

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 minimum international standards in indicators related to the Millennium Development Goals and to core functionings. It constitutes the first

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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.

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 income 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 in 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.

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 were not perfectly comparable and significant adjustments and assumptions were required.³ This approach developed into the ‘dollar-a-day’ or ‘extreme’ poverty measure reported by the World Bank.⁴

Leaving aside the challenges of data comparability, from the start economists have recognized some 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 a person will meet his/her minimum needs (Sen, 1981:28). Second, people may face different prices, reducing the accuracy of the poverty line (Sen, 1981:28). 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).^{5,6} Fourth, affordable quality services, such as water, health and education, are frequently not provided through the market.⁷ Fifth, using the indirect method provides no way to verify the intra-household distribution of income.⁸ 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. Important as income is, 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.^{9,10} The MPI constitutes the first implementation of the direct method to measure poverty in an internationally comparable way, having such a wide coverage of developing countries.¹¹ This was enabled by the availability of multi-topic household surveys which collect information associated with key basic needs and functionings, greater 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* minimum internationally comparable standards in indicators related to the Millenium Development Goals (MDG) and to core functionings.¹²

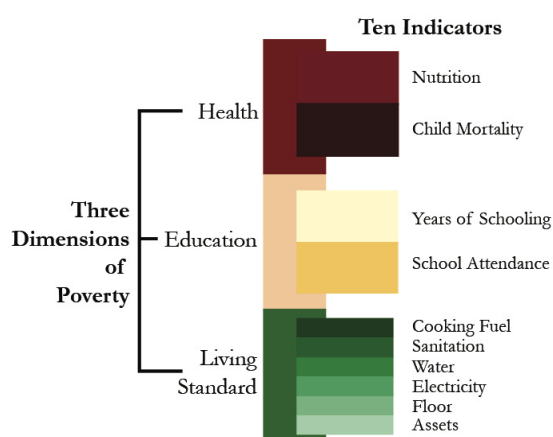
The key difference between the MPI and the “dollar-a-day” measures is precisely that the first applies the direct method whereas the second applies the indirect method. The two methods are complements. As noted by Sen (1981), they are not “...two alternative ways of measuring the same thing, but represent 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. Hence the MPI intends to complement income poverty analyses in the developing world, by bringing information from a different angle, focused directly on actual deprivations.

The MPI is one particular implementation of the direct method. The direct method has traditionally used a counting approach to identify the poor and the 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 which 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 the axioms are joint restrictions on identification and aggregation procedures. These new poverty measures are

described as multidimensional rather than unidimensional, 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 Millennium Development Goals (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 I: Dimensions and Indicators of MPI



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 employs. It offers the key results of the 2010 MPI, and then presents a range of robustness tests which evaluate the extent to which the initial MPI results are reliable and stable to changes in parameters.¹⁶ 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. For a detailed presentation of this family of measures please see Alkire and Foster (2011a).¹⁷

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 cut-offs* 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 that each indicator has, such that these sum to one.
5. Creating the weighted proportion of deprivations for each person, which can be called his/her *deprivation score*.
6. Determining the *poverty cutoff*, namely, the proportion of weighted deprivations a person needs to experience in order to be considered multidimensionally poor, and identifying each person 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.¹⁸ This is the **intensity** of multidimensional poverty, A .
9. Computing the M_0 measure as the product of the two previous partial indices: $M_0 = H \times A$.
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. First, the measure is robust when using ordinal or cardinal variables as it dichotomizes the individuals' achievements into 'deprived' and 'non-deprived'.

Secondly, 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.

Thirdly, 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 (subgroups need to be mutually exclusive and collectively exhaustive of the population). This enables poverty comparisons across subgroups.¹⁹

Fourthly, 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 has been identified as poor and is 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 (including the deprivations of the non-poor). Analogous to the population subgroup decomposability, the break-down by censored headcounts enables analysis of the contribution of deprivations in each indicator to overall poverty.²⁰

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.

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, as well as other methodological decisions. Within these constraints, decisions on the MPI parameters – deprivation cutoffs, weights and the poverty cutoff – are based on normative arguments addressed in turn below. We hope that the bottleneck of data availability can be addressed in the post-2015 era.

(a) Dimensions, indicators and unit of analysis

The potential dimensions that a measure of poverty might cover are broad and include health, education, living standards (which might have 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.

Despite being conditioned by data availability, the chosen dimensions are vitally important. First of all, they have intrinsic and instrumental value (Sen 1992, 1999): 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 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 and the validity, strengths, and limitations of the MPI indicators are well documented.

Regarding the unit of analysis, ideally the MPI would have used the person, in order to analyse intra-household inequalities and decompose poverty by gender and age, but health and sometimes education variables did not permit this. 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 household members' achievements to identify each member as poor, despite its limitations, allows for interaction, smoothing, and mutual sharing within the household, and can create policy efficiencies (Basu and Foster, 1998, Angulo et al 2013).

Table I details 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 ages in which they would attend classes one to eight, are being exposed to a learning environment. Similar indicators are used in the MDGs, UNESCO (2010) and the basic needs approach. When a child is not in school, all household members are considered deprived.²¹

Health was the most challenging 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 using the weight-for-age indicator for children and the Body Mass Index (BMI) for adults. 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 in the household.

The standard of living dimension comprises six indicators. Three are standard MDG indicators related to health that also particularly affect women: safe drinking water, improved sanitation, and the use of clean cooking fuel. Two are non-MDG indicators: electricity and flooring material. Both provide some rudimentary indication of the quality of housing. The final indicator covers the ownership of some consumer goods: radio, television, telephone, bicycle, motorbike, car, truck and refrigerator. The living standard indicators are means rather than ends, yet, these means are very closely connected with the ends (functionings) they facilitate.

Table I: 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%
	Mortality	Any child has died in the family	16.7%
Health	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 or carbon..	5.6%
	Assets	The household does not own one of the following assets: radio, TV, telephone, bicycle, motorbike, refrigerator and does not own a car or 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)

(b) 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 because country implementation follows standardized guidelines, so there is relatively greater homogeneity and comparability than between national multi-topic household surveys. Also, 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 data constraints.

The surveys were implemented in 2000-2008. We used the most recent available dataset for each country that was available in 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.²³

Two country-specific surveys were used: the 2006 Encuesta Nacional de Salud y Nutrición (ENSANUT hereafter) of Mexico, and the 2004-5 Encuesta Nacional de Nutrición y Salud (ENNyS) of Argentina. No other survey with the required indicators was available for these countries.

ENSANUT is nationally representative and collects indicators that are comparable with the other

three surveys. The ENNyS' sample design and survey weights do not allow nationally representative estimates in urban areas.²⁴

Of the 104 countries, 24 are in Central and Eastern Europe and the Commonwealth of Independent States (CEE/CIS), 11 are Arab States (AS), 18 are in Latin America and the Caribbean (LAC), 9 in East Asia and the Pacific (EAP), 5 in South Asia (SA), and 37 are in Sub-Saharan Africa (SSA), covering 5,200 million people. We would have liked to have a larger and more recent dataset for China than the WHS, which covers just under 14,000 people. However, our own and others' analysis indicate that the estimates for China add value.²⁵

Table II describes the available information on each indicator provided by each survey and details the variability across surveys.

Overall, 63 of the 104 countries have all 10 indicators and 93 countries have 9 or 10 indicators. Eight countries lack two indicators and three countries lack three variables.²⁶ In all these cases, the indicators' weights are adjusted as detailed in Section 3(e).

Cross-country comparability is affected by data constraints in several ways: surveys have different years, differences in the definition of some indicators such as nutrition, 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 the 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, c) demonstrating a methodology that can be adapted to national or regional settings, and applied to improved datasets and d) presenting and demonstrating a host of robustness analyses that can be performed alongside the AF methodology .

Table II: 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. ²	The respondent (adult male or female).	All household members.	All women 10-49 years.
		All under-5-year-old children. ¹				All under-5-year-old children.
	Mortality	Non-age specific question and birth history asked to all women 15-49.	Non-age specific question asked to all women 15-49.	Non-age specific question and birth history asked to 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 to all women 10 years old and older.	Non-age specific question asked to all women 10-49.
		In 37 countries this is also asked to all males within a certain age range, or to males in a random sub-sample of households. Males' age range varies.				

Table II: Information on each MPI indicator provided in each survey (contd)

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 II: Information on each MPI indicator provided in each survey (contd)

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. Time to the water source not available.	
	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 six countries.				
	Floor	Available across all surveys except one country.				
	Assets	Available.	Available	Lacks information on radio and motorbikes.	Available	Only information on refrigerators and telephones. Given that even in slums people probably have a radio and TV, we required the household to have one of refrigerator or telephone to be considered non-deprived.

Notes: ¹In 12 DHS countries not all eligible women aged 15-49 and under-5-year old children were measured for nutritional assessment. In 11 of these countries women 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. In 2010 we decided to consider the sub-sample of eligible women and children not selected as if they were non-applicable, and thus non-deprived, as we do with women in MICS and children in WHS. ²Only Yemen, Somalia and Iraq are MICS countries with birth history. ³The 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. ⁴In Colombia the information on sharing sanitation facilities was considered unreliable (inexplicably high) and thus was ignored.

(c) Treatment of households with non-applicable population

Given the importance of children and of health, the MPI includes three indicators that are not applicable to all households yet make the measure more accurate than restricting the MPI to achievements that can be registered for every person in the sample.

The three indicators are: child school attendance, nutrition, and mortality. 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. The mortality indicator is non-applicable in DHS if households have no male or a female of reproductive age; in MICS if there are no females in reproductive age, and in WHS 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 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.

(d) Treatment of missing data and sample sizes

If a household had missing information for all members in any 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, each having 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 and mortality, if there were eligible women and/or children and information was entirely missing, we consider the household as missing the indicator.²⁷ Otherwise, we used the available

information. If any of the eight assets was missing, we assumed that the household lacked 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 (Table A.1). Eighty-five countries have a sample size of 87-100% of the original sample size. For the 19 countries with sample sizes lower than 87% we performed a bias analysis using hypothesis tests of differences in means. Such analysis is detailed at the bottom of Table A.1, where we show the countries whose MPI estimates are considered to be upper or lower bound as a result of this analysis.

(e) Indicators' Weights

The relative values of different deprivations may be obtained in 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. 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. 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 I, in the MPI weights are equally distributed across dimensions (1/3 each) and within dimensions, across indicators. Whenever there are fewer than 10 indicators in a particular dataset, the same nested weighting principle applies; in no case does a country lack all indicators from any dimension.

Because any measure must be robust to a range of plausible weights, in Section 5 (d) 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.

(f) Poverty cutoff k

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 range 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, usually those who do not meet minimum internationally agreed standards in multiple indicators of basic functionings simultaneously. When all 10 indicators are 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 10 indicators are present. Section 5 (e) observes that the MPI ranking is robust to k cutoffs from 20 to 40%.

(g) 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. Secondly, 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 the censored headcount ratios differ from MDG-related statistics, as 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 the confidence intervals for these three measures obtained using the bootstrap technique.²⁸ Further results such as the indicators' censored headcount ratios are provided in the online Supplementary Data.

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

(a) Global Poverty Estimates

About 1.67 billion people in the developing world are in acute poverty or MPI poor (Table III). That is about 32% of the total population in the 104 countries.²⁹ This headcount figure and rate lies between the total number of people living on less than \$1.25/day in the 90 countries for which we have comparable data, which is 1.53 billion people (29%), and the total number of people living with less than \$2/day, which is 2.74 billion people (53%).

How were these estimates obtained? We apply the MPI headcount ratio in each country to the 2007 population figures (UN, 2011). For 87% of the countries, covering 94% of the total population, surveys are from 2003-2007. As we stressed earlier, data issues limit accuracy and cross-country comparability of these 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.³⁰ To estimate the number of income poor we use the headcount ratios from the *World Development Indicators* (WB, 2010). We select the most recent income poverty estimate that is closest to the year of the MPI poverty estimate, with never more than five years apart. Income and MPI surveys for 66% of countries were fielded one year or less apart.³¹ The income headcount ratio is then applied to the 2007 population figure of each country.

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

Region of the World	Total				MPI poor	\$1.25/day	\$1.25/day	\$2/day	\$2/day
	Pop.	MPI	H	A	pop.	poor	poor pop.	poor	poor pop.
	(millions)				(millions)		(millions)		(millions)
CEE and CIS	398.3	0.011	0.029	0.394	11.4	0.045	18.0	0.110	43.8
LAC	491.774	0.065	0.154	0.419	75.7	0.101	49.8	0.200	98.2
<i>China</i>	<i>1321.5</i>	<i>0.056</i>	<i>0.125</i>	<i>0.449</i>	<i>164.8</i>	<i>0.284</i>	<i>375.3</i>	<i>0.363</i>	<i>676.6</i>
<i>EAP without China</i>	<i>543.1</i>	<i>0.092</i>	<i>0.196</i>	<i>0.469</i>	<i>106.5</i>	<i>0.219</i>	<i>119.1</i>	<i>0.135</i>	<i>251.1</i>
Total of EAP	1864.5	0.066	0.146	0.457	271.4	0.265	494.4	0.498	927.7
AS	212.7	0.091	0.179	0.508	38.0	0.038	8.1	0.194	41.2
<i>SA without India</i>	<i>357.0</i>	<i>0.268</i>	<i>0.515</i>	<i>0.521</i>	<i>183.9</i>	<i>0.356</i>	<i>127.0</i>	<i>0.161</i>	<i>246.3</i>
<i>India</i>	<i>1174.0</i>	<i>0.283</i>	<i>0.537</i>	<i>0.527</i>	<i>631.0</i>	<i>0.416</i>	<i>488.4</i>	<i>0.580</i>	<i>887.5</i>
Total of SA	1531.0	0.280	0.532	0.526	814.9	0.402	615.4	0.741	1133.8
SSA	703.7	0.374	0.647	0.577	455.5	0.486	342.3	0.705	496.2
Total 104 countries	5202.1	0.170	0.320	0.531	1667.0	0.294	1528.0	0.527	2741.0

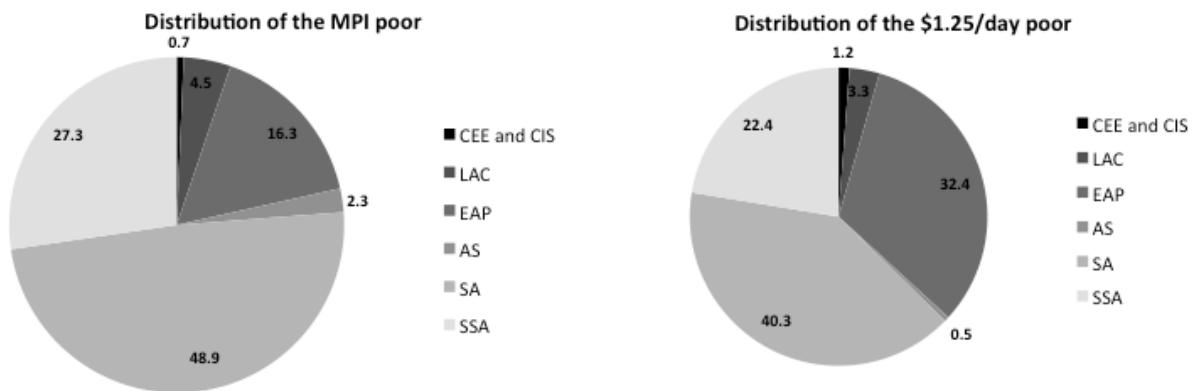
Note: Pop.: Population, expressed in millions. MPI, H, A, \$1.25/day poor and \$2/day poor are all proportions. CEE and CIS: Central and Eastern Europe and the Commonwealth of Independent States. LAC: Latin America and the Caribbean. EAP: East Asia and the Pacific. AS: Arab States. SA: South Asia. SSA: Sub-Saharan Africa.

Note that income poverty estimates within 5 years distance from the year of the MPI estimate are not available for 14 countries: Czech Republic, Slovakia, Belize, Trinidad and Tobago, Guyana, Suriname, Somalia, United Arab Emirates, Palestinian in Lebanon, Myanmar, Mauritania, Swaziland, Zimbabwe and Namibia. 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

(b) Distribution of Global Poverty

Where do the MPI poor live? Table III and Figure II depict the distributions. SA is home to 49% of the total MPI poor whereas SSA is home to 27% of the global poor, followed by EAP, with 16%. Although the average MPI of SSA is the highest across regions, SA is home to nearly twice as many multidimensionally poor people as SSA. We also find –in line with Sumner (2012)’s estimates of the distribution of global income poverty in 2007– 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.

Figure 2: Distribution of the MPI poor



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.

Note: 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.

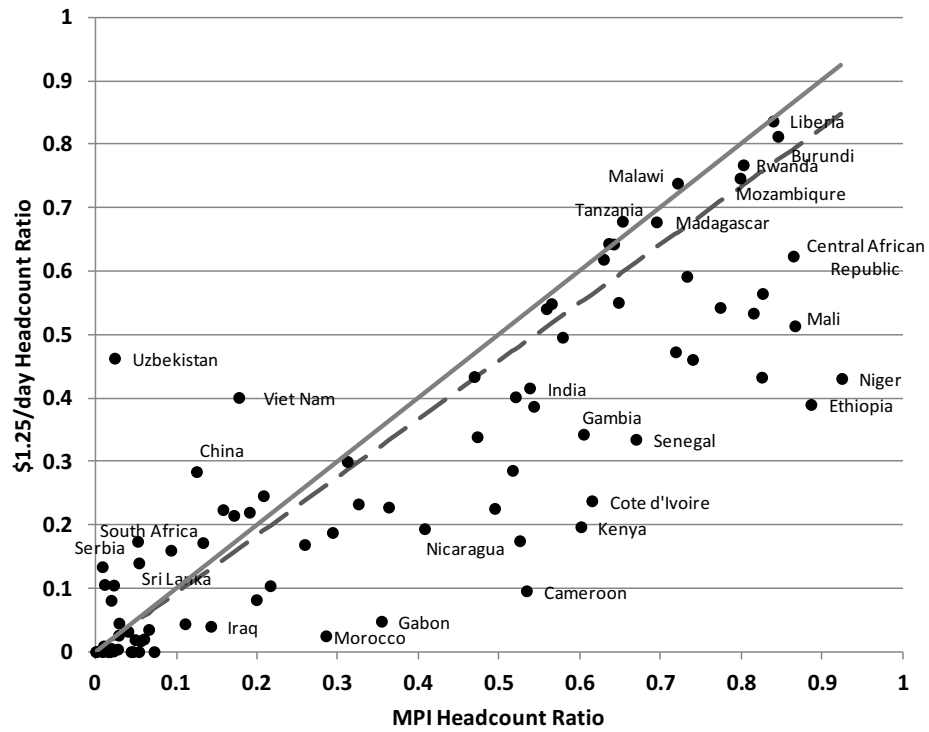
The critical situation of South Asia is not just a matter of the shattering number of poor, but also their intensity. In many areas, the intensity of poverty is as high as in African countries. For example, India’s

MPI is 0.283. Yet, when we decompose the MPI across large Indian states, we find that 8 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).³²

Globally, the MPI shows a lower incidence of MPI poverty in EAP compared to income poverty, a result that is due to the fact that China seems to have lower headcount ratios for MPI than income poverty. Naturally this finding depends upon the accuracy of China's MPI estimates which, according to Section 5, seem quite reliable. On the other hand the AS are home to a much higher proportion of the MPI poor than of \$1.25/day poor; SA and SSA also have higher MPI poverty. These findings suggest that the two measurement methods complement each other capturing distinct angles: actual failures to meet basic needs or functionings vs. failure in the ability to do so.

Discrepancies in estimates of MPI and \$1.25/day poverty at the country level are displayed in a scatterplot in Figure III. 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 headcount ratio being between 40 and 50% points higher than the income poverty one. In over 80% of low and high human development (HDI) countries, the MPI headcount ratio is higher than the \$1.25/day whereas this is only just under two-thirds in medium HDI countries.³³ 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 III: MPI poor headcount ratio vs. \$1.25/day poor headcount ratio

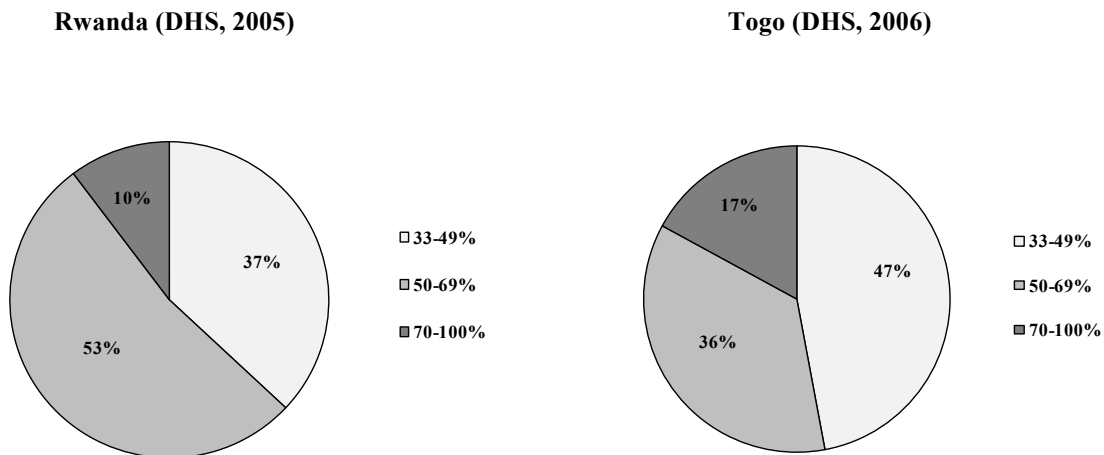


Note: The continuous grey line is the 45° diagonal. The discontinuous line depicts the ratio of the global \$1.25/day poor to the global MPI poor.

(c) Poverty's intensity

A novel insight of the MPI is that one can assess the average simultaneous deprivations, namely, poverty intensity. Countries with higher MPI headcount ratios tend to have higher average intensity: H and A have a Spearman correlation coefficient of 0.92. However, such close links do not inevitably hold. For example, Somalia and Rwanda have similar H : 81.2% and 80.2% respectively. Yet, while in Somalia the average poor person is deprived in 63.3% of the weighted indicators, in Rwanda intensity 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 IV 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 IV: Distribution of poverty intensity in two countries



(d) The poor and the deprived non-poor

Another value-added of the MPI is that it focuses on deprivations experienced by the poor. 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 their deprivations are censored and not included in the MPI –enhancing both the clarity and accuracy of the measure. We examine the pattern of deprivation using the censored headcount ratios: the proportion of people who are poor *and* deprived in each indicator.

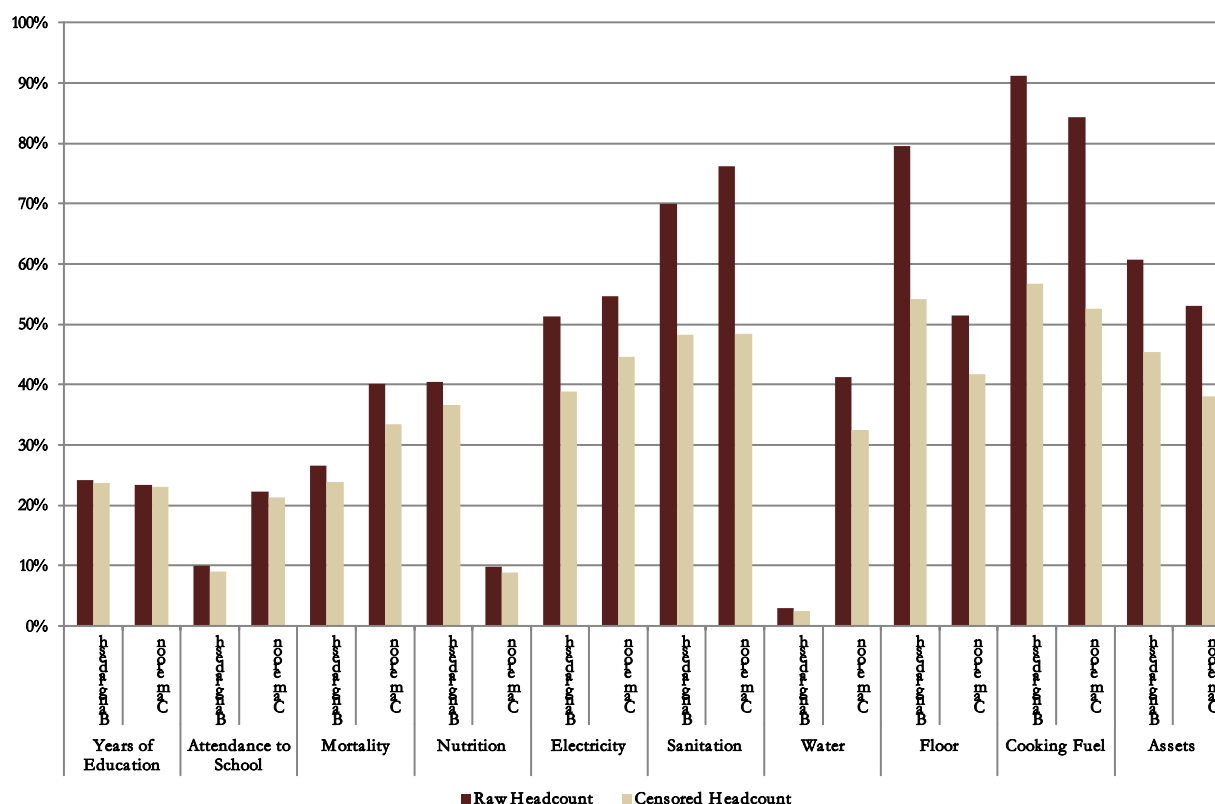
Figure V presents an example of such differences for two countries: Bangladesh and Cameroon. Both have similar MPI values: 0.292 and 0.287 respectively. In both countries the difference between the raw and censored headcounts is highest for cooking fuel. Other large differences can be seen in sanitation, 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. Discrepancies between raw and censored headcounts can be usefully analysed to distinguish wide-spread sectoral needs from data inaccuracies or personal or cultural preferences.

(e) 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.³⁴ 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 higher incidence of mortality. The censored headcount ratio of malnutrition is 30 to 70 percent higher than mortality in Nepal,

Bangladesh and India, whereas the censored headcount of mortality can be up to 3.8 times that of nutrition in African countries.³⁵

Figure V: Censored vs. Raw Headcount Ratios for two sample countries



5. ROBUSTNESS OF THE MULTIDIMENSIONAL POVERTY INDEX

As any poverty measure, the MPI involves a number of decisions on the parameters' values which affect both identification and aggregation. Given the novelty of the MPI, many wondered how these choices affect the MPI estimates (Ravallion 2011; Ferreira 2011; Thorbecke 2011, among others). This section assesses the robustness of poverty comparisons to the indicator's choice and definition, deprivation cutoffs, weights, and the poverty cutoff. Our analysis is inspired by literature on poverty orderings in the unidimensional framework initiated by Atkinson (1987) and Foster and Shorrocks (1988). Conditions and

tests of stochastic dominance are being extended to multidimensional poverty but these techniques require higher sample sizes than are available in the MPI datasets.³⁶

As stated earlier, data constraints limit cross-country comparability of MPI estimates. Aware of these underlying differences, we apply a bevy of robustness tests in order to assess how sensitive the ranking of countries by MPI are, *ceteris paribus*, to changes in key parameters.

We refer to the 2010 MPI presented in Section 3 as the *baseline MPI*, namely, with the ten indicators, cutoffs and weights described in Table I, and the 33.33% poverty cutoff. A first fundamental analysis is to evaluate the significance of the differences in the MPI estimates *within* the ranking of the baseline MPI countries. Suppose data were fully comparable and the MPI estimates of two countries, say country P and country R are denoted as MPI_P and MPI_R correspondingly. We would like to know whether country P is unambiguously poorer than country R , in which case it constitutes a significant pairwise comparison.

We evaluate pairwise comparisons in three different ways. One way uses the standard errors associated with each MPI value. Because the MPI is the mean of the censored deprivation scores, the computation of standard errors (naturally considering the complex survey design) is straightforward.³⁷ We refer to these as the analytical standard errors. Using the MPI standard errors we perform tests of differences in means between the MPI values of all possible pairs of countries. For each possible pairwise comparison, we perform two one-tailed tests. In the first test the null hypothesis is $H_0: MPI_P - MPI_R \leq 0$; the alternative hypothesis is $H_1: MPI_P - MPI_R > 0$. When the null hypothesis is rejected, one can conclude that country P is poorer than country R . The other test runs in exactly the opposite direction, such that when the null hypothesis is rejected one can conclude that country R is poorer than P . Given that our sample sizes are large, we assume a normal distribution and compute the corresponding z-statistic. If the null hypothesis is rejected at the 5% level, we consider pairwise comparisons to be significant.

Another more demanding way in which the standard errors can be used to test the significance of pairwise country comparisons is by using the confidence intervals. Denote the lower bound MPI estimate of

country P as LB_MPI_P and the upper bound as UB_MPI_P , and analogously for country R . Whenever $UB_MPI_R < LB_MPI_P$ we can say that country P is unambiguously poorer than country R , constituting a significant pairwise comparison within this methodology.³⁸

A third way to evaluate the significance of pairwise comparisons within a ranking is by using confidence intervals obtained through bootstrapping rather than analytical standard errors. The bootstrap constitutes a computationally intensive way of calculating standard errors which stands as an alternative to analytical standard errors, and is increasingly being applied (Davidson and Duclos, 2000, p. 1436; Duclos and Araar, 2006, p. 294). As all our surveys have a complex survey design we have drawn samples of clusters (with replacement) within each strata (Deaton, 1997) and computed the MPI for each of these simulated samples. For each country we performed 1000 replications, and used these estimates to create the bootstrap 95% confidence intervals and standard errors.³⁹ Whenever the upper bound MPI estimate (obtained with bootstrap) of country R is strictly lower than the corresponding lower bound MPI estimate of country P , we can say that country R is unambiguously less poor than country P , constituting a significant pairwise comparison.⁴⁰ A priori there is no evidence that the bootstrap or the analytical procedure for inference outperform the other (Duclos and Araar, 2006, p. 294); thus using both procedures is in itself a further robustness tests of our robustness results. Using these methodologies we obtain alternative estimates of the proportion of significant pairwise country comparisons within a ranking, out of the total possible pairwise comparisons. These are of direct interest and are also useful for the subsequent robustness analysis.

Turning now to testing the robustness of the MPI across alternative parameters' specifications, as a first simple exploration we compute Spearman and Kendall Tau-b (Kendall and Gibbons 1990) rank correlation coefficients between the ranking obtained with the baseline MPI and with alternative specifications.

Next we implement each of the three methodologies described above. Specifically, suppose we have four alternative specifications of the MPI: the baseline, and three different ones. For each of the three methodologies, we define a pairwise country comparison to be *robust* if we find countries P and R to have the *same* significant relationship (either P being poorer than R or *viceversa*) *across* the different specifications of the MPI.

The number of robust pairwise comparisons may be expressed in two ways. One may report the proportion of the total possible pairwise comparisons that are robust. A somewhat more precise option is to express it as a proportion of the number of significant pairwise comparisons in the baseline measure, because a pairwise comparison that was not significant in the baseline MPI cannot, by definition, be a *robust* pairwise comparison.

Importantly, the number of robust pairwise comparisons to alternative specifications of the MPI is influenced by at least three factors: the number of possible pairwise comparisons, the number of significant pairwise comparisons in the baseline distribution, and the number of alternative parameter specifications. Interpretation of the percentage of robust pairwise comparisons that is informed by these three factors can illuminate the degree to which the original results and the policy recommendations they generate are valid across alternative plausible design specifications.⁴¹

Table IV lists the percentage of significant pairwise comparisons in the baseline MPI and the percentage of robust pairwise comparisons to household composition, weights, and poverty cutoff discussed below. Each analysis involves either two or the three robustness methodologies described above. The first column in each analysis reports the percentage of comparisons for which the confidence intervals (using analytical standard errors) do not overlap; the second presents the percentage of comparisons that are statistically distinct according to the hypothesis tests. For the baseline MPI and for the analysis of alternative poverty cutoffs, a third column presents the percentage of pairwise comparisons for which the confidence intervals using bootstrap standard errors do not overlap.

Table IV: Proportion of significant pairwise comparisons in the baseline MPI and robust pairwise comparisons across alternative specifications of the MPI

	N	Prop. Over	Between MPIs by age and gender (4 MPIs) ¹					Between MPIs with alternative weights (4 MPIs) ²		Between MPIs with alternative poverty cutoffs (3 MPIs: 20%, 33.33% and 40%)		
			Baseline MPI		Bootstrapped CIs do no overlap	CIs do no overlap	Hyp. Test	CIs do no overlap	Hyp. Test	CIs do no overlap	Hyp. Test	Bootstrapped CIs do no overlap
			CIs do no overlap	Hyp. Test								
Total	102 ³	TPWC	92.2	94.3	91.2	81.1	84.5	81.4	83.9	85.9	88.9	87.3
		SPWC	100	100	100	86.2	87.9	88.3	88.9	93.1	94.2	95.7
By region												
SSA	37	TPWC	89.5	92.8	87.2	73	79	73.1	76.6	83.6	89.2	85.9
		SPWC	100	100	100	81.5	85.1	81.7	82.5	93.5	96.1	98.5
SA	5	TPWC	90	90	90	80	80	70	70	90	90	90
		SPWC	100	100	100	88.9	88.9	77.8	77.8	100	100	100
LAC	17 ³	TPWC	89	92.6	87.5	64.2	75	67.6	73.5	76.5	81.6	77.9
		SPWC	100	100	100	63.6	71.4	76	79.4	86	88.1	89.1
EAP	9	TPWC	86.1	88.9	86.1	69.4	75	63.9	66.7	77.8	80.6	77.8
		SPWC	100	100	100	80.6	84.4	74.2	75	90.3	90.6	90.3
CIS	23	TPWC	70.8	77.5	66.4	35.2	45.8	36.8	42.7	37.5	46.2	44.3
		SPWC	100	100	100	49.7	59.2	52	55.1	53.1	59.7	66.7
AS	11	TPWC	92.7	94.5	92.7	78.2	80	81.8	85.4	85.5	89	87.3
		SPWC	100	100	100	84.3	84.6	88.2	90.4	92.2	94.2	94.1

		Between MPIs by age and gender (4 MPIs) ¹					Between MPIs with alternative weights (4 MPIs) ²		Between MPIs with alternative poverty cutoffs (3 MPIs: 20%, 33.33% and 40%)			
N	Prop. Over	Baseline MPI										
		CIs do not overlap	Hyp. Test	Bootstrapped CIs do not overlap	CIs do not overlap	Hyp. Test	CIs no overlap	Hyp. Test	CIs do not overlap	Hyp. Test	Bootstrapped CIs do no overlap	
By Survey												
DHS	48	TPWC	94	95.4	92.6	84.4	87.6	84	84.8	89.9	92.5	91.7
		SPWC	100	100	100	89.8	91.8	89.3	88.9	95.7	97	99
MICS	35	TPWC	90.6	92.8	90.6	81.2	86.5	81.8	85.5	84	87.6	85.2
		SPWC	100	100	100	89.6	93.3	90.4	92.2	92.8	94.4	94.1
WHS	17	TPWC	75	83.8	72.8	48.5	55.1	47.1	52.9	53.7	62.5	59.6
		SPWC	100	100	100	64.7	65.8	62.7	63.2	71.6	74.6	81.8
With the 10 indicators	63	TPWC	94.1	95.9	93.2	85.4	88.5	84.7	86.9	89.8	92.7	91.2
		SPWC	100	100	100	87.9	89.3	90	90.7	95.4	96.7	97.8
By income category												
Low	34	TPWC	88.6	92.2	86.8	74.7	80	74.9	78.8	83.8	89.7	85.9
		SPWC	100	100	100	84.3	86.8	84.5	85.5	94.6	97.3	99
Lower Middle	38	TPWC	92	93.7	91.7	81.7	84.1	78.5	81.4	86.3	89.3	87.6
		SPWC	100	100	100	88.7	89.7	85.3	86.8	93.8	95.3	95.5
Upper Middle	21 ³	TPWC	83.8	89	81.9	64.2	70	69	75.7	71.9	78.6	74.8

		SPWC	100	100	100	69.3	71.1	82.4	85	85.8	88.2	91.3
		TPWC	64.3	75	60.7	21.4	32.1	14.3	21.4	14.3	32.1	32.1
High	8	SPWC	100	100	100	33	42.9	22.2	88.9	22.2	42.9	52.9

Notes: **TPWC**: Total possible pairwise comparisons (combinatory of N taken by two). **SPWC**: Number of significant pairwise comparisons in the baseline MPI. In the Baseline column results, these are always 100% by definition. **1**: We computed the MPI for four population subgroups: children 0 to 14 years of age, women 15 to 49 years of age, women of 50 years and older and men of 15 years and older. The unit of identification remains the household, as data does not permit individual identification. **2**: We computed the MPI for four alternative weighting structures: the baseline and three alternatives, giving 50% of the relative weight to one of the three dimensions and 25% to each of the other two in turn and equally weighting indicators within dimensions. **3**: In the comparisons across MPIs by age and gender groups the total number of considered countries was 101 because Argentina could not be decomposed due to data limitations. This applies to the groups of LAC (16 countries instead of 17) and the upper middle income group (20 countries instead of 21).

The first row of the robustness tests provides the percentages of significant and robust pairwise comparisons with respect to the total possible pairwise comparisons across states, labeled as TPWC. The second line of comparisons, SPWC, provides the percentage of robust pairwise comparisons with respect to the significant pairwise comparisons in baseline MPI. This line adjusts for the second factor—namely the varying extent of significant pairwise comparisons in the baseline MPI, and thus seems the more relevant result.⁴² The three methods provide similar but not identical assessments, with the hypothesis tests generating a percentage of robust comparisons at least as high as with the confidence intervals methodology. Across the different groups of states, the three tests nearly always show the same relative pattern of robustness.

The number of countries does seem to influence comparisons. High income countries (8), and Upper Middle Income countries (21) have relatively lower levels of robust comparisons when compared with the other two counterpart groups, with 34 or more countries each. However there are exceptions to the pattern that higher number of countries in a group generate higher robustness: SA, which has only 5 countries but very robust results, and the CEE/CIS countries, with 23 countries but very low robustness results. Also, the AS (only 11 countries) are relatively robust to MPI by population subgroups and alternative poverty cutoffs.

Finally, the number of specifications being compared may affect results. Both in the robustness to MPIs by population subgroups as well as to alternative weights, four alternative specifications are considered, so differences along the rows of the same groups seem to reflect different levels of robustness. The robustness of the poverty cutoff comparison, having 3 comparisons, exceeds the others.

(a) Robustness to sample variability

We first evaluate the robust pairwise comparisons of MPI estimates *within* the ranking of the baseline MPI or, in other words, to sample variability. The standard errors obtained with bootstrapping and in the

analytical way are marginally smaller in 80 out of 101 cases as well as on average. This can be seen in Table V.

Table V: Mean, minimum and maximum values of the standard error computed in two alternative ways (bootstrap and analytical)

	Bootstrapped Standard Error	Analytical Standard Error
Mean	0.0045	0.0052
Min and Max values	(0.000041,0.0165)	(0.000046,0.0172)
Correlation with MPI	0.64	0.70
Correlation between the two standard errors	0.97	

Note: Slovakia was dropped for comparing the two standard errors as it has an MPI of 0.

The standard error tends to be bigger the poorer the country. The Pearson correlation coefficient between the standard error and the MPI is 0.63 for bootstrap and 0.71 for analytical. In general, standard error values are low, suggesting that MPI point estimates are reliable.

Using the lower and upper bound estimates of the MPI, obtained from bootstrapping for each country (Table A.1), we find that 91.2% of the total pairwise comparisons are significant (Table IV).⁴³ When we discriminate by region, we find all regions have high proportions of significant comparisons (86 to 92.7%) except the CEE/CIS countries, with only 66.4% of significant pairwise comparisons. This is a natural result given that it is the region with most of the least poor countries. When we discriminate by surveys, DHS and MICS have 92.6 and 90.6 % of significant pairwise comparisons whereas WHS has only 72.8%. WHS surveys are used for some least poor countries and may have lower data quality. Discriminating by income level, high income countries have a low proportion of significant pairwise comparisons; the others are 81.9% or higher. The alternative methodologies of confidence intervals and hypothesis tests using analytical standard errors obtain either equal or higher proportions of significant pairwise comparisons, with the highest difference being 11 percent points in the case of CEE/CIS and

WHS countries when using hypothesis tests with analytical standard errors.⁴⁴ In summary, we find that meaningful MPI comparisons are possible for many countries.⁴⁵

(b) Household composition

One important question related to the MPI design 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 are measured, and for the 37 DHS countries where some males are interviewed for the mortality questionnaire. Thus, at first, 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 one 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.⁴⁶

Two analyses are used to evaluate the empirical impact of household size and composition. One consists of 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 5, a higher number of females, and a lower average number of members 50 years and older, compared to non-poor households. We also test whether the proportion of poor households that are female-headed and have school-aged children is 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 VI 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 or lower means.⁴⁷

The columns ‘Overall’ present results for all countries. We find that household size and the number of females do not have 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 38% of households have a significantly lower household size, or average number of females, making the overall size effect inconclusive. However, poor households are likely to have more children: 56% have significantly higher average number of children under five, and 59% are more likely to have school-aged children, only 7.5% and 5.5% of households have significantly lower means respectively and the remainder are not significantly different. 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%, with no significant difference in 38%. Interestingly, only in 11% of the countries did poor households have a significantly higher probability of being female headed, in 36.7% they have lower probability. The rest had no significant difference.

Table VI: 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	Mid	High	Overall	Low	Mid	High	Overall	Low	Mid	High	Overall	Low	Mid	High
		MPI	MPI	MPI		MPI	MPI	MPI		MPI	MPI	MPI		MPI	MPI	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

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 33 and 66 centiles of the population-weighted countries ordered by the MPI.⁴⁸ 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. In poorer countries, the number of household members 50-years and older seems to decrease the probability that a household is poor. Finally, in 72% of the 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.⁴⁹

We also performed this analysis by geographical regions. Results (available upon request) are consistent with those by MPI level. Poor households in the poorest geographical regions: SSA, SA and the AS (because of Somalia), exhibit larger average household sizes, and a higher prevalence of children and women.

Thus larger households with more children and women are more likely to be MPI poor in the poorest countries but not necessarily in other countries. We find four distinct possible explanations for these results. First, MPI poverty may be, objectively, higher among larger households and those with more children.⁵⁰ Secondly, survey designs differ. The WHS dataset uses at most one respondent per household for mortality and nutrition data, whereas 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. So household size will affect DHS and MICS but not WHS datasets. Third, the survey design and MPI indicator construction could artificially and inaccurately inflate the apparent poverty in large households. Fourth, 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.

A second set of analysis decomposes each country's MPI by respondents' age and gender.⁵¹ We consider four groups: children 0-14 years of age, women 15-49, women 50 years and older, and men of 15 years and older. The unit of identification remains the household. We compare the rankings, correlations, and the proportion of robust pairwise country comparisons across the four-subgroup MPIs.

The correlations between the baseline MPI and the MPI for the different population subgroups are quite high. The lowest correlations, between the MPI ranking for women 50 and older and the others, are still between 0.85-0.89 (Table VII). Also, in Table IV we see that 86.2% and 87.9% of the total significant pairwise comparisons in the baseline MPI (SPWC) remain significant across all three pairwise comparison methodologies.⁵² When we discriminate by geographical region, the poorest regions of SA and SSA (as well as the AS in the case of SPWC) exhibit higher levels of robustness than the other less poor regions, which does not contradict the previous results. While the previous results indicate that poor households in these regions have on average more women and children, these results indicate that this pattern is fairly homogeneous within each region such that country rankings are not altered. As with other comparisons, the robustness is otherwise strongest among DHS and MICS surveys, countries with 10 indicators, and low and lower middle income countries.

Table VII: Kendall (Tau-b) Correlation coefficients between MPI for subgroups of population

	Baseline MPI	MPI for children 0-14	MPI for women 15-49	MPI for women 50 and over
MPI for children 0-14	0.94			
MPI for women 15-49	0.95	0.93		
MPI for women 50 and over	0.89	0.85	0.86	
MPI for men 15 and over	0.97	0.92	0.94	0.89

Note: 101 countries were considered in all cases. The Spearman rank correlation coefficients are 0.97 and higher.

(c) Robustness to changes in indicators and deprivation cutoffs

There is a legitimate diversity of judgments regarding deprivation cutoffs such as the definition of adequate sanitation. 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 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 population⁵³; 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).⁵⁴ We estimate the MPI for each alternative (changing one indicator at a time), rank the countries, and compute Spearman and Kendall Tau-b (Kendall and Gibbons 1990) rank correlation coefficients between the rankings. Table VIII presents the Kendall correlations.

The rank correlation coefficients between the baseline MPI, and the alternative MPIs using stunting, wasting, and underweight with the old reference population, are all above 0.91.⁵⁵ For the mortality indicator we estimated an alternative MPI considering as deprived households where there had been a diseased child of under-5-years-of-age for the 52 countries in which this information is available, and find a rank correlation of 0.867. Across all deprivation cutoff specifications, all Kendall's Tau correlations are above 0.86, and all Spearman's rank correlations exceed 0.96, and all correlations are also significant at the 5% level. This suggests that MPI rankings are highly robust to these changes in the deprivation cutoffs.

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

(d) Robustness to changes in the indicators' weights

To test whether the MPI is robust to a plausible range of weights we estimated the MPI with three 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.⁵⁶ Table IX 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 across all three alternative weighting systems is also relatively high – no lower than 0.83.

Table IX: Correlation coefficients between MPI using alternative weighting structures

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

Note: LS: Living Standard. In all cases 104 countries were considered. 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 using the pairwise comparison methodologies described at the beginning of this section. Table IV shows that 88.3% of the SPWC were robust across all four weighting alternatives using confidence intervals, and 88.9% according to the hypothesis tests.

By geographical region, we find consistent results across both methodologies. The AS and SSA have the highest levels of robustness, with 88-90% of SPWC being robust in AS and about 92% in SSA. These are followed by LAC and SA, with about 79% of SPWC being robust in LAC and 76-78% in SA. CEE/CIS is least robust to weights, with only 52 to 55% of SWPC being robust, which is a natural result given that this region contains the least poor countries. As before, DHS and MICS surveys are highly robust as are

countries with 10 indicators.⁵⁷ Interestingly, all income level categories present at least 82% of robust pairwise comparisons across weights out of the SPWC.⁵⁸

Thus we find that the relative position of each country with respect to others tends to be highly robust to significant changes in the indicators' weights. It is important for policy that measures are robust to a range of plausible normative weights (Sen 1996).⁵⁹

(e) Robustness to changes in the poverty cutoff

We test the robustness of country rankings to a range of plausible values of the k -poverty cutoffs, 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 intended to capture the *acutely* poor, who do not meet minimum internationally agreed standards in multiple basic functionings simultaneously. The normative argument for using $k=20\%$ is that while a household may have some deprivations by choice, or due to indicator inaccuracies or data errors, households with multiple deprivations are likely poor, hence the lower threshold should exceed 16.7%, which is the highest usual weight upon a single indicator. On the other hand, cutoffs above 40% can be considered overly demanding.⁶⁰

We test the robustness across the three possible MPIs (with 20%, 33.33% and 40% poverty cutoff) using the three pairwise comparison methodologies (Table IV). We find that between 93% and 96% of the pairwise country comparisons that are significant in the baseline MPI, remain significant—meaning that one country is unambiguously less poor than another— Independently of whether we require people to be deprived in 20 or 40% of the weighted indicators.

Results discriminating by geographical region, survey, number of indicators and income category are in line with the previous robustness analyses, although at somewhat higher levels, with 90% or more robust pairwise comparisons out of SPWC in the robust categories of SA, SSA, AS, EAP, DHS, MICS, 10 indicators, and low and lower-middle income countries.⁶¹ These rigorous results suggest that across

poverty cutoff from 20-40%, 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 indicators pertaining to dimension, which raises questions as to how their poverty is ‘multidimensional’.⁶² Upon analysis we find that less than 3% of the MPI poor are deprived in indicators pertaining to only one dimension.⁶³ 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 countries lack health or education indicators, so that any observed deprivation receives a 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. 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.

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 income methods such as the \$1.25/day measure: the patterns of MPI and of \$1.25/day poverty vary considerably across countries, a topic that deserves further study.

The MPI combines poverty incidence with poverty intensity, and although these two seem to be correlated, their combination augments understanding. 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 to examine the composition of poverty by indicator.

Are these results credible? This paper, after considerable scrutiny, 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, the poverty cutoff and sample variability. The MPI does seem to be higher in larger households that have a higher more prevalence of children and women, but this may in fact reflect the deprivation certain vulnerable groups actually do experience.

The 2010 MPI was constrained by data. 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. First, the dimensions, second, comparability and third, 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—to enrich multidimensional analyses in the post-2015 MDG era. Secondly, 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. 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 gender and intra-household inequalities.

In sum, the MPI has offered new insights on 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, 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.

APPENDIX

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

Country	Survey	Year	Multidimensional			Multidimensional			Multidimensional			MPI poor	Total	% of Sample
			Poverty Index			Headcount Ratio			Poverty Intensity			people	Sample	Size used for
			MPI	MPI	MPI	H	H	H	A	A	A	(millions)	Size	Size used for
			LB	UB		LB	UB		LB	UB				MPI estimate
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	0.011	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 lower and upper bounds obtained with bootstrapping, and sample size (contd)

Country	Survey	Year	Multidimensional			Multidimensional			Multidimensional			MPI poor	Total	% of Sample
			Poverty Index			Headcount Ratio			Poverty Intensity			people	Sample Size	Size used for
			MPI	MPI	MPI	H	H	H	A	A	A	(millions)		MPI estimate
			LB	UB		LB	UB		LB	UB				
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 lower and upper bounds obtained with bootstrapping, and sample size (contd)

Country	Survey	Year	Multidimensional			Multidimensional			Multidimensional			MPI poor	Total	% of Sample
			Poverty Index			Headcount Ratio			Poverty Intensity			people	Sample	Size
			MPI	MPI	MPI	H	H	H	A	A	A	(millions)	Size	MPI estimate
			LB	UB		LB	UB		LB	UB				
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
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

Table A.1: MPI, H and A estimates with lower and upper bounds obtained with bootstrapping, and sample size (contd)

Country	Survey	Year	Multidimensional			Multidimensional			Multidimensional			MPI poor	Total	% of Sample
			Poverty Index			Headcount Ratio			Poverty Intensity			people	Sample	
			MPI	MPI	MPI	H	H	H	A	A	A	(millions)	Size	MPI estimate
			LB	UB		LB	UB		LB	UB				
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	0.505	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	0.027	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	0.016	0.015	0.017	0.041	0.038	0.045	0.390	0.384	0.395	4.503	206700	99.9
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

Table A.1: MPI, H and A estimates with lower and upper bounds obtained with bootstrapping, and sample size (contd)

Country	Survey	Year	Multidimensional			Multidimensional			Multidimensional			MPI poor	Total	% of Sample
			Poverty Index			Headcount Ratio			Poverty Intensity			people	Sample	
			MPI	MPI	MPI	H	H	H	A	A	A	(millions)	Size	
			LB	UB		LB	UB		LB	UB				MPI estimate
Montenegro†	MICS	2005	0.006	0.004	0.011	0.015	0.009	0.026	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
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

Table A.1: MPI, H and A estimates with lower and upper bounds obtained with bootstrapping, and sample size (contd)

Country	Survey	Year	Multidimensional			Multidimensional			Multidimensional			MPI poor	Total	% of Sample
			Poverty Index			Headcount Ratio			Poverty Intensity			people	Sample	Size
			MPI	MPI	MPI	H	H	H	A	A	A	(millions)	Size	MPI estimate
			LB	UB		LB	UB		LB	UB				
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	0.011	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
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

Table A.1: MPI, H and A estimates with lower and upper bounds obtained with bootstrapping, and sample size (contd)

Country	Survey	Year	Multidimensional			Multidimensional			Multidimensional			MPI poor	Total	% of Sample
			Poverty Index			Headcount Ratio			Poverty Intensity			people	Sample Size	Size used for
			MPI	MPI	MPI	H	H	H	A	A	A	(millions)		MPI estimate
			LB	UB		LB	UB		LB	UB				
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
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 a lower bound estimates, according to the bias analysis detailed below, meaning that MPI is at least as great as the reported MPI value. **:MPI estimates should be interpreted as an upper bound estimates, according to the bias analysis detailed below, 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 subsample. ✕ 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 cautious. **Bias Analysis:** For each country, we identified the indicator/s that caused the sample size reduction. We divided the sample in two groups: those missing the indicator and those having observed values for it, then compared the raw headcount ratios across the other indicators. We considered stratification and clustering when computing the standard errors and used a confidence level of 95%. 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.

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¹ Sen (1981, chapter 3) introduces this distinction and further elaborates in Sen 1997 and 1999. Here we use income to refer to monetary poverty measurement, which may use income, consumption, or expenditure data.

² These are extensively reviewed in Chapter 4 of Alkire *et al.* forthcoming, including European applications like Townsend (1979), Mack and Lansley (1985), Gordon et al. (2003), Callan, Nolan and Whelan (1993), Halleröd (1995), Layte, Nolan, Whelan (2000), Halleröd et al. (2006), and Whelan Nolan Maitre (2012), US applications like Mayer and Jencks (1989), and Latin American applications like INDEC (1984), Boltvinik (1992), Katzman (1989), Feres and Mancero (2001).

³ 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 were the estimated PPP rates. The critical importance of each methodological choice is documented by the recent empirical sensitivity analysis performed by Dhongde and Minoiu (2012).

⁴ The poverty lines were adjusted in Chen and Ravallion (2010).

⁵ *Functionings* are defined by Sen (1992) as the beings and doings that a person values and has reason to value.

⁶ For example Bourguignon et al (2008) find little or no correlation between economic growth and non-income MDGs. Ruggieri-Laderchi et al (2003) demonstrate empirical mismatches between direct and income poverty measures at the household level.

⁷ Bourguignon and Chakravarty, 2003:26; Callan, Nolan and Whelan, 1993:169

⁸ For example, there is evidence of an anti-female bias in some regions (Sen, 1990, 2003; Klasen and Wink, 2003).

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

¹⁰ The MPI replace the Human Poverty Index (HPI) which had been reported since 1997 (Anand and Sen, 1997). 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.

¹¹ An internationally comparable measure of child poverty using the direct method was developed by Gordon et al. (2003) and adopted by UNICEF (UNICEF, 2004 and 2007). However, this measure was computed for 46 countries only (using DHS data) and consisted of the headcount ratio, thus ignoring intensity. See Alkire and Roche (2012) and Roche (2013) for further discussion on child poverty measures. .

¹² Some have argued that the MPI uses very low deprivation cutoffs and therefore underestimates poverty in some regions such as Latin America (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.

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), all reviewed in Alkire et al. (forthcoming). Not all new measures can be used with ordinal data.

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

¹⁶ The MPI has been updated for each subsequent *Human Development Report*, using 25 new datasets in 2011, 16 new datasets in 2013, and 28 new datasets in 2014 (UNDP did not release a *Human Development Report* in 2012). Thus more recent MPIs employ better quality datasets which are likely to improve their robustness.

¹⁷ For a more pedagogical presentation, see Alkire and Foster (2011b).

¹⁸ 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 achievements of the non-poor. For further discussion see Alkire and Foster (2011a) and Alkire, Foster and Santos (2011).

¹⁹ Subgroup percentage contribution to overall poverty is computed as the subgroup M_θ weighted by its population share, over the overall M_θ .

²⁰ 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_θ measure.

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, older children might in fact still be completing primary school. Also, the MDG indicators include 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 child mortality provides at least rudimentary information on health functionings, and empirically, changes are observed across time (Alkire and Roche 2013, Alkire and Seth 2013).

²³ They follow a multi-stage stratified design, thus sample weights provided in the datasets were used for our computations. When using the DHS, we 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.

²⁴ In the case of Argentina we did not use the sample weights, as they were designed for health specific measures of children and women. We report Argentina's MPI estimates as a lower bound estimate of acute multidimensional poverty in urban Argentina. Rural areas in Argentina (which are not covered systematically by any survey), especially in the northern regions, are significantly poorer than urban ones.

²⁵ In terms of other users of China's WHS, Yang et al. (2006) and Liu et al. (2013) perform validity analyses of the survey and find reliability of the data. We estimated the MPI using the China Health and Nutrition Survey (CHNS), which is not nationally representative but focuses on 8-9 provinces, for 2006 and 2011. The CHNS-based MPI in both years is lower than the WHS, and declines 2006-11. These results favor the possibility that WHS 2003 figures are correct. Finally, evidence suggests that the WHS data for China may be better quality than average. First, 99.6% of the original sample was retained for China, whereas the mean WHS sample for the remaining 18 countries was only 79.6% (Table A.1). Secondly, China included 9 indicators, whereas one-third of the other WHS countries only had 7 or 8 indicators. Finally, we performed the full set of robustness tests described in Section 5 for China alone and found that China's MPI estimates are highly robust to sample variability, household composition, alternative weighting structures and the poverty cutoff

²⁶ For details on which country lacks which indicator, see 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.

²⁷ As explained at the bottom of Table II, exceptions are the 12 countries using nutritional sub-samples, where eligible women and children who were not measured were considered non-deprived. From 2013 the MPI methodology computes updated MPIs using nutritional subsamples only (Alkire, Conconi and Roche 2013).

²⁸ We have also calculated confidence intervals using analytical standard errors. Both sets of confidence intervals are used in the robustness tests presented in Section 5.

²⁹ 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.

³⁰ 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.

³¹ Given equidistant income poverty estimates, we select the more recent one. If there is no income poverty estimate within 5 years of the MPI estimate, we do not report the income poverty information this country. In 30% of the countries the year of the income and MPI poverty surveys coincide, in 36.7% they differ by one year and in 13.3 and 15.6%, by 2 and 3 years' respectively. Less than 5% of countries have 4-5 years' difference.

³² The poorest twenty-six 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 8 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 10 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).

³³ We used the 2010 HDI categories. We find a similar pattern in terms of income category (from World Bank, 2010): 87% and 84% of low 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 4 high income countries in the sample also have higher MPI than extreme poverty rates.

³⁴ The composition of MPI poverty for each country is available in the Supplementary Data as well as in on-line '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/

³⁵ This is consistent with Klasen (2008).

³⁶ See Bourguignon and Chakravarty (2002), Atkinson (2003), Duclos, Sahn and Younger (2006), Alkire and Foster, (2011a), Lasso de La Vega (2010), and Yalonzky (2012).

³⁷ We use the svy command in STATA 11. See Yalonzky (2011) for further discussion on analytical standard errors in the AF measures.

³⁸ Statistical significance of comparisons based on confidence intervals is a stronger requirement than statistical tests. If confidence intervals for two MPIs do not overlap, they are certainly statistically significant, but the converse may not hold. See Alkire et al. (forthcoming) for further intuition and discussion.

³⁹ We have used the bootstrap command of STATA 11, indicating the strata and cluster variables. Note that the confidence intervals are computed in STATA using the standard errors obtained with bootstrapping and assuming the corresponding critical value at the 95% confidence of the Normal distribution. We have implemented the bootstrap technique in 102 countries, Slovenia and Guatemala could not be included because the strata and cluster variables are missing in the datasets.

⁴⁰ Throughout this section we refer to ‘significant’ pairwise comparisons as encompassing the case in which the comparison is statistically significant using a hypothesis test, but also the case in which the confidence intervals (either using bootstrap or analytical standard errors) do not overlap.

⁴¹ Further methodological work is required to set standards of robustness which should be met by measures that will be used for policy.

⁴² Alternative specifications for this adjustment should be explored.

⁴³ We also find that between 93 to 94% of the total possible pairwise differences between China’s MPI and the MPI of each of the other countries are statistically significant, depending on the methodology.

⁴⁴ To provide an intuition for these results, it may be helpful to observe that, using the method of confidence intervals obtained from bootstrapping not overlapping, we find that 9% of the countries have an MPI that is unambiguously lower than the country that is immediately adjacent in the ranking; 22.5% of the countries have an

MPI unambiguously lower than that of the country two places after them in the ranking, for 53% it is five places after them, for 78% it is eight places and, 84% have unambiguously lower MPI than the one of the countries ten places after them. We performed the same analysis for H and A , and find higher proportions of unambiguous rankings at low distances in both the rankings than for the MPI.

⁴⁵ A further issue is measurement error, although this may be lower for the MPI than for monetary poverty estimates. See Calvo and Fernandez (2012)

⁴⁶ The effect of household size is also a topic of research in income poverty measurement addressed by Lanjouw and Ravallion (1995) among others.

⁴⁷ We do this for all countries except for Slovakia and Slovenia (excluded because they have an MPI value of zero).

⁴⁸ As it can be seen in Table IV, the groups themselves are not a third of the population each because China and India are around each of the two cut-offs: 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 cut-offs 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 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.

⁴⁹ We have also analysed the country results not weighting by their population sizes. In such case we find a more homogeneous pattern across country groups by MPI level (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.

⁵⁰ 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.

⁵¹ We are grateful to an anonymous referee for suggesting this alternative way of testing the robustness to household composition.

⁵² It is also worth noting that when this doing this analysis for the pairwise comparisons between China and each of the other countries, 87 and 92% of the significant pairwise comparisons obtained with the baseline MPI hold when we compute MPI for (four different) population subgroups (results vary depending on the methodology used).

⁵³ 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 was changed by the WHO as has the methodology used to construct the growth curves (WHO, 2006). The 2006 reference population (used in the MPI computation) has wider ethnicity coverage..

⁵⁴ 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.

⁵⁵ 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 country rankings do not change significantly.

⁵⁶ In such way, in one alternative weightings each educational indicator weighs 25%, each health indicator, 12.5%, and living standard indicator, 4.16%. In the other, each health indicators 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%.

⁵⁷ Note that despite China being a WHS country, between 88 and 92% of the significant pairwise comparisons obtained with the baseline MPI hold when we compute the MPI using the three other alternative weighting structures.

⁵⁸ These results are in line with those in Alkire et al. (2010), where we find the MPI to reject the null hypothesis of rank independence with 99% confidence for three indices of intra-group rank concordance and Friedman's test of rank independence.

⁵⁹ Decancq and Lugo 2013 provide a lucid overview on weighting in multidimensional measures.

⁶⁰ When $k=40\%$, the total number of global MPI poor is 1,145 million, which is even lower than the 1,528 who are \$1.25/day poor.

⁶¹ Again, China's estimates seem robust, with 95 to 97% of the significant pairwise comparisons obtained with the baseline MPI holding when we vary the poverty cutoff from 33.33% to either 20% or 40%

⁶² We are grateful to Anthony B. Atkinson for making this point.

⁶³ 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 poor population who is 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.