions within the current

3 For a more specific overview of these please refer to (Cherchye, et al., 2007).

[4] There are four mechanisms which form the basis of their selection: literature from participatory exercises of reference groups of population to reflect their value judgements on social capabilities, the MDGs, theory wherein several philosophical and psychological accounts of basic needs, universal values, human rights and so on are captured and lastly the data constraints.

[5] These studies can all be found on the OPHI webpage: http://www.ophi.org.uk/policy/alkire-foster-methodology/. These are all case specific applications of the MPI for Bhutan, China, Colombia, El Salvador and Mexico.

MPI in terms of measuring well being. Naturally this exercise is highly restricted by the availability of data.

While the examination of each of these concerns is not picked up within the purview of this paper, it tries to examine the literature and contribute to it by providing a more global picture of how the weights within the MPI can differ and how the picture of poverty changes when one uses more subjective definitions of poverty, i.e. when there are different indicators to examine the poverty changes. Moreover, this paper will also attempt to answer the question as to what determines these differences in weights across regions. It tries to examine this with the help of a simple conditional correlation.

Empirical Methodology

As mentioned already, there are two parts to the analyses within this study. The first part of the analysis introduces the methods to determine new weights for each country that are included in the sample. The reasoning behind this is to find statistical justification for the weights assigned to the MPI. For the second part of the analysis considers two additional indicators to determine a new multidimensional poverty index for the case of India.

When following the literature on asset index creation, there have been several proposed methods to calculate appropriate weights for the variables included (Chowdhury und Squire, 2006; Booysen, et al., 2008; Decancq und Lugo, 2013; Ravallion 2012a; Santos und Santos, 2014). When it comes to normally distributed, non-collinear data, one of the examples of establishing the "weight" of a certain variable could be a linear regression. But the problems one often runs into in developing an index of well being is that most of the variables that could be used are highly collinear, which is a problem that the OLS method is susceptible to. Therefore, it is necessary to ensure that the proposed method of constructing indices is able to remove this problem entirely, while being able to deal with the large amount of information contained within the data. Data reduction techniques that incorporate this collinearity issue, the ones that are most often used in the construction of asset indices are factor analysis (FA), principal component analysis (PCA) and Multiple Correspondence Analysis (MCA). Contingent on the data and its properties, one can decide which one of these multivariate statistical technique suits the analysis best and consequently use these in the creation of an asset index.

There have been several studies that use one of the aforementioned methods to create indices and these may not necessarily pertain to poverty analysis (Klasen, 2000; Krishnakumar und Nagar 2008; Booysen, et al. 2008). However, based on the popularity of the methods and their suitability to the data in this study, PCA and MCA are found to be most appropriate.

Principal Component Analysis

In terms of procedures to formulate an index to capture the latent or unobservable underlying concept, Principal Components (PC) is widely used in empirical applications as an aggregating technique (Krishnakumar & Nagar, 2008). Principal Component Analysis (PCA) is a statistical technique that uses the correlation between different indicators to perform an orthogonal transformation, thereby creating a set of uncorrelated latent variables. It is a method that was first applied in 1933 by Hotelling in the statistical literature but then was widely used in several branches of science, like psychology, biology, anthropology, and recently has also found wide applicability in finance and economics. In terms of the welfare literature the earliest application of PCA has been on the three dimensions of the PQLI (Ram, 1982). More recent applications are in Klasen(2000), Nagar und Basu (2002), Filmer und Pritchett (2001), Noorbakhsh (2003), McGillivray (2005).

PCA is a pure data reduction technique that seeks linear combinations of the given observed variables in such a way as to reproduce the maximum original variance. The number of latent variables or components it creates is equal to the number of original indicators that were introduced. The first principal component is the linear combination of the original variables, has the largest variance and in most cases provides an adequate summary of the original data. Therefore, the first component is usually taken for analysis while the remaining ones are generally discarded. The second principal component has the largest variance among all the linear combinations that are uncorrelated with the first principal component. The third component captures the largest variance along the linear combination that are uncorrelated with the first and the second component. The succeeding components are defined similarly, wherein each successive component explains lesser and lesser variation in comparison. By means of this transformation, PCA reduces the dimensionality of multivariate observations while ensuring a minimal loss of information.

A correlation based PCA is performed in this paper since that would standardize the variables ipso facto. However, before applying PCA, the appropriateness of this dimension reduction technique should be checked in relation with the data. A widely used test of internal consistency is Cronbach's alpha, which basically measures the ability of the proposed indictors to answer a single question (Cronbach, 1951). The maximum achievable value of the coefficient is one, and as a rule of thumb in social science research, a Cronbach's alpha of 0.7 or higher is regarded as large enough to justify the application of PCA (Nguefack-Tsague, et al., 2011). A lower value than this generally brings into question the suitability of the data in establishing a single latent determinant, which in this case is the level of deprivation in basic well-being. To circumvent this problem, the answer might lie in taking more than the first component of the Analysis.

The drawback of this method is often that there is no underlying explanatory model in this method and often the results are a black box which is hard to explain. Another important drawback, in comparison to other data driven methods like Factor analysis is that each of the components that are derived are orthogonal to each other, which might not be the case in actuality for each of the latent concepts that are sought to be measured (Krishnakumar & Nagar, 2008). Lastly, PCA is also not suitable in terms of binary data and methods like the Non-linear Principal component analysis (Coromaldi & Zoli, 2011), Polychoric PCA (Moser & Felton, 2007) or the Multiple correspondence Analysis (MCA) are more suited (Booysen, et al., 2008).

Multiple Correspondence Analysis

Multiple Correspondence Analysis (MCA) applies the same techniques as Correspondence Analysis (CA), and reduces the dimensionality of the large dataset by creating orthogonal components composing of each indicator, wherein the latter each have a given weight. It was first developed by Bencrézi in 1973, presented and then explored to a larger extent by Greenacre in 1984 and 2006. The technique as such resembles Principal Component Analysis to a large extent. The advantage in terms of this analysis however, is that MCA accounts for the variables being categorical and uses this information while constructing an indicator matrix, similar to the covariance matrix created in the PCA technique with continuous variables. Since binary data are not numerical, the association between categorical and count variables cannot be measured in terms of covariation and correlation, which makes PCA unsuitable to be applied to this type of data (Merola & Baulch, 2015). Likewise, the first column of this Indicator matrix captures the largest information between the included indicators. This is not to say that both the techniques are the same, however, both fall under the same class of Factor Analysis (FA), or more generally, geometric data analysis (GDA).

Principal Component Analysis vs. Multiple Correspondence Analysis

While Principal Component Analysis (PCA) and Factor Analysis (FA) are the most popularly employed techniques for asset index creation, there are inherent merits and demerits in these methods when comparing them to Multiple Correspondence Analysis (MCA). PCA was a technique developed largely for continuous data while MCA on the other hand imposes fewer restrictions within the data structure and therefore is considered a better technique for binary and categorical data (Booysen, et al., 2008). It disregards the distributional or linearity assumptions, on which correlation coefficients rely on, that are present in the PCA method. This is a desirable quality in the method, especially given that the deprivation matrix in this paper contains values for households which are only binary. As Booysen et al. (ibid) mentions, PCA assumes that the distances between the categorical values are the same, which the MCA doesn't. Rather MCA imposes fewer constraints on the data and thereby also reliably determines larger variation given a binary or categorical dataset. There is much debate in the asset creation literature but there is some unequivocal agreement that MCA is better than PCA, or atleast a serious alternative towards the creation for asset indices with categorical data. For example, one argument is that MCA is not simpler to implement or to understand than PCA and therefore the latter is preferred. However, in the case of deriving household welfare indices for binary or categorical indicators, it is simpler to implement MCA as it does not imply any previous computations as those implied by PCA, which reduces the categorical data into the framework of analysis. Moreover, MCA is a multivariate method that can be effectively used to analyse any mixture of binary, categorical, discrete or continuous variables (Traissac & Martin-Preveö, 2012).

In terms of computation, there are two advantages that are cited by (Ezzrari & Verme, 2013) who applied this technique for a multidimensional poverty analysis for Morocco between 2001 and 2007. MCA for starters, gives larger weight to indicators that have a fewer number of deprived individuals within any dimension. (Njong & Dschang, 2008) use both PCA and MCA, among other techniques, to study multidimensional poverty in Cameroon and find that PCA estimates unambiguously show lower levels of poverty that those that are obtained from MCA. Therefore it is a method that is more sensitive to capture deprivation in terms of wellbeing. The second computational advantage is reciprocal bi-additivity. In essence, this means that the composite indicator scores derived using MCA is the simple average of the weighted sum of each modality (binary in our case) within each indicator (Asselin, 2009). Furthermore, the weight within any given indicators is the average of the composite deprivation counts of each individual within the sample.

Data

The Demographic and Health Survey (DHS) is used for all the 22 countries[6]. The use of this particular dataset can be justified by two main reasons. First, standard guidelines have been followed in terms of the questionnaire and surveying which ensures greater homogeneity and comparability than any other nation based household survey. Second, all relevant and necessary information pertaining to health, education and standard of living is contained in the survey. This is also a reason why some of the regions in the analyses have a large number of countries while some have much fewer. Even the OPHI, while computing their global MPI, uses different datasets for several countries, especially for Latin America. Africa on the other hand does not have a more

[6] The reasons for the choices of countries in this case are to ensure that there is maximum comparability within the countries. The OPHI used the Demographic and Health Survey (DHS) data for several countries, the World Health Survey (WHS) data for other countries and the Multiple Indicator Cluster Survey (MICS) for particular countries. Besides these three main survey data, for some countries in Latin America, they also use individual surveys which have all the information that is contained to form the MPI. Therefore, although the OPHI used different sources for the data collection, the countries that are selected for this study are only those which have the Demographic and Health Survey data available.

standard and comparable survey as the DHS. Hence, relying only on this survey, there are many more African countries than South Asian, Latin American or from the EU-Asian region.

However, using on the DHS survey has its own shortcomings as well. Ideally, use of same year data for all the countries would have enabled a precise generation of the dataset without any temporal bias. This is not possible in the case of the DHS since the surveys were conducted in different years in each country. Nevertheless, to account for this issue, surveys between the years 2003 and 2007 are taken for all the countries which yield a mean year of 2005. This is similar for the Indian dataset as well, where the DHS survey of 2005 is used, thus making further comparisons possible. Nonetheless, this should not cause too much concern, since in most cases the same phase of the DHS was captured. Moreover, there should also not be a large jump in progress for the time difference that eventually did appear, given that the largest difference between two countries was around 3 years.

A more serious issue with the survey is its inadequacy when additional indicators for the African countries are considered. The process of calculating an alternative poverty index for Africa had to be abandoned due to lack of data, as the given 10 indicators were the only ones that could be found in the first place. Even within the starting sample of countries that were taken up within this analysis several countries had to be abandoned in South Asia and other regions since there were only 9 indicators or 8 indicators and the data for the other indicators was found to be mostly missing or entirely consisting of missing values. We therefore stick to examining the robustness of the MPI weights across regions using the techniques of PCA and MCA only for the sample of 22 countries, except for the case of India, where a more detailed analysis been carried out. Here there was data available for additional indicators to create new indices and test the weights therein.

Given the aforementioned reasons, there were 22 countries that were eventually found. Thereafter four regional divisions were made, based on the very same classification made by the DHS as well. From the 22 countries, some were categorized as African countries, namely Benin, Cameroon, Congo DMR, Congo Republic, Ethiopia, Ghana, Kenya, Liberia, Malawi, Mali, Mozambique, Namibia, Niger, Nigeria, Swaziland and Zambia. There were two countries in South Asia (India and Nepal), two from the Latin American and Caribbic region (Bolivia and Peru) and lastly Armenia, Azerbaijan and Moldova were part of the North Africa-West Asia-European region.

Results and Discussion

Principal Component Analysis

The paper is structured so that the results related to the PCA technique are examined first and then we move on to the MCA method. Later on some more robustness checks with regards to the PCA are undertaken to examine how the weights differ with these checks.

The Cronbach's alpha for all the variables in the case of the following countries ranges between 0.65 and 0.8, except for certain countries (Armenia and Azerbaijan) where it is as low as 0.24 and 0.27 even. Table 1 depicts the weights that were derived using PCA for all the countries in the sample, but only using the first principal component for all the countries. All countries with an α-value less than 0.65 has been shaded differently. Armenia and Azerbaijan have noticeably low values of Cronbach's Alpha. An interpretation that one makes from this test is the suitability of the variables included within the index in answering the latent question of basic well-being and capabilities. This can be construed to imply that the variables are not suitable in answering the single question that is posed by the MPI, and perhaps more than one component is required for constructing an index. Alternatively, it can be concurred that the Principal Components Analysis is not suitable for these countries. The results for those countries that are therefore shaded should perhaps be taken into context of this deficit.

Nonetheless, when looking at the values from the Table 1, some patterns can be ascertained for countries that lie within each of the regions. At the outset it is clear that the analysis shows no statistical justification for equal weighting of the dimensions. The normalized weight of the first principal component for the education dimension is around 11%. Health, on the other hand, gets a relatively low weight of around 3%, which can be justified by the fact that large scale prevalence of disease and malnutrition might mean overall poor health conditions in many of the African, Latin American and Asian nations. In the education dimension, years of schooling seem to take higher precedence over child enrolment, nearly double the weight of the latter. The standard of living indicators however, account for about 85% of the total weight on average, which in some countries can be even as high as 92% (Congo DMR). Within the standard of living indicators, Flooring and Electricity indicators are the ones that have the largest weights in the Index. Besides the standard of living indicators, the years of schooling indicator is allotted the next highest weight in this case. Moreover, when comparing the cross-dimensional or within dimension weights, we can see there is a significant variation everywhere (except for the case of health where mortality is assigned only a marginally higher weight compared to nutrition and they are mostly equal).

Table 1. The weights assigned to countries based on PCA

	Years of Schooling	Enrolment	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Assets	Cronbach's Alpha	Variation Explained
Original	**16.66**	**16.66**	**16.66**	**16.66**	**5.56**	**5.56**	**5.56**	**5.56**	**5.56**	**5.56**	-	-
Cameroon	11.73	5.04	2.22	1.16	24.08	0.40	3.96	21.48	16.27	13.67	66.36	28.19
Congo DMR	4.87	2.14	0.70	0.20	22.68	6.28	14.49	20.99	11.90	15.75	66.95	30.49
Congo Rep	5.05	1.09	0.64	0.44	20.20	7.86	10.57	18.88	15.13	20.13	66.28	27.41
Ethiopia	9.82	3.86	1.52	0.62	18.13	5.91	12.15	18.22	13.62	16.15	79.90	41.47
Ghana	11.82	5.97	2.26	3.23	22.92	6.84	10.65	10.54	16.18	9.58	61.13	23.48
Kenya	6.77	2.97	2.18	3.35	20.06	1.13	13.59	20.62	18.69	10.64	70.37	29.28
Liberia	11.33	0.55	0.10	0.28	11.64	19.00	8.07	23.57	0.18	25.27	50.71	23.13
Malawi	9.24	1.47	0.61	0.68	25.45	3.39	8.00	24.02	16.43	10.70	47.09	21.99
Mali	17.77	4.10	1.21	0.93	25.76	1.12	9.03	24.78	2.19	13.11	52.70	22.48
Mozambique	14.11	2.31	0.70	0.81	18.31	11.17	6.52	19.09	18.35	8.63	69.19	30.65
Namibia	3.93	1.42	0.69	0.96	20.31	16.39	6.03	17.39	19.92	12.95	77.59	35.67
Niger	10.64	3.56	1.16	0.34	19.73	11.24	11.23	19.47	6.11	16.52	72.16	34.45
Nigeria	10.69	7.14	4.07	2.52	18.24	7.26	9.60	16.25	17.41	6.81	73.25	30.91
Swaziland	3.49	2.48	0.69	0.47	22.17	12.93	13.63	10.13	18.97	15.04	69.55	28.65
Zambia	4.71	1.52	0.18	0.29	21.69	11.74	11.83	18.05	19.17	10.82	72.72	34.68
Armenia	3.19	6.80	5.24	0.24	5.15	14.17	7.79	4.07	21.76	31.58	24.22	13.7
Azerbaijan	2.83	3.74	5.27	3.35	4.55	7.91	6.47	20.00	11.92	33.97	27.33	14.28
Moldova	11.59	1.17	0.02	0.20	8.76	8.18	3.50	16.50	23.28	26.77	49.28	20.41
India	2.93	3.93	8.27	4.97	14.76	3.09	13.29	17.21	17.11	14.43	74.79	29.41
Nepal	9.07	4.35	2.24	3.68	17.44	11.30	2.21	18.46	15.46	15.79	69.71	29.2
Bolivia	6.81	2.59	1.05	0.27	20.79	4.30	11.86	18.43	20.05	13.85	73.94	32.25
Peru	6.87	0.77	0.60	0.04	17.29	16.06	5.53	16.33	18.44	18.05	76.17	33.08
	7.98	**3.04**	**1.88**	**1.33**	**17.91**	**8.92**	**9.34**	**17.76**	**15.35**	**16.50**	-	-

This analysis does in no way suggest that the MPI should now give nearly 85% of the weight to the standard of living indicators, but that the weights they have assigned so far do not seem to capture the correct picture just on the basis of the data analyzed. Rather, these weights seem to suggest the typical problem of double counting that has been mentioned by Klasen (2000) and Noorbakhsh (1998). PCA is a highly advantageous measure when trying to reduce the commonalities that exist within the various indicators or dimensions that are used in developing the indices of well being, as has even been noted within the authors of the HDI. In most empirical applications, one finds a high correlation existing between the selected indicators or variables in capturing the latent dimensions (Decancq and Lugo, 2010). Therefore PCA would determine the weights between these indicators on the basis of the statistical dimensionality of the data rather than the dimensions introduced within the index. Using PCA would hence correct for the overlapping information of two or more correlated indicators and provide weights accordingly, although this might not mean that those given higher weights are necessarily a measure of importance of the associated indicator. A correlation between each indicator in the MPI is presented in Table A.1 in the Appendix. This may likely be an explanation for the high weights we receive for the standard of living indicators, versus those for health and education. The low weight allotted to these clearly important indicators does not mean that they are socially less important in terms of determining welfare for an individual, but rather that the data is one which has overlapping information in terms of households which suffer from deprivation in both of these indicators. This is an important drawback of this method, when one would like to interpret the social importance of an indicator versus justifying the statistical and data driven weights.

When looking at specific cases or regions, for the case of Armenia, Azerbaijan and Moldova, they have a much higher weight than the average, and also from that the other countries, for the Household Assets indicator. This would seem to suggest that there is a high variation in the assets indicator data compared to the other variables and in the ranking system, this indicators seems to feature very often, to be assigned this high weight. Moreover, India has a much higher weight than normal for the health indicators, which is also the case, to some extent, for Nepal. The African countries however, tend to have higher weights in comparison to the other countries for the standard of living indicators aside from the Household Assets index. This can also be perceived for the Latin American countries. Surprisingly, when one compares the African and the Latin American case, we can draw certain parallels also with regard to the lower values of Health indicators. Although these are mostly visual comparisons, and they do not give a concrete value to the differences in weights, there do seem to be differences across certain countries and certain regions that can be perceived here.

The variation that is explained by the first component can also be seen in Table 1, and ranges between 13.75% for Armenia to 41.5% for Ethiopia. One can see that there is a direct correlation here between the Cronbach's Alpha and the variation explained by the first component. Although this in itself is not a very large percent, we find evidence in literature where these weights are nonetheless derived with total variation that is often less than 20% (Rutstein & Johnson, 2004; Howe, et al., 2008; McKenzie, 2005). However, given that these are binary variables, and PCA is a method better designed for continuous normally distributed data, there is a better case for using MCA to derive weights. Therefore the next stage of analysis will look at the same countries with an index derived using Multiple Correspondence Analysis.

Multiple Correspondence Analysis

As with PCA, MCA also seems to have drawn nearly the same weights for the indicators. When looking at Table 2, one can see that a much higher share of the variation is explained here (between 77% to nearly 99%) by the same number of indicators. Those countries with variation explained less than 90% have been shaded. The standard of living indicators constitute nearly 86% of the weight in this case as well, where Electricity and Flooring have the highest weights as before. These weights seem to suggest even stronger regional trends, when comparing the standard of living indicators for African countries. Health in general has an even lower weight (around 1.2% less) in comparison whereas Education now commands more weight- although this change is only marginal, amounting to not even .7%. Households assets is another indicator which get a large weight in comparison and Armenia and Azerbaijan contribute the most to this average as before. Although on average the results are also mostly similar, there are certain differences which one can observe. Moldova has a very striking increase in its weight for years of schooling. If we look at the weights for India, we observe that child mortality does not receive as high of a weight this time around and it is indeed education that has a higher weight.

Nonetheless we find that in general the results are similar or do not disprove what the Principal component analysis seems to have suggested. We also find several studies that point out the similarities between the two methods in several cases and a high correlation between a PCA generated index versus a MCA generate one (Howe, et al., 2008; Booysen, et al., 2008). Moreover, MCA has been criticized in comparison on the basis of it being unable to respect the monotonicity of ordered categories (Merola & Baulch, 2015). Therefore we choose to stick to running the robustness checks on the weights using Principal Components, which are intuitively easier to understand in comparison to MCA.

Table 2: Weights assigned to countries based on the MCA

	Years of Schooling	Enrolment	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Asset	Proportion Explained
Original	**16.66**	**16.66**	**16.66**	**16.66**	**5.56**	**5.56**	**5.56**	**5.56**	**5.56**	**5.56**	**-**
Cameroon	9.3	5.1	1.6	0.8	28.9	0.3	2.8	23.2	14.6	13.3	93.40
Congo DMR	3.6	1.5	0.6	0.1	27.6	4.7	13.2	23.7	10.4	14.6	97.13
Congo Rep	4	1	0.5	0.3	20.9	5.9	12.9	20.3	13.4	20.8	96.12
Ethiopia	8.9	3.7	1.3	0.2	20.5	5.1	6.4	21.5	14	18.2	98.68
Ghana	11.8	6	2.3	3.2	22.9	6.9	10.6	10.5	16.1	9.6	88.93
Kenya	5.5	2	1.5	2.3	22.3	0.8	12.4	22.4	21.6	9.3	92.13
Liberia	11	0.2	0	0.1	10	19.6	5.5	25.1	0.3	28.2	94.05
Malawi	6.9	0.8	0.4	0.4	38.6	1.9	5.1	23.2	15.2	7.6	90.71
Mali	16.1	3.1	1	0.6	30.7	0.7	6.4	28.5	1.4	11.5	88.24
Mozambique	13.2	1.7	0.5	0.6	19.8	9.6	5.1	21.5	19.9	8.1	96.82
Namibia	3.5	1	0.5	0.6	22.8	15.8	4.6	17.5	21.8	11.7	97.86
Niger	9.4	2.8	1.1	0.2	22.6	9.8	10	22.1	4.8	17.1	95.74
Nigeria	9.6	6.8	3.7	2.1	21.3	6.1	8.5	17.1	18.8	6.1	93.58
Swaziland	2.8	1.7	0.5	0.3	26.4	11.3	12.2	8.3	21.3	15.3	95.53
Zambia	3.4	1	0.1	0.2	27	9.7	9.8	18.1	21.8	8.9	96.94
Armenia	2.3	3.4	2.1	0	2.6	9.5	3.3	1.5	2.32	59.2	85.14
Azerbaijan	1.5	1.7	2.3	1.5	3.7	4.1	3.1	15.8	15.5	50.7	81.94
Moldova	55.8	0.2	0	0.1	2.4	3	1	6.7	12.5	18.4	76.82
India	8	2.9	2.1	2.8	15	12.7	2.4	19.2	19.5	15.6	97.75
Nepal	7.9	2.6	1.6	2.4	18.2	8.9	1.8	21.3	16.9	18.6	95.92
Bolivia	6	2.2	0.8	0.2	23.2	3.2	10.2	19	45.3	13.3	95.94
Peru	5.7	0.5	0.4	0	17.3	16.1	4.1	16.1	19.5	20.4	98.27
	9.37	**2.36**	**1.13**	**0.86**	**20.21**	**7.53**	**6.88**	**18.30**	**15.77**	**18.02**	**-**

Robustness checks

Significant differences across regions?

Although the previous tables seem to suggest that there exists a regional trend in terms of weight assigned by PCA and MCA techniques, are there really any perceivable regional differences? The next bit of analyses would seem to suggest the same. I run a correlation on the scores of each of the countries, conditioned on the region as well as the HDI score for each country, to find how well these regional differences can explain the weighting differences across our results. Table 3 is the where we run a conditional correlation including the HDI values for each country and the regional dummies, onto the MPI values for each indicator derived by the Principal Component Analysis. As the results show, being from a certain regions has a significant impact on the weight of a particular indicator. Child Mortality, Nutrition, Electricity and Assets all are found to be affected by a certain region. For example, in the case of Child mortality and Nutrition, there is a positive effect of being an Asian nation, which means that the weights for Asian countries are higher in the health dimension. Likewise, in terms of standard of living indicators, Electricity has a negative significant coefficient for the EU-Asia region, while assets seem to have a significantly higher weight in the same.

This exercise was also conducted for the MCA derived weights, where the results are presented in Table 4. As can be seen, although the significance disappears for Child Mortality, Nutrition is still significant for Asia. Moreover, now weights in Flooring and Cooking are also negatively significant in the EU-Asia region. In both tables we see that Africa does not seem to have a significant impact on any of the standard of living indicators. As can also be seen, in the case of several indicators, HDI also is significantly correlated, although the sign is slightly concerning. This correlation however has very few countries included for some regions and there might be concerns that it is affected by the small sample size in one region versus another. This would have to be carried out for a larger sample with a more equal distribution of countries to be more credible.

Correlation between normative MPI and data driven MPI

To check how the ranks within households change with the MPI calculated using PCA in comparison to the normatively weighted indices, we calculate the Rank correlations for each country. The new weighted MPI is highly and positively correlated with the original MPI with the correlation score ranging from the lowest of 0.7 for Liberia to .955 for Peru. For the two Latin American countries, these two MPI's give nearly the same rank to the household. The results can be found in Table A.4 in the Appendix.

Table 3. Conditional correlation with HDI on PCA Weights

	Years of Schooling	Child Enrolment	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Assets
HDI	-23.62**	2.535	5.103	5.433*	3.408	5.776	-1.803	-26.99**	40.86**	-10.70
Africa	-3.549	1.978	1.682	2.259*	2.549	-0.592	0.819	-5.079	4.774	-4.847
Asia	-4.686	2.869	5.257**	5.057***	-2.386	-2.051	-1.241	-3.935	3.694	-2.580
Eu-Asia	-0.788	2.203	2.643	1.069	-12.92***	-0.143	-2.762	-3.647	-0.575	14.91***
Constant	22.54***	-0.00232	-2.565	-3.457	16.78**	6.342	9.895	35.32***	-7.917	23.07**
Observations	22	22	22	22	22	22	22	22	22	22
R-squared	0.308	0.117	0.462	0.563	0.739	0.038	0.172	0.342	0.410	0.689

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Latin America is the omitted dummy category

Table 4. Conditional correlation with HDI on MCA Weights

	Years of Schooling	Child Enrolment	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Assets
HDI	-33.38	3.341	2.677	4.600*	-1.519	9.031	4.589	-35.64**	42.74*	-4.404
Africa	-6.074	2.026	1.094	1.824**	3.532	-0.230	2.338	-6.059	-7.594	-4.573
Asia	-3.335	1.944	1.686	3.249***	-3.897	2.620	-4.303	-3.102	-7.241	-0.467
Eu-Asia	14.28	0.391	0.846	0.397	-17.34***	-4.187	-4.719	-9.272**	-22.63***	25.95***
Constant	28.04	-0.871	-1.180	-2.958*	21.26*	3.646	4.099	41.24***	3.984	19.78
Observations	22	22	22	22	22	22	22	22	22	22
R-squared	0.205	0.079	0.158	0.469	0.665	0.090	0.429	0.605	0.490	0.601

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Latin America is the omitted dummy category

Differences with changed weighting

Another concern when using PCA as a tool for creating indices is whether the first component is enough to explain a required amount of variation within the data. Since the first principal component fails to explain a substantial amount of variation in our case, more principal components that explain a greater percentage of the total variation in the data can be chosen. Parallel Analysis or PA is a method for determining the number of components to retain from a PCA. This programme generates a random dataset, having an equal number of observations and variables as the original dataset and uses this generated data to compute a correlation matrix. Thereafter it calculates the eigenvalues from the correlation matrix which generally do not vary tremendously in their consecutive order and then determines how many of them are required to capture a relatively large degree of variation in the data (if the dataset is indeed random). As performed in this paper as well, ten replications are generally sufficient. The eigenvalues generated by the PA and the eigenvalues of the principal components are compared, and those principal components whose eigenvalues are greater than the average eigenvalues of the PA are retained. For the various countries, this exercise varies in the number of principal components required, from one up to three principal components that are needed to be retained. The graphs for some of these countries are within the Appendix in Table A.3, and in line with the parallel analysis the first three components for these countries were used in the construction of the index. Table 3 shows the results for these countries.

The PCA constructed indices for certain countries which seemed to require three components according to the parallel analysis have been shown in the Table. There were also some countries for which only two components were adequate to explain a considerable share of variation. The indices have been constructed with the same analysis as its basis and the results are presented in Table 5. The results, even with different number of components used to construct the final index, based on the parallel analysis, seems to show that the standard of living indicators deserve a higher weight share. Although they definitely represent around 65% of the total weight now, rather than 85% as before, this is still greater than the 33% they are currently accorded. The health dimension also receives a higher weight, seeming to suggest that it is only in the second and third components to which it is more correlated. Nonetheless, these two indicators now command nearly 18% of the total weight, out of which child mortality has been allocated more weight than nutrition. Also, education, the last dimension, has nearly the same weight as the health component and years of schooling has more weight therein, although on average this is only a marginally higher difference between the two indicators. The three countries in the North Africa- West Asia-Europe region, i.e. Armenia, Azerbaijan and Moldova, as shown in the shaded regions still have the highest

Table 5. MPI constructed using two or three components based on Parallel analysis

	Years of Schooling	Enrolment	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Asset	Proportion Explained
Original	**16.66**	**16.66**	**16.66**	**16.66**	**5.56**	**5.56**	**5.56**	**5.56**	**5.56**	**5.56**	-
1st component	**7.98**	**3.04**	**1.88**	**1.33**	**17.91**	**8.92**	**9.34**	**17.76**	**15.35**	**16.50**	-
Cameroon	8.15	9.35	11.32	5.97	13.33	12.37	7.80	11.95	8.98	10.78	51.83
Congo DMR	6.49	10.53	10.75	5.72	16.37	4.52	10.36	15.11	8.65	11.51	42.58
Congo Rep	8.28	8.90	10.05	7.52	13.43	5.18	9.77	13.30	10.13	13.46	40.61
Ethiopia	8.00	7.16	9.73	7.35	14.24	5.73	9.54	14.41	10.79	13.05	52.82
Ghana	6.59	9.50	8.91	8.20	12.08	13.49	8.03	10.68	12.11	10.41	47.68
Kenya	9.07	9.13	8.58	7.81	12.41	10.01	8.92	11.92	12.42	9.73	55.22
Liberia	10.21	8.83	9.61	6.29	11.77	12.28	8.63	12.66	6.87	12.84	45.35
Malawi	12.12	12.63	10.10	6.13	15.01	4.99	4.43	11.85	12.92	9.83	44.91
Mali	12.42	11.32	14.68	8.68	16.14	1.84	5.70	15.57	1.53	12.13	35.87
Mozambique	10.42	7.30	10.81	8.26	13.47	8.04	4.72	13.83	13.22	9.92	42.57
Namibia	6.09	2.76	8.87	11.32	15.41	12.54	4.57	13.19	15.10	10.14	47.64
Niger	8.65	8.77	12.88	6.17	14.70	8.74	8.34	14.50	4.58	12.68	46.41
Nigeria	7.57	11.23	11.41	9.75	13.54	6.22	7.15	11.47	12.27	9.40	44.06
Swaziland	10.65	6.02	6.74	6.17	15.85	9.18	9.93	8.11	14.36	12.98	40.38
Zambia	6.51	5.30	10.89	6.73	16.15	8.72	8.79	13.41	14.30	9.20	46.71
Armenia	15.28	3.91	7.61	11.52	9.40	9.85	7.14	9.25	11.26	14.78	35.20
Azerbaijan	13.22	4.85	11.81	5.63	12.73	7.21	5.57	10.02	14.81	14.15	36.14
Moldova	11.87	8.27	8.24	2.74	8.85	11.45	14.23	8.27	11.63	14.44	42.14
India	8.98	6.24	11.71	10.85	11.21	9.95	2.51	13.11	13.19	12.27	43.29
Nepal	7.11	8.96	10.43	9.73	12.51	7.94	4.43	13.54	11.64	13.71	41.41
Bolivia	10.59	11.33	9.06	2.10	14.83	4.50	8.45	13.15	14.29	11.68	45.24
Peru	9.32	6.31	11.06	4.33	12.92	12.10	4.15	12.21	13.82	13.78	44.26
Average	**9.44**	**8.12**	**10.24**	**7.23**	**13.47**	**8.49**	**7.42**	**12.34**	**11.31**	**11.95**	-

Table 6. MPI constructed only with Poor HH (with weighted average score more than 0.33)

	Years of Schooling	Child Enrolment	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Assets	Correlation
Original	**16.66**	**16.66**	**16.66**	**16.66**	**5.56**	**5.56**	**5.56**	**5.56**	**5.56**	**5.56**	**-**
Cameroon	16.94	0.73	20.39	2.55	22.50	0.02	0.08	20.03	6.41	10.36	0.65
Congo DMR	4.87	1.05	6.34	4.40	21.54	3.49	13.89	20.77	6.87	16.79	0.93
Congo Rep	8.25	1.42	7.40	6.41	12.83	5.45	11.38	21.96	8.80	16.08	0.80
Ethiopia	5.25	0.29	0.60	0.52	25.24	4.89	11.70	20.93	14.08	16.49	0.96
Ghana	23.97	0.47	13.84	5.66	19.44	0.06	7.55	18.53	5.46	5.00	0.42
Kenya	8.12	0.02	7.21	0.49	16.79	5.21	11.16	25.58	12.32	13.08	0.86
Liberia	16.35	4.77	4.93	1.49	5.64	9.67	9.72	23.31	0.00	24.11	0.88
Malawi	19.93	0.46	16.21	5.73	10.47	5.39	3.96	13.72	7.50	16.65	0.27
Mali	20.37	2.84	10.67	5.92	17.37	1.45	3.77	18.77	0.32	18.53	0.82
Mozambique	16.54	0.15	7.02	1.47	13.15	12.97	1.79	22.43	19.11	5.36	0.88
Namibia	3.99	0.30	6.27	5.16	17.52	17.31	6.72	12.75	18.68	11.30	0.94
Niger	8.51	0.04	1.28	0.54	22.77	9.28	14.30	23.19	1.57	18.51	0.97
Nigeria	10.75	0.00	5.86	5.78	23.35	6.26	3.71	22.19	10.21	11.88	0.73
Swaziland	5.19	0.23	14.03	2.39	16.65	6.91	8.44	18.93	10.01	17.22	0.53
Zambia	5.87	0.19	7.69	3.30	20.34	6.05	9.92	17.82	17.52	11.30	0.90
Armenia	16.24	0.12	7.55	17.17	4.81	12.37	0.86	12.26	12.57	16.03	0.24
Azerbaijan	17.39	0.91	12.84	12.74	5.63	2.71	2.26	8.64	13.48	23.41	0.54
India	12.30	0.30	5.58	5.93	15.96	10.89	1.10	15.01	16.80	16.12	0.52
Nepal	14.78	0.00	5.97	6.90	18.59	7.72	5.47	9.09	9.21	22.26	0.66
Average	**12.15**	**0.75**	**7.85**	**5.11**	**16.01**	**7.12**	**7.10**	**18.10**	**10.25**	**15.56**	**0.85**
All HHS	**7.98**	**3.04**	**1.88**	**1.33**	**17.91**	**8.92**	**9.34**	**17.76**	**15.35**	**16.50**	**-**

weight in terms of assets though, seeming to suggest that in these particular countries, household assets data can take a range of values and thus has a large amount of variation.

Weights with only multidimensionally poor households

The fact the all households are within the PCA analysis and therefore there is not much scope to differentiate between multidimensionally poor and rich households, in the following bit of analysis, only those household which have a weighted deprivation score of more than 0.33 are taken within the PCA analysis. The results for the same can be seen in the Table 6. The results seem to differ to quite an extent when looking at the indicators, and overall weighting between the dimensions to some extent. Education is around 13%, which is 2% more than before while Health has increase by around 10% in this case. The standard of living dimension is now around 74%, which is nearly 11% more than before. Nonetheless, this is the dimension which still has the largest weight in the index, as before. Within the dimensions, the weights of Years of schooling, Child Mortality and Nutrition and that of Cooking Fuel have changed to a large degree. Upon looking at the correlation between these weights and those derived from the normal PCA however, on average there is quite a large correlation between the MPI scores for the households, at around 85%, although this value fluctuates between 0.24 for Armenia and 0.97 for Niger. This would suggest that the ranking order seems to not have been affected by these changes in the weights.

Changes in the Indicators: India

The World Bank's World Development Indicators are an extensive list of more than a hundred indicators that are considered important in the realm of development. Although no household level data is available for a lot of these variables, the Indian DHS contained data on the access to financial market as well as the ownership of property for households, and these are thereby used for creating a new multidimensional poverty index, using PCA and MCA techniques.

Initially, variables related to access to financial institutions, consumption, property and land ownership, and type of employment were considered for the specific case of the Indian DHS. Adequate data concerning access to financial institutions, and property and land ownership was found within the data. On the other hand, the lack of data availability and quality led to the consumption indicator being dropped. I also intended to include data on type of employment, but the large number of missing values for the types of employment meant that this had to be dropped from the analyses as well. Thus, a new MPI with 12 indicators is calculated and the weights are assigned using the technique of PCA and MCA.

A substantial theoretical and empirical literature shows the importance of efficient financial systems for long-term economic development (Levine, 2005). A lack of access to the financial sector may bring about lower levels of growth and investment and higher levels of inequality (Galor & Zeira, 1993; Banerjee & Newman, 1993). Greater financial sector reforms lead to broadening of financial access services, and to better functioning financial systems, which serve to equalize opportunities (Demirguc-Kunt & Levine, 2008). (Beck & Demirgüç-Kunt, 2008) focus also on the framework within which the outreach programs need to work and therefore play a more crucial role in development of poor households. The theory literature on land access and ownership however is relatively more conflicted in explaining improvements in well being, especially in poor agrarian populations where other land ownership and access systems already exist (Dani, 1995; Binswanger, et al., 1995; Besley & Burgess, 2000; Bakshi, 2008). Nonetheless land redistribution has been a top agenda since the formulation of the World Bank's "Land Reform Policy paper" in 1997, which focuses on, among other issues, the egalitarian distribution of land among productive users. There have been extensive macro economic reforms thereafter which have thus tried to remove inequality in land distribution and discontinue distortionary policies (Deininger & Binswanger, 1999). There is however ample evidence which also states that land reform has been beneficial in the goal of reducing poverty (Rural Poverty Rerport 2001, 2010; Keswell & Carter, 2014) This has therefore been an important topic within the restructuring framework of several developing countries and is consequently considered important to be included within the analysis.

The results for both the PCA and MCA using the original 10 indicators and with the additional two indicators are shown in Table 7. The first principal component explains about 29.5% of the total variation. This variation is even less than before, where the PCA with 10 indicators explained about 35% of the variation in the dataset. The dimensional cut-off for access to financial institutions is defined in terms of ownership of a bank or post office account. For property and land ownership indicator, a household is defined as being deprived if it does not own agricultural land or a house. However, in the cases where the household owned cattle when it owned neither agricultural land nor a house, it is considered non-deprived in this category.

The addition of property and land ownership, and access to financial institutions has shuffled the weights a little. The most observable change is in the standard of living indicator, wherein its weight has fallen from nearly 80% to around 72% in the case of PCA and from 84% to 73% in the case of MCA. Access to financial institutions has proven to be an important indicator with the statistical weight assigned to it being nearly 10% both via MCA and PCA. Property ownership is something that does not receive as much weight per se however, which might be in line with what the empirical literature suggests.

Table 7. PCA and MCA constructed indices with additional variables for India

Indicator	PCA (%)	MCA	PCA	MCA
Years of Schooling	7.91	8	2.93	8
Enrolment	3.23	3.3	3.93	2.9
Child Mortality	2.09	2.1	8.27	2.1
Nutrition	2.82	2.9	4.97	2.8
Electricity	12.72	12.7	14.76	15
Drinking Water	11.88	12	3.09	12.7
Sanitation	2.71	2.7	13.29	2.4
Flooring	15.37	15.3	17.21	19.2
Cooking fuel	16.26	16.3	17.11	19.5
Assets	13.84	13.9	14.43	15.6
Property/ Land ownership	0.92	0.6		
Access to Financial Institutions	10.25	10.3		
Variation Explained	29.41	92.53	34.95	97.75

Conclusion

Given that MCA and PCA are both oft used techniques when one builds indices, the weights that are determined for each country using this technique seems to suggest that statistically, not the most appropriate techniques are currently being applied to this weighting. This exercise has revealed that an equal standardized weight across regions may not be the most ideal construct to deliver the best results when determining the level of multidimensional poverty with a given dataset. Naturally this all is dependent on the line of thinking that is followed when determining the weights in the first place. Whether they are to be equal, or data driven or normative are all judgements that the AF method has likely been rigorously put under.

Although the original purpose of this study was to perhaps arrive at a more suitable weight proportion for each indicator within each dimension for country, there seems to be no such common weight that could be used for comparisons across regions. The regional differences in multidimensional poverty are not only conceptually challenged here, but statistically as well. What can be said after this analysis is that to use equal (and to an extent arbitrary) weights across the globe may not be an optimal way to proceed. Given that the MPI is and will further become one of the more well known methods to calculate multidimensional poverty, the current weighting scheme, which is seemingly, empirically proven and helps to make the index more comparable across nations, seems to be underutilizing its potential in terms of detecting poverty with regard to its regional character. The question of a trade-off between a data driven and statistically sounder method and comparability across nations is one which is not clearly answered. However the study seems to suggest that there are regional differences in weights and that one needs to keep this in account.

The other question then is whether the indicators that are used for the global MPI are also entirely applicable in measuring poverty in each country. Naturally this was a set up that was determined in order to maintain comparability, however there is again the tradeoff one needs to make between dissimilarities in poverty and in measurement. Although this paper tackled the singular case of India with two additional indicators, one cannot conclusively say which indicators are the best when capturing a more multidimensional aspect of poverty.

Admittedly, the sample is too small to generalize and draw conclusions on the basis of it. More countries from Asia and Latin America would have to be included into the analysis before conclusively accepting or rejecting the theory or story behind these equal weights. If one requires having a better regional picture for determining weights statistically, this would imply a more thorough analysis with many more lands from each region. However, given the data constraints that this particular study had, there is not too many more countries that could have been taken up form these particular regions. The next steps could be to perhaps take up later years, where a larger sample seems to be made available due to the difference in outreach of the Demographic and Health Surveys.

This study has led to several questions that have yet to be answered, related to the differences in multidimensional poverty within countries and regions across the globe. The part of analysis that just focused on India alone showed a significant degree of variation when looking at statistically derived weights and when introducing more indicators. Now the question remains as to what possible improvements or changes can be made and what are necessary for a better comparison of poverty across these countries, and those not in the purview of this study as well. This paper does not have to scope to answer all questions and challenges related to the Multidimensional Poverty Index completely, but it has been an attempt in that very direction.

Bibliography

Alkire, S., 2002. Dimensions of Human Development. *World Development,* Volume 30(2), pp. 181-205.

Alkire, S. & Foster, J., 2011. Counting and multidimensional poverty measurement. *Journal of Public Economics,* August, 95(7–8), pp. 476-487.

Alkire, S. & Santos, M. E., 2014. Measuring Acute Poverty in the Developing World: Robustness and Scope of the Multidimensional Poverty Index. *World Development,* July , Volume 59, pp. 251-274.

Asselin, L.-M., 2009. *Analysis of Multidimensional Poverty: Theory and Case Studies.* Dordrecht: Springer.

Atkinson, A. B., 2003. Multidimensional Deprivation: Contrasting Social Welfare and Counting Approaches. *The Journal of Economic Inequality,* Volume 1(1), pp. 51-65.

Bakshi, A., 2008. Social Inequality in Land Ownership in India: A Study with Particular Reference to West Bengal. *Social Scientist,* 36(9/10), pp. 95-116.

Banerjee, A. V. & Newman, A. F., 1993. Occupational Choice and the Process of Development. *Journal of Political Economy,* 101(2), pp. 274-98.

Beck, T. & Demirgüç-Kunt, A., 2008. Access to Finance: An Unfinished Agenda. *World Bank Economic Review,* 22(3), pp. 383-396.

Besley, T. & Burgess, R., 2000. Land Reform, Poverty Reduction, and Growth: Evidence from India. *The Quarterly Journal of Economics,* 115(2), p. 389–430.

Binswanger, H. P., Deininger, K. & Feder, G., 1995. Power Distortions Revolt and Reform in Agricultural Land Relations. In: J. Behrman & T. Srinivasan, eds. *Handbook of Development Economics, Volume III.* Amsterdam: Elsevier Science B.V..

Booysen, F. et al., 2008. Using an Asset Index to Assess Trends in Poverty in Seven Sub-Saharan African Countries. *World Development,* Volume 36(6), p. 1113–1130.

Brandolini, A., 2007. On Synthetic Indices Of Multidimensional Well-Being: Health And Income Inequalities In France, Germany, Italy And The United Kingdom. *CHILD Working Papers*.

Chakravarty, S. R. & D'Ambrosio, C., 2006. The Measurement of Social Exclusion. *Review of Income and Wealth,* Volume 52(3), p. 377 – 398.

Cherchye, L., Moesen, W., Rogge, N. & Van Puyenbroeck, T., 2007. An Introduction to "Benefit of the Doubt" Composite Indicators. *Social Indicators Research,* Volume 82(1), p. 111–145.

Chowdhury, S. & Squire, L., 2006. Setting weights for aggregate indices: An application to the commitment to development index and human development index. *Journal of Development Studies,* Volume 42(5), pp. 761-771.

Clark, D. & McGillivray, M., 2007. Measuring Human Well-being: Key Findings and Policy Lessons. *UNU Policy Brief*, 7 March.

Coneval, 2009. *Launch of Mexico's New Poverty Measure.* [Online]
Available at: http://www.ophi.org.uk/launch-of-mexico%E2%80%99s-new-poverty-measure/

Coromaldi, M. & Zoli, M., 2011. Deriving Multidimensional Poverty Indicators: Methodological Issues and an Empirical Analysis for Italy. *Social Indicators Research,* 107(1), pp. 37-54.

Cronbach, L. J., 1951. Coefficient alpha and the internal structure of tests. *Psychometrika ,* 16(3), pp. 297-334.

Dani, R., 1995. The Dynamics of Political Suppport for Reform in Economies in Transition. *Journal of the Japanese and International Economies,* 9(4), p. 403–25.

Decancq, K. & Lugo, M. A., 2013. Weights in Multidimensional Indices of Wellbeing: An Overview. *Econometric Reviews,* pp. 7-34.

Deininger, K. & Binswanger, H., 1999. The evolution of the World Bank's land policy : principles, experience, and future challenges. *World Bank Research Observer,* 14(2), pp. 247-76.

Demirguc-Kunt, A. & Levine, R., 2008. Finance and economic opportunity. *Policy Research Working Paper Series 4468, The World Bank*.

Despotis, D. K., 2004. A reassessment of the human development index via data envelopment analysis. *Journal of the Operational Research Society,* Volume 56(8), p. 969–980.

Despotis, D. K., 2005. Measuring human development via data envelopment analysis: the case of Asia and the Pacific. *Omega,* Volume 33(5), p. 385–390.

Deutsch, J. &. S. J., 2011. On various ways of measuring pro-poor growth. *Economics - The Open-Access,* Volume 5, pp. 1-57.

Development, I. F. f. A., 2001. *Rural Poverty Report 2001: The Challenge of Ending Rural Poverty,* Oxford: Oxford University Press.

Development, I. F. f. A., 2010. *Rural Poverty Report 2011 New Realities, New Challenges: New Opportunities for Tomorrow's Generation,* Rome: IFAD.

Dhongde, S. & Haveman, R., 2015. *Multi-Dimensional Poverty Index: An Application to the United States.* [Online]
Available at: http://papers.ssrn.com/abstract=2588584

Dotter, C. & Klasen, S., 2014. The Multidimensional Poverty Index : achievements, conceptual and empirical issues. *Human Development Reports Occasional Paper.*

Ezzrari, A. & Verme, P., 2013. A Multiple Correspondence Analysis Approach to the Measurement of Multidimensional Poverty in Morocco 2001–2007. In: *Poverty and Social Exclusion around the Mediterranean Sea.* Boston: Springer, p. 181–209.

Filmer, D. & Pritchett, L. H., 2001. Estimating Wealth Effects Without Expenditure Data—Or Tears: An Application To Educational Enrollments In States Of India. *Demography,* Volume 38(1), p. 115–132.

Galor, O. & Zeira, J., 1993. Income Distribution and Macroeconomics. *The Review of Economic Studies,* 60(1), p. 35–52.

Gordon, D. & Pantazis, C., 1997. *Breadline Britain in the 1990s.* Bristol: Summerleaze House Books.

Greenacre, M., 2006. From simple to multiple correspondence analysis. In: *Multiple correspondence analysis and related.* London: Chapman & Hall, p. 41–76.

Greenacre, M. J., 1984. *Theory and applications of correspondence analysis.* London: Academic Press.

Hotelling, H., 1933. Analysis of a complex of statistical variables into principal components. *Journal of Educational Psychology,* Volume 24, p. 417–441.

Howe, L. D., Hargreaves, J. R. & Huttly, S. R., 2008. Issues in the Construction of Wealth Indices for the Measurement of Socio-Economic Position in Low-Income Countries. *Emerging Themes in Epidemiology,* Volume 5 (1): 3..

Jayaraj, D. & Subramanian, S., 2010. A Chakravarty – D'Ambrosio View of Multidimesional Deprivation: Some Estimates for India. *Economic and Political Weekly,* Volume 45(6), p. 53 – 65.

Keswell, M. & Carter, M. R., 2014. Poverty and Land Redistribution. *Journal of Development Economics, Land and Property Rights,* 110(September), p. 250–61.

Klasen, S., 2000. Measuring Poverty and Deprivation in South Africa. *Review of Income and Wealth,* Volume 46(1), p. 33–58.

Krishnakumar, J. & Nagar, A. L., 2008. On Exact Statistical Properties of Multidimensional Indices Based on Principal Components, Factor Analysis, MIMIC and Structural Equation Models. *Social Indicators Research,* Volume 86(3), p. 481–496.

Levine, R., 2005. Finance and Growth: Theory and Evidence. In: P. Aghion & S. Durlauf, eds. *Handbook of Economic Growth.* Amsterdam: North Holland Elsevier Publishers.

Mahlberg, B. & Obersteiner, M., 2001. *Remeasuring the HDI by data envelopment analysis. Interim report IR-01-069,* s.l.: International Institute for Applied System Analysis.

McKenzie, D. J., 2005. Measuring Inequality with Asset Indicators. *Journal of Population Economics ,* 18 (2), p. 229–60.

Melyn, W. & Moesen, W., 1991. Towards a synthetic indicator of macroeconomic performance:. *Katholieke Universiteit Leuven, Public Economic Working Paper 17*.

Merola, G. & Baulch, B., 2015. *Using Sparse Catergorical Principal Components to estimate asset indices new methods with and application to rural South East Asia.* Rome, s.n.

Morris, M. D., 1979. *Measuring the condition of the world's poor: The physical quality-of-life index.* New York: Pergamon Press for the Overseas Development Council.

Moser, C. & Felton, A., 2007. The Construction of an Asset Index Measuring Asset Accumulation in Ecuador. *SSRN Electronic Journal*.

Nagar, A. L. & Basu, S. R., 2002. Weighting socioeconomic indicators of human development : a latent variable approach. In: *Handbook of applied econometrics and statistical inference.* s.l.:Dekker, pp. 609-641.

Nguefack-Tsague, G., Klasen, S. & Zucchini, W., 2011. On Weighting the Components of the Human Development Index: A Statistical Justification. *Journal of Human Development and Capabilities,* Volume 12(2), pp. 183-202.

Njong, A. M. & Dschang, P. N., 2008. Characterising weights in the measurement of ultidimensional poverty: An application of data-driven approaches to Cameroonian data. *OPHI Working Paper No. 21*.

Noorbakhsh, F., 1998. The Human Development Index: Some Technical Issues and Alternative Indices. *Journal of International Development,* Volume 10 (5), p. 589–605.

Noorbakhsh, F., 2003. Human Development and Regional Disparities in India. *Working Papers 2003_12, Business School - Economics, University of Glasgow*.

Ram, R., 1982. Composite indices of physical quality of life, basic needs fulfilment, and income: A principal component representation. *Journal of Development Economics,* Volume 11, p. 227–247.

Ravallion, M., 1997. Good and bad growth: The human development reports. *World Development,* pp. 631-638.

Ravallion, M., 2011. On multidimensional indices of poverty. *Journal of Economic Inequality,* June, Volume 9(2), pp. 235-248.

Ravallion, M., 2012a. Mashup Indices of Development. *World Bank Research Observer,* Volume 27(1), pp. 1-32.

Ravallion, M., 2012b. Troubling tradeoffs in the Human Development Index. *Journal of Development Economics,* Volume 99(2), pp. 201-209.

Ravallion, M. & Chen, S., 2011. Weakly Relative Poverty. *The Review of Economics and Statistics,* Volume 93(4), pp. 1251-1261.

Rippin, N., 2012a. Distributional Justice and Efficiency: Integrating Inequality Within and Between Dimensions in Additive Poverty Indices. *Courant Research Centre: Poverty, Equity and Growth - Discussion Papers 128*.

Rippin, N., 2012b. Operationalising the Capability Approach: A German Correlation Sensitive Poverty Index. *Courant Research Centre: Poverty, Equity and Growth - Discussion Papers 132*.

Rutstein, S. & Johnson, K., 2004. *The DHS Wealth Index,* Calverton: ORC Macro.

Santos, M. E. & Santos, G., 2014. Composite Indices of Development. In: *International development: ideas, experience, and prospects.* Oxford: Oxford University Press.

Santos, M. E., Villatoro, P., Mancero, X. & Gerstenfeld, P., 2015. A Multidimensional Poverty Index for Latin America. *OPHI Working Paper 79*, January.

Sen, A., 1984. *Resources, Values and Development.* Oxford: Basil Blackwell.

Silber, J., 2011. A comment on the MPI Index. *Journal of Economic Inequality,* Volume 9(3), pp. 479-81.

Traissac, P. & Martin-Preveö, Y., 2012. Alternatives to principal components analysis to derive asset-based indices to measure socio-economic position in low- and middle-income countries: the case for multiple correspondence analysis. *International Journal of Epidemiology,* Volume 41(4), pp. 1207-8.

Ura, K., Alkire, S. & Zangmo, T., 2012. *Bhutan's Gross National Happiness Index 2010,* s.l.: The Centre for Bhutan Studies.

Appendix

Table A.1 The countries in the sample, which DHS was taken and observations within

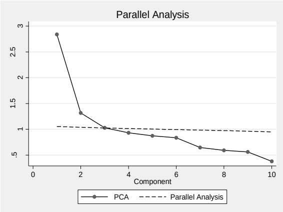
Country	Year	Observations[7]
Cameroon	2004	8910
Congo DMR	2007	8115
Congo Republic	2005	5245
Ethiopia	2005	12612
Ghana	2003	4831
Kenya	2003	7484
Liberia	2007	34344
Malawi	2004	12587
Mali	2006	12156
Mozambique	2003	11356
Namibia	2006	8031
Niger	2006	7045
Nigeria	2003	6964
Swaziland	2007	45163
Zambia	2007	6995
India	2005	103371
Nepal	2006	8290
Bolivia	2003	18584
Peru	2004-06	45010
Armenia	2005	24888
Azerbaijan	2006	30114
Moldova	2005	10745

Table A.2 Correlations between each indicator for India at 5% significance level

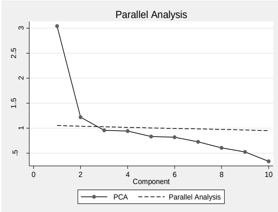
	Years of Schooling	School Attendance	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Flooring	Cooking Fuel	Assets
Years of Schooling	1.000									
School Attendance	0.1629*	1.000								
Child	0.0545*	0.1502*	1.000							
Nutrition	0.0337*	0.1293*	0.1577*	1.000						
Electricity	0.3187*	0.1794*	0.1425*	0.1570*	1.000					
Sanitation	0.2570*	0.1362*	0.1252*	0.1628*	0.3126*	1.000				
Drinking	0.0854*	0.0679*	0.0426*	0.0549*	0.1437*	0.1292*	1.000			
Flooring	0.2863*	0.1715*	0.1484*	0.1839*	0.5009*	0.4016*	0.1985*	1.000		
Cooking	0.2828*	0.1786*	0.1681*	0.2170*	0.4074*	0.4328*	0.2107*	0.5349*	1.000	
Asset Ownership	0.3621*	0.1513*	0.0990*	.1191*	0.3939*	0.4062*	0.1532*	0.3916*	0.4331*	1.000

[7] These are observations after the multiple entries for each household have been removed, therefore only single entries per household exist.

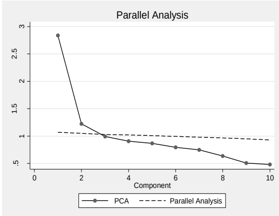
Table A.3 The graphs with parallel analysis showing how many components to consider



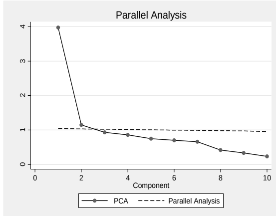
Cameroon



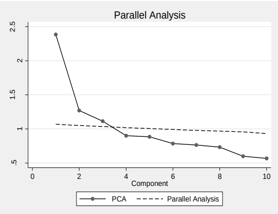
Congo DMR



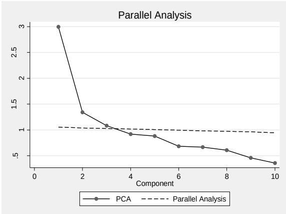
Congo Republic



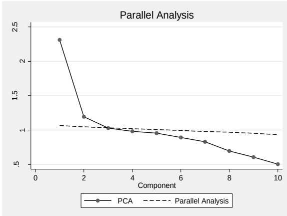
Ethiopia



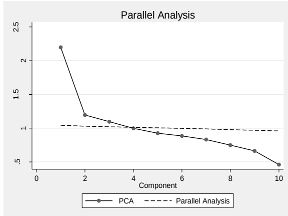
Ghana



Kenya



Liberia



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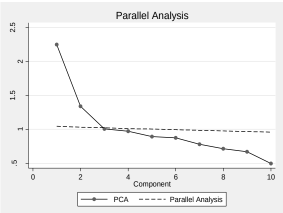
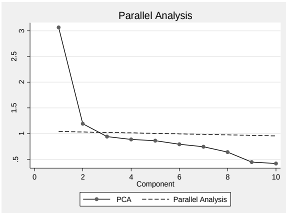
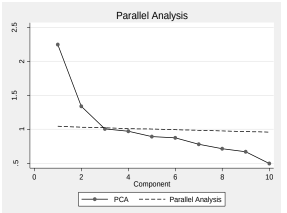


Mali



Mozambique



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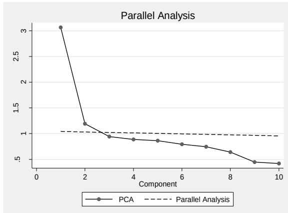

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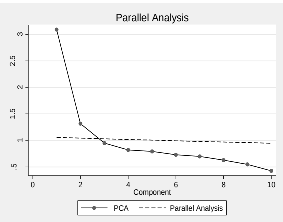
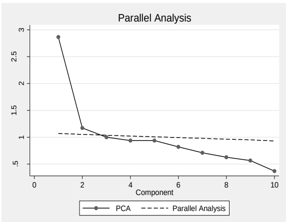


Nigeria



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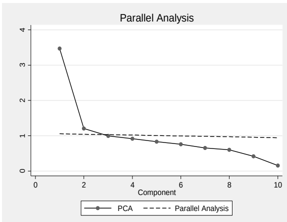
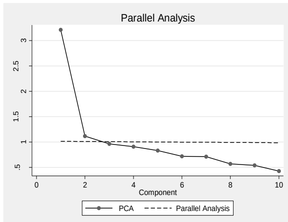
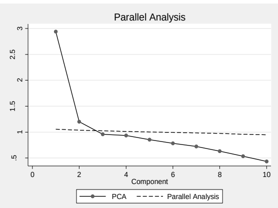


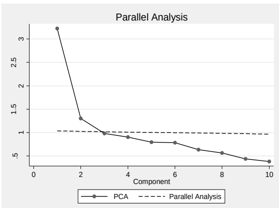
Zambia



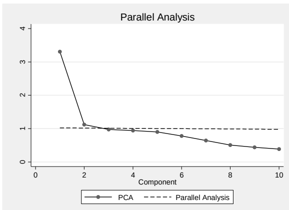
India



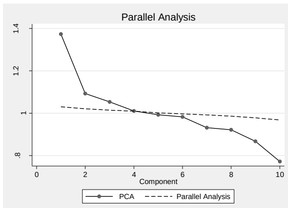
Nepal



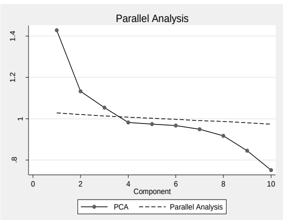
Bolivia



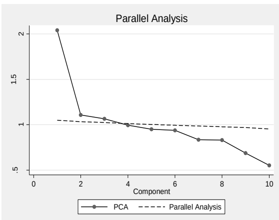
Peru



Armenia



Azerbaijan



Moldova

Table A.4 The rank correlations between original MPI and PCA constructed MPI

Country	Spearman's Correlation
Cameroon	.8965
Congo DMR	.7916
Congo Republic	.8186
Ethiopia	.9146
Ghana	.8816
Kenya	.9049
Liberia	.6949
Malawi	.7953
Mali	.7659
Mozambique	.8473
Namibia	.9062
Niger	.8277
Nigeria	.9059
Swaziland	.8614
Zambia	.8215
India	.9134
Nepal	.8838
Bolivia	.9017
Peru	.9501
Armenia	.9541
Azerbaijan	.8960
Moldova	.8158