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Measuring Acute Poverty in the Developing World: Robustness and Scope of the Multidimensional Poverty Index

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Abstract

This paper presents the Multidimensional Poverty Index (MPI), a measure of *acute poverty*, understood as a person's inability to meet simultaneously minimum international standards in indicators related to the Millennium Development Goals and to core functionings. It constitutes the first implementation of the direct method to measure poverty for over 100 developing countries. After presenting the MPI, we analyse its scope and robustness, with a focus on the data challenges and methodological issues involved in constructing and estimating it. A range of robustness tests indicate that the MPI offers a reliable framework that can complement global income poverty estimates.

Keywords: poverty measurement, multidimensional poverty, capability approach, MDGs, basic needs, developing countries.

JEL classification: I3, I32, D63, O1

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The Oxford Poverty and Human Development Initiative (OPHI) is a research centre within the Oxford Department of International Development, Queen Elizabeth House, at the University of Oxford. Led by Sabina Alkire, OPHI aspires to build and advance a more systematic methodological and economic framework for reducing multidimensional poverty, grounded in people's experiences and values.

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1. Introduction

There are essentially two methods to measure poverty, the *direct* method and the *indirect* or income approach.[1] The direct method shows whether people satisfy a set of specified basic needs, rights, or – in line with Sen's capability approach – *functionings*. The indirect method determines whether people's incomes fall below the poverty line – the income level at which some specified basic needs can be satisfied. Both methods have been extensively applied. The direct method has been implemented with measures of relative deprivation in Europe, measures of hardship in the US, and official measures of Unsatisfied Basic Needs in Latin America, for example.[2] The income method has been implemented in official poverty measures for most countries of the world.[3]

International poverty comparisons have used income poverty measures since the important contribution of Ravallion, Datt and van de Walle (1991), which estimated the magnitude of income poverty in the developing world. The authors used data from household surveys, the coverage of which had grown significantly. Then as now, data was not perfectly comparable and the authors had to make significant adjustments and assumptions.[4] This approach developed into the 'dollar-a-day' or 'extreme' poverty measure reported by the World Bank.[5]

Leaving aside the challenges of data comparability, from the start there has been recognition of the basic limitations of the income method. First, the pattern of consumption behavior may not be uniform, so attaining the poverty line level of income does not guarantee that a person will meet his or her minimum needs (Sen 1981, p. 28). Second, different people may face different prices, reducing the accuracy of the poverty line (Sen 1981, p. 28). Third, the ability to convert a given amount of income into certain *functionings* varies across age, gender, health, location, climate and conditions such as disability – i.e. people's conversion factors differ (Sen 1979).[6,7] Fourth, affordable quality services, such as water, health and education, are frequently not provided through the market.[8] Fifth, using the indirect method

[1] Sen (1981, chapter 3) introduces this distinction and discusses the pros and cons of each method; this is further elaborated in Sen 1997 and 1999. Here we use income to refer to monetary poverty measurement, which may use income, consumption or expenditure data.

[2] Applications in Europe include Townsend (1979), Mack and Lansley (1985), Gordon et al. (2000), Callan, Nolan and Whelan (1993), Halleröd (1995), Layte, Nolan, Whelan (2000), Halleröd et al. (2006), and Whelan Nolan Maitre (2012) to mention a few. Applications in the US include Mayer and Jencks (1989). For applications in Latin America see for example INDEC (1984), Boltvinik (1992), Katzman (1989), Feres and Mancero (2001).

[3] In some regions of the world, such as the US and Latin America, an absolute poverty line approach is used, whereas in others, such as Europe, a relative poverty line approach is used.

[4] For example, the paper estimated poverty for 86 developing countries, of which there were empirical estimates for 22 countries and extrapolations for the other 64 countries. They used consumption data for 12 countries, whereas for others they used income data which was "adjusted pro rata according to an average propensity to consume estimated from national accounts" (p. 352). Grouped data (as opposed to individual records) was another source of potential inaccuracy as well as the estimated PPP rates. The critical incidence of each methodological choice for the particular global poverty estimate has remained over time, as documented by the recent empirical sensitivity analysis performed by Dhongde and Minoiu (2012).

[5] The World Bank computes different members of the Foster, Greer and Thorbecke (1984) family of poverty measures (which include the headcount ratio and the poverty gap) for several alternative poverty lines. The poverty lines were adjusted in Chen and Ravallion (2010). For simplicity, we refer here to the 'dollar-a-day' income poverty measure.

[6] *Functionings* are defined by Sen (1992) as the beings and doings that a person can achieve.

[7] For example Bourguignon et al (2008) find little or no correlation between economic growth and non-income MDGs. Also, Ruggieri-Laderchi et al (2003) demonstrate empirical mismatches between direct and income poverty measures.

[8] Bourguignon and Chakravarty (2003), p. 26; Callan, Nolan and Whelan (1993), p.169.

provides no way to verify the intra-household distribution of income.[9] Sixth, participatory studies indicate that people who experience poverty describe their state as comprising deprivations in addition to low income. Finally, from a conceptual point of view, income is a general purpose means to valuable ends. Measurement exercises should not ignore the space of valuable ends.

Motivated by the possibility of implementing a direct approach, between 2009 and 2010, the Oxford Poverty and Human Development Initiative, in collaboration with the United Nations Development Program's Human Development Report Office, developed the Multidimensional Poverty Index (MPI). The first round of estimates was released in July 2010 (Alkire and Santos 2010) and in November in the Human Development Report (UNDP 2010), raising intense interest and debate.[10,11] The MPI constitutes the first implementation of the direct method to measure poverty in an internationally comparable way, having wide coverage of developing countries. This was enabled by the availability of multi-topic household surveys that collect information associated with key basic needs and functionings, computational power, and the new Alkire and Foster measurement methodology.

The MPI has a similar spirit to that which once motivated the development of the 'dollar-a-day' measure. First, it attempts to assess the magnitude of poverty in the developing world. Second, aiming at that, it has to manage data constraints. Thus just like the 'dollar-a-day' measure, it is forced "to make a necessarily rough but methodologically consistent assessment" of poverty (Ravallion, Datt and van de Walle 1991, p. 345). Third, it has an underlying concept of absolute poverty. The 'dollar-a-day' measure aimed to quantify "the extent of absolute poverty in the developing world, interpreted as the inability to attain consumption levels which would be deemed adequate in only the poorest countries" (Ravallion, Datt and van de Walle, 1991, p. 346). The MPI aims to quantify *acute* poverty, understood as a person's inability to meet *simultaneously* the minimum internationally comparable standards in indicators related to the Millenium Development Goals (MDGs) and to core functionings.[12]

The key difference between the MPI and the 'dollar-a-day' measures is precisely that the first applies the direct method whereas the second applies the indirect method. The two measures are complements. As noted by Sen (1981), they are not "...two alternative ways of measuring the same thing, but represent two alternative conceptions of poverty." While the MPI identifies those who *actually fail* to meet the accepted conventions of minimum needs or functionings, the $1.25/day method identifies those who do not have the income usually required to meet certain needs. Both concepts are of interest in assessing poverty (Sen 1981, p. 27–28). Hence the MPI intends to complement income poverty analyses in the developing world by bringing information from a different angle – a focus on actual deprivations.

The MPI is one particular implementation of the direct method in terms of functional form and parameters. The direct method has traditionally used a counting approach to identify the poor and the

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[9] For example, there is evidence of an anti-female bias in some regions as girls have a greater probability of being aborted and/or of perishing in childhood (Sen 1990, 2003; Klasen and Wink 2003).

[10] See for example the academic forum published in the *Journal of Economic Inequality*, volume 9 numbers 2 and 3.

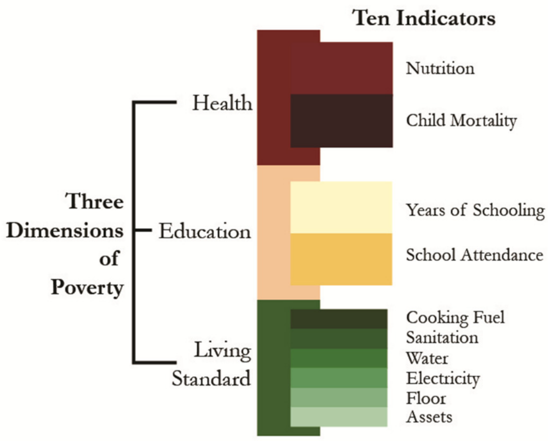
[11] The MPI replaced the Human Poverty Index (HPI) which had been reported since 1997 (Anand and Sen 1997). The MPI shares the same motivation with the HPI: the desire to move from the unidimensional space to a multidimensional one and to consider the ends of development rather than means. Dealing with the data constraints of the time, the HPI used aggregate data. The MPI uses individual-level data to identify the *people* who experience overlapping deprivations.

[12] Some have argued that the MPI uses very low deprivation cutoffs and therefore underestimates poverty in some regions of the world, such as in Latin American countries (Boltvinik 2012). Indeed, the MPI leaves out many people who are poor according to standards in their societies. Yet, the MPI is aimed at measuring *acute* poverty, using cross-country norms. The MPI can (and is being) supplemented by the construction of national MPIs, tailored to their specific contexts. These alternative specifications of the MPI are analogous to the national poverty measures vs. the 'dollar-a-day' measures.

headcount ratio measure for aggregation.[13] The MPI uses one member of a new family of poverty measures developed by Alkire and Foster (2007, 2011a; AF henceforth), the Adjusted Headcount Ratio or M_0 measure. The AF measures belong to a new generation of poverty measures that have renewed interest in the direct method by using solid aggregation methodologies based on axiomatic frameworks analogous to those which enabled the advances in income poverty measurement in the '70s and '80s.[14] The AF measures additionally elaborate the identification step, making explicit the use of a *dual cutoff approach* and axioms that are joint restrictions on identification and aggregation procedures. These new poverty measures are described as multidimensional rather than unidimensional measures, and in essence they implement the direct vs. indirect method.

The MPI applies the M_0 measure to a set of ten deprivations related to the MDGs across three dimensions: health, education and standard of living (see Figure I). The information provided by the MPI differs from what individual MDG indicators can offer, what has been called by Ravallion (2011) a *dashboard approach*. How? The MPI identifies people with *joint disadvantages*. This has been widely recognized as its novelty and strength, because understanding the deprivations people face at the same time is of independent ethical and policy interest.[15]

Figure 1: Dimensions and indicators of MPI



[13] Counting approaches identify the poor based on the number of dimensions in which their achievements fall below a threshold.

[14] This 'new generation' of axiomatic poverty measures includes those by Chakravarty, Mukherjee and Renade (1998), Tsui (2002), Bourguignon and Chakravarty (2003), Chakravarty and Silber (2008), Bossert, Chakravarty and D'Ambrosio (2009), and Alkire and Foster (2011a). Not all new measures can be used with ordinal data.

[15] See Stiglitz, Sen, Fitoussi (2009), Bourguignon and Chakravarty (2003), Deaton (2011), Ravallion (2011), and Ferreira (2011).

After a concise presentation of the MPI's construction, this paper clarifies the data challenges faced when constructing an internationally comparable multidimensional poverty measure and explains the methodology the MPI employed. It offers key results and then presents a range of robustness tests which evaluate the extent to which the 2010 MPI results are reliable and stable to changes in parameters. The last section concludes.

2. The MPI's Structure

The MPI's mathematical structure corresponds to one member of a family of multidimensional poverty measures proposed by Alkire and Foster (2007, 20011a), the M_0 or Adjusted Headcount Ratio. [16] For a detailed presentation of this family of measures, please see Alkire and Foster (2011a). Constructing this measure entails the following steps.

1. Defining the set of *indicators* which will be considered in the multidimensional measure. Data for all indicators needs to be available for the same person or household.
2. Setting the *deprivation cutoffs* for each indicator, namely the level of achievement (normatively) considered sufficient in order to be non-deprived in each indicator.
3. Applying the cutoffs to ascertain whether each person is *deprived* or not in each indicator.
4. Selecting the relative weights or value that each indicator has, such that these sum to one.
5. Determining the *poverty cutoff*, namely, the proportion of weighted deprivations a person needs to experience in order to be considered multidimensionally poor.
6. Creating the weighted proportion of deprivations for each person, which can be called his/her *deprivation score*, and identifying him/her as multidimensionally poor or not according to the selected poverty cutoff.
7. Computing the proportion of people who have been identified as multidimensionally poor in the population. This is the *headcount ratio* of multidimensional poverty H, also called the **incidence** of multidimensional poverty.
8. Computing the average share of weighted indicators in which poor people are deprived. This entails adding up the deprivation scores of the poor and dividing them by the total number of poor people.[17] This is the **intensity** of multidimensional poverty, A.
9. Computing the M_0 measure as the product of the two previous partial indices: $M_0=H \text{ x } A$. Analogously, M_0 can be obtained as the sum of the weighted deprivations that the poor (and *only* the poor) experience, divided by the total population.

There are various reasons for choosing the M_0 measure as the structure for the MPI over other available measures. In the first place, given that there is yet no satisfactory procedure to 'cardinalize' ordinal

[16] For a more pedagogical presentation, see Alkire and Foster (2011b).

[17] The deprivations experienced by people who have not been identified as poor (ie. those whose weighted deprivation score is below the poverty cutoff) are not included; this *censoring* of the deprivations of the non-poor is consistent with the Poverty Focus Axiom which – analogous to the unidimensional case – requires a poverty measure to be independent of the data of the non-poor. For further discussion see Alkire and Foster (2011a).

variables, the measure is robust when using categorical, ordinal or cardinal variables, as it dichotomizes the individuals' achievements into 'deprived' and 'non-deprived'.

Second, by adjusting the incidence of multidimensional poverty by the intensity, M_0 satisfies **dimensional monotonicity** (Alkire and Foster 2011a): if a poor person becomes deprived in an additional indicator, M_0 will increase.

Third, the measure is **decomposable by population subgroups**, meaning that the M_0 of the overall society can be obtained as the population-weighted sum of subgroup poverty levels (total subgroups exhausting the population). This enables comparing poverty across subgroups.[18]

Fourth, after identification, M_0 can be **broken down by indicator**. The overall M_0 can be expressed as the weighted sum of the proportion of the total population who have been identified as poor and are deprived in each indicator (weights referring to the *relative* weight of each indicator). These proportions are the so-called *censored headcount ratios*, as opposed to the *raw* (or uncensored) *headcount ratios* which are simply the deprivation rates in each indicator (without excluding – i.e. *censoring* – the deprivations of the non-poor). Analogous to population subgroup decomposability, this break-down enables analysis of the contribution of deprivations in a specific indicator to overall poverty.[19]

For these reasons, the M_0 is intuitive yet a technically solid measure. It summarizes a complex phenomenon such as multidimensional poverty in one number. Yet it can be unfolded into an array of intuitive and consistent subindices which include poverty incidence and intensity, indicators' censored headcount ratios, percent contributions by indicators, and comparisons across population subgroups. The overall M_0 has a direct intuition also: it reflects the proportion of weighted deprivations that the poor experience out of all the total potential deprivations that society could experience.

The M_0 measure is the mathematical *structure* of the MPI. In the next section we explain the *content* of the MPI, that is, the particular selection of dimensions, indicators, deprivation cutoffs, weights and poverty cutoff, some of which are constrained by data availability.

3. Data Challenges and Methodological Issues

A poverty measure using the direct method considers all indicators pertaining to the same unit of analysis – individuals or households. Normally, they must come from the same survey or data source. Given that the MPI is designed to be an internationally comparable measure for the developing world, the requirement was more demanding: we needed to use comparable indicators present in household surveys of 100+ developing countries. While the collection of data from household surveys has improved steadily, data limitations constrain the dimensions, the indicators and the unit of analysis chosen for the MPI. Other methodological decisions are also linked to data limitations such as the treatment of households with non-applicable population for certain indicators and the treatment of missing values. Within these constraints, decisions on the MPI parameters – deprivation cutoffs, weights

[18] Subgroup percentage contribution to overall poverty is computed as the subgroup M_0 weighted by its population share over the overall M_0.

[19] The percentage contribution of an indicator to overall poverty is computed as the censored headcount ratio multiplied by its relative weight, divided by the overall M_0 measure. When several indicators belong to the same dimension, the dimensional contribution can be obtained simply by summing the percentage contributions of all indicators within that dimension.

and the poverty cutoff – are based on normative arguments. We address each of these decisions in turn. Still, we hope that the bottleneck of data availability can be addressed directly in post-2015 MDG discussions.

3.1 Dimensions, indicators and unit of analysis

The potential dimensions that a measure of poverty might reflect are broad and include health, education, living standards (which might include income, housing, infrastructure, services and assets), work, empowerment, the environment, safety from violence, social relationships, and culture (Alkire 2008). Yet, the MPI includes only three dimensions: health, education and living standards. Comparable data of sufficient quality are not available from the same survey in the public domain for 100+ developing countries to consider *any* other dimension. Nor were all relevant indicators for the chosen dimensions available. For example, it was not possible to include income or quality of education because these variables were missing in most surveys that contained health variables such as nutrition.[20]

Despite being conditioned by data, the chosen dimensions are vitally important. First of all, they have intrinsic and instrumental value: health and education can both be valuable in themselves as well as instrumental to many other vital outcomes. Similarly, although the living standard variables are resources, they provide an imperfect proxy for the basic amenities of housing and services and general purpose assets which are identified as important in the MDGs, in participatory exercises and in human rights. Second, parsimony: having only three dimensions – which mirror the dimensions included in the Human Development Index (HDI) – simplifies communication. Third, consensus: while there could be some disagreement regarding how to include work, empowerment or physical safety in an internationally comparable poverty measure, the contribution of the chosen dimensions is widely recognized across political and ideological divides. Fourth, interpretability: there are substantial literatures and fields of expertise on each dimension. Fifth, data: while MPI indicators are limited, their validity, strengths and limitations are well documented.

In terms of the unit of analysis, ideally the MPI would have used the person as the unit of analysis, in order to analyse intra-household inequalities and decompose poverty by gender and age. However, health and, sometimes, educational indicators are not available for all household members. Thus, the MPI uses any available information on all members of each household in order to identify all household members as poor or not. Using overall household achievements to identify each person as poor, despite its limitations, allows for interaction, smoothing and mutual sharing within the household, and can create policy efficiencies (Basu and Foster 1998).

Table 1 displays the ten indicators, weights and deprivation cutoffs used. The deprivation cutoffs used for each indicator are based to a large extent on international standards such as the MDGs.

Despite data constraints, each indicator conveys a distinctive insight. For education we use two indicators: whether someone in the household has five years of education and whether all children of school age are attending school. While information on educational achievements and the quality of education would be desirable for both indicators, years of schooling provides a rough proxy of basic educational skills: literacy, numeracy and understanding of information. All household members are considered non-deprived if at least one person has five years of schooling. School attendance is used to indicate whether children, at the age in which they would attend classes one to eight, are being exposed to a learning environment. This indicator is used in the MDGs, UNESCO (2010) and the basic needs

[20] Additional questions are available in the Gallup International survey but the data are not publicly available.

approach. When a child is not in school, all household members are considered deprived.[21] This indicator is sensitive to policy changes.

Health was the most difficult dimension to measure. We use two health indicators that relate to but are defined differently from standard health indicators. The first identifies a person as deprived in nutrition if anyone in their household is undernourished. Under-nutrition usually indicates a functioning failure which can have life-long effects in terms of cognitive and physical development in the case of children and which makes any person vulnerable to other health threats. The second indicator is whether a child in the household has died. The death of a child is a total health functioning failure – one that is direct and tragic, and that influences the entire household. Most, although not all, child deaths are preventable, being caused by infectious disease or diarrhea.[22] In the MPI all household members are considered deprived if there is record of a person being malnourished; similarly, all members are considered deprived if there has been at least one observed child death (of any age) in the household.

The standard of living dimension comprises six indicators. There are three standard MDG indicators that are also related to health and particularly affect women: safe drinking water, improved sanitation and the use of clean cooking fuel. There are two non-MDG indicators: electricity and flooring material. Both of these provide some rudimentary indication of the quality of housing. The final indicator covers the ownership of some consumer goods, each of which has its own literature: radio, television, telephone, bicycle, motorbike, car, truck and refrigerator. The living standard indicators are means rather than ends; they are not direct measures of functionings. Yet, these means are very closely connected with the ends (functionings) they are supposed to facilitate.

[21] The length of primary school across countries varies from three to eight years (UNESCO 2010) with a median of six years. Given the prevalence of children starting school late and repeating grades, many of the older children might in fact still be completing primary school. Also, the MDGs indicators on schooling include an indicator on orphans' vs. non-orphans' school attendance at ages 10–14, which would normally exceed primary school. In light of these considerations, the cutoff is taken as 8 years from the age at which the child could have started primary school in that country.

[22] The year of death of the child is not recorded in most surveys. However it provides at least rudimentary information on health functionings, and empirically, changes are observed across time (Alkire and Roche 2013, Alkire and Seth 2013).

Table 1: Dimensions, indicators, cutoffs and weights of the MPI

Dimension	Indicator	Deprived if…	Relative Weight
Education	**Years of Schooling**	No household member has completed five years of schooling	16.7%
	Child Attendance to School	Any school-aged child is not attending school in years 1 to 8	16.7%
Health	**Mortality**	Any child has died in the family	16.7%
	Nutrition	Any adult to child for whom there is nutritional information is malnourished*	16.7%
Living Standard	**Electricity**	The household has no electricity	5.6%
	Sanitation	The household's sanitation facility is not improved (according to MDG guidelines), or it is improved but shared with other households**	5.6%
	Water	The household does not have access to safe drinking water (according to MDG guidelines) or safe drinking water is more than 30 minutes walking from home, roundtrip.***	5.6%
	Floor	The household has dirt, sand or dung floor.	5.6%
	Cooking Fuel	The household cooks with dung, wood o carbon.	5.6%
	Assets	The household does not own more than one of the following assets: radio, television, telephone, bicycle, scooter or refrigerator, and does not own a car or a truck.	5.6%

*Adults are considered malnourished if their BMI is below 18.5. Children are considered malnourished if their z-score of weight-for-age is below minus two standard deviations from the median of the reference population. This was estimated following the algorithm provided by the WHO Child Growth Standards (WHO 2006). http://www.who.int/childgrowth/software/en/

**A household is considered to have access to improved sanitation if it has some type of flush toilet or latrine, or ventilated improved pit or composting toilet, provided that they are not shared.

*** A household has access to safe drinking water if the water source is any of the following types: piped water, public tap, borehole or pump, protected well, protected spring or rainwater, and it is within a distance of 30 minutes' walk (roundtrip).

3.2 Data sources used

Three main datasets were used to compute the MPI: the Demographic and Health Survey (DHS), the Multiple Indicators Cluster Survey (MICS) and the World Health Survey (WHS). These surveys were selected for two reasons. First, country implementation follows standardized guidelines, so there is relatively greater homogeneity and comparability than between other national multi-topic household surveys. Second, they contain relevant and internationally comparable information on health indicators such as nutrition and mortality which are vital to multidimensional poverty but are missing from standard income and expenditure surveys. All the questions used to construct the MPI indicators were harmonized one-by-one to ensure the strongest comparability possible given the data constraints.

The surveys were implemented in different years. We used the most recent available dataset for each country (from the year 2000 and available until April 2010). Whenever more than one survey dataset was available, we generally privileged DHS over MICS, and MICS over WHS, because of data quality and indicator availability.

We used DHS datasets, Phase 4 or higher, for 48 developing countries. MICS 2 or MICS 3 datasets were used for 35 developing countries, and WHS datasets for 19 countries.

All three datasets are nationally representative. They follow a multi-stage stratified design, thus when the sample is not self weighted, we used the sample weights provided in the datasets. When using the DHS, we have only considered the *de jure* members, excluding the *de facto* members. This was necessary for comparability across surveys and avoids over-estimation of poverty for DHS datasets.

Additionally, two country-specific surveys were used: the Encuesta Nacional de Salud y Nutrición (ENSANUT) of Mexico, conducted in 2006, and the Encuesta Nacional de Nutrición y Salud (ENNyS) of Argentina conducted in 2004–2005. No other survey with the required indicators was available for these countries. ENSANUT is nationally representative and collects indicators that are comparable with those in the other three surveys. The ENNyS dataset was conducted only in urban areas, and the sample design and survey weights do not allow nationally representative estimates in urban areas. We report these estimates as a lower bound estimate of acute multidimensional poverty in the urban areas of Argentina.[23]

Of the 104 countries, 24 are in Central and Eastern Europe and the Commonwealth of Independent States (CIS), 11 are Arab States, 18 are in Latin America and the Caribbean, 9 are in East Asia and the Pacific, 5 are in South Asia and 37 are in Sub-Saharan Africa. We would have liked to have a larger and more recent dataset for China than the WHS, which covers just under 4,000 households.[24] Our robustness checks suggest that (unlike other WHS datasets) the estimates for China are quite

[23] It is well known that rural areas in Argentina (which are not covered systematically by any survey), especially in the northern regions, are significantly poorer than urban ones.

[24] We also performed estimations using the China Health and Nutrition Survey (CHNS), but it is not nationally representative. In the covered areas, the CHNS provided a lower MPI than the WHS.

stable across parameter choices. Still, given the small sample size we refrain from a detailed analysis of China.

Table 2 briefly describes the available information on each indicator provided by each survey. It can be seen that there is variability across surveys, especially among the health indicators.

Overall, 63 of the 104 countries have all ten indicators and 93 countries have nine or ten indicators. Eight countries lack two indicators and three countries lack three variables.[25] In all these cases, the indicators' weights are adjusted following the structure detailed in Section 3.5.

Cross-country comparability is affected by data constraints in several ways: we use different surveys that have differences in the definition of some indicators such as nutrition, we use different years, and eleven countries lack more than one indicator. Therefore, the value added of this study is not in determining the precise position of each country in an 'international ranking' but rather in a) providing a more comprehensive and accurate picture of global acute poverty, b) providing a poverty estimate in each of the 104 countries as well as the associated partial indices reflecting incidence, intensity and composition, and c) demonstrating a methodology that can be adapted to national or regional settings and applied to improved datasets.

[25] For details on which country lacks which indicator, see tables in the Supplementary Data. Of the 30 countries lacking one indicator, 13 are WHS countries lacking child school attendance, five countries lack mortality, eight countries lack nutritional information, and four lack one living standard indicator.

Table 2: Information on each MPI indicator provided in each survey

Dimension	Indicator/Survey	DHS	MICS	WHS	ENSANUT (Mexico)	ENNyS (Argentina)
Health	**Nutrition**	All women 15–49 years All under-5-year-old children[1]	All under-5-year-old children [2]	The respondent (adult male or female)	All household members	All women 10–49 years All under-5-year-old children
	Mortality	Non-age specific question and birth history asked of all women 15–49 In 37 countries, this is also asked of all males within a certain age range, or to males in a random sub-sample of households. Males' age range varies.	Non-age specific question asked to all women 15–49	Non-age specific question and birth history asked of all female respondents. Also there are questions on sibling's mortality applicable to female respondents of any age and male respondents up to 25 years. Of these, we only considered respondents of up to 25 years with siblings dying at age 15 or younger.	Non-age specific question asked of all women 10 years old and older	Non-age specific question asked to all women 10–49

Table 2: Information on each MPI indicator provided in each survey (cont.)

Dimension	Indicator/Survey	DHS	MICS	WHS	ENSANUT (Mexico)	ENNyS (Argentina)
Education	**Years of Education**	All household members' years of education	Years of education non-available. We construct it using the highest educational level achieved and the highest grade completed in that level, considering the duration of each educational level in each country.[3]	Respondent's years of education and level of education for other household members. We consider that at least someone in the household has completed five years of education if: (a) any household member has completed secondary school or more, or (b) the respondent has completed five years of education or more, or (c) the maximum level of education of the household is incomplete or complete primary and the median number of years of education of all respondents with that educational level is five or more.	Same as in MICS	Same as in MICS but only available for females aged 10–49 and household head
	Child School Attendance	Child currently attending school or not in most countries. In a few, it refers to previous year (age is adjusted).	Child currently attending school or not	Not available	Child currently attending school or not	

Table 2: Information on each MPI indicator provided in each survey (cont.)

Dimension	Indicator/Survey	DHS	MICS	WHS	ENSANUT (Mexico)	ENNyS (Argentina)
Living Standard	**Water**	Source of drinking water and time to the water source roundtrip (only 6 DHS countries lack time to water variable)			Source of drinking water source not available.	Time to the water
	Sanitation	Type of facility and sharing condition[4]			Type of facility. Sharing not available.	
	Electricity	Available. In the few countries in which this was not available, if the country had a coverage of 95% or higher (IEA 2009), we assumed that no one is deprived in electricity.				
	Cooking Fuel	Available across all surveys except for six countries				
	Floor	Available across all surveys except for one country				
	Assets	Available	Available	Lacks information on radio and motorbikes	Available	Only information on refrigerators and telephones. Given that even in slums people have a radio and TV, we required the household to have only one of refrigerator or telephone to be considered non-deprived.

Notes: [1]In 12 DHS countries not all eligible women between 15 and 49 years of age and under-5-year old children were measured for nutritional assessment. In 11 of these countries females and children were measured only in a 50% random sub-sample of households and in Senegal in a 33% random sub-sample of households. These countries are signaled in Table A.1. To keep consistency with the methodology, we decided to consider the sub-sample of eligible women and children not selected to be measured as if they were a non-applicable population, and thus non-deprived. This is in fact what we do with women in MICS and children in WHS.[2] Only Yemen, Somalia and Iraq are MICS countries with birth history.[3] The duration of each level as well as the age at which children start school in each country was taken from UNESCO (2010). Given that UNESCO determines the duration according to the International Standard Classification of Education, this information was contrasted with each dataset and country-specific information and adjusted whenever necessary.[4] In Colombia, the information on sharing sanitation facilities was considered unreliable (inexplicably high) and thus was ignored.

3.3 Treatment of households with non-applicable population

Ideally, the MPI would reflect the same achievements for each person in the sample. However such an index would exclude all child-related information, because not every household has a child member. Given the importance of children and of health, the MPI includes three indicators that are not applicable to all households yet, we feel, make the measure more accurate than the alternative.

The three indicators are as follows. Child school attendance is non-applicable for households with no children of school age; nutrition is non-applicable for households that have no under-five-year-old children and no women aged 15–49 in DHS, and for households that have no under-five-year-old children in MICS. Finally, the mortality indicator is non-applicable in DHS households if households have no information from either a male or a female in reproductive age, in MICS households if there are no females in reproductive age, and in WHS households if the respondent is a male older than 25 years. In all cases, the procedure followed is to consider the households that do not have the relevant eligible population to be non-deprived in the relevant indicators. Households that *do* have applicable populations but have missing values are considered to have missing data and are excluded from the sample.

3.4 Treatment of missing data and sample sizes

Whenever a household had missing information for all its members in an indicator, it was excluded. If there was missing information for some members, we used the available information as follows. For years of education, if at least one member has five or more years of education we classify the household as non-deprived. If we have information on two-thirds (or more) of household members, and these each report less than five years of education, the household is classified as deprived; otherwise it is considered missing. For child school attendance, if we have information for at least one of the children in the household, the household is classified according to this value.

For nutrition, in DHS countries, if nutritional information was entirely missing and there were eligible children and/or women, we consider the household as missing this indicator.[26] Otherwise, we used the available information. Similarly, for child mortality, households that had eligible members who did not respond to the mortality question are considered missing; otherwise the household is considered non-deprived.

In the case of the eight assets, if any item was missing, we assumed that the household does not own this asset. The indicator takes a missing value if there is missing information for all assets.

Households that had any indicator missing (according to the procedures described above), were dropped from the sample. In most countries the resulting sample reduction is mild. Eighty-five countries have a sample size of 87% or higher of the original sample size (see Table A.1 in the Appendix). For the 19 countries with sample sizes lower than 87% of the original sample, we

[26] As explained at the bottom of Table 2, exceptions are the 11 countries in which females and children were measured in only a 50% sub-sample of households and Senegal (in 33% sub-sample). There, eligible women and children in the sub-sample not measured were considered as non-deprived. Note that the 2013 MPI methodology computes updated MPIs using nutritional sub-samples only (Alkire, Conconi and Roche 2013).

performed a bias analysis using hypothesis tests of differences in means. Specifically, for each country, we identified the indicator/s that caused the sample size reduction. We then divided the sample in two groups: those missing the indicator and those having observed values for the indicator. Then we compared the raw headcount ratios across the other indicators. We considered stratification and clustering when computing the standard errors and use a confidence level of 90%.

For each country we considered the number of indicators in which the group with missing information in a particular variable had significantly higher raw headcount ratios than the group with non-missing information, as well as the number of indicators for which the group with missing information had a significantly lower proportion of deprivations. Whenever the first number was higher than the second number, we understand that if we could have included the group with missing information, the MPI would have presumably been higher. Thus, in such cases, we consider the country's MPI estimate to be a lower bound estimate. When the opposite holds, we consider the country's MPI estimate to be an upper bound. Table A.1 shows the countries whose MPI estimates are considered to be upper or lower bound.

3.5 Indicators' weights

The relative values of different deprivations may be obtained many ways, including participatory processes, expert opinion, survey questions, prices, statistical analysis or subjective evaluation. National or local poverty measures may have even more scope for such inputs than an international one. Given that people, countries and contexts will value dimensions differently, we follow Sen (1996) in proposing that the values (or weights) should be explicit and transparent so as to be open to public debate, and further, that key comparisons must be robust to a plausible range of weights. The MPI weights reflect the normative assessment – defended previously in the HDI and HPI – that achievements in health, education and living standards are roughly equal in intrinsic value. Having roughly equal weights across dimensions also eases the interpretation of the index for policy (Atkinson et al. 2002). Clearly, the weighting structure determines the assumed trade-offs across deprivations. Yet by making weights explicit and transparent, so are the trade-offs.

As detailed in Table 1, in the MPI weights are equally distributed across dimensions (1/3 each) and within dimensions, across indicators. Whenever there are fewer than ten indicators in a particular dataset, the same nested weighting principle applies; in no measure does a country lack all indicators from any dimension.

Because any measure must be robust to a range of plausible weights, in Section 5.3 we compare three alternative weighting structures, applying a 25% to 50% weight on each dimension. The results suggest that the MPI ranking is robust to changes in weights.

3.6 Poverty cutoff

The poverty cutoff *k* reflects the share of weighted indicators in which a person must be deprived in order to be considered multidimensionally poor. When calculating MPI we implement the full set of possible poverty cutoffs; a *k* cutoff of 33.33% was selected because it has a normative justification and provided a wide distribution of poverty results. This cutoff captures the *acutely* poor, namely those who do not meet minimum internationally agreed standards in [usually] multiple indicators of basic functionings simultaneously. When all ten indicators present, this implies that a person must be deprived in at least two (education or health) to six (living standard) indicators in order to be identified as multidimensionally poor. When there is one or more missing indicators, the other indicators present in the dimensions receive higher weight. Thus the 33.33% cutoff may be met with a lower number of deprivations than when the full ten indicators are present. Section 5.4 presents robustness analyses for a range of admissible relative *k* cutoffs (20 to 40%) and observes that the MPI ranking is robust to such changes.

3.7 Two clarifications on MPI indicators vis-a-vis other standard indicators

The MPI indicators differ from traditional education, health and living standard indicators in two ways. First, identification of who is poor uses data from all household members. Second, deprivations of those who are deprived in less than 33.33% of the weighted indicators are *censored* and not reflected in the final poverty measure. Because of these two differences – considering all household members' achievements, and censoring the deprivations of the non-poor – the censored headcount ratios are computed differently from MDG-related statistics, and their numerators and denominators differ.

4 MPI Findings

Appendix Table A.1 presents the MPI estimation results and those of each of its components H (the headcount ratio) and A (the intensity). We also provide for the first time, the bootstrapped confidence interval for these three measures. The table contains the original sample size in each survey and the proportion used for the MPI computations. Further results such as the indicators' censored headcount ratios are provided in the Supplementary Data.

What can we learn from the MPI results which complement what we can learn from income poverty estimates? Here we emphasize five points.

4.1 Global poverty estimates

About 1.67 billion people in the developing world are in acute poverty or MPI poor (Table 3). That is about 32% of the total population in the 104 countries.[27] This headcount figure lies between the total number of people living on less than $1.25/day in the 90 countries for which we have

[27] We consider only the countries for which we have performed estimations. This is a methodological difference from Chen and Ravallion's global poverty figures (2010, p. 1598) which assume that countries without surveys have the poverty rates of their region.

comparable data, which is 1.53 billion people (29%), and the total number of people living on less than $2/day, which is 2.74 billion people (53%).[28]

How were these estimates obtained? We apply the MPI headcount ratio in each country to the 2007 population figures (taken from UN 2011). The MPI estimates rely on surveys implemented over an 8-year span (2000–2008). However, 87% of the countries' estimates covering 94% of the total population are within a range of five years: 2003–2007. As we stressed earlier, data issues limit cross-country comparability and the accuracy of these first global estimates. Still, these figures provide a rough estimate of the global and regional numbers of the acutely poor and also indicate the analyses that would be possible with more frequent and more comparable data.[29] To estimate the number of income poor we use the headcount ratios from the *World Development Indicators* (World Bank 2010). We select the income poverty estimate that is closest to the year of the MPI poverty estimate and never further away than five years. Income and MPI surveys for 66% of countries were fielded one year or less apart.[30] Given equal distance in the years of two income poverty estimates to the MPI estimate, we select the most recent one. The income headcount ratio is then applied to the 2007 population figure of each country.

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[28] Note that income poverty estimates within five years distance from the year of the MPI estimate are not available for 14 countries. The total number of MPI poor excluding these 14 countries is 1.63 billion, which still lies in-between the two income poverty estimates, whether 2007 or 2010 population figures are used.

[29] We could have used a weighted aggregation of the MDG trends for each country to extrapolate MPI values to 2007. However, the MDG trends in each indicator are not linear. Further, this would assume that changes in the joint distributions perfectly mirror the changes in the individual MPI indicators. Given that a value-added of the MPI is its direct link with the joint distribution, we chose not to make those assumptions.

[30] If there is no income poverty estimate within five years of the MPI estimate, we do not report the income poverty information for this country. In 30% of the countries, the year of the income poverty estimate coincides with that of the MPI estimate; in 36.7% there is one year difference; in 13.3% and 15.6% there are two and three years' distance, respectively. Less than 5% of countries have four and five years' difference between survey years.

Table 3: Summary MPI and income poverty estimates by UN regions

Region of the World	Total Pop. (millions)	H	A	MPI	MPI poor pop. (millions)	$1.25/day poor	$1.25/day poor pop. (millions)	$2/day poor	$2/day poor pop. (millions)
CEE and CIS	398.3	0.029	0.394	0.011	11.4	0.045	18.0	0.110	43.8
LAC	491.8	0.154	0.419	0.064	75.6	0.101	49.8	0.200	98.2
EAP	1864.5	0.146	0.457	0.066	271.4	0.265	494.4	0.498	927.7
AS	212.7	0.179	0.508	0.091	38.0	0.038	8.1	0.194	41.2
SA	1531.0	0.532	0.526	0.280	814.9	0.402	615.4	0.741	1133.8
SSA	703.7	0.647	0.577	0.374	455.5	0.486	342.3	0.705	496.2
Total 104 countries	**5202.1**	**0.320**	**0.522**	**0.167**	**1666.8**	**0.294**	**1528.0**	**0.527**	**2741.0**

Note: Pop. is Population, expressed in millions. H, A, MPI, $1.25/day poor and $2/day poor are all proportions.

CEE and CIS: Central and Eastern Europe and the Commonwealth of Independent States. LAC: Latin America and the Caribbean. EAP: East Asia and the Pacific. AS: Arab States. SA: South Asia. SSA: Sub-Saharan Africa.

4.2 Distribution of global poverty

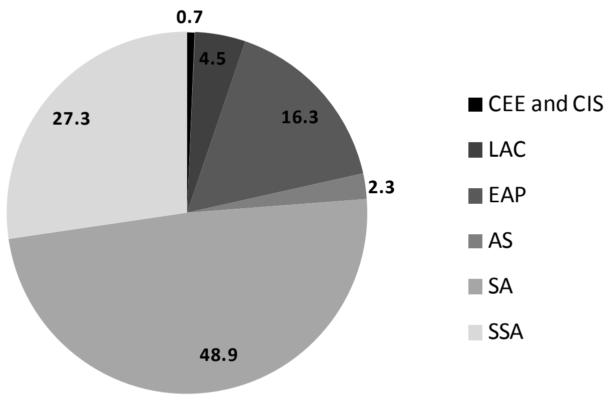
Where do the MPI poor live? Table 3 and Figure 2 depict the distributions. South Asia is home to 49% of the total MPI poor whereas Sub-Saharan Africa is home to 27% of the global poor, followed by East Asia and the Pacific, with 16%.[31] Despite the fact that that our findings are constrained by data of uncertain quality in China, [32] we can state that although the average MPI of Sub-Saharan Africa is the highest across regions, South Asia is home to nearly twice as many multidimensionally poor people as Sub-Saharan Africa. We also find that over two thirds of the MPI poor (69%) live in lower middle income countries whereas only just below a third live in low income countries. This result is in line with Sumner's (2012) estimates of the distribution of global income poverty in 2007 and constitutes – as he points out – a thought-provoking result.

[31] Interestingly, the distribution of the MPI poor across the regions of the developing world with estimates 2000–08 are very similar to the distribution of the extreme poor in 2007 (Sumner 2012, Table 1, option of "adjusted base years").

[32] Recall that China's MPI uses 2002 WHS data, and their accuracy is uncertain.

The critical situation of South Asia is not just a matter of the shattering number of poor but also the intensity of poverty. In many areas, the intensity of poverty is as high as in African countries. For example, India's MPI is 0.283. Yet, when we decompose the MPI across large Indian states, we find that eight states have poverty levels as acute as the 26 poorest African countries (that is, MPI values higher than 0.30) and are home to 423.6 million multidimensionally poor persons, more than the 26 poorest African countries combined (407.7 million).[33]

Figure 2: Distribution of the MPI poor



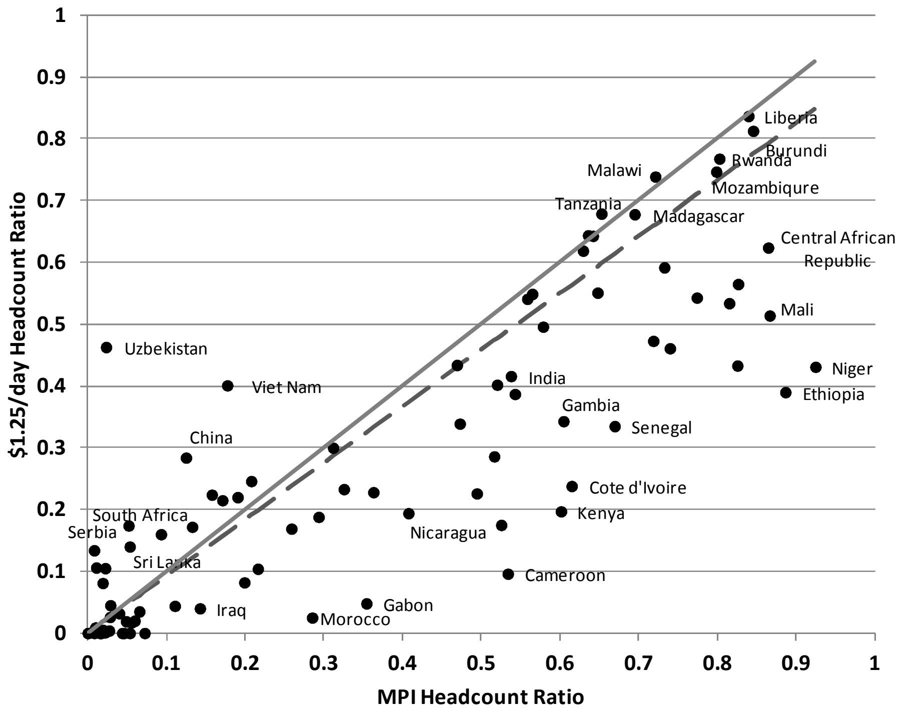
Note: CEE and CIS: Central and Eastern Europe and the Commonwealth of Independent States. LAC: Latin America and the Caribbean. EAP: East Asia and the Pacific. AS: Arab States. SA: South Asia. SSA: Sub-Saharan Africa. Proportions are calculated over the total number of poor people in each case, considering 104 countries in the case of the MPI poor and 90 countries in the case of the income poor. Computations were done using 2007 population figures from UN (2011). Further details on the computation are described in the text and in Table 3.

Differences between MPI and income global poverty estimates evidently result from discrepancies in estimates at the country level. These are displayed in the scatter plot of the income and the MPI poverty headcount ratios in Figure 3. Interestingly, there is ample variation across countries. For most countries (69 out of 90), the MPI headcount ratio is higher than the \$1.25/day headcount ratio – as depicted by the continuous diagonal – and also higher than what the overall income to MPI poor ratio would predict if it held for each country –as depicted by the discontinuous line. There are some striking differences such as those of Ethiopia, Niger, Cameroon and Kenya, with the MPI

[33] The poorest 26 African countries are (in decreasing order): Niger, Ethiopia, Mali, Burkina Faso, Burundi, Somalia, the Central African Republic, Guinea, Sierra Leone, Liberia, Mozambique, Angola, Rwanda, Benin, Comoros, Madagascar, DR Congo, Senegal, Malawi, Nigeria, Tanzania, Cote d'Ivoire, Mauritania, Chad, Zambia and Gambia. The eight Indian states (in decreasing order) are Bihar, Jharkhand, Madhya Pradesh, Uttar Pradesh, Chhattisgarh, Orissa, Rajasthan and West Bengal. This comparison considers the eight poorest large Indian states. Meghalaya and Assam are small states with MPI values also above 0.30. If we include these, the total MPI poor in the ten poorest Indian states is 444 million people. The Indian states population figures were estimated applying the DHS data population shares of each state (after sample drop) to India's 2007 population. Further analysis on decompositions at the sub-national level for a large sample of countries is provided in Alkire, Roche and Seth (2011).

headcount ratio being between 40 and 50% points higher than the income poverty one. Most low and high human development countries (which have income poverty information) belong to this category (88 and 81% respectively). Interestingly, just under two-thirds of medium human development countries have a higher incidence of acute poverty than $1.25/day poverty.[34] Of the 104 countries all but four (Hungary, Croatia, Montenegro and Slovenia) have an MPI headcount ratio that is lower than the $2/day headcount ratio.

Figure 3: MPI poor headcount ratio vs. $1.25/day poor headcount ratio



Note: The continuous grey line is the 45° diagonal. The discontinuous line depicts the ratio of the global $1.25/day poor to the global MPI poor.

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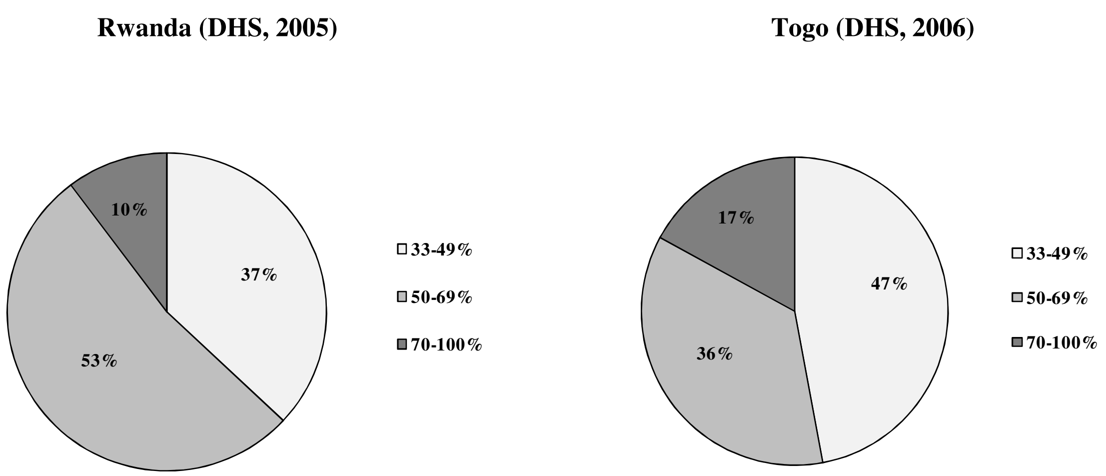
[34] We used the 2010 HDI categories. We find a similar pattern in terms of the income category (World Bank 2010): 87% and 84% of lower and upper middle income countries correspondingly have a higher MPI headcount ratio than a $1.25/day headcount ratio whereas this is 65% for low income countries. The four high income countries in the sample also have a higher MPI than extreme poverty rates.

4.3 Poverty's intensity

One particular insight that can be drawn from the MPI is that one can assess the degree of average simultaneous deprivations, namely, poverty intensity. We find that countries with higher MPI headcount ratios tend to have higher average intensity. Indeed, H and A have a Spearman correlation coefficient of 0.92. However, such a close link does not inevitably hold. For example, Somalia and Rwanda have very similar incidences of multidimensional poverty: 81.2% and 80.2%, respectively. Yet, as Figure 4 depicts, while in Somalia the average poor person is deprived in 63.3% of the weighted indicators, in Rwanda it is only 53.2%. Thus, their MPI values are quite distinct: Somalia's MPI is 0.514 whereas Rwanda's MPI is 0.426. Furthermore, because poverty intensity A is an average, countries with similar poverty intensities can exhibit remarkably different distributions of such intensity. For example, as Figure 4 depicts, Togo and Rwanda have similar intensities. However, while in Togo almost half of the poor experience relatively low intensities (33 to 49%), 17% of the poor experience high intensities (70% and over) and 36% of the poor are placed in the middle range (50 to 69%). In Rwanda, just over half of the poor are in the middle range (59 to 69%), just below 40% of the poor experience relatively low intensities (33 to 49%) and only 10% of the poor experience high intensities (70% and over).

Figure 4: Distribution of poverty intensity in two countries

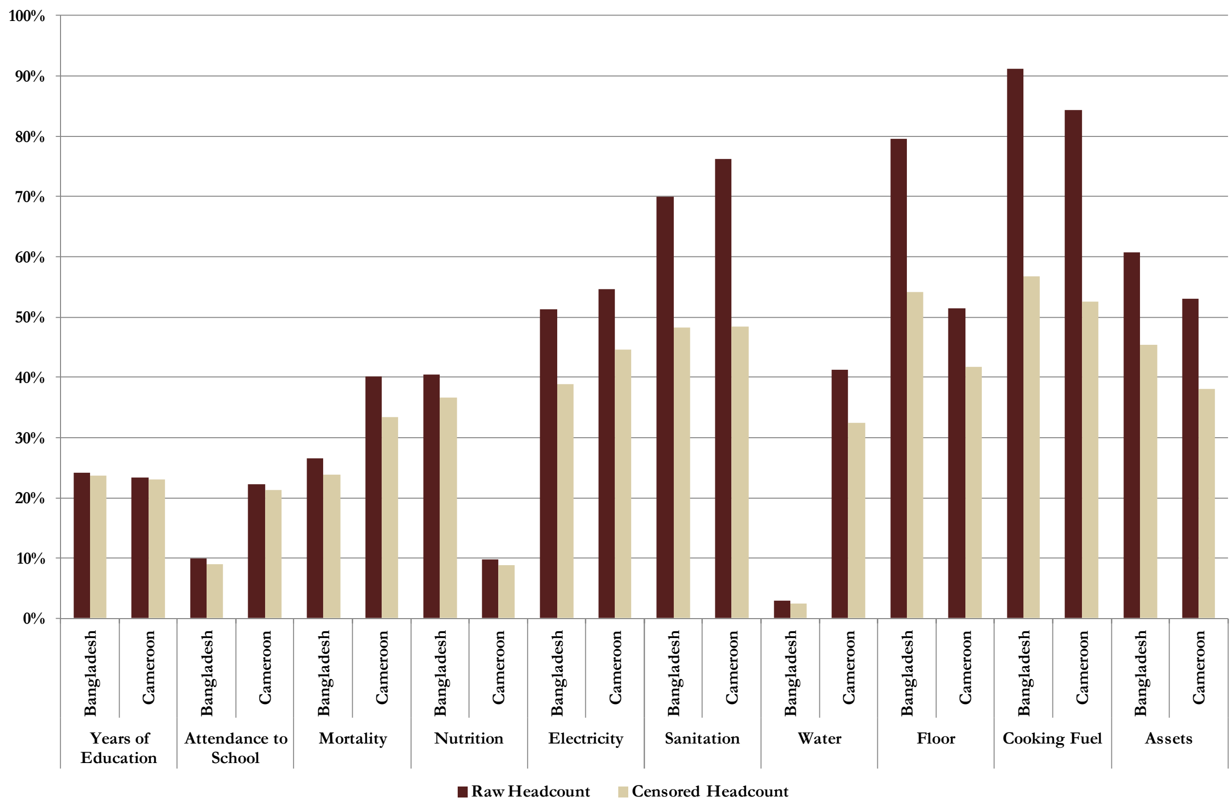


4.4 The poor and the deprived non-poor

There is an interesting divergence between traditional deprivation rates in single indicators and the MPI censored headcounts in the same indicators, which reflects the value added of the MPI in looking across indicators for the same person. As a particular application of the Alkire and Foster (2011a) family of measures, the MPI reflects the joint distribution of achievements. People who experience deprivation in some indicators yet whose weighted sum of deprivations is less than 33.33% are not considered poor. Thus the deprivations they experience are censored and not included in the MPI. We examine the pattern of deprivation using the censored headcount ratios: the proportion of people who are poor *and* deprived in each indicator. These can be contrasted with what we call the raw headcount ratios: the total proportion of people deprived in each indicator, regardless of whether they are identified as MPI poor or not. The magnitude of the discrepancy provides information on the share of people who are deprived but not poor.

Figure 5 presents an example of such differences for two sample countries: Bangladesh and Cameroon. These two countries have similar MPI values: 0.292 and 0.287, respectively. In both countries the difference between the raw and censored headcounts is highest for cooking fuel. Other large differences can be seen in sanitation, assets, electricity, and in the case of Bangladesh, floor. Given that weights affect who is identified as poor, the differences between the raw and the censored headcount ratios across all countries are larger among the living standard indicators than among the health and education indicators. In fact, the, the raw and censored headcount ratios differ most for cooking fuel and sanitation, followed by assets, water and electricity. Differences were lowest for malnutrition and years of schooling.[35] Discrepancies between raw and censored headcounts can be usefully analysed at the national level to distinguish widespread sectoral needs from data inaccuracies or personal or cultural preferences.

Figure 5: Censored vs. raw headcount ratios for two sample countries



4.5 What deprivations do the poor experience?

A fundamental advantage of the AF family of direct measures is that it can determine the (post-identification) contributions of each deprivation to overall poverty.[36] Such information provides real insights into the challenges that multidimensionally poor households experience simultaneously and into the need for policies to address interconnected deprivations. For example, examining the indicators' contributions, we find different patterns of health deprivations in the two poorest regions: South Asia has a relatively higher incidence of malnutrition whereas Sub-Saharan Africa has a relatively higher incidence of mortality. The censored headcount ratio of malnutrition is 30 to 70% higher than the mortality censored headcount ratio in Nepal, Bangladesh and India, whereas the censored headcount of mortality can be up to 3.8 times that of nutrition in African countries.[37]

5. Robustness of the Multidimensional Poverty Index

As with any poverty measure, the MPI involves a number of decisions on the parameters' values which affect both the identification and aggregation steps. This section assesses the robustness of poverty comparisons to these decisions. Key decisions are: the indicator's choice and definition, deprivation cutoffs, weights and the poverty cutoff. Given the novelty of the MPI, many wondered how these choices affect the MPI estimates (Ravallion 2011; Ferreira 2011; Thorbecke 2011, among others). Our analysis is inspired by literature on poverty orderings in the unidimensional framework initiated by Atkinson (1987) and Foster and Shorrocks (1988).[38] Conditions and tests of stochastic dominance are being extended to the multidimensional case (Bourguignon and Chakravarty 2002; Atkinson 2003; Duclos, Sahn and Younger 2006; Alkire and Foster 2011a and Lasso de La Vega 2010; Yalonetzky 2012) but these techniques require higher sample sizes than are available in the MPI datasets.[39]

This section evaluates how changes in each parameter affect relative MPI values, *ceteris paribus*. As stated earlier, data constraints limit cross-country comparability of MPI estimates. Aware of these underlying differences, we nonetheless apply a significant bevy of robustness tests in order to assess how sensitive the relative values of MPI across countries are to changes in key parameters.

5.1 Household composition

The first question is whether observed deprivations reflect household size and composition. A household has the possibility of being deprived in three MPI indicators – nutrition, school attendance and mortality – only if it contains children or women of reproductive age, except for the countries for which we use WHS where adults (male or female) are measured, and for the 37 DHS countries were males are interviewed for the mortality questionnaire (although in most of them this is only in a random

[36] The composition of MPI poverty for each country is available in the Supplementary Data as well as in the 'country briefings' and data tables which are regularly updated. The latest versions can be found on www.ophi.org.uk/policy/multidimensional-poverty-index/mpi-country-briefings/

[37] This is consistent with findings by Klasen (2008).

[38] They derived the conditions for variable-line and variable-measure poverty orderings which are linked to stochastic dominance relations. Ravallion (1994) and Jenkins and Lambert (1997) provide graphical tools connected to Foster and Shorrocks' (1988) results. Davidson and Duclos (2000) and Barret and Donald (2003) developed related statistical tests.

[39] For example, Duclos, Sahn and Younger's (2006) test becomes too demanding in terms of the size of the dataset with more than two dimensions.

sub-sample). Thus, in general, households having more children and women seem more likely to be identified as poor. On the other hand, larger households seem more likely to have a member with five years of schooling and to own more than one of the assets, so might be less likely to be identified as poor.[40]

To evaluate the empirical impact of household size and composition, we perform hypothesis tests of differences in means. In each country we test whether MPI poor households have a significantly higher average size, a higher average number of children under five years of age, a lower average number of members of 50 years of age and over, and a higher number of females, compared to non-poor households. We also test whether the proportion of poor households which are female-headed and which have children of school age are significantly higher than the proportion of non-poor households with such characteristics. We considered stratification and clustering when computing the standard errors and use a confidence level of 95%.

Table 4 presents the proportion of population-weighted countries (using 2007 population values) for which we find that poor households have a significantly higher mean of the considered characteristics than non-poor households. We also present the population-weighted proportion of countries with a significantly lower mean and with non-significant higher and lower means.[41]

The columns 'Overall' present the results for all countries. We find that the results for household size and number of females do not demonstrate a clear bias: 50% of poor households across all population-weighted countries have a significantly higher household size and 48% have a higher average number of females, but on the other hand 38% of households have a significantly lower household size or lower average number of females, making the overall size effect inconclusive. However, poor households are likely to have more children: 56% have a significantly higher average number of children under five, and 59% are more likely to have school-aged children, and only 7.5% and 5.5% of households have significantly lower means respectively. Having a higher number of people aged 50 and above is associated with lower poverty in 42% of the population-weighted countries and with higher poverty in 20%. Interestingly, only in 11% of the countries did poor households have a significantly higher probability of being female headed. In 36.7% of them they have lower probability, and in the rest, there is no significant difference.

Discriminating by MPI level and by geographical region unveils an interesting pattern by country groups. We group the countries into 'Low', 'Middle' and 'High-MPI' countries. These correspond to the 33rd and 66th centiles of the population-weighted countries ordered by the MPI.[42] We find that the poorer the country, the more likely poverty is to be associated with larger households, a higher number of under-5-year-old children and females, and the presence of school-aged children. For example, in only 18.6% of the low-poverty countries do poor households have a significantly larger size than non-poor households;

[40]The effect of household size is also a topic of research in income poverty measurement. Lanjouw and Ravallion (1995) show that the empirical result that large families tend to be poorer is particularly sensitive to the assumed household-size elasticity of the cost of living. However, they find a stronger relationship between household size and child stunting, although not for wasting, which suggests that this issue requires exploration for the MPI.

[41] We do this for all countries except for Slovakia and Slovenia (excluded because they have an MPI value of zero).

[42] As it can be seen in Table 4, the groups themselves are not a third of the population each because China and India are around each of the two cutoffs: the cumulative population share is 16.7% before China and it is 42% after it; the cumulative population share before India is 62%, and after India it is 84%. We have tried various other possible MPI cutoffs to group the countries, namely at the 33rd and 66th centiles of the countries not population weighted; at the 25th and 75th centiles, both population weighted and unweighted; and two sets of *ad hoc* cuts: one at an MPI of 0.16 and 0.33, and the other at 0.21 and 0.42. Results with these alternative groupings are consistent with conclusions detailed here.

while in 76% of them, they have a significantly lower size. Yet, in 47.3% of the middle-MPI countries, poor households are larger as against 23% in which they are smaller. And in 85% of the poorest MPI countries, poor households exhibit a significantly larger household size than non-poor ones. A similar pattern repeats for the number of under-five-year-old children, the presence of school-aged children and the number of females. The number of household members 50-years and older seems to have the opposite effect: in poorer countries, they decrease the probability that a household is poor. Finally, in 72% of high MPI poverty countries, poor households are less likely to be female headed, while this is 44% among middle MPI poverty countries and 15% among low MPI poverty countries.[43]

We also performed analysis by geographical regions. Results (available upon request) are consistent with those by MPI level. Poor households in the poorest geographical regions – Sub-Saharan Africa, South Asia and the Arab States (because of the presence of Somalia) – exhibit larger average household sizes and a higher prevalence of children and women. These variables have much lower significant differences between poor and non-poor households among countries in the less poor regions of Latin America and the Caribbean, and East Asia and the Pacific.

In summary, larger households, with more children and women, are more likely to be MPI poor in the poorest countries but not necessarily in other countries. There are distinct possible explanations for these results. The first relates to the survey design. For 12 of the 39 countries in the low MPI poverty group, WHS data was used. In the DHS and MICS, usually all eligible females in households are interviewed about mortality, and all eligible females and children are measured for nutrition. The WHS interviewed at most one respondent per household on the questions of mortality, and only one person (male or female) was measured for nutrition. Thus, it is likely that countries for which the MPI uses WHS data (many of which are the least poor) would not exhibit a strong impact of household size and the presence of females and children. The second explanation is that MPI poverty is, objectively, higher among larger households and those with more children. This is likely to explain at least part of the effect of household composition.[44] The third possibility is that the survey design and MPI indicator construction artificially and inaccurately inflate the apparent poverty in large households. Datasets for multiple low, middle, and high MPI countries having information on all indicators for all household members could be used to ascertain whether this is the case. A fourth possible interpretation is that the MPI indicators may be slightly biased but in a justified way: almost 30% of the 49 MDG indicators refer to children or women, suggesting that these group-specific vulnerabilities may be a priority. The MPI mirrors this priority.

[43] We have also analysed the country results not weighting by their population sizes. In such cases, we find a more homogeneous pattern across country groups by MPI level (with a less strong effect on high MPI countries) and a stronger overall association between household size and the presence of children and women and the probability that a household is poor.

[44] To test this, the MPI could be computed only for living standard and years of schooling indicators to observe whether the same household composition effects are apparent when limited to those seven variables. This can be combined with indicator-specific systematic reviews which explore the interrelations between child- and woman-specific indicators and household size.

Table 4: Results of hypothesis tests of differences in means between poor and non-poor households (102 countries)

	Poor households have (2007-population weighted percentage of countries where poor households have)															
	Significantly Higher Average				Significantly Lower Average				Non-significantly Higher Average				Non-significantly Lower Average			
	Overall	Low MPI	Mid MPI	High MPI	**Overall**	Low MPI	Mid MPI	High MPI	**Overall**	Low MPI	Mid MPI	High MPI	**Overall**	Low MPI	Mid MPI	High MPI
No Countries	102	39	29	34	102	39	29	34	102	39	29	34	102	39	29	34
Pop. Share (%)	100	16.6	45	38	100	16.6	45	38	100	16.6	45	38	100	16.6	45	38
Household Size	**49.6**	18.6	47.3	85.2	**38.2**	76.3	22.8	3.4	**7.5**	0.7	29.8	4.1	**4.6**	4.3	0.1	7.2
Under-5-year-old children in hh	**56.3**	22.4	48.4	97.9	**7.5**	7.14	23.6	0	**9.2**	7.3	27.9	2.1	**26.9**	63.2	0	0
Probability of school-aged children	**59.4**	16.2	79.9	97.2	**5.5**	12.9	0	0	**6.8**	5.3	19.5	2.2	**28.2**	65.7	0.6	0.5
Higher number of females	**47.8**	17.0	39.8	85.8	**38.1**	76.8	22.8	2.9	**11.3**	2.4	32.7	10.7	**2.7**	3.8	4.8	0.5
Probability of being female headed	**11.1**	5.9	15.7	14.5	**36.7**	10.9	27.2	69.9	**45.2**	78.9	54.6	3.1	**7.1**	4.3	2.5	12.5
Over 50 year old members in hh	**19.4**	12.9	24.9	23.9	**42.5**	15.2	44.1	72	**33.6**	64.8	24.4	3.4	**4.6**	7.1	6.6	0.7

Note: Low MPI: countries with MPI 0.053 or lower; Mid MPI: countries with MPI higher than 0.053 and up to 0.283; High MPI: countries with MPI higher than 0.283.

5.2 Robustness to changes in the indicators and deprivation cutoffs

There is a legitimate diversity of judgments regarding what would or would not count as a deprivation in a number of indicators. If small changes in any cutoff would lead to a considerable re-ranking of countries, this should be made explicit and the accuracy of that cutoff closely examined. To test the sensitivity of the MPI to deprivation cutoffs, we implemented different versions of the MPI using different cutoffs and, in some cases, indicators. In particular we investigate a) three different measures of child nutrition (weight-for-age – the underweight indicator, weight-for-height – the wasting indicator, and height-for-age – the stunting indicator) and a different reference population;[45] b) child mortality with and without age restrictions; c) including child school attendance versus using years of education only; d) considering the water source without time to water; and e) using higher deprivation cutoffs for water (requiring piped water), sanitation (requiring a flush toilet) and floor (considering a household having a palm bamboo/wood plank floor to be deprived).[46]

We estimate the MPI for each alternative (changing one indicator at a time), rank the countries, then compute two rank correlation coefficients between the rankings: Spearman and Kendall Tau-b (Kendall and Gibbons 1990). Table 5 presents the Kendall correlations.

Neither the change in the reference population nor the change in the children's nutritional indicators produces a significant change in country rankings. The rank correlation coefficients between the 2010 MPI, which uses the underweight indicator and the new reference population, and three alternative MPIs, one using stunting, another using wasting, and another using underweight with the old reference population, are all above 0.91 (Table 5).[47]

For the mortality indicator we estimated an alternative MPI considering as deprived households where there had been a diseased child of under five years of age only for the 52 countries in which this information is available. This reduces the MPI, except for the case of Somalia and Mexico. The biggest reduction is 0.045 in Cote d'Ivoire. The rank correlation between the rankings of the two MPIs is 0.867.

In sum, all Kendall's Tau correlations are above 0.86, and all Spearman's rank correlations exceed 0.96, which suggests that the rankings are highly robust to these changes in the deprivation cutoffs. All correlations are also significant at the 5% level.

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[45] Children who are more than two standard deviations (SD) below the median of the reference population (z-scores) are considered underweight, wasted or stunted, respectively. The reference population from which the median is calculated has recently been changed by the WHO as has the methodology used to construct the growth curves (WHO 2006). The new reference population (used in the MPI computation) has wider ethnicity coverage than the old one (used for robustness check).

[46] We focus on testing these choices, which cover the three dimensions. Tests on the years of education cutoff, cooking fuel and the asset indicator are left for further research.

[47] When the stunting is used, the MPI is always higher (the average increment is 0.0139). When wasting is used, MPI tends to be lower, except for ten countries. Yet, all in all, country rankings do not change significantly.

Table 5: Correlation coefficient between alternative specifications of the MPI

		Excluding Child School Attendance	Using weight-for-age (Sel. Measure)	Using weight-for-age Old ref. pop.	Using weight-for-height	Using height-for-age
Using weight-for-age (Selected Measure)	Rank Corr.	0.891				
	N (countries)	85				
Using weight-for-age Old reference population	Rank Corr.	0.862	0.917			
	N(countries)	72	72			
Using weight-for-height (wasting)	Rank Corr.	0.883	0.980	0.912		
	N (countries)	74	74	72		
Using height-for-age (stunting)	Rank Corr.	0.891	0.960	0.914	0.972	
	N countries)	74	74	72	73	
Using under-5 mortality (not at any age)	Rank Corr.	0.917	0.867	0.893	0.916	0.903
	N (countries)	52	52	72	74	74
Excluding distance from the water indicator	Rank Corr.	0.897	0.988	0.955	0.951	0.972
	N (countries)	99	83	74	43	50
Using higher living standard depriv. cutoffs (floor, water, sanitation)	Rank Corr.	0.868	0.924	0.960	0.957	0.914
	N (countries)	104	85	43	73	99

Note: The reported rank correlation coefficient is the Kendall Tau-b (which corrects for tied ranks). Spearman and Pearson correlations are no lower than the reported ones.

5.3 Robustness to changes in the indicators' weights

As explained in Section 2.3, the MPI has a structure of nested weights in which each of the three dimensions receives an equal relative weight of one-third and each of the indicators within each dimension receives an equal weight. To test whether the MPI is robust to a plausible range of weights, we have estimated the MPI with three other alternative weighting structures, giving 50% of the relative weight to one of the three dimensions and 25% to each of the other two in turn.[48]

Changing the indicators' weights affects the poverty estimates. However, the country rankings are robust to such changes. Table 6 presents the correlation between the country rankings obtained with the baseline of equal weights and that obtained with the other three alternatives. The correlation is 0.89 or higher using Kendall Tau-b and higher with the Spearman correlation. Interestingly, the rank correlation between the three alternative weighting systems is also relatively high – none lower than 0.83.

Table 6: Correlation coefficients between MPI using alternative weighting structures (104 countries)

	Equal Weights 33% each	50% Education 25% Health 25% LS	50% Health 25% Education 25% LS
50% Education 25% Health 25% LS	0.889		
50% Health 25% Education 25% LS	0.925	0.835	
50% LS 25% Health 25% Education	0.901	0.852	0.863

Note: LS: Living Standard. The Spearman rank correlation coefficients are 0.95 and higher.

We also compared the MPIs for all possible pairs of countries across the four different weighting structures and found that in 88.7% of the total possible pairs, one country has higher poverty than the other regardless of the weighting system.

In Alkire et al. (2010) we compute three indices of intra-group rank concordance and Friedman's test of rank independence for these results. As anticipated we find a high degree of rank concordance (0.975 or

[48] In this way, in one alternative weighting each educational indicator weighs 25%; each health indicator, 12.5%; and living standard indicator, 4.16%. In the other, each health indicator weighs 25%; each education indicator, 12.5%; and the living standard indicators, 4.16%. In the final weighting structure each living standard indicator weighs 8.33% and each health and education indicator weighs 12.5%.

higher) and the test rejects the null hypothesis of rank independence. The same analysis is performed considering only the 75 poorest countries and discriminating by survey. While robustness remains strong, we find that country rankings among the WHS countries are least robust. Among non-WHS countries, the minimum of Kendall's Tau-b is 0.910, whereas in WHS it is 0.635. Rank concordance indices are also reduced to between 0.81 and 0.86 for countries using WHS surveys, whereas they remain high for the other countries. Even so, the tests of rank concordance on all of the sub-groups of countries – including the WHS countries – reject the null hypothesis of rank independence with 99% confidence.

In summary, we can say that while the weighting structure affects the magnitude of each country poverty estimate, the relative position of each country with respect to others is highly robust to changes in the indicators' weights.

5.4 Robustness to changes in the poverty cutoff

Alkire and Foster (2011a) and Lasso de La Vega (2010) developed the conditions for M_0 orderings across k values, based on the vectors of weighted attainments. Here we follow a practical equivalent approach, using bootstrapping to test the poverty orderings (Davidson and Duclos 2000, p. 1436).

We test the robustness of country rankings to the selection of the k-poverty cutoff within a range of admissible values, in this case between k=20% and k=40%. This can be interpreted as a test of a restricted form of dominance. The selection of 1/3 as a poverty cutoff is intended to capture the *acutely* poor, namely those who do not meet minimum internationally agreed standards in multiple indicators of basic functionings simultaneously. The normative argument for the lower bound is that while a household may have one shortfall by choice, or due to indicator definitions, it is more likely that households with multiple deprivations in these very primitive indicators are poor, hence the lower threshold should exceed 16.7%, which is the highest usual weight upon a single indicator. The empirical reason is that individual indicators may be inaccurate proxies for deprivation occasionally. On the other extreme, cutoffs above 40% can be considered overly demanding.

The testing proceeds as follows. We estimated the MPI for the different selected k values and bootstrapped them. As all the surveys used have a complex survey design we have drawn samples of clusters (with replacement) within each strata (Deaton 1997). For each country we have performed 1000 replications and with these estimates, we have created the bootstrap 95% confidence intervals.[49] Given two countries, A and B, we say that B dominates A if A's (bootstrapped) lower bound MPI estimate is greater than B's (bootstrapped) upper bound MPI for all the considered k values. That is, B has lower poverty than A regardless of the k cutoff and considering alternative samples. We perform this comparison for all the possible pairs of countries.

We find that 87.4% of all possible pairwise comparisons of bootstrapped estimates are robust to a change of k between 20 and 40%, meaning that one country is unambiguously less poor than another, independently of whether we require people to be deprived in 20, 33 or 40% of the weighted indicators. We also performed these comparisons within the UN regions. We find that, within the mentioned k range, 90% of the pairwise comparisons of the five Asian countries are robust; this is 85.9% for the 37 Sub-Saharan African countries, 87.3% for the Arab countries, 77.9% among the Latin American and

[49] We have used the bootstrap command of STATA 10, indicating the strata and cluster variables. We have bootstrapped the MPI for 102 countries, Slovenia and Guatemala could not be bootstrapped because the strata and cluster variables are missing in the datasets.

Caribbean countries and 77.8% among the East Asia and Pacific countries. The lowest proportion of robust pairwise comparisons is among the Central and Eastern Europe and the CIS, where it is 44.3%.

The level of robustness to *k* values by regions seems to be inversely associated with the proportion of countries in each region that lack one or more indicators and directly related to the MPI level and survey quality. The region of Central and Eastern Europe and the CIS, which presents the lowest robustness, is the one with the highest proportion of countries that lack one or more indicators (34%), followed by Latin America and the Caribbean and East Asia and the Pacific, where 22 and 15% of countries lack at least one indicator, correspondingly. Additionally, about 30% of the countries in Central and Eastern Europe and the CIS and in Latin America and the Caribbean regions use WHS data. Finally, these countries tend to have low MPIs, thus are more sensitive to parameter changes.

When we test for robustness considering only countries with ten indicators we find that 91.2% of the comparisons are robust. When we discriminate by survey, we find that 91.7% of comparisons among DHS countries, 85.2% among MICS countries and only 59.6% among WHS countries are robust, analogous to the results with the robustness to weights.[50]

These results suggest that even if one would think that acute poverty should refer to people deprived in 20% of the weighted indicators rather than in a third, or – alternatively – in 40% of the weighted indicators, such changes would not affect the ranking results dramatically. Within this range, rankings are quite stable and robust, particularly for poorer countries and regions.

A different potential critique to the *k* cutoff is that requiring people to be deprived in 33.33% of the weighted indicators implies that some poor people will be deprived in only one dimension, which raises questions as to how their poverty is 'multidimensional'.[51] Upon analysis we find that less than 3% of the MPI poor are deprived in indicators pertaining to only one dimension.[52] More precisely, 2.8% of the 1.67 billion poor are deprived only in education, 2.2% are deprived only in health, and 2.5% only in living standards. As with any average, there is variation underneath. Four countries have more than 33.33% of poor deprived only in education and seven countries have high proportions deprived only in health. In all but one case, these are countries that lack an indicator within that dimension, so that any observed deprivation receives 33.33% weight. Additionally, all are among the least poor countries, with MPI values of 0.083 or lower, and most use WHS data. In all but four countries, the proportion of people deprived only in the living standard dimension is 15% or lower.[53]

In summary, the 33.33% *k* cutoff seems to identify a set of multiply deprived people, and less than 3% of the poor are deprived only in one of the dimensions.

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[50] We also tested robustness across income categories, which are directly related to average MPI values, and found 85.9% of robust comparisons across low income countries, 87.6% across lower middle income countries, 74.8% across upper middle income countries but only 32.1% among high income countries, showing again that low MPI estimates are less robust.

[51] We are grateful to Anthony B. Atkinson for making this point.

[52] We find that, on average, 17.6% of MPI poor people across our 104 countries are deprived in exactly 33.33% of the weighted indicators. When we consider only the 63 countries that do not lack any indicator, the weighted average of the proportion of the poor population who are deprived in just 33.33% of indicators is 14.1%. By survey, we find that the proportion of poor deprived in just 33.33% is 15% for DHS countries, 17% for MICS countries and much higher – 32% – for WHS countries.

[53] The four exceptions are Zimbabwe, with 17% of the poor deprived only in living standard; Kenya, with 20%; Chad with 24%; and Peru with 26%. These countries do not lack any living standard indicator and only one is a WHS country (Chad). Except for Peru which has an MPI of 0.086, the other three have middle-range MPI values, 0.18 to 0.34.

5.5 Robustness to sample variability

The bootstrapping technique was also used to test the robustness of the MPI country rankings that use k=33.33%. MPI estimates, as well as its components H and A, may vary with the particular sample used in each country. Bootstrapped standard errors range from 0.00004 in the case of Belarus to 0.0165 in the case of Chad, with an average of 0.0045.[54] The standard error tends to be bigger the poorer the country: the Pearson correlation coefficient between the standard error and the MPI point estimate is 0.63. Consistent with this, the average standard error among WHS countries is the lowest (0.0034) as there are many low poverty countries among these, whereas the average standard error among MICS countries is 0.0053 and among DHS countries is 0.0045. In general, we can see that these values are low and thus provide reliable point estimates. This is also confirmed by analysing the rankings with the upper and lower bound estimates.

If data were fully comparable, a country would have an unambiguously lower MPI if the upper bound MPI estimate is strictly lower than the lower bound MPI estimate of another, in other words, if their confidence intervals do not overlap. Table A.1 in the Appendix presents the lower and upper bound estimates of the MPI, H and A for each country. We did not expect countries with adjacent ranks to have unambiguously different MPIs. Yet 9% of the countries do have an MPI that is unambiguously lower than the country that is immediately adjacent in the ranking.[55] Moreover, 22.5% of the countries have an MPI unambiguously lower than that of the country two places after them in the ranking, 53% have an unambiguously lower MPI than the one of the country five places after them, 78% have an unambiguously lower MPI than the one of the country eight places after them in the ranking, 84% have an unambiguously lower MPI than the one of the country ten places after them.

We performed the same analysis for the MPI components, H and A. For both H and A, the bootstrapped estimates have higher proportions of unambiguous rankings at low distances in the rankings. For example 16% of the countries have a multidimensional headcounts H unambiguously lower than the country that immediately follows in the ranking and 30% have an unambiguously lower A. The rate of increase in the proportion of unambiguous rankings as we increase the difference in rankings is slower than with the MPI.

Naturally sample variability or standard errors of MPI, H and A should always be reported. This section shows that meaningful comparisons are possible for many countries. Of course, the problem of the heterogeneity in the survey years and design remains, as well as the issue of missing indicators in certain countries.[56]

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[54] Alternatively, standard errors for the MPI and its component measures H and A can be computed analytically (Yalonetzky 2011).

[55] Belarus is less poor than UAE; Argentina is less poor than Mexico; Turkey is less poor than Colombia; Indonesia is less poor than Djibouti; Gabon is less poor than Bolivia; Namibia is less poor than Nicaragua; Rwanda is less poor than Angola; Angola is less poor than Mozambique; and Ethiopia is less poor than Niger.

[56] A further issue is measurement error, although this may be lower for the MPI than for monetary poverty estimates. See Calvo and Fernandez (2012)

6. Concluding Remarks

The 2010 MPI presented in this paper constitutes the first internationally comparable poverty measure using the direct method to measure poverty for over 100 countries. It applies the AF dual-cutoff methodology and M_0 measure to ten indicators across the dimensions of health, education and living standards. It complements information provided by indirect methods such as the $1.25/day poverty line. And the measures are not the same: the relative rate of MPI and of $1.25/day poverty vary considerably across countries, a pattern that deserves further study in future – as does the issue of whether MPI and income measures identify the same households as poor.

The MPI combines poverty incidence with poverty intensity, and although these two seem to be correlated, their combination leads to a different ranking of countries. Analysis of the distribution of poverty intensities among the poor offers additional information regarding the relative burden experienced by different groups. Moreover, it is the inclusion of intensity that enables the MPI to be broken down in order to examine the proportion of the population who are poor and deprived in each particular indicator.

Are these results credible? After considerable scrutiny, evidence suggests they are. The extensive robustness analysis in this paper indicate that the 2010 MPI results are stable to changes in indicators' deprivation cutoffs (and even in some indicators such as child nutrition), indicators' weights, poverty cutoff (the proportion required to be considered multidimensionally poor) and sample variability. The MPI does seem to be higher in larger households and in those households that have a higher number of children and women, but this may in fact reflect the deprivation certain vulnerable groups actually do experience.

However, the 2010 MPI was constrained by data.[57] Although the past twenty years (1990–2010) have witnessed great progress in data collection worldwide, there are still three fronts on which considerable improvement is needed to improve the precision of direct poverty estimates: the dimensions, comparability, and unit of analysis.

In terms of dimensions, no multi-purpose survey collects good quality information on the indicators used in the MPI *plus* dimensions such as income or consumption, work and livelihoods, or violence. Nor are better indicators, for example of quality of education or ventilation of cooking smoke, available. There is thus an urgent need to collect data on a small number of valuable dimensions – within the same survey – in order to enable a stronger multidimensional analysis in the post-2015 MDG era. Second, comparability requires further standardization of some variables such as water and sanitation, as well as respondents for health indicators such as nutrition. Comparability also requires surveys to be updated at least every three to five years. Third, to study intra-household inequalities across gender and age groups would require individual-level information on key indicators. This is usually collected for educational indicators, but not for health or assets. Were some countries to collect indicators at the individual level, it would be possible to complement the MPI with an individual poverty measure that would illuminate intra-household inequalities.

In sum, the MPI has offered new insights on our knowledge of global poverty. By exemplifying what multidimensional measures can accomplish, it has fostered the development of new national poverty measures, as well as exercises of public reasoning and debate which may be intrinsically valuable (Sen

[57] Since 2010 the MPI has been updated by OPHI as new data emerge, and 36 new datasets underlie the MPI released in UNDP's *Human Development Report* on 14 March 2013.

2009). This paper has focused on presenting overall results and, particularly, scrutinising the robustness of the 2010 MPI to various parameter choices. Robustness analyses of the kind undertaken here would be required for any subsequent versions of the MPI, as well as for national exercises.

References

Alkire, S. and Foster, J. E. (2007). Counting and Multidimensional Poverty Measures. OPHI Working Paper No 7.

Alkire, S. and Foster, J. E. (2011a). Counting and Multidimensional Poverty Measurement. *Journal of Public Economics,* 95(7–8), 476–487.

Alkire, S. and Foster, J. E. (2011b). Understandings and Misunderstandings of Multidimensional Poverty Measurement. *Journal of Economic Inequality*, 9(2), 289–314.

Alkire, S. and Roche, J. M. (2013). How Successful are Countries in Reducing Multidimensional Poverty? Insights from the Inter-Temporal Analyses of Twenty-Two Countries. OPHI Working Paper. Forthcoming.

Alkire, S. and Santos, M. E. (2010). Acute Multidimensional Poverty: A New Index for Developing Countries. OPHI Working Paper No 38.

Alkire S. and Seth, S. (2013). Multidimensional Poverty Reduction in India between 1999 and 2006: Where and How? OPHI Working Paper No 60.

Alkire, S. (2008). Choosing Dimensions: The Capability Approach and Multidimensional Poverty. In Kakwani, N. and Silber, J. (Eds.), *The Many Dimensions of Poverty*. Basingstoke: Palgrave-MacMillan.

Alkire, S., Conconi, A. and Roche, J.M. (2013). Multidimensional Poverty Index 2013: Brief Methodological Note and Results. OPHI. www.ophi.org.uk/multidimensional-poverty-index/.

Alkire, S., Foster, J. E. and Santos, M. E. (2011). Where Did Identification Go*? Journal of Economic Inequality,* 9(3), 501–505.

Alkire, S., Roche, J. M. and Seth, S. (2011). Sub-national Disparities and Inter-temporal Evolution of Multidimensional Poverty across Developing Countries**.** OPHI Research in Progress No 32a.

Alkire, S., Roche, J. M., Santos, M. E. and Seth, S. (2011). Country Briefings. OPHI Multidimensional Poverty Index Country Briefing Series. Available at: www.ophi.org.uk/policy/multidimensional-poverty-index/mpi-country-briefings/.

Alkire, S., Santos, M. E., Seth, S. and Yalonetzky, G. (2010). Is the Multidimensional Poverty Index Robust to Different Weights? OPHI Research in Progress No 22a.

Anand, S. and Sen, A. K. (1997). Concepts of Human Development and Poverty: A Multidimensional Perspective. In United Nations Development Program (UNDP) *Human Development Report 1997 Papers: Poverty and Human Development.* New York.

Atkinson, A. B. (1987). On the Measurement of Poverty. *Econometrica*, 55(41), 749–64.

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

Atkinson, A. B., Cantillon, B., Marlier, E. and Nolan, B. (2002). *Social Indicators. The EU and Social Inclusion*. Oxford: Oxford University Press.

Barrett, G. and Donald, S. (2003). Consistent Tests for Stochastic Dominance. *Econometrica*, 71(1), 71–104.

Basu, K. and Foster, J. E. (1998). On Measuring Literacy. *Economic Journal*, 108(451), 1733–49.

Boltvinik, J. (1992). El Metodo de Medicion Integrada de la Pobreza. Una propuesta para su desarrollo. *Comercio Exterior,* 42(4), 354–365.

Boltvinik, J. (2012). Medición multidimensional de la pobreza. AL de precursora a rezagada. La experiencia contrastante de México ¿una guía para la región? Presented at the Seminario Internacional Multidimensionalidad de la pobreza. Alcances para su definición y evaluación en América Latina y el Caribe", Clacso-Crop, Universidad de Chile, Santiago de Chile, November, 22–23, 2012.

Bossert, W., Chakravarty, S. R. and D'Ambrosio, C. (2009). Multidimensional Poverty and Material Deprivation with Discrete Data. *Review of Income and Wealth*, 59(1), 29–43.

Bourguignon, F. and Chakravarty, S. R. (2002). Multidimensional Poverty Orderings. DELTA Working Paper No 2002-22.

Bourguignon, F. and Chakravarty, S. R. (2003). The Measurement of Multidimensional Poverty. *Journal of Economic Inequality,* 1(1), 25–19.

Bourguignon, F.s, Bénassy-Quéré, A., Dercon, S., Estache, A., Gunning, J. W., Kanbur, R., Klasen, S., Maxwell, S., Platteau, J-P. and Spadaro, A. (2008). Millennium Development Goals at Midpoint: Where Do We Stand and Where Do We Need to Go? *European Report on Development.* http://ec.europa.eu/development/icenter/repository/mdg_paper_final_20080916_en.pdf

Callan, T., Nolan, B., and Whelan, C. T. (1993). Resources Deprivation and the Measurement of Poverty. *Journal of Social Policy,* 22(2), 141–172.

Calvo, C. and Fernandez, F. (2012). Measurement Errors and Multidimensional Poverty. OPHI Working Paper No 50.

Chakravarty, S. R. and Silber, J. (2008). Measuring Multidimensional Poverty: The Axiomatic Approach. In Kakwani, N. and Silber, J. (Eds.), *Quantitative Approaches to Multidimensional Poverty Measurement.* New York: Palgrave Macmillan.

Chakravarty, S. R. Mukherjee, D. and Ranade, R. R. (1998). On the Family of Subgroup and Factor Decomposability Measures of Multidimensional Poverty. In Slottje, D. J. (Ed.), *Research on Economic Inequality 8*, 175–1794. Stanford, CT and London: JAI Press.

Chen, S. and Ravallion, M. (2012). The Developing World Is Poorer Than We Thought, But No Less Successful in The Fight Against Poverty. *Quarterly Journal of Economics*, 125(4), 1577–1625.

Davidson, R. and Duclos, J-Y. (2000). Statistical Inference for Stochastic Dominance and for the Measurement of Poverty and Inequality. *Econometrica*, 68(6), 1435–1464

Deaton, A. (2011). Measuring Development: Different Data, Different Conclusions? In *Measure for Measure: How Well Do We Measure Development? Proceedings of the 8th AFD-EUDN Conference, 2010.* STIN, France. http://www.afd.fr/webdav/site/afd/shared/PUBLICATIONS/RECHERCHE/Scientifiques/Conferences-seminaires/03-VA-Conferences-seminaires.pdf

Deaton, A. (1997). *The Analysis of Household Surveys. A Microeconometric Approach to Development Policy.* Washington DC: The World Bank.

Demographic and Health Surveys, (Various Years and Countries), ORC Macro, Calverton, Maryland, USA. http://www.measuredhs.com/. Accessed from January 2010.

Dhongde, S. and Minoiu, C. (2013). Global Poverty Estimates: A Sensitivity Analysis. *World Development.* In press.

Duclos, J-Y., Sahn, D. and Younger, S. (2006). Robust Multidimensional Poverty Comparisons, *The Economic Journal*, 116(514), 943–968.

Feres, J. C. and Mancero, X. (2001). El método de las necesidades básicas insatisfechas (NBI) y sus aplicaciones a América Latina, *Series Estudios Estadísticos y Prospectivos.* Santiago, Chile: CEPAL.

Ferreira, F. (2011). Poverty Is Multidimensional. But What Are We Going To Do about It? *Journal of Economic Inequality*, 9(3), 493–495.

Foster, J. E. and Shorrocks, A. (1988). Poverty Orderings and Welfare Dominance. *Social Choice and Welfare*, 5(2–3), 179–198.

Foster, J.E., Greer, J., and Thorbecke, E. (1984). A Class of Decomposable Poverty Indices. *Econometrica,* 52(3), 761–766.

Gordon, D., Levitas, R., Pantazis, C., Patsios, D., Payne, S., Townsend, P., Adelman, L., Ashworth, K., Middleton, S., Bradshaw, J. and Williams, J. (2000). *Poverty and Social Exclusion in Britain.* New York: Joseph Rowntree Foundation.

Halleröd, B, Larsson, D., Gordon, D. and Ritakallio, V-M. (2006). Relative Deprivation: A Comparative Analysis of Britain, Finland and Sweden. *Journal of European Social Policy,* 16(4), 328–345.

Halleröd, B. (1995). The Truly Poor: Direct and Indirect Consensual Measurement of Poverty in Sweden. *Journal of European Social Policy,* 5(2): 111–129.

Instituto Nacional de Estadísticas y Censos (INDEC) (1984). *La Pobreza en la Argentina, Indicadores de Necesidades Básicas Insatisfechas a partir de los datos del censo nacional de Población y Vivienda 1980.* Buenos Aires. Presidencia de la Nación. Secretaría de planificación.

International Energy Agency (IEA), World Energy Outlook. (2009). Paris. http://www.iea.org/textbase/nppdf/free/2009/weo2009.pdf

Jenkins, S. P., and Lambert, P. J. (1997). Three 'I's of Poverty Curves, With an Analysis of UK Poverty Trends. *Oxford Economic Papers*, 49(3), 317–327.

Katzman, R. (1989). La heterogeneidad de la pobreza. El caso de Montevideo. *Revista de la CEPAL*, 37(4), 141–152.

Kendall, M. G. and Gibbons, J. D. (1990). *Rank Correlation Methods* (Fifth Edition). New York: Oxford University Press.

Klasen, S. (2008). Poverty, Undernutrition and Child Mortality: Some Inter-Regional Puzzles and their Implications for Research and Policy. *Journal of Economic Inequality*, 6(1), 89–115.

Klasen, S. and Wink, C. (2003). Missing Women: Revisiting the Debate. *Feminist Economics*, 9(2–3), 263–299.

Lanjouw, P. and Ravallion, M. (1995). Poverty and Household Size. *The Economic Journal* 105(433), 1415–1434.

Lasso de la Vega, M. C. (2010). Counting Poverty Orderings and Deprivation Curves, Studies in Applied Welfare Analysis: Papers from the Third ECINEQ Meeting. *Research on Economic Inequality*, 18, 153–172.

Layte, R., Nolan, B. and Whelan, C. T. (2000). Targeting Poverty: Lessons from Monitoring Ireland's National Anti-Poverty Strategy. *Journal of Social Policy,* 29(4), 553–575.

Mack, J. and Lansley, S. (1985). *Poor Britain*. London: George Allen and Unwin.

Mayer, S. E and Jencks, C. (1989). Poverty and the Distribution of Material Hardship. *The Journal of Human Resources*, 24(1), 88–114.

Ravallion, M. (1994). *Poverty Comparisons, Fundamentals of Pure and Applied Economics*. Switzerland: Harwood Academic Publishers.

Ravallion, M. (2011). On Multidimensional Indices of Poverty. *Journal of Economic Inequality,* 9(2), 235–248.

Ravallion, M., Datt, G. and Van de Walle, D. (1991). Quantifying Absolute Poverty in the Developing World. *Review of Income and Wealth,* 37(4), 345–361.

Ruggeri-Laderchi, C., Saith, R., & Stewart, F. (2003). Does it matter that we do not agree on the definition of poverty? A comparison of four approaches. Oxford Development Studies, 31(3), 243-274.

Sahn, D. and Younger, S. (2010). Living Standards in Africa. In Anand, S., Segal, P. and Stiglitz, J. S. (Eds.), *Debates on the Measurement of Global Poverty.* Initiative for Policy Dialogue Series. Oxford and New York: Oxford University Press.

Sen, A. K. and Foster, J. E. (1997). *On Economic Inequality: After a Quarter Century.* Annex to the Expanded Edition of A.

Sen. *On Economic Inequality.* Oxford: Clarendon Press.

Sen, A. K. (1979). Equality of What? In McMurrin (Ed.), *Tanner Lectures on Human Values*. Cambridge: Cambridge University Press.

Sen, A. K. (1981). *Poverty and Famines. An Essay on Entitlement and Deprivation*. Oxford: Oxford University Press.

Sen, A. K. (1990). More Than 100 Million Women Are Missing. *The New York Review of Books*, 37(20), December 20.

Sen, A. K. (1992). *Inequality Reexamined.* Cambridge: Harvard University Press.

Sen, A. K. (1996). On The Foundations of Welfare Economics: Utility, Capability and Practical Reason. In F. Farina, F. Hahn and S. Vannucci (Eds.), *Ethics*, *Rationality, and Economic Behaviour* (1st ed., 50–65). Oxford: Clarendon Press.

Sen, A. K. (1999). *Development as Freedom*. Oxford: Oxford University Press.

Sen, A. K. (2003). Missing Women – Revisited, *British Medical Journal*, 327(6), 1297–1298.

Stiglitz, J. E., Sen, A., and Fitoussi, J-P. (2009). *Report by the Commission on the Measurement of Economic Performance and Social Progress.*

Sumner, A. (2012). Where do the Poor Live? *World Development*, 40(5), 865–877.

Thorbecke, E. (2011). A Comment on Multidimensional Poverty Indices, *Journal of Economic Inequality, 9*(3), 45–87.

Townsend, P. (1979). *Poverty in the United Kingdom*. Middlesex: Penguin.

Tsui, K. (2002). Multidimensional Poverty Indices, *Social Choice and Welfare,* 19(1), 69–93.

UN (2003). *Indicators for Monitoring the Millennium Development Goals. Definitions, Rationale, Concepts and Sources*. United Nations: New York.

UN (2011). Department of Economic and Social Affairs, Population Division. *World Population Prospects: The 2010 Revision*. http://esa.un.org/wpp/Excel-Data/population.htm. Accessed July 2011.

UNDP (2010). *The Real Wealth of Nations. Pathways to Human Development.* New York: Macmillan.

UNESCO (2010). UNESCO Institute for Statistics database, Table 1. Education systems. http://stats.uis.unesco.org/unesco/TableViewer/tableView.aspx?ReportId=163

UNICEF (2010). Multiple Indicator Cluster Surveys, (Various Years and Countries), United Nations Children's Fund, http://www.unicef.org/statistics/index_24302.html Accessed from January 2010.

Whelan, C. T., Layte, R. and Maître, B. (2004). Understanding the Mismatch between Income Poverty and Deprivation: A Dynamic Comparative Analysis. *European Sociological Review,* 20(4), 287–302.

Whelan, C. T., Nolan, B. and Maître, B. (2012). Multidimensional Poverty Measurement in Europe: An Application of the Adjusted Headcount Approach. Geary WP2012/11.

WHO Multicentre Growth Reference Study Group (2006). *WHO Child Growth Standards: Length/Height-for-Age, Weight-for-Age, Weight-for-Length, Weight-for-Height And Body Mass Index-for-Age: Methods and Development.* Geneva: World Health Organization.

World Bank (2004). *World Development Report 2004: Making Services Work for Poor People*. World Bank: Washington D.C.

World Bank (2010). *World Development Indicators*, 2010. http://data.worldbank.org/data-catalog/world-development-indicators. Accessed July 2011.

World Health Survey. http://www.who.int/healthinfo/survey/en/index.html. Datasets accessed from January 2010.

Yalonetzky, G. (2011). A Note on the Standard Errors of the Members of the Alkire Foster Family and its Components. OPHI Research in Progress No 25a.

Yalonetzky, G. (2012). Conditions for the Most Robust Multidimensional Poverty Comparisons Using Counting Measures and Ordinal Variables. ECINEQ Working Paper No 257.

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Appendix

Table A.1: MPI, H and A estimates with bootstrapped lower and upper bounds, and sample size

Country	Survey	Year	Multidimensional Poverty Index			Multidimensional Headcount Ratio			Multidimensional Poverty Intensity			MPI poor people (millions)	Total Sample Size	% of Sample Size used for MPI estimate
			MPI	MPI LB	MPI UB	H	H LB	H UB	A	A LB	A UB			
Albania	MICS	2005	0.004	0.002	0.006	0.01	0.006	0.015	0.381	0.366	0.392	0.03	20233	99.7
Angola	MICS	2001	0.452	0.435	0.469	0.774	0.748	0.798	0.584	0.578	0.592	13.557	29817	90.3
Argentina[*]	ENNyS	2005	0.011	0.009	0.012	0.029	0.025	0.033	0.376	0.371	0.382	1.128	169848	97.4
Armenia	DHS	2005	0.004	0.003	0.005	0.011	0.008	0.013	0.362	0.351	0.372	0.033	24888	97.2
Azerbaijan	DHS	2006	0.021	0.018	0.024	0.053	0.046	0.06	0.394	0.387	0.4	0.469	30114	98.4
Bangladesh	DHS	2007	0.292	0.28	0.304	0.578	0.559	0.597	0.504	0.499	0.51	83.237	50215	93.9
Belarus	MICS	2005	0	0	0	0	0	0.001	0.351	0.333	0.389	0.002	20475	99.6
Belize	MICS	2006	0.024	0.015	0.033	0.056	0.038	0.077	0.426	0.395	0.455	0.016	7673	92.7
Benin	DHS	2006	0.412	0.401	0.424	0.718	0.703	0.734	0.574	0.567	0.581	5.827	89371	94.1
Bolivia	DHS	2003	0.175	0.169	0.181	0.363	0.352	0.373	0.483	0.478	0.487	3.433	80546	96.9
Bosnia and Herzegovina[†]	MICS	2006	0.003	0.002	0.004	0.008	0.006		0.372	0.355	0.398	0.031	21063	99.3
Brazil[††]	WHS	2003	0.083	0.075	0.092	0.216	0.198	0.236	0.383	0.373	0.396	41.001	18085	87.8
Burkina Faso	MICS	2006	0.536	0.5	0.561	0.826	0.775	0.858	0.649	0.635	0.662	12.44	38504	93.6

Table A.1: MPI, H and A estimates with bootstrapped lower and upper bounds, and sample size (cont.)

Country	Survey	Year	Multidimensional Poverty Index			Multidimensional Headcount Ratio			Multidimensional Poverty Intensity			MPI poor people	Total Sample Size	% of Sample Size used for MPI estimate
			MPI	MPI LB	MPI UB	H	H LB	H UB	A	A LB	A UB	(millions)		
Burundi†	MICS	2005	0.53	0.518	0.541	0.845	0.831	0.857	0.627	0.62	0.634	6.513	41301	98.4
Cambodia♦	DHS	2005	0.251	0.244	0.259	0.52	0.506	0.534	0.484	0.48	0.487	7.107	72342	99.1
Cameroon♦	DHS	2004	0.287	0.279	0.297	0.533	0.52	0.55	0.539	0.532	0.545	9.79	49478	96.7
Central African Republic†	MICS	2000	0.512	0.5	0.527	0.864	0.85	0.878	0.593	0.585	0.601	3.596	92466	91.6
Chad†	WHS	2003	0.344	0.311	0.376	0.629	0.58	0.678	0.547	0.527	0.566	6.524	24524	64
China†	WHS	2003	0.056	0.048	0.064	0.125	0.105	0.144	0.449	0.44	0.46	164.836	13986	99.6
Colombia*	DHS	2005	0.04	0.038	0.042	0.093	0.089	0.097	0.433	0.428	0.438	4.124	153749	84.5
Comoros	MICS	2000	0.408	0.383	0.429	0.739	0.71	0.768	0.552	0.538	0.568	0.502	27060	74.6
Cote d'Ivoire††	DHS	2005	0.353	0.338	0.368	0.615	0.594	0.634	0.574	0.565	0.584	11.459	23747	96.4
Croatia††	WHS	2003	0.016	0.011	0.021	0.044	0.031	0.058	0.363	0.352	0.379	0.193	2948	98.4
Czech Republic††	WHS	2003	0.01	0.006	0.016	0.031	0.017	0.049	0.334	0.334	0.334	0.322	2712	95.9
DR Congo♦	DHS	2007	0.393	0.373	0.415	0.732	0.7	0.761	0.537	0.526	0.55	44.5	47602	97.7
Djibouti	MICS	2006	0.139	0.119	0.161	0.293	0.258	0.338	0.473	0.461	0.487	0.246	28014	88.1
Dominican Republic	MICS	2000	0.048	0.039	0.056	0.111	0.093	0.128	0.433	0.42	0.45	1.053	17759	95.2
Ecuador**†	WHS	2003	0.009	0.006	0.012	0.022	0.015	0.03	0.416	0.391	0.44	0.306	22667	59

Table A.1: MPI, H and A estimates with bootstrapped lower and upper bounds, and sample size (cont.)

Country	Survey	Year	Multidimensional Poverty Index			Multidimensional Headcount Ratio			Multidimensional Poverty Intensity			MPI poor people	Total Sample Size	% of Sample Size used for MPI estimate
			MPI	MPI LB	MPI UB	H	H LB	H UB	A	A LB	A UB	(millions)		
Egypt†	DHS	2008	0.024	0.022	0.027	0.06	0.054	0.065	0.407	0.4	0.416	4.583	90118	99.6
Estonia†	WHS	2003	0.026	0.018	0.037	0.072	0.051	0.1	0.365	0.356	0.375	0.097	2750	97.2
Ethiopia♦	DHS	2005	0.562	0.555	0.569	0.886	0.879	0.893	0.635	0.63	0.64	68.86	66388	97.5
Gabon†	DHS	2000	0.161	0.152	0.169	0.354	0.336	0.37	0.455	0.449	0.46	0.504	30736	73.4
Gambia	MICS	2006	0.324	0.31	0.337	0.604	0.585	0.623	0.536	0.525	0.544	0.961	45720	98.2
Georgia	MICS	2005	0.003	0.002	0.004	0.008	0.006	0.01	0.352	0.343	0.364	0.035	44265	93.7
Ghana♦	DHS	2008	0.144	0.134	0.154	0.312	0.293	0.33	0.462	0.455	0.47	7.077	46061	99
Guatemala*†	WHS	2003	0.127			0.259			0.491			3.455	25820	63.9
Guinea♦	DHS	2005	0.506	0.496	0.516	0.825	0.814	0.836	0.613	0.606	0.619	7.733	37589	97.6
Guyana†	DHS	2005	0.053	0.046	0.06	0.134	0.118	0.15	0.395	0.384	0.407	0.101	10898	95.2
Haiti♦	DHS	2006	0.299	0.286	0.312	0.564	0.543	0.584	0.53	0.523	0.537	5.424	46678	99.2
Honduras†	DHS	2006	0.159	0.154	0.164	0.325	0.316	0.334	0.489	0.486	0.492	2.329	92183	95.9
Hungary††	WHS	2003	0.016	0.011	0.02	0.046	0.033	0.058	0.343	0.335	0.352	0.461	4298	98.6
India	DHS	2005	0.283	0.278	0.289	0.537	0.53	0.546	0.527	0.523	0.531	630.98	516251	95.9
Indonesia†	DHS	2007	0.095	0.092	0.099	0.208	0.2	0.215	0.459	0.455	0.463	48.257	175142	97.1

Table A.1: MPI, H and A estimates with bootstrapped lower and upper bounds, and sample size (cont.)

Country	Survey	Year	Multidimensional Poverty Index			Multidimensional Headcount Ratio			Multidimensional Poverty Intensity			MPI poor people	Total Sample Size	% of Sample Size used for MPI estimate
			MPI	MPI LB	MPI UB	H	H LB	H UB	A	A LB	A UB	(millions)		
Iraq	MICS	2006	0.059	0.055	0.063	0.142	0.134	0.152	0.413	0.406	0.419	4.126	116106	88.8
Jordan[♦×]	DHS	2007	0.01	0.007	0.012	0.027	0.021	0.033	0.355	0.348	0.362	0.153	80539	57.9
Kazakhstan	MICS	2006	0.002	0.002	0.003	0.006	0.004	0.008	0.369	0.356	0.38	0.091	54121	99.4
Kenya	DHS	2003	0.296	0.285	0.308	0.601	0.584	0.618	0.493	0.486	0.502	22.529	36687	96.5
Kyrgyzstan[†]	MICS	2006	0.019	0.015	0.023	0.049	0.04	0.058	0.388	0.374	0.404	0.25	24731	90.7
Lao[†]	MICS	2006	0.267	0.245	0.289	0.472	0.441		0.565	0.548	0.58	2.802	33551	97.9
Latvia[**†††]	WHS	2003	0.006	0.003	0.01	0.016	0.008	0.025	0.379	0.353	0.407	0.037	2283	79.6
Lesotho[♦]	DHS	2004	0.215	0.208	0.221	0.469	0.456	0.481	0.458	0.455	0.461	0.987	34091	96.8
Liberia	DHS	2007	0.485	0.474	0.495	0.839	0.826	0.853	0.577	0.572	0.583	2.918	34344	96.6
Macedonia	MICS	2005	0.008	0.005	0.011	0.019	0.013		0.409	0.388	0.426	0.039	26423	97.3
Madagascar	DHS	2004	0.402	0.38	0.421	0.695	0.665	0.721	0.578	0.568	0.587	13.183	37446	97.2
Malawi	DHS	2004	0.381	0.37	0.391	0.721	0.702	0.738	0.528	0.523	0.533	9.795	59714	95.5
Mali	DHS	2006	0.558	0.549	0.567	0.866	0.856	0.875	0.644	0.639	0.649	12.143	73045	97.4
Mauritania	MICS	2007	0.352	0.338	0.365	0.617	0.597	0.636	0.571	0.562	0.579	1.982	58646	85.7
Mexico	ENSANUT	2006	0.015	0.014	0.017	0.04	0.036	0.043	0.389	0.384	0.394	4.346	206700	99.9

Table A.1: MPI, H and A estimates with bootstrapped lower and upper bounds, and sample size (cont.)

Country	Survey	Year	Multidimensional Poverty Index			Multidimensional Headcount Ratio			Multidimensional Poverty Intensity			MPI poor people	Total Sample Size	% of Sample Size used for MPI estimate
			MPI	MPI LB	MPI UB	H	H LB	H UB	A	A LB	A UB	(millions)		
Moldova	DHS	2005	0.007	0.006	0.008	0.019	0.016	0.022	0.367	0.359	0.376	0.069	31297	96
Mongolia	MICS	2005	0.065	0.058	0.071	0.158	0.143	0.172	0.41	0.403	0.417	0.414	26718	95.8
Montenegro†	MICS	2005	0.006	0.004	0.011	0.015	0.009		0.416	0.391	0.447	0.01	9602	93.9
Morocco	DHS	2004	0.139	0.131	0.146	0.285	0.271	0.297	0.488	0.481	0.495	8.838	62891	94.6
Mozambique	DHS	2003	0.483	0.473	0.492	0.798	0.787	0.809	0.605	0.6	0.61	17.409	62262	95.2
Myanmar†††	MICS	2000	0.154	0.144	0.165	0.318	0.301	0.337	0.483	0.475	0.492	14.907	132534	79.1
Namibia	DHS	2007	0.187	0.179	0.193	0.396	0.382	0.408	0.472	0.466	0.477	0.854	40794	96.9
Nepal	DHS	2006	0.35	0.333	0.365	0.647	0.622	0.67	0.54	0.532	0.549	18.37	42271	99.2
Nicaragua	DHS	2001	0.211	0.204	0.218	0.407	0.393	0.419	0.519	0.512	0.525	2.266	60889	95.6
Niger♦	DHS	2006	0.642	0.634	0.649	0.924	0.918	0.93	0.694	0.689	0.7	12.888	47420	97.2
Nigeria	DHS	2003	0.368	0.353	0.383	0.635	0.614	0.657	0.579	0.569	0.589	93.374	35269	96
Occupied Palestinian Territories	MICS	2006	0.003	0.002	0.004	0.007	0.004	0.009	0.382	0.367	0.395	0.025	29126	97
Pakistan†	DHS	2007	0.264	0.257	0.271	0.494	0.483	0.504	0.534	0.529	0.541	81.252	109148	96.7
Paraguay†	WHS	2003	0.064	0.057	0.073	0.133	0.119	0.147	0.485	0.469	0.505	0.811	24771	87.5

Table A.1: MPI, H and A estimates with bootstrapped lower and upper bounds, and sample size (cont.)

Country	Survey	Year	Multidimensional Poverty Index			Multidimensional Headcount Ratio			Multidimensional Poverty Intensity			MPI poor people	Total	% of Sample Size used for MPI estimate
			MPI	MPI LB	MPI UB	H	H LB	H UB	A	A LB	A UB	(millions)	Sample Size	
Peru	DHS	2005	0.086	0.074	0.1	0.199	0.172	0.232	0.432	0.423	0.441	5.601	54843	98.2
Philippines††	DHS	2003	0.089	0.084	0.095	0.19	0.18	0.2	0.47	0.462	0.478	16.868	60866	99.1
Republic of Congo	DHS	2005	0.27	0.257	0.282	0.558	0.537	0.58	0.483	0.476	0.491	2.082	29868	96.9
Russian Federation*†	WHS	2003	0.005	0.003	0.007	0.013	0.009	0.018	0.389	0.371	0.416	1.812	11079	81.8
Rwanda♦	DHS	2005	0.426	0.42	0.432	0.802	0.791	0.812	0.532	0.529	0.534	7.789	47163	98.9
Sao Tome and Principe**	MICS	2000	0.236	0.218	0.253	0.516	0.48	0.55	0.458	0.449	0.467	0.081	14251	63.7
Senegal♦	DHS	2005	0.384	0.354	0.412	0.669	0.629	0.705	0.574	0.56	0.588	7.678	67485	94.4
Serbia†	MICS	2005	0.003	0.003	0.004	0.008	0.006		0.4	0.381	0.425	0.082	33273	96.4
Sierra Leone	MICS	2005	0.489	0.477	0.502	0.815	0.8	0.828	0.6	0.592	0.61	4.463	42693	91.5
Slovakia**†	WHS	2003	0			0						0	6838	84.1
Slovenia**†	WHS	2003	0			0						0	2166	76.8
Somalia	MICS	2006	0.514	0.483	0.542	0.812	0.774	0.846	0.633	0.621	0.647	7.088	33557	90.8
South Africa**††	WHS	2003	0.022	0.015	0.029	0.052	0.037	0.068	0.42	0.4	0.442	2.531	10633	57.4
Sri Lanka*†	WHS	2003	0.021	0.016	0.026	0.053	0.041	0.066	0.387	0.375	0.399	1.081	28847	67

Table A.1: MPI, H and A estimates with bootstrapped lower and upper bounds, and sample size (cont.)

Country	Survey	Year	Multidimensional Poverty Index			Multidimensional Headcount Ratio			Multidimensional Poverty Intensity			MPI poor people	Total Sample Size	% of Sample Size used for MPI estimate
			MPI	MPI LB	MPI UB	H	H LB	H UB	A	A LB	A UB	(millions)		
Suriname†††	MICS	2000	0.063	0.039	0.086	0.126	0.083	0.165	0.497	0.459	0.534	0.064	17071	92.1
Swaziland	DHS	2007	0.184	0.176	0.191	0.414	0.398	0.428	0.445	0.439	0.45	0.469	21523	97.2
Syrian Arab Republic	MICS	2006	0.021	0.018	0.023	0.055	0.05	0.061	0.375	0.368	0.382	1.068	107369	81.8
Tajikistan	MICS	2005	0.068	0.06	0.078	0.171	0.15	0.192	0.4	0.391	0.409	1.129	40340	97.6
Tanzania†	DHS	2008	0.367	0.355	0.38	0.652	0.633	0.67	0.563	0.557	0.569	26.793	43493	99
Thailand	MICS	2005	0.006	0.005	0.008	0.016	0.014	0.02	0.385	0.378	0.392	1.118	137006	98.8
Togo	MICS	2006	0.284	0.267	0.305	0.543	0.516	0.575	0.524	0.513	0.535	3.067	32326	96.1
Trinidad and Tobago†	MICS	2006	0.02	0.017	0.023	0.056	0.049	0.066	0.351	0.345	0.359	0.075	18680	97.4
Tunisia*†	WHS	2003	0.01	0.008	0.013	0.028	0.022	0.036	0.371	0.361	0.384	0.286	25290	78.7
Turkey†	DHS	2003	0.028	0.024	0.031	0.066	0.058	0.073	0.42	0.409	0.431	4.586	46233	97.3
Ukraine†	DHS	2007	0.008	0.007	0.009	0.022	0.019	0.025	0.355	0.349	0.362	1.005	33598	96.6
United Arab Emirates**†	WHS	2003	0.002	0.001	0.003	0.006	0.003	0.009	0.353	0.336	0.382	0.031	6411	56.9
Uruguay†	WHS	2003	0.006	0.004	0.01	0.017	0.012	0.028	0.347	0.337	0.359	0.056	8389	98.8
Uzbekistan	MICS	2006	0.008	0.006	0.011	0.023	0.018	0.029	0.362	0.354	0.371	0.616	52018	98.5

Table A.1: MPI, H and A estimates with bootstrapped lower and upper bounds, and sample size (cont.)

Country	Survey	Year	Multidimensional Poverty Index			Multidimensional Headcount Ratio			Multidimensional Poverty Intensity			MPI poor people (millions)	Total Sample Size	% of Sample Size used for MPI estimate
			MPI	MPI LB	MPI UB	H	H LB	H UB	A	A LB	A UB			
Viet Nam††	DHS	2002	0.084	0.076	0.092	0.177	0.162	0.194	0.472	0.465	0.478	15.06	31279	99.5
Yemen†	MICS	2006	0.283	0.26	0.307	0.525	0.492	0.561	0.539	0.524	0.555	11.525	26082	99.2
Zambia	DHS	2007	0.328	0.319	0.338	0.642	0.625	0.658	0.512	0.507	0.518	7.735	34909	97.8
Zimbabwe	DHS	2006	0.18	0.172	0.187	0.397	0.382	0.411	0.453	0.449	0.457	4.953	41749	95.4

Notes: MPI, H and A are our own estimates. LB and UB refer to the lower and upper bound estimates of the 95% bootstrapped confidence intervals. All the headcount ratios are expressed as proportions of the population. The total sample size for DHS countries only considers usual residents. The reduction in sample size is due to households with missing information in some of the indicators. * MPI estimates should be interpreted as lower bound estimates, meaning that MPI is at least as great as the reported MPI value. **:MPI estimates should be interpreted as upper bound estimates, meaning that MPI is less than or equal to the reported MPI value. †, ††, †††: Data for these countries lacks one, two and three of the MPI indicators correspondingly. ♦ In these countries not all eligible children and females were measured for anthropometric information but rather only those in a 50% random sub-sample of households and in the case of Senegal in a 33% random sub-sample. × In Jordan we have used children's anthropometric information in the MPI. However, the country DHS report considered these data unreliable. Thus, these estimates should be interpreted with caution