Oxford Poverty & Human Development Initiative (OPHI)
Oxford Department of International Development
Queen Elizabeth House (QEH), University of Oxford

Sub-national Disparities and Inter-temporal Evolution of Multidimensional Poverty across Developing Countries

Sabina Alkire[§], José Manuel Roche[†] and Suman Seth[‡]

December 2011

Preliminary Draft released as Research In Progress.
Not for Citation without Permission.

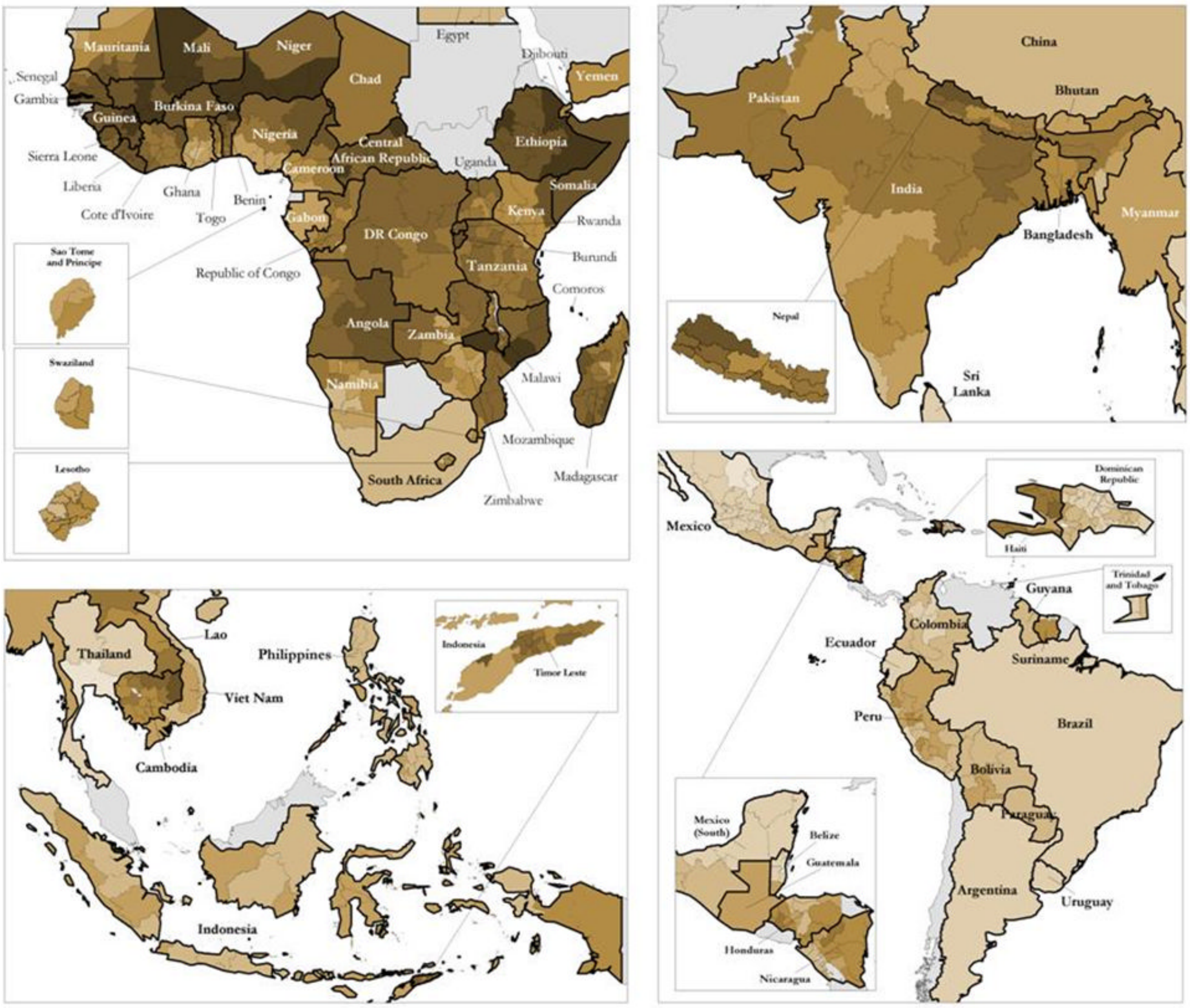
Abstract

In 2010, the Oxford Poverty and Human Development Initiative (OPHI) in collaboration with the United National Development Programme (UNDP) introduced a new multidimensional measure of acute poverty for developing countries, referred to as the Multidimensional Poverty Index (MPI) (Alkire and Santos, 2010). A number of updates and innovative analyses have been introduced in 2011 as explained in Alkire et al. (2011). This paper focuses on the new analyses of sub-national decompositions and changes over time. It analyses the incidence, intensity and composition of multidimensional poverty at sub-national levels for 66 developing countries, and presents poverty estimates for 683 sub-national regions which cover 1.4 billion of the 1.65 billion MPI poor people identified by the MPI in 2011. The results show wide within-country disparities in poverty levels across geographical regions and across low-income and lower-middle-income countries. It confirms previous research which shows that even though the incidence of poverty in low-income countries is much higher, a larger number of poor people live in middle-income countries. In addition, it shows that the poorest sub-national regions of middle-income countries are no less poor than the low-income countries as a whole. In fact, there are also a larger number of severely poor people in middle-income countries than in low-income countries. The paper then further investigates the composition of poverty by analysing which indicators are major contributors to the MPI in each sub-national region. It identifies eleven "poverty profiles" across regions and finds striking examples of regions that have similar compositions but different MPI levels as well as regions with different compositions and similar MPI levels. Finally, the paper analyses changes over time for ten countries and their 158 sub-national regions for which we have comparable data across two different periods of time, providing information regarding the reduction of each indicator within each region. While poverty went down in all countries, the ten countries differ in terms of the rate, spatial patterns, relative reduction of incidence or intensity, and the indicators in which poverty was reduced.

[§] Director, Oxford Poverty and Human Development Initiative, Department of International Development, 3 Mansfield Road, Oxford OX1 3TB, UK +44 1865 271915, sabina.alkire@qeh.ox.ac.uk.
[†] Research Officer, Oxford Poverty and Human Development Initiative, Department of International Development, 3 Mansfield Road, Oxford OX1 3TB, UK +44 1865 271915, jose.roche@qeh.ox.ac.uk.
[‡] Research Officer, Oxford Poverty and Human Development Initiative, Department of International Development, 3 Mansfield Road, Oxford OX1 3TB, UK +44 1865 271915, suman.seth@qeh.ox.ac.uk.

Multidimensional Poverty Index (MPI) at the Sub-national Level

The thematic maps show the MPI results at the lowest level of disaggregation permitted by the existing data. The figures are available at the sub-national level for 683 regions of 66 countries and at the national level for the remaining 43 countries. The poverty estimates correspond to the most recent available data.



Map design: *Diaz, Y., G. Robles, and J.M. Roche*

OPHI - MPI Team

OPHI Research Team: Sabina Alkire (Director), James Foster (Research Fellow), John Hammock (Co-Founder and Research Associate), José Manuel Roche (coordination MPI 2011), Maria Emma Santos (coordination MPI 2010), Suman Seth, Paola Ballon, Gaston Yalonetzky, and Diego Zavaleta.

Data Analysts and MPI Calculation since 2011: Mauricio Apablaza, Adriana Conconi, Ivan Gonzalez DeAlba, Ana Mujica, Gisela Robles Aguilar, Juan Pablo Ocampo Sheen, Sebastian Silva Leander, Christian Oldiges, Nicole Rippin, and Ana Vaz.

Special Contributions: Mauricio Apablaza (analysis of family planning); Yadira Diaz (maps design and preparation); Maja Jakobsen (research assistance since October 2011); Nicole Rippin (methodological inputs); Christian Oldiges (research assistance for regional decomposition and standard errors); Gisela Robles Aguilar (research assistance in tables, data compilation and maps preparation); John Hammock, Sabina Alkire and James Jewell (new Ground Reality Check field material); Maria Emma Santos (methodological inputs and adjustments of MPI methodology); and Gaston Yalonetzky (design and programming for standard error calculation).

Communication Team: Paddy Coulter (Director of Communications), Joanne Tomkinson (Research Communications Officer), Heidi Fletcher (Web Manager), Moizza B Sarwar (Research Communications Assistant), and Cameron Thibos (Design Assistant).

Administrative Staff: Tery van Taack (OPHI Project coordinator) and Laura O'Mahony (OPHI Project Assistant).

OPHI prepared the MPI for publication in the UNDP *Human Development Report*, and we are grateful to our colleagues at the Human Development Report Office (HDRO) for their support.

Acknowledgements

We warmly acknowledge the contribution of many colleagues and co-workers, who participated in the update of the MPI in 2011. In particular, we are grateful to our colleagues at the HDRO and UNDP for their substantive engagement and particularly to Jeni Klugman, Milorad Kovacevic, Khalid Malik, and Emma Samman. This analysis uses data from the Demographic and Health Surveys (USAID), UNICEF Multiple Indicator Cluster Surveys, WHO World Health Surveys and national household surveys.

OPHI gratefully acknowledges support from the UK Economic and Social Research Council (ESRC)/(DFID) Joint Scheme, Robertson Foundation, UNDP Human Development Report Office, UK Department of International Development (DFID), and private benefactors for this work. All errors remain our own.

Contents

List of Tables

List of Figures

List of Appendices

Acronyms:

***A*:**	The **intensity** of multidimensional poverty, measured by the proportion of weighted indicators in which the average multidimensional-poor person is deprived
Arab:	Arab States
DHS:	Demographic and Health Survey
CEE/CIS/CA:	Europe and Central Asia
EAP:	East Asia and the Pacific
ENSANUT:	National Survey of Health and Nutrition for Mexico (Encuesta Nacional de Salud y Nutricion, 2006)
ENNVM:	National Study on Household Living Standards for Morocco (Enquête Nationale sur les Niveaux de Vie des Ménages 2007)
ENNyS:	National Survey of Nutrition and Health, for Argentina (Encuesta Nacional de Nutricion y Salud, 2004-2005
H:	Headcount ratio, or the proportion of the population who are identified as poor
HDI:	Human Development Index
LAC:	Latin America and Caribbean
LIC:	Low-Income Country
LMIC:	Lower-Middle Income Country
MDG:	Millennium Development Goal
MPI:	Multidimensional Poverty Index
MIC:	Middle Income Country
MICS:	Multiple Indicator Cluster Survey
NIDS:	South Africa: National Income Dynamics Study
PEPFAM:	Pan Arab Population and Family Health Project (المشروع العربى لصحة الأسرة)
PNDS:	National Survey of Demographic and Health for Brazil (Pesquisa Nacional de Demografia e Saúde 2006)
SA:	South Asia
SSA:	Sub-Saharan Africa
UMC:	Upper-Middle Income Country
UN:	United Nations
WHO:	World Health Organization
WHS:	World Health Survey

1. Introduction

In 2010 The Oxford Poverty and Human Development Initiative (OPHI) in collaboration with the United National Development Programme (UNDP) introduced a new multidimensional measure of acute poverty for developing countries, referred to as the Multidimensional Poverty Index (MPI) (Alkire and Santos, 2010). A number of updates and innovations have been introduced in 2011 as explained in Alkire, Santos, Roche and Seth (2011). This paper specifically focuses on the analysis of sub-national decompositions and changes over time. It moves beyond national aggregates by analysing multidimensional poverty at the sub-national level. It presents a comprehensive decomposition analysis of the MPI at the sub-national level for 66 countries, obtaining comparable poverty estimates for 683 sub-national regions. The results show wide within-country disparity in poverty levels that a national aggregate cannot reveal.

The MPI is based on the poverty measure referred to as the Adjusted Headcount Ratio: one of the family of measures developed by Alkire and Foster (2007, 2011). The MPI consists of three dimensions and ten indicators reflecting direct deprivation,s and identifies a person as poor in two steps. In the first step, using a deprivation cut-off for each of the ten indicators, it identifies the indicators in which a person is deprived or not. In the second stage, a deprivation score is obtained for each individual by taking a weighted average of the ten indicators, and a person is identified as MPI poor if she is deprived in one third or more of the ten weighted indicators.

Three main features of the MPI can be used as important tools for policy analysis and are particularly helpful in the current paper. The first is that the MPI can be expressed as a product of the *incidence of poverty* or the proportion of the population that are deprived in at least a third of the weighted indicators (Headcount ratio H) and the *intensity of poverty* or the average deprivation score among the poor (A). This form of expression is highly analogous in spirit to the poverty gap measure, which can be expressed as a product of the incidence of poverty (H), and the income gap measure or the normalized achievement shortfall from the poverty line (I). Note that a fall in the incidence of poverty does not necessarily imply that the average intensity of deprivation of the remaining poor has fallen. Using comparable inter-temporal datasets for ten countries across two periods each, we find that a decrease in the MPI of certain countries was obtained through a relatively greater decrease in the incidence, whereas in other countries the decrease was mainly the result of a reduction in the intensity, and in yet others it was the result of a decline in both incidence and intensity.

The second important feature of the measure is that it is decomposable across population subgroups, which can be geographic regions, ethnic or religious groups. We use this feature to create poverty measures for regions within a country. The third helpful feature of the MPI is that it can be broken down into the indicators in which poor people are deprived. In other words, it is possible to compute the contribution of each indicator to overall poverty. We use this feature to generate the poverty profiles associated with a poverty level in a particular region. Analysis of these profiles are revealing; for example we can identify the indicators that are responsible for changes in the MPI over a period of time.

We have already learned from previous studies that even though the incidence of income poverty in low-income countries is much higher, more poor people live in middle-income countries than in the low-income countries (Kanbur, 2011 ; Sumner, forthcoming 2011). In this paper, we confirm that the above statement is true when poverty is assessed according to the MPI. Furthermore we show that the poorest sub-national regions of middle-income countries are no less poor than the low income countries as a whole. There are also a larger number of severely poor people in middle-income countries than in low-income countries. An MPI poor person is identified as severely poor if the person is deprived in 50 percent of the weighted indicators. We find for example that in Namibia, an upper-middle income country with a population of less than 2.5 million, 40 percent of people are MPI poor – more than in Kyrgyzstan, a low-income country. A comparison of sub-national regions across different geographic regions, but within the same income category, also yields interesting evidence. For example, Nepal, a low-income country in South Asia, is much poorer than Cambodia, a low-income country in the East Asia and Pacific region, but the poorest region of Cambodia is even poorer than the poorest region of Nepal. We also see that the 26 poorest sub-national regions of South Asia have more poor people and a higher combined MPI than the 38 countries of Sub-Saharan Africa combined.

This paper analyses the composition of poverty across and within countries – in one time period and across time. We find, for example, that different sub-national regions with a similar MPI may have a very different composition of poverty while sub-national regions with a different MPI may also have a similar composition of poverty. For example, Bariasal, a sub-national region in Bangladesh – a low-income country – has a similar level of poverty as Ziguinchor, a sub-national region in Senegal – a lower-middle-income country. However, the composition of poverty is very different in these two regions. In Barisal, the major contributor to poverty is nutrition, whereas in Ziguinchor, the major contributor to poverty is child mortality. On the other hand, the level of poverty in Orissa, a sub-national region in India – a lower-middle-income country – is quite different from the level of poverty in Chittagong, a lower-middle-income region in Bangladesh; but the contributions of the three dimensions – health, education, and standard of living – are highly similar. We analyse the composition of poverty and identify different "poverty profiles" across the regions under study.

In terms of dynamic analysis, the paper compares changes in MPI for ten countries and their 158 sub-national regions for which comparable results across time are available. Trends in the MPI over time show different patterns of MPI poverty reduction – in terms of spatial distribution, the relative reduction of incidence or intensity, and the indicators in which poverty was reduced. For example, Ethiopia, a low-income country, reduced its MPI over a period of five years mainly by reducing the average intensity of poverty rather than its incidence; while Nigeria, a lower-middle-income country, reduced its MPI also over a period of five years, but mainly by reducing the incidence of poverty rather than the average intensity across the poor.

The paper is divided into seven sections. In the second section, we present the methodology and the data that are used for our analysis in this paper. In the third section, we analyse the geographical disparities in MPI across countries and across sub-national regions. The fourth section is dedicated to understanding the distribution of poverty or where the poor people reside. In the fifth section, we analyse the composition of multidimensional poverty across the indicators. We discuss the results of changes over time for ten countries in the sixth section. Finally we provide some concluding remarks.

2. Methodology and Data

The MPI uses particular dimensions, indicators, weights and cut-offs to implement a general multidimensional measure called the Adjusted Headcount Ratio (M_0) proposed by Alkire and Foster (2011, 2007).[1]

This section is divided into six subsections. In the first subsection, we outline the Alkire and Foster methodology (AF) and its useful properties. In the next three subsections, we discuss different properties and consistent sub-indices of the AF methodology that we use in the following sections. We introduce the MPI methodology following Alkire and Santos (2010) and Alkire et al. (2011) in the fifth subsection. In the sixth subsection, we outline the data used in this paper.

2.1. The Adjusted Headcount Ratio (M_0)

Let us start by assuming that the population size of a country is n and there are d indicators under consideration.[2] We denote the achievement of person i in indicator j by $x_{ij} \in \mathbf{R}_+$ for all $i = 1, ..., n$ and all $j = 1, ..., d$. The achievements of all n persons in all d indicators are summarized by an $n \times d$– dimensional matrix X. Thus, row i of matrix X represents the achievement vector of person i, summarizing the person's achievement in all d indicators. Similarly, column j of the matrix represents the vector of achievements in indicator j, summarizing the achievements of all n persons in that indicator. A person is deprived in an indicator if her achievement falls below a threshold, which we refer to as the *deprivation cut-off*.[3] In other words, person i is deprived in indicator j if and only if $x_{ij} < z_j$, where z_j is the deprivation cut-off of indicator j. The deprivation cut-offs of all d indicators are summarized by the *deprivation cut-off vector z*.

Each indicator in constructing the M_0 may not necessarily be weighted equally. We denote the weight attached to indicator j by w_j, such that $w_j > 0$ for all j and $\Sigma_j w_j = 1$.[4] The weights of

[1] Alkire and Foster (2011, 2007), in fact, proposed an entire class of multidimensional poverty indices, which is an extension of the class of single-dimensional FGT measures (Foster, Greer and Thorbecke, 1984). The Adjusted Headcount Ratio is one multidimensional poverty measure in their class.

[2] Alkire and Foster denote each column of an achievement matrix as a 'dimension'. In this report, we change terminology and refer to each column of an achievement matrix as an 'indicator'; whereas the term 'dimensions', in the current context, refers to conceptual groupings of indicators that do not appear in the matrix.

[3] In the single-dimensional analysis of poverty, a person is identified as poor if and only if the person is deprived in that dimension. However, this equivalence does not hold in multidimensional context.

[4] Note that Alkire and Foster (2011) require the weights to sum to *d*. Here the weights sum to 1. This is easy to explain as the weights are 1/3 per dimension and then 1/6 or 1/18 per indicator. However note that with this weighting structure M_0 is *not*

all d indicators are represented by the *weight vector* w. Now, given the achievement matrix X, the deprivation cut-off vector z, and the weight vector w, we attach a deprivation status score g_{ij} to each person i in each indicator j, such that $g_{ij} = w_j$ if person i is deprived in indicator j and $g_{ij} = 0$, otherwise. We summarize the deprivation status score of n persons in d indicators by the matrix g, such that the ij^{th} element of g is g_{ij}. The matrix g in that case summarizes the *deprivation profile* of the entire country. From the deprivation matrix g, we construct a *deprivation score* c_i for each person i such that $c_i = \Sigma_j\, g_{ij}$. Thus, if person i is deprived in all indicators, then $c_i = 1$ because $\Sigma_j\, w_j = 1$; if person i is not deprived in any indicator, then $c_i = 0$; and if person i is only deprived in indicator j, then $c_i = w_j$. The *deprivation score vector* is denoted by the notation c.

The AF methodology identifies the multidimensionally poor using a *poverty cut-off*, which in this notation would be a cut-off $k \in (0,1]$, such that a person i is poor if and only if $c_i \geq k$.[5] An identification function $\rho_i(k)$ is applied to each person i to represent her poverty status: $\rho_i(k) = 1$ if $c_i \geq k$ – that is, if person i is identified as poor – and $\rho_i(k) = 0$, otherwise. Based on the identification function, we obtain a *censored deprivation matrix* $g(k)$, such that its ij^{th} element is $g_{ij}(k) = g_{ij}\times\rho_i(k)$. In other words, the deprivation in each indicator is censored in such a way that the deprivation status of each non-poor person is zero in all indicators and the resulting poverty measure reflects only the deprivations of poor persons.[6] This identification step allows us to construct a *censored deprivation score vector* $c(k) = (c_1(k), ..., c_n(k))$ such that $c_i(k) = \Sigma_j\, g_{ij}(k)$. Thus, $c_i(k) = c_i$ if $c_i \geq k$ and $c_i(k) = 0$, otherwise. Then the Adjusted Headcount Ratio of matrix X given deprivation cut-off vector z, poverty cut-off k and weight vector w is $M_0(X;\, z,k,w) = (q/n)\times[\Sigma_i\, c_i(k)/q] = H\times A$, where q is the number of poor.[7] Thus, $H = q/n$ is simply the proportion of the population that is identified as multidimensionally poor or the *Multidimensional Headcount Ratio* (H) and $A = \Sigma_i\, c_i(k)/q$ is the *average deprivation score* among the poor, which intuitively reflects the average 'intensity' of poverty among the poor. For notational simplicity, instead of writing $M_0(X;\, z,k,w)$ reiteratively, we simply use the notation $M_0(X)$ assuming a given deprivation cut-off vector z, a poverty cut-off k and a weight vector w.

2.2 Properties

The Adjusted Headcount Ratio or M_0 has several desirable properties, such as *dimensional monotonicity*, *deprivation focus*, *poverty focus,* and *subgroup decomposability* in addition to standard properties.[8] The first two of these three properties – dimensional monotonicity and

---

the mean of the censored matrix, which it is if the weights sum to d as in Alkire and Foster 2011 or Alkire and Santos 2010. Rather, using the current notation M_0 is the mean of the matrix times d. That is, $M_0 = d(\mu[g_{ij}(k)])$.

[5] If the poverty cut-off $k \in (0,\min_j \{w_j\}]$, then the approach for identifying the poor is called the *union approach*; if the poverty cut-off $k = 1$, then the identification approach is referred as the *intersection approach*.

[6] This property is known as *poverty focus*, which requires that an increment in the achievement of a non-poor person in any indicator should not change the level of poverty in a country.

[7] When the Adjusted Headcount Ratio is estimated from a sample survey, where each person n has a different weight W_i, then $M_0(X;\, z,k,w,W) = [\Sigma_i\, W_i\times c_i(k)]/[\Sigma_i\, W_i]$.

[8] The standard properties of a poverty measure are *symmetry* or *anonymity*, *population invariance*, *scale invariance*, and *normalization*, which are common to both single-dimensional and multidimensional poverty measurement. The first four are called *invariance* properties as they require a poverty measure to remain unchanged for various transformations of data. *Symmetry* requires that permutation of achievements across people should not change a poverty measure; *population*

deprivation focus – can be explained as follows. The *dimensional monotonicity* property requires that if a poor person becomes deprived in an additional indicator in which she was not deprived earlier, then poverty increases (because $c_i(k)$ increases). Note that while the M_0 satisfies this property the multidimensional headcount ratio (H) does not satisfy the dimensional monotonicity property as it only reflects the number of poor and not the share indicators in which the poor are deprived (A). The *deprivation focus* property requires that if the achievement of a poor person increases in an indicator in which she is not already deprived, then the level of poverty remains unaltered. With this property, we assume that the indicators in which poor people are deprived are intrinsically important and improvements in their non-deprived indicators should not cause their deprived indicators to be overlooked. In other words, an increase in achievement in the non-deprived indicators should not compensate for deprivations; this approach resonates with a human rights approach to development.

The last of these properties – *subgroup decomposability* – is the most important property in context of the current analysis. In this paper, our principal interest is in dividing the entire country's population into different population subgroups to understand sub-national poverty and how a sub-national region contributes to overall poverty.[9] Suppose, there are m such population subgroups in our reference country whose achievement matrix is X. Let us denote the achievement matrix of population subgroup l by X_l which has a population size of n_l for all $l = 1, ..., m$, such that $\Sigma_l\, n_l = n$. Then the relation between the subgroup Adjusted Headcount Ratios and that of the country as a whole is:

$$M_0(X) = \Sigma_l \frac{n_l}{n} M_0(X_l).$$

The share of subgroup l to the overall poverty is given by $(n_l/n)\times[M_0(X_l)/M_0(X)]$. Subgroup l has higher poverty than subgroup l' if and only if $M_0(X_l) > M_0(X_{l'})$. Thus, subgroup decomposability is a useful property for understanding the contribution of a subgroup to the overall poverty.

2.3 Censored Headcount Ratio

The Adjusted Headcount Ratio is decomposable by sub-group and can be broken down by indicators (after identification), like all other measures in the Alkire-Foster class. Decomposability across the population is assured by the subgroup decomposability property discussed above; whereas the ability to break down the MPI across indicators is useful for policy because the *adjusted headcount ratio* is constituted by the weighted average of censored headcount ratios. That means that the MPI has, associated with it, a set of consistent

invariance requires that if the population with the same achievements are cloned a finite number of times, a poverty measure should not change; *scale invariance* requires that if all achievements are increased or decreased by a same factor, then a poverty measure should not change; and *normalization* requires that if there are no poor in a country then the poverty measure should be equal to zero.

[9] Subgroup decomposability is related to subgroup consistency, which requires overall poverty to increase if poverty increases in one subgroup and remains fixed in the others, if the population is constant. See Foster and Sen (1997).

measures for each of the ten component indicators, which we call censored headcount ratios. The *censored headcount ratio* of an indicator is obtained by adding up the total number of poor people who are deprived in that particular indicator and dividing by the total population. The censored headcount ratios reflect the absolute levels of people who are poor and deprived in each indicator. If the censored headcount ratio of indicator j is denoted by $h_j(X)$, then M_0 can be expressed as:

$$M_0(X) = \Sigma_j \, w_j h_j(X).$$

Even though the censored headcount ratio refers to a particular indicator, it is, in fact, a function of the entire achievement matrix X and may be affected by a change in the deprivation cut-off vector (z), the poverty cut-off (k), or the set of weights (w).[10]

As the above expression suggests, at times it can be useful to break down the M_0 according to the contribution to poverty that is due to each indicator. This entails a consideration not only of the censored headcount ratio, but also of the relative weight on that indicator. One natural way of reflecting this is to calculate the *contribution* of each indicator to poverty, or, perhaps more intuitively, the *percentage contribution* such that the sum of the contributions is equal to 100%. Recall that the adjusted headcount ratio is formulated as $M_0 = (1/n)\times[\Sigma_i \, c_i(k)] = (1/n)\times[\Sigma_i \Sigma_j \, g_{ij}(k)] = (1/n)\times[\Sigma_j \Sigma_i \, g_{ij}(k)] = \Sigma_j \Sigma_i \, [g_{ij}(k)/n] = \Sigma_j \, w_j h_j$.[11] The percentage contribution of an indicator j to overall poverty is $Contr_j = w_j h_j(X)/M_0(X)$.

2.4 Changes across Time

We have already shown that the adjusted headcount ratio can be expressed in various ways. For example, it can be expressed as a product of the multidimensional headcount ratio and the intensity of deprivation among the poor or $H\times A$. It can also be expressed as a weighted average of censored headcount ratios $\Sigma_j w_j h_j(X)$ and a population weighted average of subgroup poverty $\Sigma_l (n_l / n) M_0(X_l)$. These provide useful frameworks for breaking down the overall change in the adjusted headcount ratio across two time periods into various factors. Two types of change in poverty are generally of interest: absolute change across two time periods and percentage change across two time periods. The *absolute change* provides the difference in level of any focal indicator across two periods (j_y in period 2 minus j_x in period 1); whereas the *percentage change* in poverty expresses the change relative to the initial poverty level $(j_y - j_x)/j_y$. Looking at either one of them alone may be insufficient. Looking merely at the absolute change is not enough because it does not contain any information about the level of poverty in the initial period. Similarly, looking at the percentage change is incomplete because, say, a 50 percent fall in poverty for a country which had a very high

[10] For the union approach, the censored headcount ratio of a dimension is equal to the raw headcount ratio of that dimension. The *raw headcount ratio* is the proportion of the population that are deprived in that dimension, regardless of whether they are identified as poor. For the intersection approach, the *censored headcount ratio* of every dimension is equal to 100%.

[11] Recall that $g_{ij} = w_j$ if person i is deprived in indicator j and $g_{ij} = 0$, otherwise. Thus, technically $h_j = (\Sigma_i \, g_{ij}\times\rho_i(k)/n)/w_j$. In other words, h_j is the number of deprivations in j^{th} column of $g(k)$ divided by the total population n.

level of poverty initially implies a very different kind of achievement compared to a 50 percent fall in poverty for a country with a very low level of poverty to begin with.

For two different time periods t_x and t_y such that $t_x < t_y$, let us denote a country's achievement matrices by X and Y, respectively. Then the annual absolute change in the adjusted headcount ratio between period t_x and t_y is denoted by:

$$\Delta M_0(X,Y;\ z,k,w) \ = \ \frac{[M_0(Y;\ z,k,w)\ - M_0(X;\ z,k,w)]}{t_y - t_x}.$$

The annual percentage change in the adjusted headcount ratio between period t_x and t_y is denoted by:

$$\delta M_0(X,Y;\ z,k,w) = 100 \times \frac{[M_0(Y;\ z,k,w)\ - M_0(X;\ z,k,w)]}{(t_y - t_x)M_0(X;\ z,k,w)}.$$

For notational simplicity, we express the annual absolute and percentage (relative) changes in poverty by ΔM_0 and δM_0, respectively. We express the annual change in other factors using analogous notation.

The Adjusted Headcount Ratio (M_0) conveys simultaneously the information about the incidence of poverty and the intensity of poverty. Similarly, changes in M_0 over time can be the effect of changes in incidence or intensity or the interaction between both. Thus the M_0 provides an incentive to bring someone out of poverty – to reduce the headcount. It also provides an incentive to reduce the intensity of poor people's poverty – even if they remain multidimensionally poor. Following Apablaza and Yalonetzky (2011), we decompose the change of M_0 as follows:

$$\delta M_0 = \delta H + \delta A + \delta H \times \delta A$$

We now turn to one particular implementation of this methodology, the international Multidimensional Poverty Index (MPI).

2.5 The Multidimensional Poverty Index (MPI)

The Multidimensional Poverty Index or the MPI is an Adjusted Headcount Ratio developed by Alkire and Santos (2010) using three dimensions of well-being: *health*, *education*, and *standard of living*. These are the same the same three dimensions as the *Human Development Index* (HDI). The health dimension consists of two indicators which are defined distinctively from standard indicators, *nutrition* and *child mortality*; the education dimension consists of two similarly distinctive indicators, *years of schooling* and *child school attendance*; and the standard of living dimension consists of six indicators, *access to electricity*, *access to an improved sanitation facility*, *access to drinking water*, *type of flooring material*, *type of cooking fuel*, and *asset ownership*. The MPI has ten indicators and so it is an M_0 with $d = 10$.

Table 2.1 reports the dimensions, indicators, deprivation cut-offs, and weights for constructing the MPI.[12]

The first column of Table 2.1 reports the three dimensions, where corresponding weights are in parentheses. The second column reports the indicators; again the weights are reported in parentheses. Each of the three dimensions is equally weighted (1/3 each) under the implicit assumption that each of them is equally important to a person's well-being. Similarly, each indicator within a dimension is also equally weighted. As a result, each indicator of the health and education dimensions receives a 1/6 weight; whereas each indicator of the standard of living dimension receives a 1/18 weight. Note that the weights of all indicators sum up to one. Out of the ten indicators, eight are related to the Millennium Development Goals.

Table 2.1: Dimensions, Indicators, Deprivation Cut-offs, and Weights of MPI

Dimension (Weight)	Indicator (Weight)	Poverty Cut-off
Health (1/3)	Nutrition (1/6)	*Any adult or child in the household with nutritional information is undernourished*[13]
	Child mortality (1/6)	*Any child has died in the household*[14]
Education (1/3)	Years of schooling (1/6)	*No household member has completed five years of schooling*
	Child school attendance (1/6)	*Any school-aged child in the household is not attending school up to class 8*[15]
Standard of Living (1/3)	Access to electricity (1/18)	*The household has no electricity*
	Access to improved sanitation (1/18)	*The household´s sanitation facility is not improved or it is shared with other households*
	Access to safe drinking water (1/18)	*The household does not have access to safe drinking water or safe water is more than 30 minutes walk round trip*
	Type of flooring material (1/18)	*The household has a dirt, sand or dung floor*
	Type of cooking fuel (1/18)	*The household cooks with dung, wood or charcoal.*
	Asset ownership (1/18)	*The household does not own more than one of: radio, TV, telephone, bike, motorbike or refrigerator, and does not own a car or truck*

A person is identified as poor if the deprivation score of that person is greater than or equal to 1/3. What is the justification behind this poverty cut-off? Given that there are three dimensions, the weight of each dimension is 1/3 and a poverty cut-off of 1/3 implies that a

[12] For a thorough and detailed presentation of the indicators and poverty cut-offs, as well as the treatments of households lacking eligible members and of missing responses see Alkire and Santos (2010) and Alkire, Santos, Roche, and Seth (2011).
[13] An adult is considered undernourished if his/her BMI is below 18.5 m/kg^2. A child is considered undernourished if his/her body weight, adjusted for age, is more than two standard deviations below the median of the reference population. Precisely, a z-score is calculated for each child and the child is identified as deprived in nutrition if and only if his/her z-score is less than −2. If a household has no woman or child whose nutritional status has been measured, we treat the household to be non-deprived in this indicator. To guarantee strict comparability of the nutritional indicators for children across surveys, the z-score has been estimated following the algorithm provided by the WHO Child Growth Standards. This algorithm uses a reference population constructed by the WHO Multicentre Growth Reference Study (MGRS).
[14] If no woman in a household has been asked this information, we treat the household to be non-deprived in this indicator.
[15] If a household has no school-aged children, we treat the household as non-deprived in this indicator. The data source used to determine the age children start schooling is: United Nations Educational, Scientific and Cultural Organization, Institute for Statistics database, Table 1. Education systems
[UIS, http://stats.uis.unesco.org/unesco/TableViewer/tableView.aspx?ReportId=163 accessed 20-12-2011].

person is identified as poor if she is deprived only in one health indicator and three standard of living indicators, then his/her deprivation score is 1/3 and the person is identified as poor.

The MPI, being an Adjusted Headcount Ratio, inherits its characteristics. The MPI is the product of the *incidence of poverty* and *intensity of poverty*. The *incidence of poverty* is the multidimensional headcount ratio (H) and the *intensity of poverty* is the average deprivation score among the poor (A). Thus, MPI = $H \times A$. As an Adjusted Headcount Ratio, the MPI can naturally be decomposed across population subgroups and can be represented as a weighted average of censored headcount ratios of the ten selected indicators. While comparing the MPI of a country across two points in time t_x and t_y with achievement matrices X and Y, the percentage change in the MPI can be broken down into percentage changes in the incidence and the intensity of poverty to understand the source of the change, i.e., $\delta MPI = \delta H + \delta A + \delta H \times \delta A \times (t_y - t_x)$.

2.6 Data for Sub-national Analysis

Among the 109 countries, the MPI 2011 was computed using Demographic and Health Surveys (DHS) for 54 countries, Multiple Indicators Cluster Surveys (MICS) for 32 countries, World Health Surveys (WHS) for 17 countries, and six countries were computed using country specific surveys.[16]

We conducted the decomposition analysis for 66 countries using surveys that satisfy three criteria: (i) the survey of the country is representative at the sub-national level, (ii) the incidence of poverty (H) and the MPI are both large enough so that a meaningful sub-national analysis can be pursued, and (iii) the sample size after the treatment of missing and non-response data is reasonably high both at the national level and at the sub-national level. For borderline cases, we performed additional bias analyses to exclude those cases where the sample reduction leads to statistically significant bias.

Let us now elaborate each of these three criteria. The *first criterion* requires that the survey dataset should be representative at the sub-national level according to the metadata of the sample design and to basic tabulates in the country survey report.[17] The first criteria, thus, excludes 24 country surveys from our analysis, out of which 17 are World Health Surveys (WHS), two are Demographic Health Surveys (DHS), two are Multiple Indicator Cluster Surveys (MICS), the ENNYS survey of Argentina, the NIDS survey of South Africa, and the ENNVM survey of Morocco. This leaves 85 countries with a survey design representative at the sub-national level. The *second criterion* requires that we only include those countries for the decomposition analysis whose MPI is larger than 0.005 and the incidence of poverty is higher than 1.5 percent. The survey dataset may not have enough observations on the poor for conducting any statistically significant inter-regional analysis otherwise. This eliminates a

[16] For a list of the particular country datasets and years from which the MPI have been computed, see Alkire et al (2011).

[17] The report had to explicitly indicate that the sample design allows for representative results at the sub-national level for which MPI decompositions were estimated. In addition, the report also had to provide estimations at this level among the basic tabulates on child mortality rate or a similar indicator.

further eight countries from our analysis, out of which two are DHS, five are MICS, and the PAPFAM survey.

The third criterion prevents computation bias arising from missing and non-response data. One requirement of the MPI computation is that the data for all indicators under consideration must be available from the same survey. The second requirement is that only the intersection of non-missing data for all indicators can be used. In other words, if usable data for a respondent are available for some indicators under consideration and are missing for the rest, then we treat the respondent as having missing data and drop the respondent from the MPI calculations. Missing data are common in any survey and out of the 78 countries that have passed our first two criteria, only ten surveys have less than 1 percent of the sample missing, but 64 and 71 countries have less than 10 percent and less than 15 percent of the sample missing respectively. We assume that a sample drop of more than 15 percent at the national level affects the accuracy of the estimate and comparability across sub-national estimations. This requirement eliminates six more surveys, out of which two are DHS and four are MICS.[18]

We apply the same rule to sub-national regions but with minor adjustments. Among the 71 countries with less than a 15 percent sample drop, eleven countries have a total of 32 sub-national regions with more than a 15 percent sample drop. We face a trade-off here. On the one hand, inclusion of these countries could cause the statistics of these 32 sub-national regions to be biased; on the other hand, eliminating these eleven countries would cause a loss of 157 sub-national regions, out of which 125 regions have less than a 15 percent sample drop. Therefore, we select two more lenient sub-criteria for the sub-national regions. One is that we definitely eliminate those countries which have at least one region with more than a 25 percent sample drop, which eliminates four out of the eleven countries (three are MICS and the other is the PNDS survey of Brazil). In the second sub-criteria, we conduct a *bias test* for the remaining sub-national regions with sample size between 75 and 85 percent. We identify the major cause of the sample reduction in a region and divide the entire sample of that region into two groups based on this major cause. For example, if a majority of the sample has been dropped due to the nutrition and toilet indicators, then the entire sample is divided into two groups: one that contains the sample with missing values of nutrition and toilet indicators and the other that contains the sample with non-missing values of nutrition and toilet indicators. Then we check the headcount ratios of the remaining indicators and the share of urban and rural population across these two groups. If there is systematic and statistically significant (at a 1 percent significance level) difference between the headcount ratios across these two groups, then that region does not satisfy the bias test. If a sub-national region with more than 20 percent of a country’s population share (measured by the weighted sample share before sample drop) does not pass the bias test, we exclude the country from our analysis. This excludes one MICS survey only. A few regions of Mauritania, the Dominican Republic, and Nicaragua did not pass the bias test, but none of these has a

[18] The weighted sample shares before and after the treatment of missing samples of some of the sub-national regions in each of these seven countries varied from 8 to 15 percent. Such large disparities may cause a loss of representativeness while computing the sub-national statistics.

population share of more than 9 percent of its country's population. Hence, these countries are retained in our analysis.[19]

In the end, 66 survey datasets with 683 sub-national regions satisfy all three selection criteria and are analysed in this paper. Out of these survey datasets 48 are DHS, 17 are MICS, and one is the ENSANUT survey.[20] As is evident from Table 4, the 66 countries cover 3.18 billion of the 5.3 billion people covered by the 109 countries. Based on the World Bank income categories from 2011, our analysis covers 612.6 million from 25 LICs, or 80.5 percent of the LIC population, and 2.2 billion from 29 LMICs or 91.1 percent of the global LMIC population. The coverage for the UMCs is only 14.2 percent, which is significantly lower than the country-level coverage for MPI 2011 mainly because we were not able to use the World Health Survey datasets covering around 1.5 billion people including China.

The data includes one survey from 2010, eight from 2009, seven from 2008, eleven from 2007, eighteen from 2006, fourteen from 2005, three from 2004, and one each from 2003, 2002, 2001, and 2000. The population of the seven countries whose are older than 2005 is 240.4 million or 7.56 percent of 3.18 billion.[21] Only 5.52 percent of the population among LMICs and 2.98 percent of the population among LICs are from surveys older than 2005.

3. Geographical Disparities in Multidimensional Poverty: National and Sub-National Perspectives

In 2011, the MPI has been computed for 109 countries across the globe.[22] If we aggregate the people living in our 109 countries using 2008 population data, these countries cover 5.3

[19] The sub-national regions that failed the bias test (apart from the Northern region of Somalia) are Atlántico Norte (RAAN), Chontales, Atlántico Sur (RAAS) and Jinotega of Nicaragua; Independencia and Pedernales of the Dominican Republic; and Hodh El GharbiInchiri of Mauritania. The population share of the Northern region of Somalia was more than 20 percent and so Somalia was eliminated. The rest of the regions failed the test, but are retained because their weighted sample shares were not large enough. However, caution should be taken when drawing any conclusion based on these sub-national regions.

[20] Countries for which **DHS** has been used are Bangladesh (2007), Benin (2006), Bolivia (2008), Cambodia (2005), Cameroon (2004), Colombia (2010), Cote d'Ivoire (2005), DR Congo (2007), Dominican Republic (2007), Egypt (2008), Ethiopia (2005), Ghana (2008), Guinea (2005), Haiti (2006), Honduras (2006), India (2005), Indonesia (2007), Jordan (2009), Kenya (2009), Lesotho (2009), Liberia (2007), Madagascar (2009), Malawi (2004), Mali (2006), Moldova (2005), Mozambique (2009), Namibia (2007), Nepal (2006), Nicaragua (2006), Niger (2006), Nigeria (2008), Pakistan (2007), Peru (2004), Philippines (2008), Republic of Congo (2009), Rwanda (2005), Sao Tome and Principe (2009), Senegal (2005), Sierra Leone (2008), Swaziland (2007), Tanzania (2008), Timor Leste (2009), Turkey (2003), Uganda (2006), Ukraine (2007), Viet Nam (2002), Zambia (2007), and Zimbabwe (2006). Countries for which **MICS** has been used are Angola (2001), Belize (2006), Burundi (2005), Central African Republic (2000), Djibouti (2006), Gambia (2006), Lao (2006), Macedonia (2005), Mauritania (2007), Mongolia (2005), Montenegro (2005), Suriname (2006), Tajikistan (2005), Thailand (2005), Togo (2006), Trinidad and Tobago (2006), and Uzbekistan (2006).

[21] Among these seven countries with a survey older than 2007, the Central African Republic (4m) and Malawi (14m) are LICs; Angola (18m), Cameroon (19m) and Viet Nam (86m) are LMICs; and Peru (29m) and Turkey (71m) are UMCs.

[22] In comparison to MPI 2010, the MPI 2011 includes five completely new countries (Bhutan, Maldives, Timor-Leste, Uganda, and Vanuatu) and updated figures for 20 countries for which more recent data is now available (Albania, Bolivia, Brazil, Colombia, Dominican Republic, Jordan, Kenya, Lesotho, Madagascar, Morocco, Mozambique, Nicaragua, Nigeria, Occupied Palestinian Territories, Philippines, Republic of Congo, Sao Tome and Principe, Sierra Leone, South Africa, and Suriname). For further details on updates in MPI 2011 see Alkire, Roche, Santos, and Seth (2011).

billion people – or 78.6 percent of the global population and 93.4 percent of people in developing countries.[23]

These countries are located in six different geographical regions: Sub-Saharan Africa (SSA), South Asia (SA), East Asia and the Pacific (EAP), Latin America and Caribbean (LAC), Arab States (Arab), and Europe and Central Asia (CEE/CIS/CA).[24] If these countries are divided by the World Bank income categories, then they cover 92.1 percent of the population from 31 low-income countries (LIC), 97.5 percent of the population from 42 lower-middle-income countries (LMIC), and 89.8 percent of the population from 28 upper-middle-income countries (UMC).[25] Together the LICs and LMICs are well represented; MPI countries cover 96 percent of their population. Given that our selection of indicators is not designed for high income countries, the population coverage is only 18 percent for the high income non-OECD countries, and 2.9 percent for the high income OECD countries, respectively.

A person is identified as *poor* according to the MPI (this can occasionally be called MPI poor) if the person is deprived in one-third or more of the ten weighted indicators, whereas a person is identified as *severely poor* if the person is deprived in half or more of the ten weighted indicators. The term 'severe poverty' follows the terminology used by the UNDP's 2011 *Human Development Report* which is the first to publish these as a column in the table on the MPI (UNDP, 2011). Note that the persons who are in severe poverty are a subset of the MPI poor; all severely people are already counted in the MPI but in certain analyses we also report the subset of MPI poor who experience *half or more* deprivations.[26]

3.1 Overview of 2011 Results by Income Category and Geographical Region

Of the 5.3 billion people in these 109 countries, about 1.65 billion people – 31.1 percent of their combined population – live in multidimensional poverty according to the MPI. This exceeds the total number of people in those countries estimated to live on US $1.25 a day or less using the most recent estimates of the World Bank's measure of 'extreme' income poverty. It is less than the total number of people living on less than US $2 a day.[27] For the

[23] All population references in this report are based on 2008 population data (United Nations, 2011) unless otherwise indicated, updating the Alkire and Santos 2010 figures, which used 2007 population data. As the survey data come from years 2000-2010, this implies an assumption that the level of poverty has not changed since the year of the survey, which is a strong assumption. On the other hand, unless we use any one particular population year, no analysis on international comparison is possible. The average year of the survey weighted by the country population is 2005. Two possible alternatives to year 2008 could have been either 2005 or the most recent survey year which is year 2010. Therefore, in this paper, we also verify the crucial results for these two additional years. We re-affirm the need to exercise care in comparing MPI values between countries not only due to differences in the survey years, but also due to the differences in number of indicators, indicator definition, data quality, and sampling frame. Where such comparisons are made several alternative methodologies have been implemented and documented to ensure that the results are as robust as possible.

[24] The classification of geographical regions is based on the UNDP classification of countries found in UNDP (2011).

[25] The World Bank income categories are based on the Gross National Incomes estimated using the Atlas Method. For the methodology, please see page 405 of the World Development Indicators (2010) of the World Bank.

[26] Note that because the basic building block of the MPI is the individual deprivation profile, it is possible in a similar manner to identify those who are deprived in 90 percent or more, in 80 percent or more, and so on. These are actually reported in the MPI country briefs

[27] Based on the available latest income figures for 103 out of 109 countries, we find that the total number of people living on $1.25 a day or less and $2 or less are 1.34 billion and 2.5 billion, respectively, by 2008 population figures; whereas the number of MPI poor in these 103 countries is 1.62 billion (we do not have income poverty data for 6 countries). Because the income poverty data also comes from different years, if we use the $1.25 a day and $2 a day poverty figures that are closest

purposes of this paper, two overall findings are important to grasp. These relate to the division of MPI poor people across countries as categorized by their **income per capita**, and the division of MPI poor people across countries as classified by **geographical regions**. The findings are below:

I. Most MPI poor people live in middle income countries. Using 2008 population data, we find that about 1.19 billion MPI poor people live in middle-income countries, while 460 million MPI poor people live in low-income countries.[28] This finding confirms the Sumner finding, using an entirely different poverty measure. We also find, that most people living in *severe poverty* live in MICs. It would be natural to assume that the MPI poor people in middle income countries experienced less intense poverty than their counterparts in low income countries. And to some extent that will be true. But that overall story hides the real comparison. We find that the number of severely poor people in MICs is 586.2 million, and that in LICs is 285 million. So, around twice as many people in severe poverty live in MICs.[29]

II. In terms of geographical region, of the 1.65 billion MPI poor people, half live in South Asia (50.1 per cent or 826.9 million people) and 28.7 percent in Sub-Saharan Africa (473.3 million). The combined MPI for Sub-Saharan Africa is the highest (0.360) followed by South Asia (0.280). While this story of MPI poverty gives a broad overview, it can be sharpened by further analysis both of differences between countries and between sub-national regions of countries. For example, as was just stated, Sub-Saharan Africa has the highest combined MPI rate of the world regions. However the poorest 26 sub-national regions of South Asia (home to 519 million MPI poor people), have higher MPI poverty than Sub-Saharan Africa's 38 countries (which 473.3 million MPI poor people call home). The combined MPI of those 26 South-Asian regions is 0.366. So both regions have a comparable population of people experiencing a comparable intensity of poverty which requires attention.

The remainder of this paper adds detail and sophistication to these headline findings, using both cross-national analyses, and comparisons of sub-national regions and of changes over time. In doing so, it demonstrates some ways in which a multidimensional measure of

to the MPI survey year (whether earlier or later than it), the total number of people living on $1.25 a day or less and $2 or less are 1.56 billion and 2.8 billion, respectively, by 2008 population figures. The number of poor people living on $1.25 a day or less is much closer in this case, but still lower than the number of MPI poor. We also compare the number of MPI poor and the number of people living in $1.25 or less and $2 a day or less for those 80 countries for which the difference in the survey years for MPI and $1.25/day poverty is not more than three years. We still find that the number of poor living in $1.25 or less (1.42 billion by 2008 population figures) is lower than the number of MPI poor (1.49 billion), and that the number of people with $2 or less is much higher (2.6 billion).

[28] This result holds even for other methods of assessing the number of people living in middle income countries. For example, since the MPI estimates refer to different survey years, we performed further checks assuming various hypotheses regarding the rate of decrease of MPI since the survey year. A realistic but yet optimistic hypothesis is to consider the annual compound reduction in the number of income poor between 1999 and 2005 across six geographical regions according to the World Development Indicator 2008. We assume that all countries reduced MPI poverty at their global regional annual rate between 2000 and 2010. If we assume this poverty reduction rate and apply it to the number of MPI poor in the corresponding survey year population, we find that total projected MPI poor in 2008 would be 1.49 billion, out of which 432 million would reside in LICs, 1.05 billion would reside in MICs, of which 938.1 million would reside in LMICs. We see that still more than double the number of MPI poor would reside in MICs as in LICs as we have found using the 2008 population figures.

[29] To check this comparison, we use the same estimates of poverty reduction as described in the paragraph above, and find that there would be 803 million severely poor in 109 countries, out of which 270.5 million would be from LICs, 532.4 million would be from MICs.

poverty can add value to traditional comparative analyses of poverty across regions and over time.

3.2 Distribution of MPI Poor across Geographic and Income Categories

Recent studies have exposed a shift in the spatial distribution of global poverty revealing that a larger share of the world poor population lives in MICs rather than in LICs, which questions the country classifications for foreign aid and international cooperation (Kanbur, 2011; Sumner, 2011). In order to deepen the own finding mentioned above, that MICs are home to more than twice as many MPI poor people as LICs, and to more people in severe poverty also, we analyse further this subject based on the MPI focusing on a sub-set of results that are available at sub-national regions.

Table 3.1: Distribution of MPI Poor across Geographical Regions and Income Categories (all aggregations are population-weighted using 2008 populations)

World Region	Number of Countries	2008 Total Population (in Millions)	Total Sub-National Regions	MPI	MPI Headcount Ratio (%)	Population in Severe Poverty (%)
All Countries						
Total	**109**	**5,299.9**	**-**	**0.163**	**31.1%**	**16.4%**
Geographic Region						
Arab States	11	217.7	-	0.077	15.3%	7.4%
Europe and Central Asia	24	399.5	-	0.011	2.9%	0.4%
Latin America and Caribbean	18	497.5	-	0.032	7.2%	2.2%
Sub-Saharan Africa	38	752.3	-	0.360	62.9%	41.2%
South Asia	7	1,554.2	-	0.280	53.2%	28.0%
East Asia and Pacific	11	1,878.7	-	0.065	14.3%	5.2%
Income Category						
High Income	8	41.2	-	0.010	2.9%	0.0%
Upper Middle Income	28	2,179.0	-	0.041	9.3%	3.0%
Lower Middle Income	42	2,378.9	-	0.218	41.5%	21.9%
Low Income	31	700.9	-	0.367	65.6%	40.7%
Sub-national Analysis						
Total	**66**	**3,180.2**	**683**	**0.235**	**43.9%**	**24.3%**
Geographic Region						
Arab States	3	85.0	11	0.024	5.9%	1.1%
Europe and Central Asia	7	156.7	36	0.019	4.8%	0.8%
Latin America and Caribbean	11	228.2	155	0.048	10.7%	3.5%
Sub-Saharan Africa	33	674.7	328	0.379	66.1%	43.5%
South Asia	4	1,532.7	52	0.283	53.9%	28.4%
East Asia and Pacific	8	502.9	101	0.082	17.6%	6.7%
Income Category						
High Income	1	1.3	5	0.020	5.6%	0.3%
Upper Middle Income	11	344.2	128	0.024	5.8%	1.2%
Lower Middle Income	29	2,222.1	290	0.228	43.2%	22.9%
Low Income	25	612.6	260	0.381	68.1%	42.3%

In this section, first we show that the 66 countries that we decompose out of the 109 countries preserve the representativeness of different categories of countries that are of interest in this analysis. In other words, the 66 countries cover a significant proportion of the 109 country population and the poverty figures for the 66 countries are not lower than those for 109 countries. In Table 3.1, we report the MPI, the percentage of MPI poor and the percentage of people in severe poverty across all 109 countries and also across 66 countries. The population weighted MPI of the 109 countries is 0.163. Of the total population in the 109 countries, 31.1 percent are MPI poor. The proportion of population that are severely poor is a little over half of that – 16.4 percent. The population weighted MPI of the 66 countries is 0.235. The proportion of MPI and severe poverty in these countries are 43.9 percent and 24.3 percent, respectively. Thus the subset of 66 countries has a higher level of MPI than the full sample.

We are primarily interested in two different categorizations of countries chosen for sub-national analysis: one that classifies countries by four geographic regions and the other that classifies countries by two income categories. These six categories together consist of majority of the developing countries. The four geographical regions are Latin America and Caribbean (LAC), East Asia and the Pacific (EAP), Sub-Saharan Africa (SSA), and South Asia (SA). Our sub-national analysis covers 98.6 percent of SA population, 89.7 percent of SSA population, 45.9 percent of LAC population, and 26.8 percent of the EAP population of the 109 countries. Although the representativeness of the EAP and LAC regions are much smaller compared to the SA and SSA regions, we chose to conduct decomposition analysis for these two geographic regions as the retained sample covers more than one hundred sub-national regions for illustrating the disparity at more disaggregated level.[30] In the second categorization, relative to the 109 countries, our sub-national analysis covers 87.5 percent of LIC population and 93.4 percent of LMIC population. We have already mentioned previously that the LICs and LMICs considered for sub-national analysis covers 80.5 percent of the global LIC population and 91.1 percent of global LMIC population. The proportion of MPI poor and the proportion in severe poverty are slightly higher for LICs and LMICs considered for sub-national analysis.

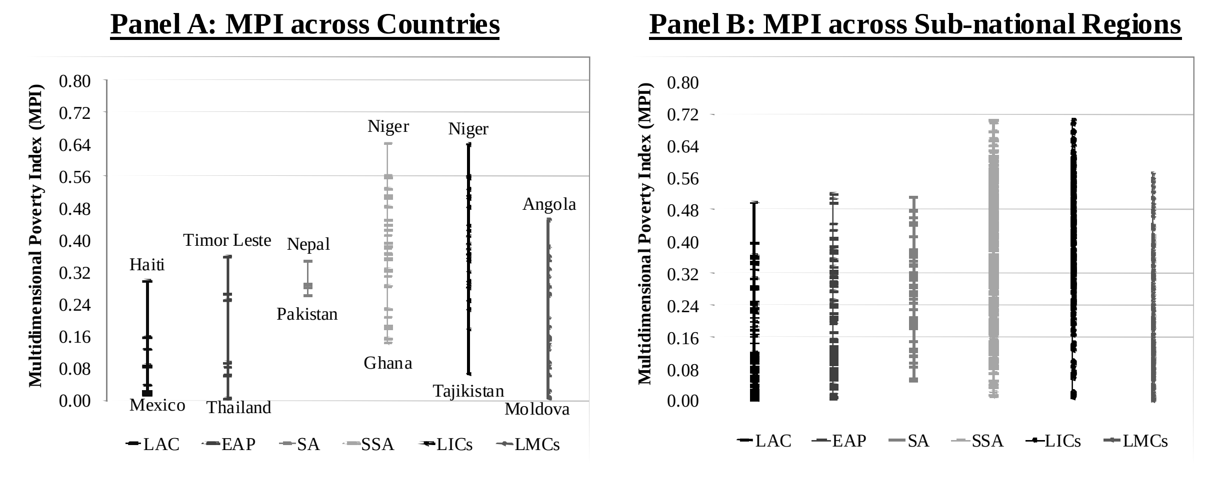
3.3 Cross-National Disparity in MPIs

The four geographical regions for sub-national analysis consist of 56 countries out of which 11 are LAC countries, 8 are EAP countries, 33 are SSA countries, and 4 are SA countries. In terms of the MPI, SSA is the poorest region with an average MPI value of 0.379. In this region, 66.2 percent of the population is MPI poor and 43.5 percent of people are severely poor. In SA, the second poorest region in terms of MPI (0.283), 53.9 percent of the people are MPI poor and 28.4 percent of the population are in severe poverty. Multidimensional poverty in LAC countries and EAP countries are much lower. The 25 LICs for our sub-national analysis have 260 regions, which cover 80.5 percent of the global population in this category. The average MPI in the LICs is 0.381; 68.1 percent of the population is MPI poor and 43.3

[30] The other two geographical regions – Arab States and Europe and Central Asia – cover only 11 sub-national regions from 3 countries and 36 sub-national regions from 7 countries, respectively, which is not large enough to study the disparity. This is evident from Table 3.1.

percent of the population are in severe poverty. The 29 LMICs, out of 66 countries chosen for sub-national analysis, have an average MPI of 0.228. In these LMICs, 43.2 percent of the population are MPI poor and 22.9 percent of the population are severely poor.

Figure 3.1: Disparity in MPI across Countries and Sub-national Regions



	LAC	EAP	SA	SSA	LICs	LMICs
Number of Countries[31]	11	8	4	33	25	29
Average MPI (Population Weighted)	0.048	0.082	0.283	0.379	0.381	0.228
Standard Deviation of MPIs (Population Weighted)						
Across Countries	0.065	0.048	0.011	0.116	0.118	0.101
Across Sub-National Regions	0.081	0.059	0.102	0.172	0.147	0.142

Although considering the range across sub-national MPIs is an intuitively simple way of understanding disparity, it will hide within-country disparities. For example, it is possible that two regions have the same national MPI values, but in one region, the majority of the population experiences around the average intensity and in the other region, the intensity of poverty varies widely across the poor population. The national values will not distinguish these two situations. Therefore, we additionally compute the population weighted standard deviation that is sensitive to such disparity.[32] If the weighted average MPI of a country or regional group of m countries is denoted by $\bar{\mathrm{M}}$, the MPI of each of the subgroup l is denoted by MPI_l, and the population share of subgroup l to the total population is denoted by $N_l = n_l/n$, then the standard deviation across the subgroups' MPIs is $\sqrt{\sum_{l=1}^{m} N_l(\bar{\mathrm{M}} - \mathrm{MPI}_l)^2}$. In the case of a country-level analysis, a country can be considered as subgroup in a wider

[31] Note that the four categories of geographic regions cover 56 countries and the two income categories cover 54 countries (29 LMICs and 25 LICs). The 54 LMICs and LICs cover some countries from Arab region and Europe and Central Asian region.

[32] Please note that the standard deviation here refers to the between-country or between-sub-national MPI values, and does not reflect the within-country or within-sub-national poverty. It could be that most disparity in poverty is within rather than between sub-national regions in some countries, so this should not be interpreted as an overall measure of the disparity in poverty across a country, but only that which can be attributed to regional differences. Note also that the number of regions in any country, as well as the distribution of the population across regions, will also affect the standard deviation.

geographical region. Similarly, in a sub-national analysis, a subgroup is the sub-national region within a country. We report the population weighted standard deviation across country MPIs in the first row of the bottom half of the Figure 3.1. The population weighted standard deviation across sub-national MPIs are reported in the second row of Figure 3.1 that we will analyse subsequently. Although the range of MPIs across countries appears to be larger among EAP countries than among LAC countries, the population weighted standard deviation is actually the opposite. This is because the population share of the least poor LAC country, Mexico, is 48.7 percent the population of the 11 LAC countries. For the EAP region, on the other hand, the most populous country in the subsample, Indonesia, with a similar population share (46.7 percent of the 8 EAP countries), has an MPI that is much closer to the average MPI, which is visible in its lower standard deviation.

Among the 25 LICs in the subsample, Tajikistan has the lowest poverty and Niger has the highest poverty; whereas among the 29 LMICs, Moldova has lowest and Angola has highest poverty. Even though the average MPI in the LMICs (0.228) is significantly lower than that in the LICs (0.381), what we see from Panel A of Figure 3.1 is that the LICs do not necessarily have higher poverty than all LMICs. Tajikistan, an LIC, has less poverty than 27 out of 29 LMICs; whereas Angola, the poorest of the LMICs, is poorer than all but seven LICs. The population weighted standard deviation is larger among LICs than across LMICs.

This country-level analysis leaves us to conclude that poverty in most LAC countries is much lower than SA countries, or many of the SSA countries, or the LICs except Tajikistan. Does the country-level analysis provide the clearest picture about the disparity in poverty? Would the conclusion change if we delve deeper and analyse poverty at the sub-national level?

3.4 Sub-National Disparity in MPI

Analysis of poverty merely at the national level actually masks the disparity across more disaggregated levels. What do we see when we present the same graph in Panel B as in Panel A of Figure 3.1 but across sub-national regions? The interpretation of the graph in Panel B is the same as that in Panel A, but instead captures the range in MPI values across sub-national regions as well as across countries. As expected, the range in MPI values is much larger across sub-national regions in each category, but they do not necessarily follow the sample pattern across countries. The standard deviation across SA sub-national regions is ten times larger than the standard deviation across SA countries. In fact, the standard deviation of SA sub-national regions is nearly twice that of EAP sub-national regions; the standard deviation of SA countries is less than a quarter of the standard deviation for EAP countries. Similarly, the standard deviation across SSA countries and LICs are almost the same, but the standard deviation across SSA sub-national regions (0.172) is much larger than the standard deviation (0.147) across LIC sub-national regions.

Recall that the value of MPI for a geographic region provides some indication of the *concentration* of poverty in that region – in terms of people who are poor *and* intensity of deprivations. From the country-level analysis, we see that only a few LAC and EAP countries have larger MPIs than the SSA and SA countries. Now, let us look at the LAC sub-national regions. While there is no country with an MPI larger than 0.32, there is actually one region of Haiti with an MPI larger than 0.48 with 0.7 million MPI poor. A further eight sub-national regions of Haiti and Honduras have an MPI between 0.32 and 0.48 with a total of 3.3 million MPI poor. What about South Asia? Only one SA country – Nepal – has an MPI above 0.32 with 18.7 Million MPI poor. However, there are eight sub-national regions in India and Bangladesh, combined (not including Nepal) with an MPI strictly larger than 0.32 and these have 382.8 million MPI poor. On the positive side, while only three South Asian countries have MPIs smaller than 0.16 – and while none of these are included in this analysis, their combined population of MPI poor is 1.3 million, but the eight sub-national regions of our sub-sample with an MPI *smaller* than 0.16 have 35.3 million MPI poor. All of these eight regions are also in India. If we compare the sub-national regions across SA and EAP regions, we see that Cambodia, an EAP country with a population of 13.8 million, has an MPI of 0.251, which is much lower than the MPI of Nepal (0.350), which also has more MPI poor than the population of Cambodia. However, the poorest region of Cambodia, Mondol Kiri and Rattanak Kiri, is poorer than even the Western Mountain region, the poorest region of Nepal. An interesting observation can be made here even though the population of Western Mountain is nearly five times as high as the population of Mondol Kiri and Rattanak Kiri. We find that 82.8 percent people in Mondol Kiri and Rattanak Kiri of Cambodia are poor as compared to 89.5 percent of people in Western Mountain of Nepal. This is because the average deprivation among the poor in Mondol Kiri and Rattanak Kiri is much higher than that of both the Western Mountain region and Oecussi.[33]

Similar instances are found for the LICs and LMICs. Nigeria (an LMIC) is Africa's largest oil producer, but its North East region has higher poverty than the poorest region of Liberia, an LIC still recovering from a prolonged civil war. The North East of Nigeria also has over five times more MPI poor people than the whole of Liberia.[34] In Namibia, an UMIC, 40 percent of Namibians are MPI poor – more than in Kyrgyzstan (an LIC) or Philippines (an LMIC). Disparities in regional poverty are also large in Namibia. The regions of Kunene, Kavango and Ohangwena in Namibia are much poorer, for example, than the poorest region of Philippines (Armm). Among the LICs, Ethiopia has the largest sub-national disparity in terms of the range of sub-national MPIs for its regions, and among the LMICs, it is Cameroon that has the largest sub-national disparity in MPI by region, again in terms of range. Table 3.2 shows how the disparity across countries may be different for similar MPI levels and also how regions with different MPIs may have similar disparity. The table also reports the population weighted standard deviation across sub-national MPIs and shows how a range of sub-national MPIs may not reveal the disparity when the population of these regions is taken into account.

Consider the first two pairs of countries in Table 3.2: Malawi and Senegal, and Mali and Ethiopia. Malawi, an LIC, and Senegal, an LMIC, have very similar MPI values of 0.381 and

[33] The MPI data for Nepal and Cambodia are one year apart; both are DHS surveys having ten indicators of MPI, so their MPI figures can be compared as described, understanding that the surveys differ by one year.

[34] Again, Nigeria, Liberia, and Namibia all have DHS data from 2007 or 2008 and contain all 10 indicators.

0.384, respectively, have 11 geographical regions, and also relatively similar population sizes of 11.8 Million and 14 Million, respectively. But the sub-national disparity in MPI is starkly different. The sub-national MPIs vary from 0.136 to 0.538 in Senegal; whereas in Malawi, they vary from 0.247 to 0.479. This difference in disparity is also reflected by the population weighted standard deviation, where Malawi has a standard deviation of 0.060 beside Senegal's standard deviation of 0.155.[35] A similar pattern is visible for the other pair of countries, with some differences. Ethiopia and Mali are both LICs and have similar overall MPI values of 0.562 and 0.558, respectively. Even though the population of Ethiopia is more than five times larger than that of Mali, both countries have a similar number of sub-national regions: 11 and 9, respectively. The sub-national disparity, however, is much larger according to the range of MPIs in Ethiopia. In Mali, the MPIs range from 0.231 to 0.624; whereas those in Ethiopia range from 0.070 to 0.654. Interestingly enough, however, unlike the previous comparison between Malawi and Senegal, the population standard deviation does not support the view. The population weighted standard deviation in Ethiopia is much lower than that in Mali: for Ethiopia the standard deviation is 0.096; whereas Mali's is 0.121. Why is there a disagreement between these two measures of disparity? It is because in Ethiopia, 83.5 percent of its population live in three sub-national regions with MPIs of 0.566, 0.585, and 0.593, whereas the population shares of the two sub-national regions with extreme MPIs are less than 4 percent. The population in Mali, on the other hand, is more evenly distributed across its sub-national regions.

Table 3.2: Comparison of Disparity in MPI within Countries across Geographical Regions

Country	MPI	Standard Deviation	Range of MPI	Lowest MPI	Highest MPI
Similar MPI but different Disparity					
Malawi (SSA)	0.381	0.060	0.232	0.247	0.479
Senegal (SSA)	0.384	0.155	0.402	0.136	0.538
Mali (SSA)	0.558	0.121	0.393	0.231	0.624
Ethiopia (SSA)	0.562	0.096	0.584	0.070	0.654
Different MPI but Similar Disparity					
Cambodia (EAP)	0.251	0.077	0.441	0.079	0.520
Nicaragua (LAC)	0.128	0.086	0.277	0.029	0.306
Nepal (SA)	0.350	0.097	0.312	0.200	0.512
Ghana (SSA)	0.144	0.097	0.321	0.035	0.356
Similar MPI and Similar Disparity					
Madagascar (SSA)	0.357	0.103	0.370	0.178	0.547
Timor Lesté (EAP)	0.360	0.115	0.381	0.127	0.508

The next two pairs of countries have different MPIs but similar disparity by the population weighted standard deviation. First consider Nepal and Ghana: Nepal is an LIC while Ghana is an LMIC, but both countries have a similar population size (29 and 23 million, respectively)

[35] Malawi and Senegal have 2004 and 2005 DHS data with all 10 indicators; similarly Ethiopia and Mali have 2005 and 2006 DHS data and 10 indicators.

and a similar number of sub-national regions (13 and 10, respectively). Ghana's MPI is less than half the MPI of Nepal (0.144 vs. 0.350), but it has the same population weighted standard deviation in MPIs across their sub-national regions. The disparity in terms of the range of MPIs is about 0.3 for both, although the ranges of each are distinct as we might expect from their different MPI values. In Ghana, sub-national MPIs range from 0.035 to 0.356; whereas in Nepal, the sub-national MPIs range from 0.200 to 0.512.[36]

A different pattern is seen for the other pair of countries: Cambodia, an LIC in the EAP region and Nicaragua, an LMIC in LAC region. Cambodia's population is 2.45 times larger than that of Nicaragua, but the number of MPI poor in Cambodia is 4.6 times larger than in Nicaragua. The MPI of Nicaragua is almost half the MPI of Cambodia and the difference between the highest and lowest sub-national MPIs is also much larger than in Nicaragua, but the population weighted standard deviation is similar, in fact, lower in Cambodia. The reason is that the most populous sub-national region of Nicaragua covering almost a quarter of its population has an MPI that is almost half of the country's MPI. For Cambodia, however, a third of its population lives in sub-national regions where MPI ranges between 0.236 and 0.256, around its MPI level of 0.251.[37]

Now consider the final pair of countries: Madagascar, an LMIC, and Timor Leste, an LIC.[38] These two countries surrounded by oceans from two different parts of the world have different sizes. The population of Madagascar is nearly twenty times larger than that of Timor Leste. However, both have similar MPI values and similar disparity across their sub-national regions. The sub-national MPIs of Madagascar range from 0.178 to 0.547 and for Timor Leste they range from 0.127 to 0.508.

Thus, we see that mere analysis of country-level poverty does not reveal the wide disparity that exists within countries, which may be crucial for policy decision making and decisions on the distribution of resources. However, this section shows that the ranking of poverty might look very different when considered in terms of sub-national regions rather than countries; country-level analysis does not reveal the spatial distribution of MPI poor and severely poor. It may be possible that a region has a lower incidence of poverty but due to a large population size has a larger number of MPI and severely poor people. In the next section, we analyse where majority of the poor people live.

4. Distribution of Poverty across World Regions and Country Categories: Where do Poor people Live?

In the previous section, we discussed how country-level analysis masks the disparity in the sub-national level. In this section, we ask where the poor people live. Indeed, they are not uniformly distributed across all world regions and also not uniformly within any country.

[36] Note that in this comparison the DHS surveys are two years apart: 2006 and 2008, with all 10 indicators.
[37] Cambodia and Nicaragua have DHS surveys from 2005 and 2006, with all 10 indicators
[38] Both have 2009 DHS surveys with all 10 indicators.

Since the MPI is based on direct deprivations, it allows us to compare across sub-national regions in different countries. To understand the distribution of MPI poor, we classify the sub-national regions into three MPI categories:

High MPI: MPI $\geq$ 0.32
Middle MPI: 0.13 $\leq$ MPI < 0.32
Low MPI: MPI < 0.13

The categorization was done in such a way that each MPI category covers a similar size of population ordered by the sub-national MPI.[39] The 66 countries are home to 3.18 billion people and each of the three MPI categories cover more than one billion people: the High MPI category covers 1.01 billion people from 250 sub-national regions, the Middle MPI category covers 1.04 billion people from 174 sub-national regions and the Low MPI category covers 1.13 billion people from 259 regions.[40] This is evident from the final two columns of the top half of Table 4.1, which depicts the distribution of MPI poor across the three MPI categories and across countries and sub-national regions in four geographic regions and in two income categories.

The intuition behind the MPI level can be grasped by considering the concentration of deprivations across society. In a region with High MPI, a significant proportion of the population are poor, and the average intensity is high – thus the concentration of poverty across people and for each person – is high. In Low MPI regions, we find the opposite.

4.1 Distribution of MPI Poor by Categories

The distribution of MPI poor across different categories is not uniform. The top half of Table 4.1 below reports the distribution of MPI poor classifying the countries into the three MPI categories and the bottom half reports the distribution of MPI poor, classifying the sub-national regions across three MPI categories. Note that the distribution of population across the three MPI categories is not the same when we classify the countries across these three MPI categories instead of their sub-national regions. Only 0.45 billion people live in *countries* with an MPI larger than 0.32 or the High MPI countries; whereas the Low MPI countries are home to more than twice that and Middle MPI countries are home to four times the population living in High MPI countries. Thus, if we try to identify the places with high poverty, a sub-national analysis yields quite a different picture than that based on the country-level analysis. Delving deeper, when we focus on geographical regions, we find that no LAC country falls in the High MPI category and only two LAC countries – Haiti and Honduras – fall in the Middle MPI category. Similarly, none of the four SA countries or 33 SSA countries

[39] From our sample of 109 countries, we find that the minimum incidence of poverty with an MPI larger than 0.32 is more than 60 percent and the minimum average intensity of poverty is more than 50 percent.
[40] Because we cannot disaggregate beyond the sub-national level, it has not been possible to distribute the population exactly equally across these three groups.

falls in the Low MPI category, and only one SA country and one EAP country fall in the High poverty MPI category.[41]

Table 4.1: Distribution of Poor across Different MPI categories

MPI Category	LAC	SSA	SA	EAP	LMIC	LIC	MPI Poor	Population (in Billions)
	MPI Poor in Countries (in Millions)							
High MPI ≥ 0.32	0.0	317.3	18.7	0.7	44.2	292.5	336.7	0.45
Number of Countries	*0*	*22*	*1*	*1*	*6*	*18*	*24*	
Middle MPI	7.9	128.9	806.9	10.0	829.8	123.3	954.0	1.80
Number of Countries	*2*	*11*	*3*	*2*	*12*	*6*	*19*	
Low MPI < 0.13	16.6	0.0	0.0	77.7	86.5	1.1	106.6	0.93
Number of Countries	*9*	*0*	*0*	*5*	*11*	*1*	*23*	
Total	**24**	**446**	**826**	**88**	**961**	**417**	**1,397**	**3.18**
Number of Countries	***11***	***33***	***4***	***8***	***29***	***25***	***66***	
	MPI Poor in Sub-national Regions (in Millions)							
High MPI ≥ 0.32	4.0	350.0	396.9	2.9	469.4	284.3	753.8	1.01
Number of Regions	*9*	*206*	*18*	*17*	*69*	*180*	*250*	
Middle MPI	9.3	76.2	393.6	17.5	364.2	127.4	496.8	1.04
Number of Regions	*26*	*94*	*27*	*26*	*98*	*65*	*174*	
Low MPI < 0.13	11.1	20.1	35.1	68.0	127.3	5.0	146.8	1.13
Number of Regions	*120*	*28*	*7*	*58*	*123*	*15*	*259*	
Total	**24**	**446**	**826**	**88**	**961**	**417**	**1,397**	**3.18**
Number of Regions	***155***	***328***	***52***	***101***	***290***	***260***	***683***	

The picture is starkly different when we look at the distribution of MPI poor at the sub-national level. Four million MPI poor live in nine High MPI sub-national regions of two LAC countries – Haiti and Honduras and 9.3 million MPI poor live in Middle MPI sub-national regions of six LAC countries – Bolivia, Haiti, Honduras, Nicaragua, Peru, and Suriname. There is only one SA country with an MPI larger than 0.32, which is Nepal home to 18.7 million MPI poor. Surprisingly, there are 18 high MPI sub-national regions containing an additional 396.9 million MPI poor in South Asia alone. On a positive note, there are seven Low MPI sub-national regions in the SA region, all from India. Also, these seven Low MPI sub-national regions in India are home to 35.1 million MPI poor, which is almost equal to the total number of MPI poor in 18 Latin American and Caribbean countries (35.6 million). Certainly, the number is larger than the number of MPI poor in all LAC countries selected for sub-national analysis, which is 24 million. Similarly, there are 28 Low MPI sub-national regions in the SSA region, where there are no Low MPI countries. On the other hand, there are 2.9 million MPI poor in 17 High MPI sub-national regions of six EAP countries: Cambodia, Indonesia, Lao, Philippines, Timor Leste, and Viet Nam, when there is only one High MPI country.

[41] In fact, none of the 18 LAC countries out of 109 countries have an MPI larger than 0.32. On the other hand only South Africa among the 38 SSA countries, and Bhutan, Sri Lanka and Maldives among the SA countries have an MPI of less than 0.13. However, computation of the MPIs of Sri Lanka and Maldives is based on the World Health Survey.

We find a similar narrative when we look at the two income categories: LIC and LMIC. First recall that at a national level the LMICs are home to more than twice as many poor as in the LICs. Even if we assume that the rest of the LICs for which MPI has not been computed have 68.1 percent of their population as MPI poor (the average for 29 countries in our analysis), the number of MPI poor in the LMICs would be larger. Only six out of 29 LMICs fall into the High MPI category with 44.2 million MPI poor, whereas 18 out of 25 LICs fall into the High MPI category with 292.5 million MPI poor. The distribution of MPI poor across these three categories for LICs does not change much when we move from country-level analysis to sub-national analysis. However, the distribution of MPI poor changes drastically across the three MPI categories for the LMICs, where 469.4 million or 48.9 percent of all MPI poor in LMICs live in High MPI sub-national regions. In fact, twice as many MPI poor live in LMICs as in LICs. Overall, out of the 1.4 billion MPI poor from 66 countries, 336.7 million reside in High MPI countries, 954 million reside in Middle MPI countries, and 106.6 million reside in Low MPI countries. However, the distribution of MPI poor across sub-national regions is quite different. Out of this 1.4 billion MPI poor, 753.8 million reside in High MPI sub-national regions (more than double the number in comparisons with looking at countries alone), 496.8 million reside in Middle MPI sub-national regions, and 146.9 million reside in Low MPI countries.

This analysis merely demonstrates the value of going beyond a country-wide aggregate. Of course with the MPI, we do have each person's c_i score, so essentially we could restrict attention to people rather than geographical regions. But many policies and programmes are administered by sub-national regions, so this spatial analysis is needed to complement a person-only based description of poverty. Furthermore, this data provides a way to advance the discussion as to the extent to which between-regional inequalities drive with-country differences in the level and intensity of multidimensional poverty, versus other kinds of circumstances such as ethnicity or religion or household type or climatic and geographic/topological features or migration or political parties or public and private institutions and their governance.

4.2 Distribution of People in Severe Poverty across MPI Categories

An obvious question that follows after this analysis is – *where do the severely poor people reside*? Whereas the MPI *value* can be thought of as the *concentration* of poverty in a given group, those in *severe* poverty are so-defined individually – by their own poverty profile. In /this sense, when we identify where the severely deprived live, we are identifying the poorest of the poor, person by person. Thus we identify severely poor people individually regardless of whether they live in 'high MPI' areas or in 'low MPI' areas (because the incidence is low and the intensity of others may be low also).

The bottom of Table 4.2 shows that in the 56 included countries most severely poor people live in South Asia (435 million) followed by Sub-Saharan Africa (294 million); this pattern is similar to that for the 109 countries. Similarly, most severely poor people live in lower middle income countries rather than low income countries within the countries included. But do most of the severely poor people live in sub-national regions where the level of MPI is High?

Table 4.2: Distribution of Severe Poverty across Different MPI categories

MPI Category	LAC	SSA	SA	EAP	LMIC	LIC	Severely Poor
	Severe Poverty in Sub-national Regions (in Millions)						
High MPI	2.4	254.4	238.4	1.7	294.0	203.0	497.0
As a Share of MPI Poor	*60.9%*	*72.7%*	*60.1%*	*59.0%*	*62.6%*	*71.4%*	*65.9%*
Middle MPI	3.7	32.8	186.4	8.5	174.8	55.0	231.5
As a Share of MPI Poor	*40.0%*	*43.1%*	*47.4%*	*48.5%*	*48.0%*	*43.2%*	*46.6%*
Low MPI	2.0	6.5	10.0	23.4	40.3	1.4	44.1
As a Share of MPI Poor	*18.1%*	*32.4%*	*28.6%*	*34.4%*	*31.7%*	*27.8%*	*30.0%*
Total	**8**	**294**	**435**	**34**	**509**	**259**	**773**
As a Share of MPI Poor	***33.4%***	***65.8%***	***52.7%***	***38.0%***	***53.0%***	***62.2%***	***55.3%***

Table 4.2 depicts the distribution of severe poverty across four different geographic regions and two income categories. The table also reports the percentage of MPI poor people that are severely poor. The High MPI sub-national regions of the four SA countries have a larger number of *MPI poor* (396.9 million) than those in the High MPI sub-national regions of the rest of the 62 countries (356.9 million), but the High MPI sub-national regions of the 33 SSA countries have larger number of *severely poor* (254.4 million) than those in the High MPI sub-national regions of the rest of the 33 countries (242.6 million). This is partially because the largest fraction (72.7 percent) of the MPI poor in the High MPI SSA countries is severely poor. It is also because, in South Asia, 186.4 million severely poor people live in regions having Middle MPI rather than High MPI. In the other three geographic regions, 59 to 61 percent of MPI poor are severely poor. For the Middle MPI countries, 40 to 48 percent of the MPI poor are in severe poverty, and for the Low MPI countries, 18 to 34 percent of the MPI poor are severely poor. Thus, as we gradually move from the High MPI countries to the Low MPI countries, the percentage of severe poverty to MPI poor decreases. Overall, 65.8 percent of the MPI poor in SA countries are severely poor; whereas only 33.4 percent of the MPI poor are severely poor in LAC countries.

For the LMICs and LICs, 53 percent and 62.2 percent of MPI poor are in severe poverty, respectively. Although the larger fraction of MPI poor are severely poor for High MPI sub-national regions in LICs, the larger fraction of MPI poor are severely poor for Middle and Low MPI sub-national regions in LMICs. In LICs, 71to 72 percent of MPI poor are in severe poverty; whereas in LMICs, 60 to 63 percent of MPI poor are in severe poverty.

4.3 Distribution of Poor across Fragile and Non-Fragile States

Given that in this section we are interested in where the MPI and severely MPI poor people reside, it would be of interest to compare the pattern of poverty in the countries referred as *fragile states*. How do we identify a country as fragile state? This is not an easy question as the definitions of fragile and failed states differ considerably. It is also not easy to determine in which year's listing to use to identify a country's status as fragile (or failed) – in the year of the survey or in a uniform year. In what follows we use the classification of the OECD (2011), which identifies 45 countries as fragile states, home to 1.16 billion people.[42] Out of them, the MPI was computed for 36 countries covering 90.3 percent of the population of the 45 countries, and sub-national analysis was conducted on 26 countries covering 76.2 percent of the population of the 45 countries. Table 4.3 outlines our findings for the fragile states.

The population-weighted MPI of the fragile countries is much larger than that of the non-fragile countries. The population weighted MPI of the 36 fragile states is 0.309; whereas the same for the 73 non-fragile states is only 0.127 across all 109 countries. The total MPI poor population in these 36 countries is 586.2 million, which represents an average incidence or headcount ratio of poverty at 55.8 percent. Indeed, by this analysis 35% of all MPI poor people live in fragile states – but the caveats listed in the footnote above are important to consider. Of the MPI poor people living in fragile states, 60.3 percent or 353.2 million people are severely poor.

Table 4.3: MPI and Severe Poverty in Fragile and Non-Fragile Countries

	Number of Countries	Population (2008, in Millions)	Average MPI	Percentage MPI Poor	Percentage Severe Poverty	Share of MPI Poor who Live in Severe Poverty	Distribution of MPI Poor in Sub-national Regions		
							High MPI	Middle MPI	Low MPI
Non-Fragile States	40	2,294.3	0.198	38.0%	19.7%	52.0%	54.1%	31.2%	14.7%
Fragile States	26	886.0	0.330	59.4%	36.1%	60.7%	53.7%	42.7%	3.5%

The 26 fragile countries among the 66 countries are home to 886 million people according to 2008 population figures. In these 26 countries, 59.4 percent of the population is MPI poor (a bit higher) and 60.7 percent of the MPI poor or 36.1 percent of the population are severely poor (about the same). All 26 fragile countries are either LICs or LMICs. For this reason, the fraction of severely poor to MPI poor is also higher for the fragile countries. What is most perplexing is that when we consider the distribution of MPI poor across the sub-national regions in three MPI categories, we find that an almost similar fraction of MPI poor live in High MPI sub-national regions in both fragile and non-fragile countries (54.1 percent vs. 53.7 percent). A large fraction of MPI poor live in Low MPI sub-national regions in non-fragile states.

[42] The 45 countries that are considered fragile states by the OECD (2011) are Afghanistan, Angola, Bangladesh, Burkina Faso, Burundi, Cameroon, the Central African Republic, Chad, Comoros, the Democratic Republic of Congo, the Republic of Congo, Côte d'Ivoire, Eritrea, Ethiopia, Georgia, Guinea, Guinea-Bissau, Haiti, Iraq, Kenya, Kiribati, Lebanon, Liberia, Malawi, Myanmar, Nepal, Niger, Nigeria, North Korea, Pakistan, Papua New Guinea, Sao Tome And Principe, Sierra Leone, Solomon Islands, Somalia, Sri Lanka, Sudan, Tajikistan, Timor-Leste, Togo, Uganda, Uzbekistan, Occupied Palestinian Territory, the Republic of Yemen, and Zimbabwe. **Important note**: ideally, we would test the robustness of our findings by exploring the list of countries that were classified 'fragile' during the year of their survey, calculating their combined MPI etc and comparing the results with this set of countries. However the lists of fragile (and failed) states are not issued annually, and the criteria change over time and between institution, so we are not able to provide this analysis at this time.

What we see in this section is that extending the analysis of poverty to a sub-national level provides a different picture as to where the MPI and severely poor people reside. After analysing where the poor people live, we now try to understand how different dimensions and indicators contribute to overall multidimensional poverty. The patterns of deprivation in different sub-national regions within the same country or geographical region may not be identical. At the same time, however, different regions with different levels of MPI may have similar deprivation profiles. The next section is devoted towards understanding another type of decomposition but across dimensions and indicators instead of population subgroups.

5. Poverty Profiles and MPI Decomposition across Indicators

The previous section focused primarily on analysing the disparities in multidimensional poverty at the sub-national level and the extent to which the MPI varies across regions. We have also analysed the distribution of the MPI poor population across income categories and geographical regions revealing how national aggregates mask the important deprivations suffered by a large number of people in certain sub-national regions. In this section, we begin to analyse the composition of multidimensional poverty in each particular context - to distinguish sub-national regions where the MPI is driven mainly by high levels of deprivation in health from those where it is the result of deprivation in living standards, for example. This section will concentrate on identifying the prevalent dimensions and indicators that drive the MPI in different sub-national regions. Once again, the information and analysis here and in the appendices opens far more questions than it addresses, and additional systematic work will be required to complement and complete the analysis of poverty profiles.

One important property of the MPI is that it is decomposable across indicators after the identification step. Recall from Section 3, that after the identification of the poor, we can compute the *percentage contribution of an indicator j* to the overall poverty as $w_j h_j(X)/M_0(X)$, where, w_j is the weight attributed to the indicator j, $h_j(X)$ is the *censored headcount ratio* of indicator j, and $M_0(X)$ is the *Adjusted Headcount Ratio*, which in this case is the MPI.[43] Together, the contributions of each indicator provide the 'composition' of poverty – that is, the proportion of the deprivations experienced by poor people in each particular indicator (weighted). We refer to this as the percentage 'contribution' of each indicator to the MPI and denote it by $Contr_j(X)$. The censored headcount ratio and the contribution of each indicator to the MPI of each sub-national region can be found in Table 3.3 in the Appendix. The equivalent figures for the 109 countries can be found in Tables 1.2 and 1.3 in the Appendix.

[43] Recall that the censored headcount ratio is computed by dividing the number of poor people who are deprived in the indicator j by the total population. The Adjusted Headcount Ratio respects the poverty focus axiom so it is only sensitive to changes in the level of achievements among the poor. Therefore, the dimensional contribution can only be computed after identifying the poor and censoring the deprivation matrix.

Table 5.1: Percentage Contribution of Indicators to the MPI at Sub-national Regions: Illustrative Comparisons

	MPI	Education		Health		Living Standards					
		YS	SA	CM	N	E	S	W	F	CF	AO
A. Similar MPI, different composition											
Ziguinchor (Senegal)	0.319	8.6	9.4	22.4	5.4	9.8	10.4	9.3	7.8	11.2	5.8
Barisal (Bangladesh)	0.318	11.2	5.0	12.7	22.4	9.3	8.0	0.4	10.7	11.0	9.4
Jinotega (Nicaragua)	0.306	18.3	8.7	8.1	3.1	10.1	11.3	9.3	9.5	11.3	10.2
B. Similar composition, different MPI											
Orissa (India)	0.339	11.5	7.7	11.7	22.1	7.1	10.0	3.3	8.3	10.3	8.0
Eastern Terai (Nepal)	0.322	13.9	8.2	13.6	21.9	6.0	9.9	0.6	9.5	10.5	5.9
Chittagong (Bangladesh)	0.290	11.5	5.8	14.2	22.2	7.2	8.8	0.5	10.3	11.0	8.6
C. Sub-national regions of Togo											
Savanna	0.576	15.0	18.5	14.2	14.2	8.4	8.5	5.8	3.4	8.6	3.4
Kara	0.366	15.7	17.1	13.7	11.1	9.4	10.1	5.7	2.0	10.2	5.0
Maritime (w/o Lomé)	0.315	12.9	10.7	16.0	10.2	10.5	10.8	7.4	4.1	11.2	6.2
Central	0.306	13.5	15.2	18.0	6.9	10.1	10.9	6.1	2.9	11.0	5.5
Plateau	0.297	12.7	12.6	14.4	5.8	10.8	11.2	8.4	5.5	11.4	7.1
Lomé	0.070	13.4	13.2	18.1	11.3	7.8	11.8	2.8	0.4	13.2	8.0

Note: YS= Years of Schooling, SA= School Attendance, CM= Child Mortality, N= Nutrition, E=Electricity, S=Improved Sanitation, W=Safe Drinking Water, F=Flooring, CF=Cooking Fuel, AO=Assets Ownership.

The National MPI each of these countries: Bangladesh (0.292), India (0.283), Nepal (0.350), Nicaragua (0.128), Senegal (0.384), and Togo (0.284).

5.1 Similar MPI but Different Composition

Clearly, if the intensity of poverty in a given region were 100%, then the percent contribution of each indicator would simply be equivalent to its weight w_j. However, with lower levels of intensity, the percentage contributions could vary greatly in theory. A first question is whether this potential variation is witnessed in practice. Alternatively, we might find that all regions having an intensity in some range – say 0.5 to 0.6 – would have very similar compositions of poverty. We do not observe uniformity in the composition of poverty across levels of intensity at the country level or among sub-national regions. Consider Barisal (Bangladesh), Jinotega (Nicaragua) and Ziguinchor (Senegal) in Section A of Table 5.1. These three regions have a relatively similar MPI (between 0.306 and 0.319), yet their composition of poverty is very different.[44] In Jinotega, the health indicators together contribute only 11 percent to MPI, in comparison with Ziguinchor and Barisal where the two health indicators together contribute more than 28 percent to the respective MPIs. Ziguinchor and Barisal are quite different also. In Ziguinchor, the contribution of child mortality to MPI

[44] Note that at the national level the differences in MPI are important: Bangladesh (0.292), Nicaragua (0.128), and Senegal (0.384).

is largest (22 percent), while the contribution of under-nutrition is only 5 percent. We observe quite the opposite profile in Barisal, where the contribution of under-nutrition is largest (22 percent) and child mortality contributes only 13 percent to the MPI. There are further differences in the contribution of education and living standards indicators in these three sub-national regions. For example, the contribution of unsafe drinking water in Barisal is only 0.4 percent, but in both Ziguinchor and Jinotega, it is 9.3 percent. Similarly, the contribution of years of schooling in Jinotega is 18 percent, which is much higher than the contribution of the same in the other two regions.

5.2 Similar Composition but Different MPI

The corresponding issue was whether countries and sub-national regions which have very similar compositions of MPI have striking similarities in other ways. This also requires further study. What we do observe descriptively is that other sub-national regions have different MPI values but similar poverty profiles. Consider the three sub-national regions from South Asia depicted in Section B in Table 5.1: Orissa (India), Eastern Terai (Nepal), and Chittagong (Bangladesh). These three regions have MPI values that range from 0.290 in Chittagong to 0.339 in Orissa; Eastern Terai is in between with an MPI equal to 0.322.[45] Yet composition of MPI is very similar. They all have relatively high combined contributions of the living standards deprivations (over 43 percent), and relatively low combined contributions of education deprivations (less than 22 percent). Even though we observe some differences within the dimensions, these three regions show similar patterns in the composition of deprivations. Finally, one might wonder how the poverty profiles vary across sub-national regions of the same country. The dimensional contributions in the sub-national regions of Togo demonstrate that they actually do differ (see Section C in Table 5.1 above). The regions of Savanna and Kara, with MPIs of 0.576 and 0.366, respectively, have the lowest contribution from living standards indicators (less than 42 percent) in comparison to the other regions. In contrast, Central and Plateau, with MPIs of 0.306 and 0.297, respectively, have the lowest contribution from nutrition (less than 7 percent).

5.3 MPI Level and Composition of Indicators

The example in sections 5.2 and 5.3 were illustrative. In what follows, we provide an initial yet more systematic classification of the poverty profiles across sub-national regions. It is important to recall precisely what is being classified. Naturally, a high contribution does not mean that the absolute number of people deprived in that particular indicator is high in absolute terms. It conveys the contribution of a particular indicator relative to other indicators to the overall MPI. However, recall that by knowing the MPI value and percentage contribution of an indicator, we already know the information associated with the censored headcount because this can be computed as $M_0(X)\times Contr_j(X)/w_j$; where $Contr_j(X)$ is the contribution of dimension j. So in the previous example, the censored headcount of child mortality in Ziguinchor is 43 percent (22.4×0.319/0.167) which is just equivalent to the

[45] Note that at the national level the differences in MPI are also quite important: Bangladesh (0.292), India (0.283), Nepal (0.350).

censored headcount of nutrition in Barisal – 43 percent (22.4×0.318/0.167) – because they both have the same MPI value and same contribution in those indicators. However, Lomé and Central region of Togo have exactly the same contribution from child mortality (18 percent) but very different MPI values (0.070 and 0.306 respectively). So the censored headcount of child mortality in both regions is different, 8 percent in Lomé and 33 percent in Central. By analysing the MPI value and the percentage contribution jointly, we can evaluate the poverty profile while taking into account the overall poverty and deprivation in each indicator. We now turn to this analysis.

We start by classifying the 497 sub-national regions according to the combined contribution of the indicators in each of the three dimensions: living standard, health and education. We restrict this analysis to the set of countries and sub-national regions that have information for all ten indicators in order to guarantee strict comparability and to facilitate interpretation.[46] Recall that in the MPI, each dimension has equal weight (one third each). If each of the ten indicators had equal average censored headcounts, and if deprivations in each dimension were equally prevalent, the contribution of each dimension would be relatively equal to their weight (33 percent each). If one dimension has higher censored headcount ratios relative to another then its contribution would be higher. Some of this difference is due to generalized and more systematic differences among censored headcounts due to the indicators; the remainder is due to region-specific poverty compositions. So, as an introductory exercise we classify the regions according to the contribution of each dimension (Living Standards, Health and Education) as follows:[47]

- ✓ Dimensional Contribution is lower than 23 percent: this is equivalent to 70 percent of its original weight
- ✓ Dimensional Contribution is between 23 to 43 percent: this is this equivalent to 70 percent to 130 percent of its original weight
- ✓ Dimensional Contribution is higher than 43 percent: this is equivalent to 130 percent of its original weight

Table 5.2 shows the distribution of regions and poor people according to the dimensional contributions and regional MPI levels. The 'unweighted' figures refer to the total number of sub-national regions and percentage of these regions. The 'weighted' figures refer to the distribution of the regions weighted by the number of poor population in each region, so when weighted, it reflects the distribution of MPI poor. Both figures, weighted and unweighted, are important so it is possible to distinguish not only the most common profiles

[46] A total of 49 countries and 497 sub-national regions have information for all ten indicators, covering 2.3 billion people (using 2008 estimates, UNDESA, 2008). This represents 72 percent of the population in the 66 countries under study, and covers 63 percent of the world population in LMICs and LICs. As with the 66 countries, coverage of the UMCs is relatively low for these 49 countries with 11 percent of the world population. Please see Table 3.1 in the appendix for the list of regions with less than 10 indicators.

[47] Note that it may also be desirable to use dimension-specific contributions that are based on the actual average dimensional contributions since the choice of indicators – and its associated censored headcounts – also contributes to the dimensional contributions. Child mortality and undernutrition are serious deprivations, but the censored headcounts on these tend to be lower than those in cooking fuel or in water. Thus the fact that health deprivations rarely exceed 43% does not suggest that health is the least urgent priority in the high MPI countries, as the subsquent analysis will show.

among the regions, but also in which profile the majority of poor people live. The level of MPI is presented for illustrative purposes in this table to show how dimensional compositions vary across different levels of MPI. Figure 5.1 below presents the kernel density graphs for dimensional contribution by the regional MPI level.[48] The same three categories of MPI have been used as were used in the previous section: High MPI (MPI larger than 0.32), Middle MPI (MPI between 0.13 and 0.32), and Low MPI (MPI less than 0.13).

Table 5.2: Distribution of Regions and MPI Poor People by Dimensional Contribution and Regional MPI level

	Regional MPI Level					
	Less than 0.13		Between 0.13 and 0.32		More than 0.32	
	Unweighted 1	Weighted 2	Unweighted 1	Weighted 2	Unweighted 1	Weighted 2
Total	199	82.8	119	382.1	179	689.3
Living Standard	100	100	100	100	100	100
Less than 23%	20.6	3.3	0.0	0.0	0.0	0.0
23 - 43%	42.2	23.9	13.4	29.0	27.4	50.3
More than 43%	37.2	72.8	86.6	71.0	72.6	49.7
Health	100	100	100	100	100	100
Less than 23%	30.7	10.1	29.4	4.4	58.7	28.1
23 - 43%	52.3	80.0	70.6	95.6	40.8	71.6
More than 43%	17.1	10.0	0.0	0.0	0.6	0.3
Education	100	100	100	100	100	100
Less than 23%	29.6	70.1	51.3	80.7	26.8	55.5
23 - 43%	54.3	27.2	48.7	19.3	71.5	44.3
More than 43%	16.1	2.7	0.0	0.0	1.7	0.2

Notes:

1 The unweighted figures refer to the simple mean of regions. The table includes only the 497 regions that have information for all 10 indicators (see Table 3.3 in the appendix for the list of regions with fewer than 10 indicators).

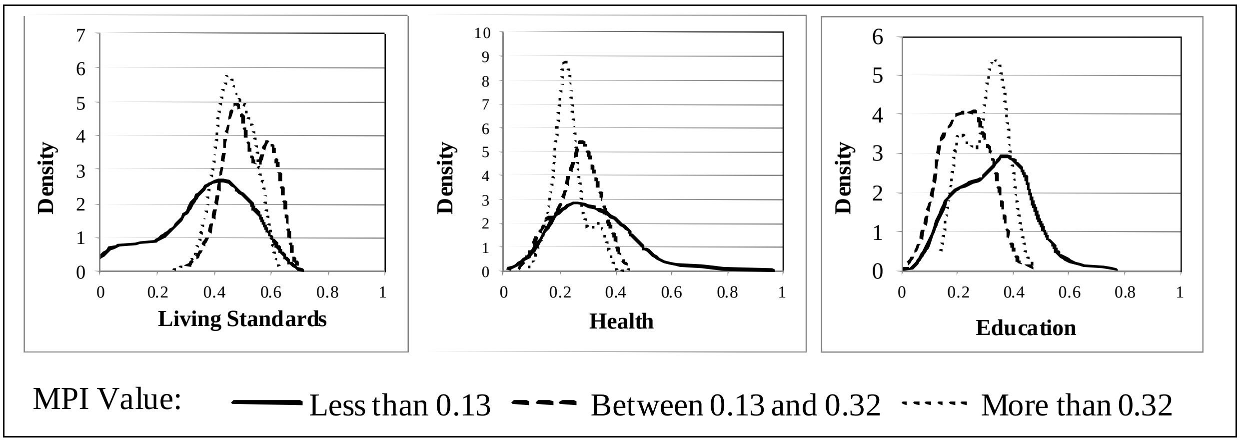
2 The weighted figures refer to the distribution of regions weighted by the total poor population in each region. Hence, it reflects the percentage of poor people who live in regions whose average composition is as indicated. It includes only the 497 regions that have information for all 10 indicators. Of course it would also be possible to do such analysis across poor people within a sub-region or country, to identify the types of actual poverty profiles people experience.

Table 5.2 and Figure 5.1 show that dimensional contributions vary considerably across regions with some association to the level of MPI. A few differences are striking. Regions with an MPI greater than 0.13 nearly always have more than a 23 percent contribution from living standards indicators, whereas this is not the case for the health and education dimensions, showing that the relative contribution of living standards is never the lowest in high poverty areas. In the middle MPI category, the highest contribution comes from living

[48] The kernel density graphs refer to the regions unweighted by population.

standards in 86.6 percent of the regions (71 percent of the MPI poor). In high poverty areas living standard deprivations also contribute more than 43% in 72.6 percent of the regions, which are home to 49.7 percent of poor people living in high MPI areas. Interestingly, 21.6 percent of the low MPI regions have a less than 23 percent contribution of living standards, but they represent only 3.3 percent of the poor population living in these regions. In the health domain, the health contribution is almost never greater than 43 percent for the middle and high MPI regions – but this is in part because the censored headcounts of child mortality and under-nutrition are usually lower than living standard deprivations. In the middle MPI category 70.6 percent of the regions (95.6 percent weighted) the health contribution falls in the middle range. The other striking observation is that educational deprivations hardly ever comprise more than a 43 percent contribution for the weighted figures. Instead, over 55 percent of the weighted regions have an educational contribution under 23 percent.

Figure 5.1: Kernel Densities for Dimensional Contribution by Regional MPI Level



Note: See Appendix 5 for the kernel density graphs for each of the ten indicators

5.4. Classification of Sub-national Regions According to Poverty Profile

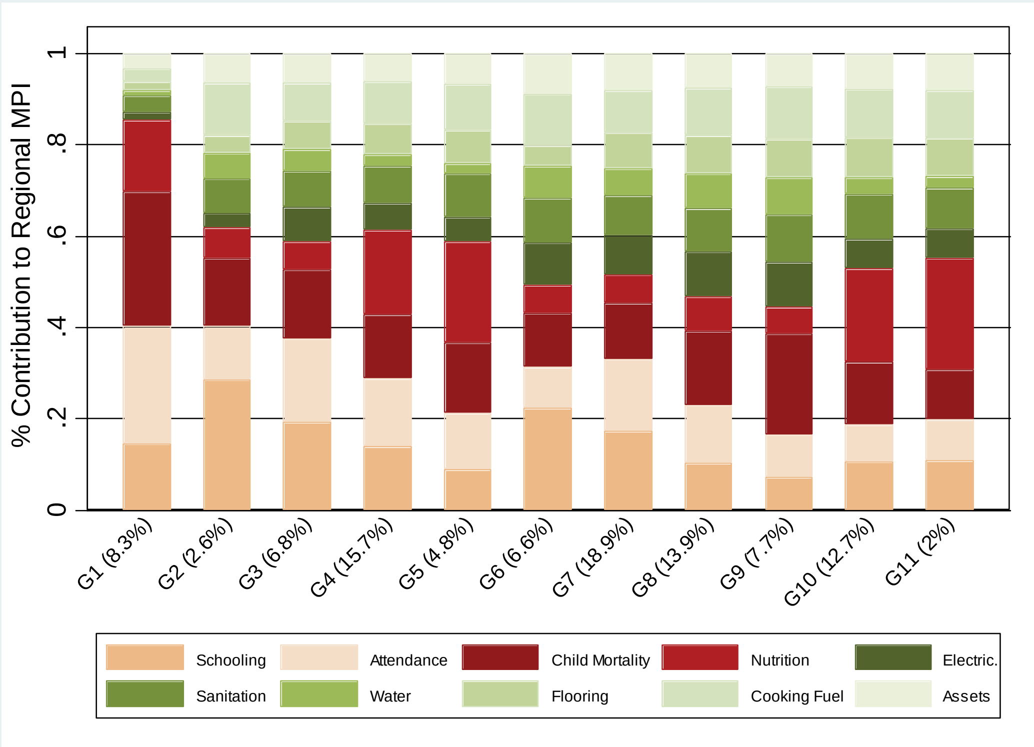
We now present a more comprehensive picture by classifying the regions according to the contribution in all three dimensions simultaneously. The same level of dimensional contribution as above are used, but for health and education, we check further if both indicators (nutrition/child mortality or year schooling/attendance) in each dimension contributes evenly or if the contribution of one indicator is considerably higher than the other. So we consider the following classifications:[49]

- ✓ The censored headcount of indicator 1 is more than twice that of the other ($CH_1/CH_2 > 2$)
- ✓ Both indicators' contribution is relatively similar ($0.5 < CH_1/CH_2 < 2$)
- ✓ The censored headcount of indicator 1 is less than half that of indicator 2 ($CH_1/CH_2 < 0.5$)

[49] We have conducted this analysis for a particular combination of indicators. However, this type of analysis is also possible and has been advanced in unpublished work by Santos and HDRO researchers for the analysis of the environmental indicators by the 2011 *Human Development Report* (UNDP, 2011). The *HDR* focuses on the analysis of the censored headcount and contribution of the indicators that are considered to be related to environmental sustainability: water, sanitation and cooking fuel.

The regions are then classified following the algorithm in Figure 5.2 which generates eleven groups according to their poverty profile. Naturally, this is only one of several different possible classifications. We use it strictly to analyse the diversity of poverty profiles across the regions under study. Note that we are *not* presuming by this methodology that the censored headcount ratios of all deprivations *should* be equal across the 10 indicators. Rather, we are using a simple algorithm to classify regions. These classifications will then be analysed alongside the overall censored headcount ratios to identify which poverty profiles are prevalent among different groups.

Figure 5.2: Classification Result and Eleven Poverty Profiles



Note: Figures in parentheses represent the percentage of unweighted regions in each group. The graph was computed as a weighted average of regions in each group based on the total number of poor population.

The eleven poverty profiles from the classification are presented in Figure 5.2, which displays the percentage contribution of each indicator for all eleven groups. In the figure, the eleven groups are abbreviated as G1, G2, ..., G11 and the percentage of unweighted regions in each are presented in brackets.[50] Very distinctive patterns can be observed in the classification. For example, G1 is constituted of those regions with a very low contribution in living standards indicators. Group from G2 to G5 are different to those from G6 to G11 in the degree of contribution of living standards indicators. Both groups G2 and G3 have high contributions in education but, in G2, years of schooling contributes more than school attendance. In G4 each dimension contributes between 23 percent and 43 percent. G5 is different from G4 in that the health dimension contributes more than 43 percent. Both groups

[50] See Table 5.3 for the percentage of poor population in each group.

G6 and G7 have a high contribution of education and living standards, but G6 is distinctive in that years of schooling is double that of school attendance. G8 has a high contribution of living standards and a relatively equal contribution of health and education. The last three groups (G9, G10 and G11) are distinctive in that living standards and health have a high contribution. The difference among them is that G9 has double the contribution of child mortality in relation to nutrition, while G11 has the inverse composition. Finally G10 has a contribution of child mortality and nutrition that ranges between 23 and 43 percent. As it can be seen, there is a wide range in poverty profiles across the sub-national regions under study. While the eleven groups are only one way to classify them, it illustrates well the variety found in the data.

Table 5.3 describes further the poverty profiles. Section A in the table presents the distribution of regions and poor people across these eleven profiles. Some profiles such as G1, G2, G3 and G6 have a considerably lower concentration of poor people within a relatively larger number of regions – between 2.6 percent and 8.3 percent of all the regions, but less than 1.8 percent of all poor people. On the contrary, other profiles that do not have that many regions, such as G5 or G10, apply to a larger percentage of poor people – together they have less than 18 percent of the regions, but over 45 percent of the poor population. Section B again confirms that regions with a very low contribution of living standards have low levels of poverty. The group with the highest level of average MPI is G7 and G8 and relatively lower in G6 and G9. It also shows that the dispersion in MPIs, measured by a standard deviation, is relatively high within each group, so profiles include regions with various levels of poverty.[51]

Section C and D present the distribution of the poor population from each income category and global region across group.[52] It shows again that profiles with a low contribution of living standards are more common among populations living in regions in low-income countries. Profiles with a higher contribution of health indicators (G4, G5, G10 and G11) are more common among regions in middle-income countries. The profile G7 with a high living standard and high education is more common among regions in low-income countries. Differences across global regions are also important as shown in section D. A large number of the population in South Asia live in regions with a high contribution of health (G4, G5, G10 and G11), and in some cases higher contribution of nutrition than child mortality (G5 and G11). In contrast the profile G9 has a high contribution of health and in particular child mortality, which is not common among South Asian countries. East Asia and the Pacific and Latin America both have many poor people with the G8 profile, whereas in Sub-Saharan Africa, G7 is the most common followed by G8 and G4.

One might wonder if some profiles are characteristic of countries and if the profiles among regions vary enough. Section F shows that although certain poverty profiles are more salient

[51] This corresponds to the weighted standard deviation explained in Section 3.

[52] The regions considered in this analysis cover 1,154 million poor people of which LICs cover 361.1 million, LMICs cover 778 million, UMCs cover 15.1 million, SA countries cover 742.9 million, SSA countries cover 377.5 million, EAP countries cover 9.5 million, and LAC countries cover 22 million. Recall that the contribution analysis includes a total of 49 countries and 497 sub-national regions that have information for all ten indicators.

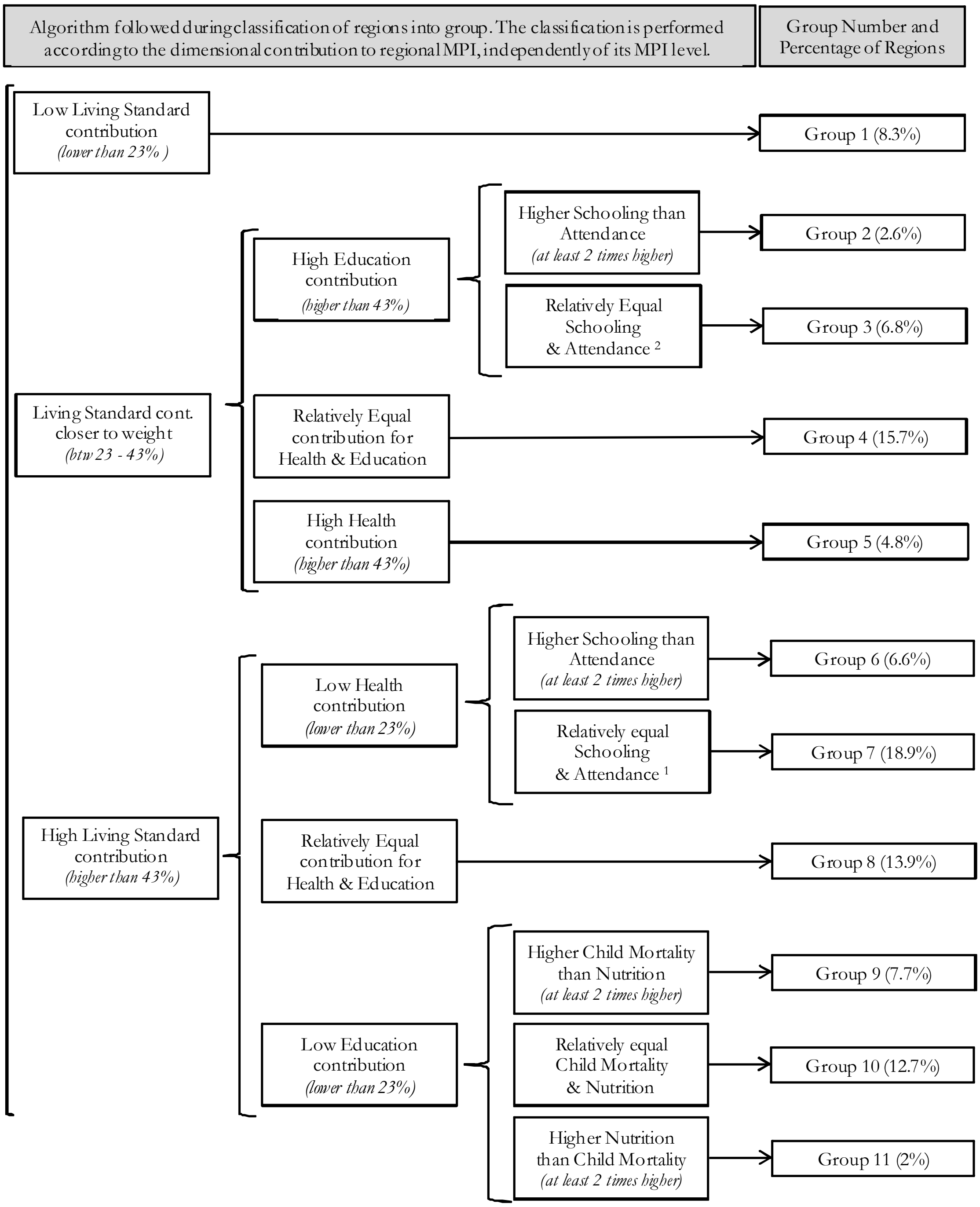
in each country, there are important variations as well. For example, we find seven different profiles among the 32 regions of Mexico. Six profiles are found among the 29 regions of India but four of them are the most common. In Nepal, most regions follow two profiles out of the four that exist in the country. Even in countries with a small number regions like Thailand or Zambia it is possible to identify several poverty profiles. The classification shows that some profiles are more characteristic of the country and that there is also some variation across their sub-national regions.

This section first illustrated that the same MPI values are actually associated with different poverty profiles, that the same profiles are associated with different MPI values, and that these vary within as well as across countries. It then identified 11 poverty profiles simply according to the relative contribution of the ten indicators, and showed that some (familiar) patterns do seem to emerge in terms of regional poverty profiles, but that the diversity among profiles within regions and countries is still considerable. The section thus provided a first systematic classification of the diversity of MPI poverty profiles among regions, income categories, and for some particular countries.

Table 5.3: Description of the Eleven Poverty Profiles

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	Total
A. Distribution:												
Number of Regions	41	13	34	78	24	33	94	69	38	63	10	497
Percent Regions	8.3	2.6	6.8	15.7	4.8	6.6	18.9	13.9	7.7	12.7	2.0	100
Poor Population (millions)	2.7	0.6	21.3	202.5	252.9	9.1	131.3	96.2	18.1	295.7	123.7	1,154.1
Percent Poor Population	0.2	0.0	1.8	17.5	21.9	0.8	11.4	8.3	1.6	25.6	10.7	100
B. Average MPI (weighted)	0.009	0.014	0.312	0.275	0.291	0.170	0.440	0.365	0.145	0.273	0.224	0.271
in brackets Std. Dev.	(.020)	(.012)	(.288)	(.205)	(.092)	(.158)	(.187)	(.115)	(.134)	(.103)	(.087)	(.162)
C. Income Category (percent poor population):												
Low income	0.0	0	4.6	6.0	2.6	1.9	30.8	18.2	1.8	34.2	0	100
Lower-middle income	0.2	0	0.5	22.9	31.3	0.2	2.4	3.3	1.4	22.0	15.9	100
Upper-middle income	9.1	3.7	4.0	20.8	0.5	6.3	10.2	33.6	4.6	6.5	0.8	100
D. Global Regions (percent poor population):												
East Asia and the Pacific	2.1	3.1	10.3	11.2	0.5	0	17.0	42.7	4.4	7.0	1.8	100
Latin America & Caribbean	4.6	1.2	2.6	11.8	0.0	14.9	21.5	30.5	10.8	2.0	0	100
South Asia	0	0	0.0	17.3	33.5	0.1	0	0.1	0	32.4	16.6	100
Sub-Saharan Africa	0.2	0	5.2	18.5	0.7	1.4	33.1	22.4	4.1	14.4	0.0	100
F. Regional Composition in Some Selected Countries												
India	0	0	1	7	7	0	0	1	0	7	6	29
Mexico	10	1	6	8	0	2	4	1	0	0	0	32
Nepal	0	0	0	1	3	1	0	0	0	8	0	13
Nicaragua	0	0	0	1	0	6	9	1	0	0	0	17
Senegal	1	0	5	2	0	0	1	1	1	0	0	11
Thailand	1	1	0	2	0	0	0	0	0	0	0	4
Zambia	0	0	0	0	0	0	0	1	5	3	0	9

Figure 5.3: Algorithm Followed During the Classification Process of Sub-national Regions According to Poverty Profile



Notes:

[1] There is not any case with more than double Attendance than Schooling in Group 7

[2] There is only one case with more than double attandance than schooling (Pelagonia in Macedonia with an MPI of 0.015)

[3] Only one region with more than double Nutrition than Child Mortality (Goa in India with an MPI of 0.085)

6. Tracking Changes over Time across Sub-national Regions

Until now we have analysed poverty only at a single point in time. This final section presents MPIs for two periods of time, at the national and sub-national level. We compare changes in MPI for ten countries for which we have comparable results across time: Jordan (2007 and 2009), Colombia (2005 and 2010), Bangladesh (2004 and 2007), Bolivia (2003 and 2008), Ethiopia (2000 and 2005), Ghana (2003 and 2008), Lesotho (2004 and 2009), Kenya (2003 and 2009), Madagascar (2004 and 2009), and Nigeria (2003 and 2008). All these countries have all ten MPI indicators from the Demographic and Health Surveys (DHS) and have been standardized to ensure comparability across time. We further analyse the changes in MPIs for the 158 sub-national regions from all countries, except Madagascar because the division of sub-national regions are not comparable across two time periods.

6.1 Incidence and Intensity of Poverty

The MPI may change because of two kinds of events: i) poor people may move out of poverty, causing a change in *H* and ii) the intensity of poor people's poverty may decrease because some deprivations are removed (*A*).[53] Table 6.1 reports the MPI, the incidence of poverty (*H*) and the intensity of poverty (*A*) for each country in both periods under study (columns 4 to 6). Figures in parentheses correspond to the 95 percent confidence intervals.[54] It also reports, below each country name, the annualized absolute and relative change across both periods. Overall, we see from this table that poverty declines are significant for all ten countries except for Jordan.[55] The largest absolute decrease in the MPI has been registered by Ghana, Bangladesh, Bolivia, and Ethiopia. Interestingly – and perhaps surprisingly – the absolute changes do not depend on the initial level of MPI. For example, the absolute decreases in MPI are similar for Bangladesh and Ethiopia, but Ethiopia's MPI falls from 0.678 to 0.562 in five years; whereas Bangladesh's MPI falls from 0.365 to 0.292 in three years. Relative to the initial MPI, the decrease in Bangladesh's MPI is much larger. For this reason, we also compute and report the annual percentage changes in the MPI. It is clear from the table that the annual percentage reduction in Bangladesh's MPI is almost twice the annual percentage reduction in Ethiopia's MPI. The largest absolute and percentage changes in the MPI among these ten countries have been achieved by Ghana with percentage falls of 10.7 percent per annum. Although its MPI is small in absolute terms, Colombia also shows a large annual decrease in MPI relative to its initial MPI (9 percent).

[53] For clarity of presentation we have not presented the interaction term in this section, because it carries a very small value but the intuition of the interaction term is a topic unto itself.
[54] The confidence interval of a point estimate depicts the standard error on that estimate. A smaller interval indicates a lower standard error of the estimate. For a detailed explanation of how the standard errors for Alkire and Foster measure, including the MPI are computed, see Yalonetzky (2011).
[55] For Jordan, the MPI in 2009 (0.008) is only slightly lower than in 2007 (0.010). A t-test shows that this difference is not significant F(1, 1801)=0.59, Probability >f =0.4415; considering the survey design for both surveys.

Table 6.1: Changes in MPI, Headcount Ratio and Intensity of Poverty over Time in Ten Countries

Country	MPI Data Source		MPI	MPI Headcount Ratio (H)	Intensity of poverty (A)
	Survey	Year			
Bangladesh	DHS	2004	.365 (.352-.378)	67.2 (65.4-69.1)	54.3 (53.6-55.0)
Bangladesh	DHS	2007	.292 (.279-.304)	57.8 (55.7-60.0)	50.4 (49.9-51.0)
Average annual absolute change			-0.024	-3.1	-1.3
Average annual percent change			-6.7	-4.7	-2.4
Bolivia	DHS	2003	.175 (.166-.184)	36.3 (34.6-37.9)	48.3 (47.6-49.0)
Bolivia	DHS	2008	.089 (.083-.096)	20.5 (19.1-21.8)	43.7 (42.9-44.4)
Average annual absolute change			-0.017	-3.2	-0.9
Average annual percent change			-9.8	-8.7	-1.9
Colombia	DHS	2005	.040 (.037-.044)	9.3 (8.6-10.0)	43.3 (42.5-44.1)
Colombia	DHS	2010	.022 (.020-.024)	5.4 (5.0-5.8)	40.9 (40.2-41.6)
Average annual absolute change			-0.004	-0.8	-0.5
Average annual percent change			-9.1	-8.4	-1.1
Ethiopia	DHS	2000	.678 (.670-.686)	93.6 (92.9-94.3)	72.4 (71.8-73.0)
Ethiopia	DHS	2005	.562 (.552-.572)	88.6 (87.6-89.6)	63.5 (62.8-64.2)
Average annual absolute change			-0.023	-1.0	-1.8
Average annual percent change			-3.4	-1.1	-2.5
Ghana	DHS	2003	.309 (.295-.322)	58.7 (56.5-61.0)	52.5 (51.7-53.4)
Ghana	DHS	2008	.144 (.133-.155)	31.2 (29.1-33.2)	46.2 (45.4-47.0)
Average annual absolute change			-0.033	-5.5	-1.3
Average annual percent change			-10.7	-9.4	-2.4
Jordan	DHS	2007	.010 (.007-.013)	2.7 (1.9-3.6)	35.5 (34.5-36.5)
Jordan	DHS	2009	.008 (.007-.010)	2.4 (2.0-2.9)	34.4 (33.8-35.0)
Average annual absolute change			-0.001	-0.1	-0.6
Average annual percent change			-6.9	-5.4	-1.6
Kenya	DHS	2003	.296 (.281-.312)	60.1 (57.7-62.5)	49.3 (48.3-50.4)
Kenya	DHS	2009	.229 (.211-.248)	47.8 (44.6-51.0)	48.0 (46.6-49.4)
Average annual absolute change			-0.011	-2.0	-0.2
Average annual percent change			-3.8	-3.4	-0.5
Lesotho	DHS	2004	.215 (.206-.224)	46.9 (45.1-48.6)	45.8 (45.4-46.3)
Lesotho	DHS	2009	.156 (.144-.167)	35.3 (33.0-37.6)	44.1 (43.5-44.8)
Average annual absolute change			-0.012	-2.3	-0.3
Average annual percent change			-5.5	-5.0	-0.7
Madagascar	DHS	2004	.402 (.371-.432)	69.5 (65.4-73.5)	57.8 (56.4-59.2)
Madagascar	DHS	2009	.357 (.344-.369)	66.9 (64.8-69.0)	53.3 (52.8-53.9)
Average annual absolute change			-0.009	-0.5	-0.9
Average annual percent change			-2.2	-0.7	-1.6
Nigeria	DHS	2003	.368 (.347-.389)	63.5 (60.4-66.7)	57.9 (56.4-59.3)
Nigeria	DHS	2008	.310 (.299-.322)	54.1 (52.4-55.8)	57.3 (56.6-58.1)
Average annual absolute change			-0.012	-1.9	-0.1
Average annual percent change			-3.1	-3.0	-0.2

Note: Figures in parentheses correspond to the 95 percent confidence interval.

One of the many interesting distinctive features of MPI is that countries appear to have different patterns in reducing the two components of the MPI: the change in the percentage of people who are multidimensionally poor (the incidence of poverty, H) and the change in the share of deprivations that each household faces at the same time (the intensity of poverty, A). Ethiopia and Madagascar, for example, reduce their MPIs mainly by reducing the intensity of poverty. Ethiopia reduced the headcount at an absolute annual rate of one percent (from 94 percent to 89 percent over a period of five years), while the intensity of poverty is reduced at a much higher rate of 1.8 percent per annum (from 72 percent to 64 percent).[56] Interestingly, in Madagascar the reduction in headcount is not statistically significant while the reduction in intensity is not only statistically significant but substantial.[57] In contrast to Madagascar, the other countries decrease overall poverty mainly by decreasing the incidence of poverty. Among them, Ghana displays the best progress of all by reducing both the incidence and the intensity of poverty at higher annual rates. Although at slower rates than Ghana, Bangladesh and Bolivia also show important reductions in both the incidence and intensity of poverty. Three other countries, Lesotho, Kenya and Nigeria, reduce MPI by decreasing the incidence of poverty, but barely reduce the intensity.[58] It is important to note that *ceteris paribus* if the headcount is reduced and nothing else changes, intensity is likely to *increase* if the marginally poor people exit poverty leaving the remaining poor people with a higher average intensity. In these ten countries though, the intensity of poverty never increases after a reduction in the incidence in poverty.

As a measure of progress, the MPI creates incentives both for bringing people out of poverty (or reducing the headcount) and reducing the intensity poverty, even if they remain multidimensionally poor. This overcomes a well-known problem associated with measures that are limited to headcount only.[59] The headcount based measures provide a clear incentive to draw 'barely poor' people over the poverty line, but do not provide an additional incentive to address the poorest of the poor because they do not reflect the intensity of deprivations. These measures do not change if the intensity of deprivation of a person is reduced but the person remains poor – and yet this too is an important change: if a programme reduces the intensity of the poorest of the poor to just below the poverty cut-off, then the MPI will reflect this change.

6.2 Reduction of Poverty across Indicators

How do reductions in different indicators drive the overall reduction in poverty? They do so differently for different countries. In fact, as shown in Table 6.2, Ghana improves evenly across all indicators except for flooring, where the reduction is not statistically significant. In contrast, Ethiopia shows greater relative improvements in nutrition and water, in comparison with other indicators. Progress across indicators is also uneven in other countries. Madagascar, for example, made great strides in reducing under-nutrition, but deprivation in sanitation appears to have risen during the period, while changes in most indicators are not

[56] Note that the difference in the reduction rate is even larger if we look at relative change: an annual reduction of 1.1 percent in H against an annual reduction of 2.5 percent in A.

[57] The multidimensional headcount was greater for DHS 2004 (69.5%) than for DHS 2009 (66.9%). However, the t-test shows that this difference is not significant F(1, 741)=1.41, Probability >f =0.2361; considering the survey design for both surveys.

[58] Note that in Kenya and Nigeria, the reduction in intensity is not statistically significant. In Jordan, neither changes in H or A are statistically significant.

[59] For some examples see: Erikson (1993), Feres and Mancero (2001) and Nolan and Whelan (1996).

statistically significant. Bolivia shows substantial improvements in school attendance and sanitation, but less progress in decreasing under-nutrition. Jordan only shows small but statistically significant improvements in under-nutrition. Kenya is another interesting case: it shows improvements in five out of six living standards indicators and a small but significant reduction in child mortality; whereas changes in other indicators are not statistically significant.

Table 6.2: Absolute and Relative Change in Censored Headcount Ratios for Ten Countries

	Education		Health		Living Standards					
	YS	**SA**	**CM**	**N**	**E**	**S**	**W**	**F**	**CF**	**AO**
Average annual absolute change in censored headcount										
Bangladesh	-1.3*	-3.9*	-1.8*	-2.3*	-3.0*	-3.4*	-0.1	-3.1*	-3.0*	-3.8*
Bolivia	-0.4*	-3.9*	-1.5*	-0.4*	-2.2*	-3.1*	-1.6*	-1.9*	-2.1*	-1.7*
Colombia	-0.2*	-0.4*	-0.4*	-0.4*	-0.2*	-0.4*	-0.2*	-0.4*	-0.6*	-0.8*
Ethiopia	-2.2*	-1.1*	-1.1*	-5.8*	-0.6*	-2.0*	-5.8*	-0.8*	-0.9*	-1.0*
Ghana	-1.3*	-4.3*	-3.9*	-2.6*	-4.0*	-5.5*	-3.5*	-0.3	-5.5*	-4.1*
Jordan	0.0	0.3	0.1	-0.6*	0.0	-0.1	-0.1	0.0	0.0	0.0
Kenya	-0.6	-0.4	-0.9*	-0.2	-2.1*	-2.7*	-2.8*	-1.8	-1.9*	-2.9*
Lesotho	-0.7*	-1.2*	-0.7*	-0.1	-2.4*	-2.5*	-1.4*	-1.6*	-1.8*	-3.5*
Madagascar	0.9	-0.2	-0.6	-4.3*	-0.4	1.2*	-1.7*	-0.5	-0.5	-1.8*
Nigeria	-0.4	-0.7	-1.6*	-0.8*	-0.2	-4.5*	-2.8*	0.2*	-1.6*	-1.4*
Average annual percent change in censored headcount										
Bangladesh	-4.7*	-18.8*	-6.1*	-5.2*	-6.2*	-5.8*	-4.4	-4.9*	-4.5*	-6.7*
Bolivia	-4.7*	-16.7*	-7.6*	-8.1*	-9.3*	-8.9*	-9.7*	-7.5*	-7.4*	-8.7*
Colombia	-6.8*	-10.4*	-8.9*	-8.8*	-8.6*	-8.9*	-5.8*	-8.7*	-8.6*	-14.8*
Ethiopia	-3.0*	-1.8*	-2.6*	-11.6*	-0.7*	-2.1*	-7.0*	-0.8*	-0.9*	-1.1*
Ghana	-5.8*	-12.7*	-13.1*	-13.4*	-9.0*	-9.6*	-11.8*	-2.1	-9.4*	-11.0*
Jordan	16.0	15.9	4.1	-34.9*	-25.3	-41.9	-27.7	16.5	-27.2	-27.1
Kenya	-4.5	-3.7	-3.4*	-0.7	-3.5*	-4.5*	-6.0*	-3.5	-3.2*	-6.4*
Lesotho	-5.6*	-7.0*	-4.3*	-1.7	-5.2*	-5.7*	-5.4*	-5.2*	-4.3*	-8.1*
Madagascar	2.1	-0.6	-2.2	-12.9*	-0.6	2.1*	-3.0*	-2.9	-0.7	-2.9*
Nigeria	-1.7	-2.3	-3.8*	-2.6*	-0.4	-7.3*	-5.7*	0.6*	-2.6*	-4.2*

Note: Figures with an asterisk have non-overlapping confidence intervals at 95 percent. See Table 4.1 in the appendix for details in confidence intervals the censored headcount ratios of all ten indicators.

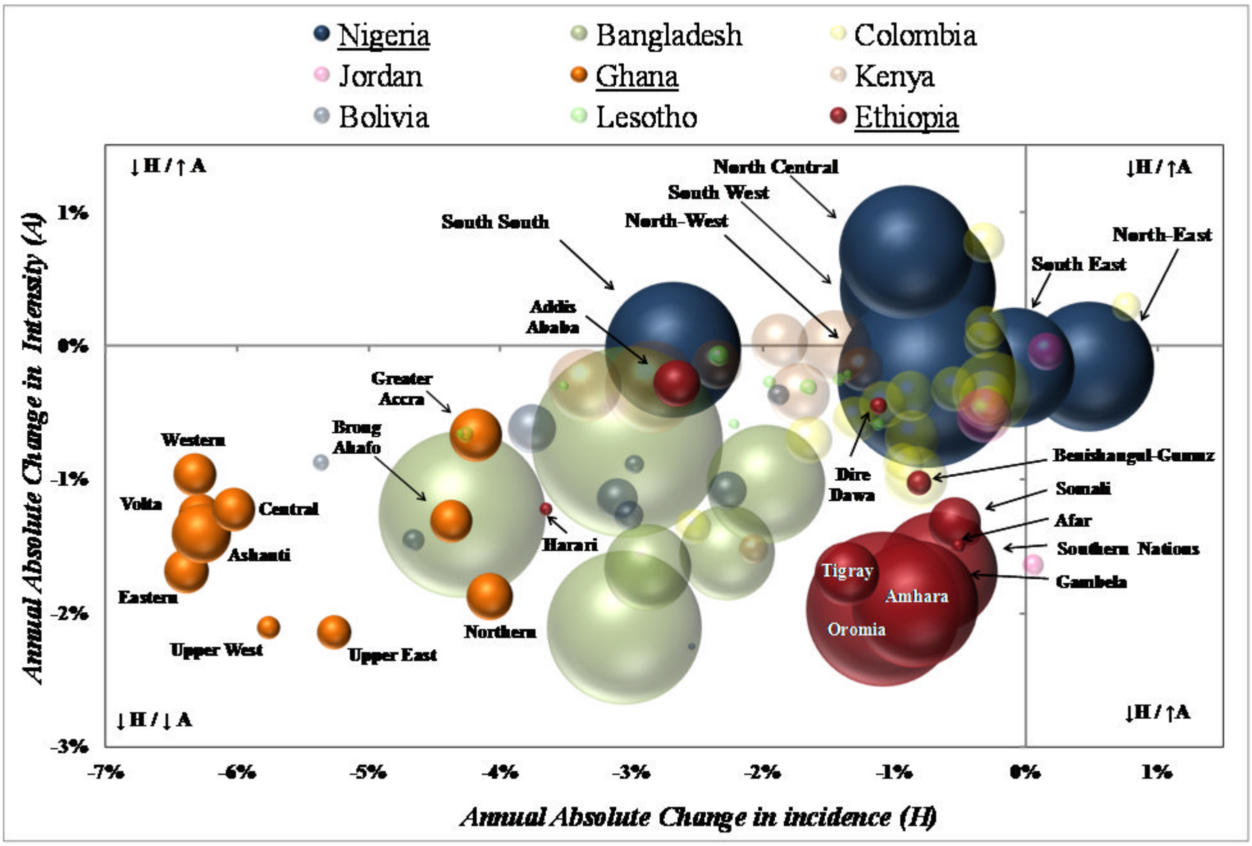
6.3 Poverty Reduction across Sub-national Regions

Inspecting the sub-national changes for these countries shows interesting and very distinctive patterns. Figure 6.1 shows the annualized absolute changes in the incidence of poverty (H) and the intensity of poverty (A) for the countries for which we have comparable estimates at the sub-national level.[60] The figure shows the percentage change in the incidence and intensity of poverty at the sub-national levels experienced within each country. The

[60] Madagascar is excluded from this analysis because the sub-national regions for which the surveys are representative changes from one year to another and it is not possible to regroup them to allow comparability. Hence for Madagascar we only report the results in the appendix but do not undertake analysis a sub-national level in this section.

horizontal axis of the figure assesses the annualized absolute change in the incidence of poverty, while the vertical axis assesses the annualized absolute change in the intensity of poverty. Each sub-national region is represented by a bubble and the size is proportional to its population size. Bubbles with the same color correspond to sub-national regions from the same country. There are four quadrants in the figure: ↑H/↑A, ↓H/↑A, ↑H/↓A, and ↓H/↓A, where ↓ symbolizes a decrease and ↑ symbolizes an increase in H or A. Naturally, the fourth quadrant (↓H/↓A) yields the best possible outcome with a decrease in both incidence and intensity, while the second quadrant (↑H/↑A) is the worst scenario with an increase in both. Note that if there is a decrease or an increase in both intensity and incidence of poverty of a sub-national region, the MPI must register a change in the same direction. However, if either H increases and A decreases or H decreases and A increases, the direction of change in MPI will depend on the magnitude of the changes in H or A. The figure does not, however, reflect the direction of change in MPI if H and A change in opposite directions. Nevertheless, given that most of the bubbles lie in ↓H/↓A coordinate, which means the MPI has fallen, this figure provides some important information about which of the two components of the MPI is responsible for the decrease in MPIs at sub-natioal levels.

Figure 6.1: Annualized Absolute Changes in Headcount Ratio and Intensity of Poverty at the Sub-national Level



Note: The graph shows the figures for 158 sub-national regions for which we have comparable data across time. The size of the bubble is proportional to the population size of each area. Nigeria, Ghana and Ethiopia are highlighted for illustrative purposes. Refer to Table 4.2 in the appendix for details on the 95 percent confidence intervals of MPI, H, A and censored headcounts in each period of time as well as the average annual absolute change and average annual percentage change.

Three countries – Ghana, Nigeria, and Ethiopia – are particularly interesting because they show very different patterns at the national and regional level.[61] The labels of the sub-national regions for these three countries have been highlighted to facilitate reading the results. Ghana shows important progress both at a national level and in all its sub-national regions. The sub-national regions of Ghana experience the highest absolute decrease in poverty reduction among all the sub-regions under study. Nigeria, in contrast, shows a mixed picture. While the region of South South shows a reduction in the incidence of poverty, the rest of the country does not show significant progress and in some cases, either incidence or intensity of poverty has increased. In the third interesting case, Ethiopia primarily reduces the intensity of poverty rather than the incidence, but this is not always the case. The poorest sub-national regions of Ethiopia reduce the intensity of poverty the most among all regions under study. In contrast, in Addis Ababa, another sub-national region of Ethiopia, the reduction is driven by lifting people out of poverty or reducing the incidence of poverty. The small region called Harari shows both an improvement in the incidence and intensity of poverty. The case of Ethiopia shows how in high MPI contexts, reduction in MPI may be seen and celebrated even if its primary mechanism was to reduce the intensity of deprivations poor people experience, not the headcount ratio.

6.4 Reduction in Poverty: Some Illustrations

Kenya and Nigeria provide an interesting comparison. While Kenya's MPI at 0.229 is lower than Nigeria's at 0.309, the national intensity of poverty fell at similar rates in both countries at about 2 percent per year. But their patterns were very different. In Kenya, progress was driven by improvements across the standard of living indicators (with less in health and education); whereas Nigeria's greatest gains were in water, sanitation and cooking fuel, and lower child mortality. But it is also interesting to look behind these country aggregates and see changes within regions of each country over time. As Table 4.2 in the appendix shows, poverty reduction was regionally balanced in Kenya, but poverty declined at a faster pace in the southern regions of Nigeria. Further analysis reveals differences in the drivers that explain the fall. As Table 4.2 in the appendix shows, the reduction of poverty in Kenya was mainly driven by living standard indicators, except for North Eastern, Nyanza and Coast regions, where there were also improvements in indicators of health and education. Note that Nairobi, where MPI declined least, also has by far the lowest MPI with only 4 percent of people poor as compared with a national average of 48 percent. Nigeria shows a very mixed picture, with statistically significant improvements in all the dimensions in the South-South region (which is not particularly poor by MPI) and in sanitation and water in other regions. However, there is also stagnation and increases in deprivation in some regions – unfortunately, particularly in those regions having the highest MPI levels.[62]

Thus in this section we have shown that the MPI and national adaptations of the Alkire and Foster methodology, provide a very rich menu of analyses. In this section we first observed

[61] Ghana's MPI falls from 0.039 in 2003 to 0.144 in 2008; Nigeria's MPI falls from 0.368 in 2003 to 0.310 in 2008; and Ethiopia's MPI falls from 0.678 in 2000 to 0.562 in 2005.

[62] The 95 percent confidence intervals are presented in Table 4.2 in the appendix.

whether poverty was significantly reduced over time, and found it was for 9 of the 10 regions and that the overall amount of reduction was not a function of the starting levels of MPI. Then we analysed, at the national level, how this was created by relative changes in incidence and intensity – to what extent poor people moved out of poverty, and to what extent the intensity of poor people was reduced. These trends were then concretized by viewing the changes in each of the censored headcounts of the indicators at the national level.

In the final two sections, we moved to look at how regions within countries created the overall national picture just examined. Due to the decomposability properties of the AF methodology we are able to repeat the entire analysis for sub-national regions: looking at overall change in MPI, at the relative contribution of changes in incidence and intensity, and then at the changes in the censored headcount. What the empirical case studies showed was that, yet again, progress at the national level can hide diversity among regions – as in the case of Nigeria. Alternatively, progress at the national level may be validated by progress in all regions – as in the case of Ghana.

7. Concluding Remarks

This empirical paper provides a first analysis of the international Multidimensional Poverty Index 2011 for 109 countries, and of the information contained in decompositions of 66 countries across 683 regions and of 10 countries across time. It describes the methodology of the MPI, drawing on the previous descriptions and bringing out in particular those properties that are particularly relevant to the decompositions presented here.

Section three provides an overview of multidimensional poverty with respect to different country classifications. For example, while the MPI and the $1.25/day measure of poverty vary in terms of the number of people who are identified as poor, as well as the national levels of poverty in many countries, both international poverty measures, interestingly, concur that most MPI poor people live in middle income countries, and indeed concur as to the rough percentage of poor people who live in each region. Using the MPI, with its ability to identify various sub-sets of poor people who are more deprived – here a group called 'severely poor' – we are able to add to the previous analysis the finding that they, too, live predominantly in middle income countries. We also find that the number of people who live in 'high MPI sub-national regions' is higher in middle income countries. Thus the MPI provides an internationally comparable measures of poverty that is admittedly data constrained, but does allow an interesting and in-depth assessment of multidimensional poverty across most developing countries and can be used to triangulate key findings that were obtained based on different definitions of poverty and different methodologies (3.1 and 3.2).

Whereas most national and international income poverty measures only use the headcount ratio, the MPI integrates both the incidence and the *intensity* or breadth of deprivations among poor people into one measure. Using this information we explore, for example, multidimensional poverty across South Asia and Sub-Saharan Africa. The MPI in Sub-Saharan Africa is higher than in South Asia. Yet if, using sub-national decompositions of the South Asian countries, we consider the 26 poorest sub-national regions, we find that these have a comparable number of poor people and level of MPI as Sub-Saharan Africa (3.2).

The ability to decompose the MPI by sub-national region has enabled the development of more detailed spatial maps of multidimensional poverty across 66 countries. The analyses of these regions shows that the range and standard deviation of MPI values across sub-national regions is considerable and in some cases exceeds that between countries, which underscores the importance of going beyond national aggregates (3.3-3.4). If we divide the 3.18 billion people living in our 66 decomposed countries into three groups of about 1 billion each, we can divide their corresponding MPI values into Low, Middle and High MPI values. Analysis of the high MPI subnational regions – that is, regions with a high *concentration* of poor people and of deprivations among the poor – is provided in sections 4.2 and 4.3 of this paper.

Section 5 illustrated the diversity of poverty profiles across ranges of MPI values and within a country. It then classified sub-national regional poverty profiles into 11 categories according to the relative contribution of the ten indicators, and analysed these according to geographical region and income category. It thus provided a first systematic classification of the diversity of MPI poverty profiles, which is important as different profiles, properly analysed in the contexts where the MPI is broadly relevant, would give rise to different policy responses.

The sixth section illustrated the powerful and detailed analyses that are possible by comparing a consistent poverty measure across countries and across regions within countries over time. Comparisons are possible not just for poverty level, nor just for the headcount and the intensity, but also for each of the ten indicators in absolute and relative terms. As the MPI is updated the number of countries for which such analysis will be feasible will rise sharply, and this should give rise to further research on the processes and drivers of change.

In all of the discussions some common points arise. One is that it is not necessary to choose between having a dashboard and having a multidimensional poverty index. The MPI, because of its measurement properties, has both. It is a single number, but can be – and indeed must be and is – naturally broken down into its components in order to provide the fullness of analysis of how it changes. The tables in the Appendix clearly show this, as they provide the MPI, H and A, and the censored headcounts and contributions of each of the 10 indicators: an overall poverty measure, and a dashboard.

Naturally many more questions could be considered and analysed using the data in the appendices. By providing an overview of the data and certain descriptions of the findings, this paper naturally raises a number of issues for further research, particularly relating to composition of poverty and to the policies, institutions, and natural or political contexts that explain the different patterns of poverty and disparity among the poor, as well as of poverty reduction observed across the countries. Our hope is that this study will catalyse further vigorous investigations that will bring the measurement of poverty closer to the constrained and contextualised work of regional and national governments and institutions in reducing such poverty.

References

ALKIRE, S. and J. FOSTER (2007) Counting and Multidimensional Poverty Measurement. *OPHI Working Papers No. 7*. Oxford, The University of Oxford.

ALKIRE, S. and J. FOSTER (2011) Counting and Multidimensional Poverty Measurement. *Journal of Public Economics*, 95 (7-8).

ALKIRE, S., J. M. ROCHE, M. E. SANTOS and S. SETH (2011) Multidimensional Poverty Index 2011: Brief Methodological Note. *Oxford Poverty and Human Development Initiative*. <http://www.ophi.org.uk/policy/multidimensional-poverty-index/mpi-data-methodology/>.

ALKIRE, S. and M. E. SANTOS (2010) Acute Multidimensional Poverty: A New Index for Developing Countries. *OPHI Working Paper No. 38*. Oxford, University of Oxford.

ERIKSON, R. (1993) Descriptions of Inequality. The Swedish Approach to Welfare Research. IN NUSSBAUM, M. and A. SEN (Eds.) *The Quality of Life*. Oxford, Clarendon Press.

FERES, J. C. and X. MANCERO (2001) El método de las necesidades básicas insatisfechas (NBI) y sus aplicaciones a América Latina. *Series Estudios Estadísticos y Prospectivos*. ECLAC-United Nations.

FOSTER, J., J. GREER and E. THORBECKE (1984) A Class of Decomposable Poverty Measures. *Econometrica*, 52 (3), 761-766.

FOSTER, J. E. and A. SEN (1997) *On Economic Inequality: After a Quarter Century*, Oxford, Clarendon Press.

KANBUR, R. (2011) Aid to the Poor in Middle Income Countries and the Future of IDA. *Paper based on Opening Plenary Address to the joint 13th EADI General Conference and DSA Annual Conference, University of York, UK.* <http://kanbur.dyson.cornell.edu/papers/AidToMiddleIncomeCountries.pdf>

NOLAN, B. and C. T. WHELAN (1996) *Resources, Deprivation and Poverty*, Oxford, Oxford University Press.

OECD (2011) Ensuring Fragile States are not Left Behind: 2011 Factsheet on Resources Flows in Fragile States. *OECD-DAC International Network on Conflict and Fragility (INCAF).*

SUMNER, A. (forthcoming 2011) Where Do The Poor Live? *World Development*.

UNDP (2011) *Human Development Report 2011: Sustainability and Equity*, New York, UNDP.

UNITED NATIONS (2011) *World Population Prospects: The 2010 Revision. CD-ROM Edition*, New York, Department of Economic and Social Affairs, Population Division.

WORLD BANK (2010) *World Development Indicators*, Washington, D.C.

YALONETZKY, G. (2011) A Note on the Standard Errors of the Members of the Alkire Foster Family and its Components. *OPHI RP 25a* <http://www.ophi.org.uk/wp-content/uploads/OPHI-RP-25a.pdf?cda6c1>.

Appendices

Appendix 1: Tables 1, 2, 3 and 4 with the estimation results
(Available at:
http://www.ophi.org.uk/policy/multidimensional-poverty-index/mpi-data-methodology/)

Appendix 2: Kernel density graphs for indicator contribution by regional MPI level