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Measuring Multidimensional Poverty: Dashboards, Union Identification, and the Multidimensional Poverty Index (MPI)

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Abstract
We analyse three approaches to measuring multidimensional poverty, using a consistent set of data for 10 indicators in 101 developing countries. First we implement a simple dashboard of deprivations in ten indicators. While most dashboards stop there, we next describe the simultaneous deprivations experienced by people which conveys information on their joint distribution, yet fails to identify multidimensional poverty. We then implement a 'union' approach to measurement, and identify people as multidimensionally poor if they experience any one or more of the ten deprivations. The resulting Union headcount ratio of poverty is very high and may reflect errors of inclusion. We then implement an intermediary identification approach following Alkire and Foster (2011): the global Multidimensional Poverty Index (MPI). Exploring the censoring process of the intermediary identification, we observe that a Union MPI (or intersection) identification approach does not avoid normative choices as often claimed; rather these are made at the stage of indicator selection, and the identification process can be highly sensitive to these choices. The latter approaches often imply equal weights –which is itself a value judgement made out of the public eye. The global MPI clearly states value judgements, and performs robustness tests for them. The paper thus discusses strengths and challenges of different measurement approaches to multidimensional poverty.

Keywords: poverty measurement, dashboard, multidimensional poverty, identification, AF measures, joint distribution

JEL classification: I3, I32, D63, O1

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Introduction

Poverty is now recognised to have many forms and dimensions, so an often-asked question is what types of measures to use for multidimensional poverty, and why. Many argue that a dashboard – a vector of indicators covering different aspects of poverty – is the best option, because it is familiar, already in use in every country, and seems to be the simplest. Others observe that large dashboards (such as are being introduced by the SDGs) risk diluting poverty-related indicators amidst many other indicators with no sense of priority. They would prefer a headline multidimensional poverty measure which collects a subset of key human poverty indicators into a consistent and compelling statistic that can be unpacked to inform integrated and multisectoral policies.

Some who evince an interest in a multidimensional poverty statistic are worried about 'weights'. They are concerned that weights are controversial and difficult to set and justify. In a similar vein, they would prefer to avoid censoring any measured deprivation. Therefore, a common suggestion is to construct a multidimensional poverty index 'without weights' that gives as a headline the percentage of people who are deprived in at least one indicator from a list.

Others favour using an index whose methodology follows that of the global Multidimensional Poverty Index (MPI) that was developed jointly by the UNDP's Human Development Report Office and the Oxford Poverty and Human Development Initiative (OPHI) in the University of Oxford using the Alkire Foster methodology, and has been published since 2010 on OPHI's website and in the annual Human Development Reports (Alkire and Santos 2010, 2014, Alkire & Foster 2011, UNDP 2010).

Some of the voices in this debate recognise the importance of somehow clarifying the joint distribution of deprivations – the simultaneous and overlapping deprivations that people experience. Because some deprivations tend to be suffered concurrently, a multi-sectoral and synergistic approach to tackling deprivations has been shown to have the largest impact in many contexts (UNDP 2010). But few concrete proposals are available as to how to present this information, other than that given by the MPI.

There are times when conceptual debates can be clarified tremendously by empirical experimentation and illustration. We believe that this is one such case. This paper uses an empirical example to explore the insights and oversights that emerge from three measurement approaches when applied to 5.2 billion people in 101 countries. The indicators considered are available from a single survey instrument for each country. First we implement a dashboard, provide the incidence of deprivations in each of ten indicators. We also illustrate descriptive representations of joint distribution of deprivations that, we argue, should be reported standardly but are not at present. Next we apply a union identification approach and identify as poor any person who is deprived in at least one of the ten indicators, obtaining the headcount ratio of these, and observe the strong normative choices made in the selection of indicators. Third we identify the multidimensionally poor using an intermediary cutoff across weighted deprivations, to obtain the global Multidimensional Poverty Index or MPI. We also implement additional cutoffs. We show the added information that is generated by the MPI in comparison with the dashboard, or Union Headcount Ratio. Using the example of cooking fuel, we discuss how improved data quality could improve identification. We observe that the MPI includes the two foregoing approaches when data sources match, yet introduces other desirable features such as permitting the inclusion of indicators that are not equal in importance, permitting the use of multiple poverty cutoffs, and depicting the intensity and dimensional breakdown of poverty.

Data and Preliminaries

Measurement options are shaped by data sources. In some cases, poverty indicators are constructed from independent data sources that cannot be merged at the unit level. In others a set of variables are constructed from the same data source – for example a multi-topic household survey. Given the relatively large and increasing availability of such data sources (Alkire 2014), this paper focuses on measures built from these sources.[1]

We draw on microdata from 101 countries which are reported in the 2015 global MPI, and which are representative of 5.2 billion people around the globe. Using each national dataset we construct comparable indicators.[2] The definition of these 10 indicators, as well as the weights considered for this example, are reported in Table 1. Alkire and Robles (2015) and the references therein detail any unusual treatment of any indicator in any country.

Table 1: The dimensions, indicators, deprivation cutoffs and weights of the global MPI

Dimensions of poverty	Indicator	Deprived if…	Weight
Education	Years of Schooling	No household member aged 10 years or older has completed five years of schooling.	1/6
	Child School Attendance	Any school-aged child+ is not attending school up to the age at which he/she would complete class 8.	1/6
Health	Child Mortality	Any child has died in the family in the five-year period preceding the survey	1/6
	Nutrition	Any adult under 70 years of age, or any child for whom there is nutritional information, is undernourished in terms of weight for age*.	1/6
Living Standard	Electricity	The household has no electricity.	1/18

[1] These indicators refer to the same unit of identification as we will shortly explore the joint distribution of deprivations on a dashboard. Complementing this, a dashboard can report statistics for different units from the same dataset – such as the percentage of children aged 0-5 who are stunted, or the percentage of school-aged girls who are not attending school.

[2] 86 country datasets have 10 complete indicators. 13 country datasets contain 9 indicators and 2 country datasets have only 8 indicators. Child mortality and Nutrition are the indicators that most commonly are missing from the datasets. Afghanistan, Indonesia, Trinidad and Tobago and Ukraine are missing Nutrition; Brazil and Egypt are missing Cooking Fuel; Barbados, Bosnia and Herzegovina, Macedonia, Saint Lucia and Suriname are missing Child Mortality; China does not have Floor; Honduras is missing Electricity; Jamaica does not have Child Mortality & Floor; and Philippines does not have School Attendance and Nutrition.

	Improved Sanitation	The household's sanitation facility is not improved (according to MDG guidelines), or it is improved but shared with other households**.	1/18
	Improved Drinking Water	The household does not have access to improved drinking water (according to MDG guidelines) or safe drinking water is at least a 30-minute walk from home, roundtrip***.	1/18
	Flooring	The household has a dirt, sand, dung or 'other' (unspecified) type of floor.	1/18
	Cooking Fuel	The household cooks with dung, wood or charcoal.	1/18
	Assets ownership	The household does not own more than one radio, TV, telephone, bike, motorbike or refrigerator and does not own a car or truck.	1/18

Note:

+ Data Source for age children start school: United Nations Educational, Scientific and Cultural Organization, Institute for Statistics database, Table 1. Education systems [UIS, http://stats.uis.unesco.org/unesco/TableViewer/tableView.aspx?ReportId=163].

*Adults are considered malnourished if their BMI is below 18.5 m/kg². 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.

**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 clean 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).

Source: Alkire and Robles (2015), drawing on and updating Alkire and Santos (2010). For details on the rationale behind each indicator, please see Alkire and Santos (2010, 2014).

1. The Dashboard Approach

If we use a dashboard approach with these 10 indicators, we would present the following dashboard:

Table 2: Dashboard of 10 Indicators for 101 Countries

Indicator	Headline for 5.2 billion people across 101 countries
Years of Schooling	13.6% live in a household in which no member has completed five years of schooling
Child School Attendance	13.6% live in a household where a child is not attending school up to class 8
Child Mortality	16.9% of people live in households where a child has died
Nutrition	26.8% have someone in their household who is undernourished
Electricity	21.8% lack electricity
Improved Sanitation	40.2% lack adequate sanitation or it is shared
Safe Drinking Water	25.1% lack safe water or must walk 30 minutes or more to obtain it
Flooring	26.5% live in houses where floors are dirt, sand, or natural
Cooking Fuel	53.0% lack clean cooking fuel
Assets	23.4% live in households that do not own more than one small asset (telephone, tv, radio, bicycle, motorcycle, & refrigerator) and do not own a car or truck.

The dashboard is both familiar and informative. When surveys can be disaggregated, maps for each indicator can be prepared – so 10 maps could be presented showing the level of deprivations in each indicator, in order to visually compare patterns.

From the dashboard we know the percentage of people deprived in each of the ten indicators and the overall population of the countries. But how are these deprivations distributed? For example, does each person have 2 or 3 deprivations, or do some people have 5 deprivations each and the rest zero? To answer such questions requires an exploration of the joint distribution of deprivations.

Let us start by asking how a dashboard might be accompanied by information on the joint distribution. Above we see that 13.6% of people are deprived in the 'years of schooling' indicator, and 14.5% are deprived in the 'school attendance' indicator. A natural question is whether the same households are deprived in both. When the indicators are drawn from the same survey and same units, it is elementary to provide this information using a simple cross-tabulation of the deprivations.

For example, the next table shows the deprivation rates of the 10 indicators across 101 countries in the second row and second column. This table also shows at its centre the proportion of population that showed coupled deprivations in any two given of the 10 indicators. We can point out that although the levels of the two education indicators are very similar (18.4% and 19.9%), their overlap is relatively low, with 8% of people experiencing both deprivations.

Table 3: Example of Joint Distribution of Deprivations.

	Years of schooling		
Attendance	Non deprived	Deprived	Total
Non Deprived	76.9	8.6	85.5
Deprived	9.5	**5.0%**	**14.5**
Total	86.4	**13.6**	100

Table 4: Average Deprivation in Pair-wise Indicators across 101 Developing Countries

		Years of schooling	School attendance	Child Mortality	Nutrition	Electricity	Sanitation	Drinking Water	Floor	Cooking Fuel	Assets
Population deprived in each indicator		14%	14%	17%	27%	22%	40%	26%	27%	53%	23%
		Percentage population simultaneously deprived in the column and row indicators									
Years of schooling	14%										
School attendance	14%	5%									
Child Mortality	17%	4%	5%								
Nutrition	27%	5%	6%	7%							
Electricity	22%	8%	7%	8%	9%						
Sanitation	40%	10%	10%	11%	15%	19%					
Drinking Water	26%	5%	5%	5%	8%	10%	13%				
Floor	27%	8%	8%	9%	12%	17%	22%	9%			
Cooking Fuel	53%	12%	12%	14%	19%	21%	33%	19%	25%		
Assets	23%	8%	7%	7%	10%	14%	19%	8%	16%	21%	

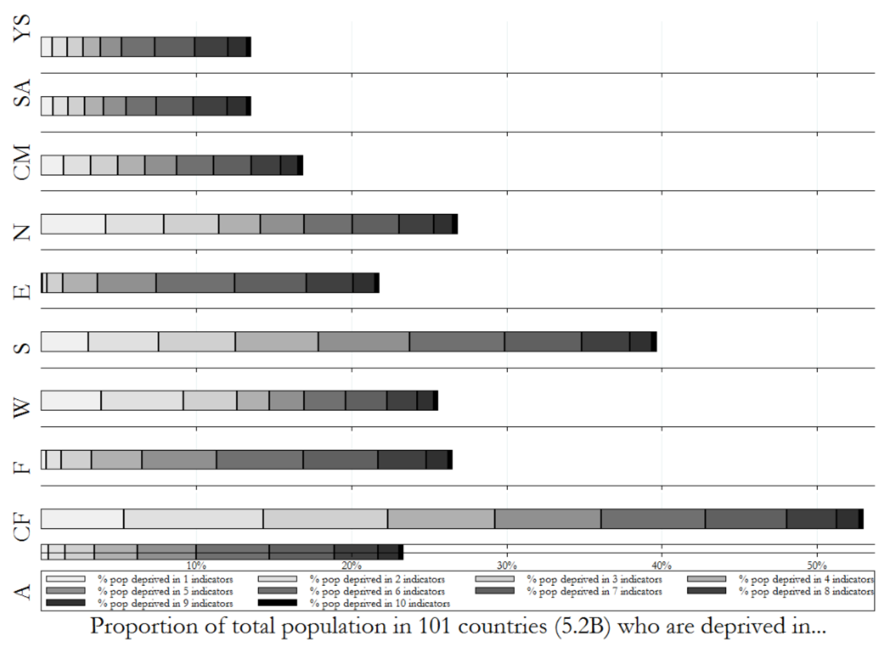
Source: Own calculations using the proportion of pairwise simultaneous deprivation by country and multiplying this by the country population. Then, a total of the population suffering each pairwise deprivation was obtained among 101 countries. The proportion expressed in this table has the 5.2 billion population of 101 countries in 2011 as a denominator.

This type of table is tremendously useful for providing information on two by two distributions. Likewise, one can generate Venn diagrammes to depict the joint distribution of three or even four indicators. Beyond that, the diagrammes or tables can be computed, but become difficult to read.

To reveal joint distributions beyond indicator pairs we propose that dashboards should at minimum illustrate joint distributions for a set of related variables in a way such as depicted in Figure 1. The graphic records the percentage of people experiencing one, two, three or more deprivations (in this case implicitly equally weighted). This shows the gradient of deprivations for each of the 10 indicators. The total length of each bar portrays the proportion of population in 101 countries that is deprived in each indicator. The lengths thus coincide with the dashboard headlines reported in Table 2. Each of the coloured segments indicate the proportion of the population enduring concurrent deprivations in that indicator and some fixed number of others. The lightest segment closest to the left axis indicates exactly 1 deprivation is suffered, which is by definition in that indicator. The adjacent next-lightest segment indicates the percentage of the population who are deprived in that indicator and one additional indicator, so a total of 2 simultaneous deprivations. The next lightest segment indicates a deprivation in that indicator plus two others for a total of three deprivations. The last grey bar in all indicators indicates 10 simultaneous deprivations and by definition it is of equal length in all bars.

These tables and gradient bar charts each add information that in no way can be obtained from the dashboard. Information required for them is computed separately from unit-level data. The achievements in each dimension must be available for each unit (often the person or the household), for example because the variables come from the same survey. The cross-tab and gradients add value by providing information regarding the joint distribution of deprivations. The information is easy to understand, but it may not be provided in the most streamlined or convenient form, for in addition to 10 maps, one has a set of cross-tabulations and counting gradients to analyse and seek to use. Yet at present even this basic descriptive information on the joint distribution of dashboard components is lacking from nearly all dashboards. Including it where possible would shine a light on interlinked deprivations. We provide this illustration in order to strongly recommend that survey reports and dashboards regularly include this information for clearly defined deprivations pertaining to the same unit of analysis.

Figure 1: Distribution of Simultaneous Deprivations According to Each of the 10 Indicators Analysed.



From the dashboard we might notice that there are 13.6 billion deprivations of various kinds affecting the 5.2 billion people in these countries. So we might wonder how many of the 5.2 billion people are deprived in <u>at least one of the 10 indicators</u>? This number cannot be obtained from the dashboard. This leads us to the first move towards multidimensional poverty measurement, which is to identify the set of persons who experience one or more deprivations. It is 3.9 billion people, or 75% of the population of these countries.

2. The Union Identification

In identifying 3.9 billion people this way, we just implemented the union approach to identification. The union approach[3] to the identification of multidimensional poverty considers a person experiencing *any* measured deprivation to be poor. Solely those not suffering any deprivation from the set of indicators are regarded as non-poor. The union approach is consistent with our original dashboard, which presents the proportion of population that suffers each particular deprivation, regardless whether they suffer other deprivations.

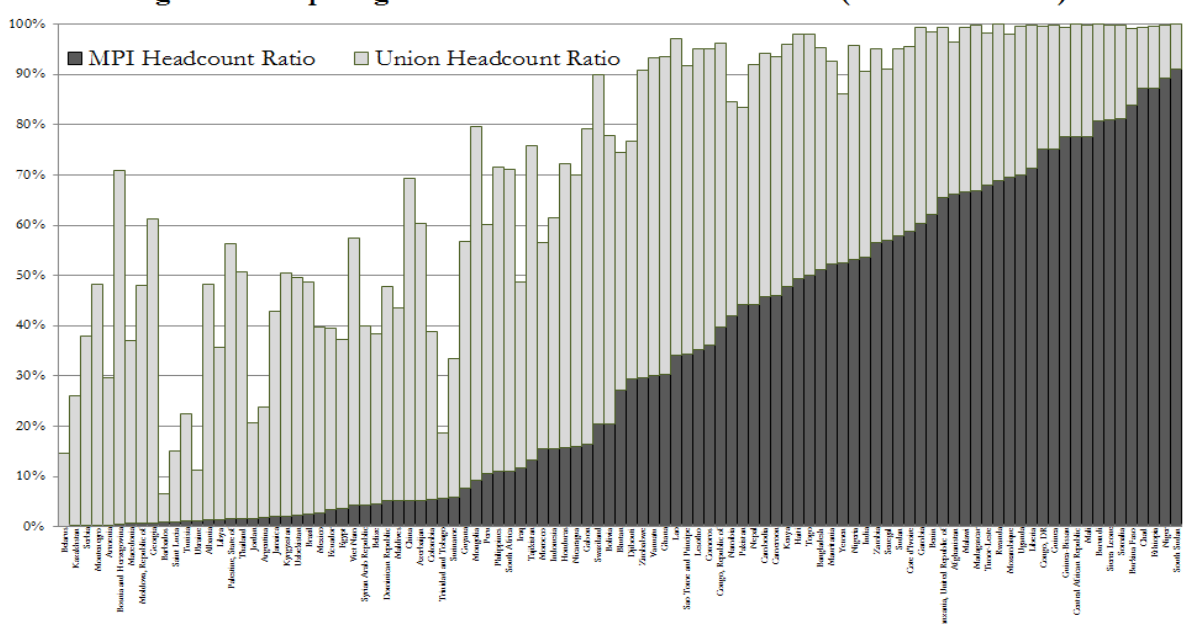
[3] Atkinson (2003) was the first to use the terms union and intersection for identifying a person as poor if they are identified in any or all possible deprivations respectively.

Using the union-based approach, the proportion of population identified as poor may be high. Of course, this will depend upon the indicator definition. Let us illustrate this using the global MPI indicators. We identify who is poor by applying a union approach to the 10 indicators of the global MPI presented on the dashboard earlier, and refer to it as the Union Headcount ratio.

As can be seen in figure 2, using the headcount ratios of poverty associated with the Union identification, 46 of the 101 countries would identify 90% or more people as poor. In 36 countries the headcount ratio would be 95% and above, in 20 countries it would be 99% and above, and in 14 countries 99.5% or more of the population would be poor. On the other hand, in only 10 countries would less than 30% of the national population be poor and in only 29 countries would poverty affect less than 50% of the population. The high Union headcount ratios might raise scepticism as to the credibility of such a measure.

In Figure 2, the union headcount ratios of poverty are shown by the height of the lighter (taller) bars. The darker bars' height gives the headcount ratio of the global MPI, which will be introduced below. The levels of poverty are high. In Thailand and Peru, union poverty headcount ratios are 51 and 60%. Such profiles include households experiencing only one deprivation, alongside profiles of acute poverty. With such large and diverse profiles of poverty, the value of this headline seems questionable.

Figure 2. Comparing Union and MPI Headcount Ratios (Global MPI 2015)



The union approach may be an appropriate identification method for a measure or deprivations in human rights, for example, if all of the dimensions are human rights, if all persons would avoid such deprivations if they could, and if each human right is accurately measured with negligible error (Alkire and Foster 2009). How certain are we that any observed deprivation is not a tragedy not related to poverty, nor a personal preference, a non-sampling measurement error, or a transitory deprivation? In the absence of special studies, it is difficult to quantify the size of these non-sampling measurement errors across this population. As an imperfect substitution we scrutinise these assumptions conceptually, using some indicators of the global MPI. If these assumptions seem unlikely to be perfectly fulfilled, then the set of union poor is likely to include some people who would not be recognised, normatively, as poor. In this case we might want to improve the data accuracy or focus on a subset of people who are multiply deprived.[4]

Data Considerations

Survey and data imperfections could mean that some measured deprivations are not accurate. For example, the survey data often asks what fuel people use to cook with, but if such houses have good ventilation, cooking with wood or charcoal may not indicate a situation of indoor air pollution and the threat of respiratory and eye infections. The problem is, the survey does not distinguish between households with and without adequate ventilation. In other cases, a toilet was shared but only with one other family of 4 – which should be adequate – but because the survey does not distinguish between those sharing with few or many households, all persons with shared sanitation are marked deprived. The school attendance and child nutrition indicators are only accurate if the age of the child was correctly remembered by the respondent and recorded correctly by the enumerator. Yet enumerators report some errors in accuracy, or anecdotally share how difficult it is for some fathers (or mothers) to provide the month of their children's birth.

Some deprivations may reflect **individual or cultural preferences, non-poverty conditions or climactic conditions**. For example, indigenous flooring may be natural, but in some climates (e.g. desert) it may not signify a deprivation (indeed it may be clean and also covered with lovely carpets). A professional actor may have a low BMI in order to play a particularly gaunt role. Water from an unprotected spring in the high mountains may be a clean source of water although in other parts of the countries it is not safe; some small assets may not be available in certain context and locally valuable assets may be relevant but excluded. Some indicators may reflect **deprivations that do not indicate poverty**: a tragic death of a child from an accident, or a temporary low BMI in a patient recovering from an illness. A wealthy person may be deprived in health insurance because he or she would seek healthcare internationally or simply pay the bill. Unless the indicators discriminate, a union based MPI will identify all of these people as poor. By including inaccurate deprivations, the Union MPI may be less policy relevant, because the 'inaccurate' deprivations may not be susceptible to change by anti-poverty policies, yet their analysis may consume the time and energy of policy makers and their aides. One clear recommendation is to

[4] If any indicator is deemed 'essential' it is elementary to design a measure such that any deprivation in that indicator guarantees that one is poor: the weight on that indicator must equal or exceed the value of the poverty cutoffs.

improve the data, although some spurious deprivations are likely to remain. A complementary strategy, discussed below, is to consider overlapping deprivations.

Design Considerations: Indicator and Weight Selection

It has been argued in that the union approach is desirable because it does not require indicator weights to identify the poor, so refrains from normative decisions. This is inaccurate. First, the normative decisions occur at the stage of indicator selection. A union approach provides an implicit incentive to design measures that omit (or include) indicators showing high uncensored incidence – such as cooking fuel or sanitation – because one high-incidence indicator alone will have a visible impact on poverty levels.

Furthermore, the only number that can be reported using union identification without fixing weights is the headcount ratio. All other information can be presented in the dashboard. This point is sometimes overlooked. For example, it is common to report (or depict using a venn diagramme) the number of people experiencing one, two, three, or some other number of deprivations simultaneously. This implicitly applies equal weights to each included indicator. But equal weighting is itself a normative choice. In fact it should drive indicator selection, because only those indicators should be chosen whose weights are roughly equal. Yet all relevant poverty-related indicators may not be equal in importance. Should ones with higher or lower importance be dropped? Not having a bank account, not having internet access, and having a primary school-aged child out of school are all salient and policy-relevant indicators of poverty. But they may not be equal. The Union (and intersection) identification approaches do not avoid normative choices; they merely drive them back to the stage of indicator selection.

If an explicit justification of equal weights – or indeed of general weights – is offered, then the union Headcount ratio can be reported alongside a Union MPI with all associated sub and partial indices described below.

3. An Intermediate Approach to the Identification of Poverty

Having explored the information conveyed by the union headcount ratio, we now move to illustrate the value added of having a summary statistic which may in addition take an intermediary approach to identification, and which is associated with a set of intuitive sub- and partial indices.[5]

The global MPI is built using the Alkire-Foster methodology, that applies a dual-cutoff approach to identification. The first cutoff are the set of deprivation cutoffs, which identify each person as deprived or non-deprived in each

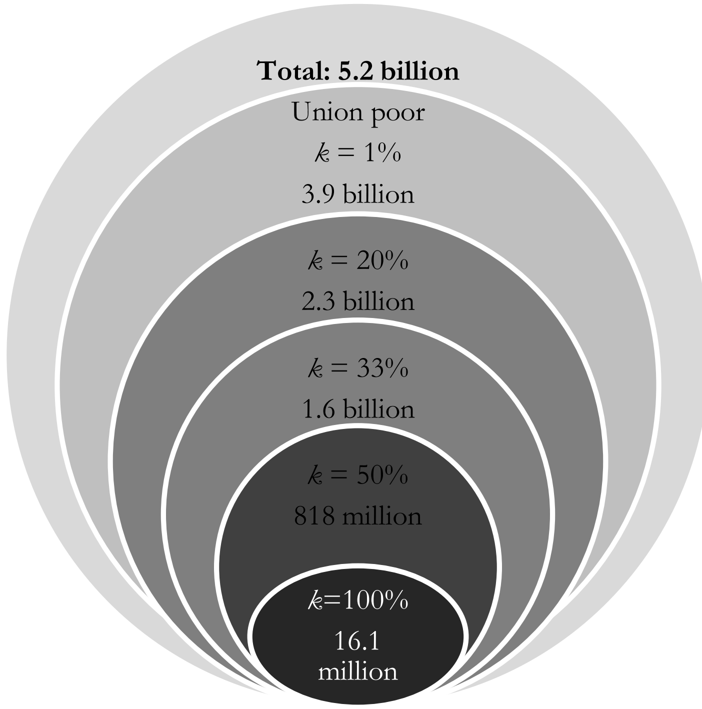
[5] As should be clear, the MPI provides a **single** summary statistic to measure poverty levels and trends but is reported with the headcount ratio, intensity, and indicator composition of poverty. Policy design and monitoring requires dimensional detail, as does policy coordination and the analysis of indicators at different levels of disaggregation.

indicator, exactly the same in this example as is reflected in the dashboard and Union headcount ratio. The second is a poverty cutoff, that is applied to the weighted sum of each person's deprivations. Each person is identified as poor if their deprivations are at or above the poverty cutoff level, and non-poor otherwise. The union approach to identification is included by this identification strategy, and occurs when the poverty cutoff is less than or equal to the minimum weight attached to any indicator. Using a non-union cutoff, people who are deprived, but in one or some combination of deprivations that is less than the poverty cutoff, are considered non-poor.

For example, let us use the nested weighting structure of the global MPI, in which each dimension is equally weighted and each indicator within a dimension is equally weighted. And let us apply five different poverty cutoffs across the weighted deprivation scores of the samples for each country. The figure below shows the gradient of simultaneous deprivations. On the largest circle we observe the total population represented among 101 countries, 5.2 billion people, of which 1.3 billion enjoy no deprivation and 3.9 billion are deprived in at least one indicator. One billion people are deprived in *only* one indicator of the possible 10, and they are included among those considered as the Union poor in the diagram. We also observe that 2.3 billion are deprived in 20% or more of the weighted indicators[6]. Furthermore, 1.6 billion are deprived in 33% or more of the weighted indicators, and 818 million are jointly deprived in 50% or more of the weighted indicators. Only a tiny proportion of the population under analysis, 3.1%, endure simultaneous deprivations in 100% of weighted indicators, but this is still just over 16 million people. This group are poor according to the intersection approach to identification. The term intersection was proposed by Atkinson (2003) for the approach that identifies people as poor only if they are concurrently deprived in *all* the indicators evaluated.

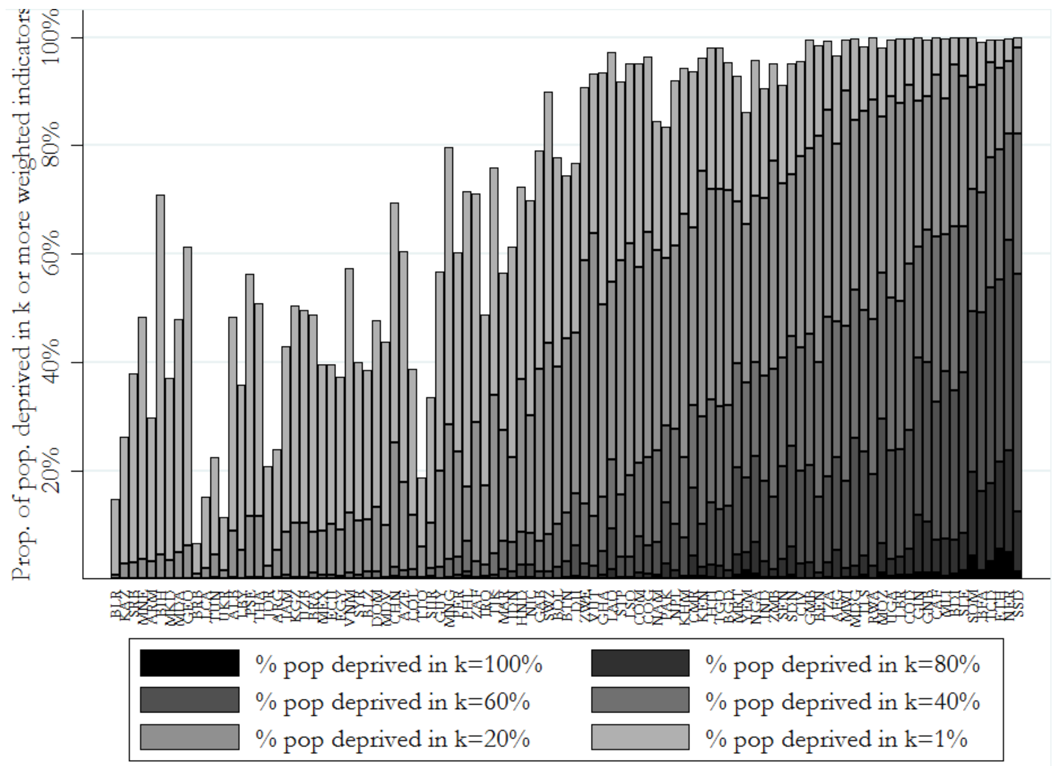
[6] On the robustness of relevant comparisons to a plausible range of weights see Alkire and Santos 2014, and Alkire Foster Seth Santos Roche and Ballon 2015, Chapters 6-8.

Figure 3: Identification Gradient Using Five Poverty Cutoffs in 101 Countries.



Poverty cutoff k	Number of Poor	Multidimenisonal Headcount ratio
Total Population	5.2 billion	100%
Union poor	3.9 billion	75%
k=20%	2.3 billion	44%
k=33%	1.6 billion	30%
k=50%	818 million	16%
Intersection poor k=100%	16.1 million	3.1%

Figure 4: Headcount Ratio at Different *k* Poverty Cutoff Levels for 101 Countries.



The current global MPI uses a poverty threshold of 33.33%. That is, it identifies as poor any household who is deprived in one-third or more of the weighted indicators.

Instead of identifying **over 75% of poor people** across these 101 countries as in the Union MPI, the **global MPI** identifies 1.6 billion poor people. That is, an average of **30% of people** across these 5.2 billion are MPI poor. In addition, two other poverty cutoffs are reported alongside the 33.33% cutoff. A person is identified as **'Vulnerable'** to poverty if she is deprived in 20% – 33.33% of weighted indicators and those deprived in 50% or more of the dimensions are identified as being in '**Severe**' poverty.

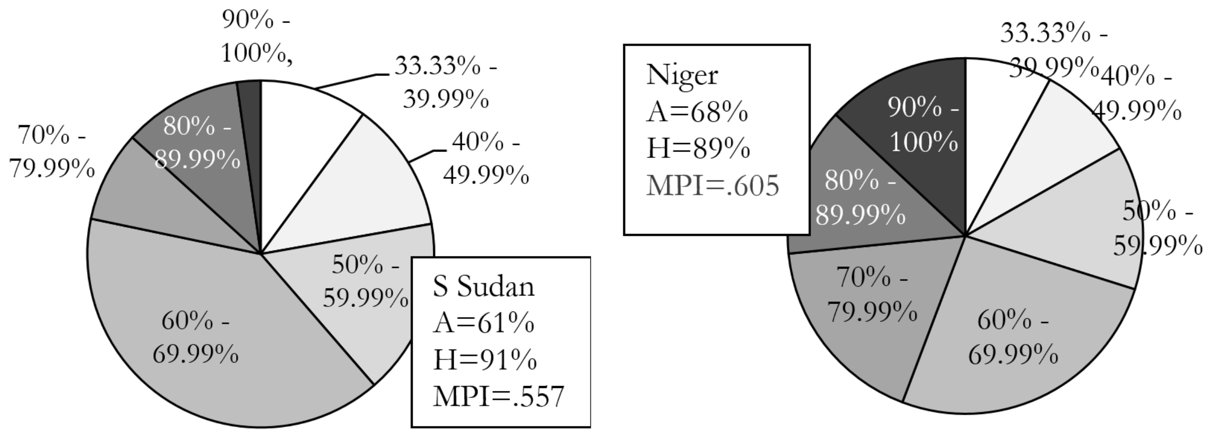
The information the MPI adds to a dashboard and to the MPI – is of two kinds:

1) A summary **headline indicator** which also reflects **joint distributions** (MPI – and H, A) for each *k*.
2) Indicator profiles showing the **composition of poverty by indicator** and the percentage of people who are poor and deprived in each indicator (censored headcount ratios) for each *k*.

As a summary headline index, the MPI reflects both the incidence or headcount ratio (H) of poverty – the proportion of the population that is multidimensionally poor – and the average intensity (A) of their poverty – the average proportion of indicators in which poor people are deprived. The MPI is calculated by multiplying the incidence of poverty by the average intensity across the poor (H×A). Note that intensity – A – is a function of the weighted deprivations people experience, so is only possible to compute, even for a Union MPI, if an explicit weighting vector is provided and justified.

Although the headcount ratio and MPI reflect the overall level of poverty for a given poverty line, of course information on the detailed distribution among the poor remains and can be drawn out using higher poverty cut-offs, or depicted graphically. On the latter, for example, in South Sudan, roughly 91% of the population (9 million people) are MPI poor whereas in Niger it is 89.3% (just over 15 million people). In South Sudan, the intensity of poverty (A) is about 61% whereas in Niger it is 68%.

Figure 5: Intensity of Deprivation Among MPI Poor in South Sudan and Niger

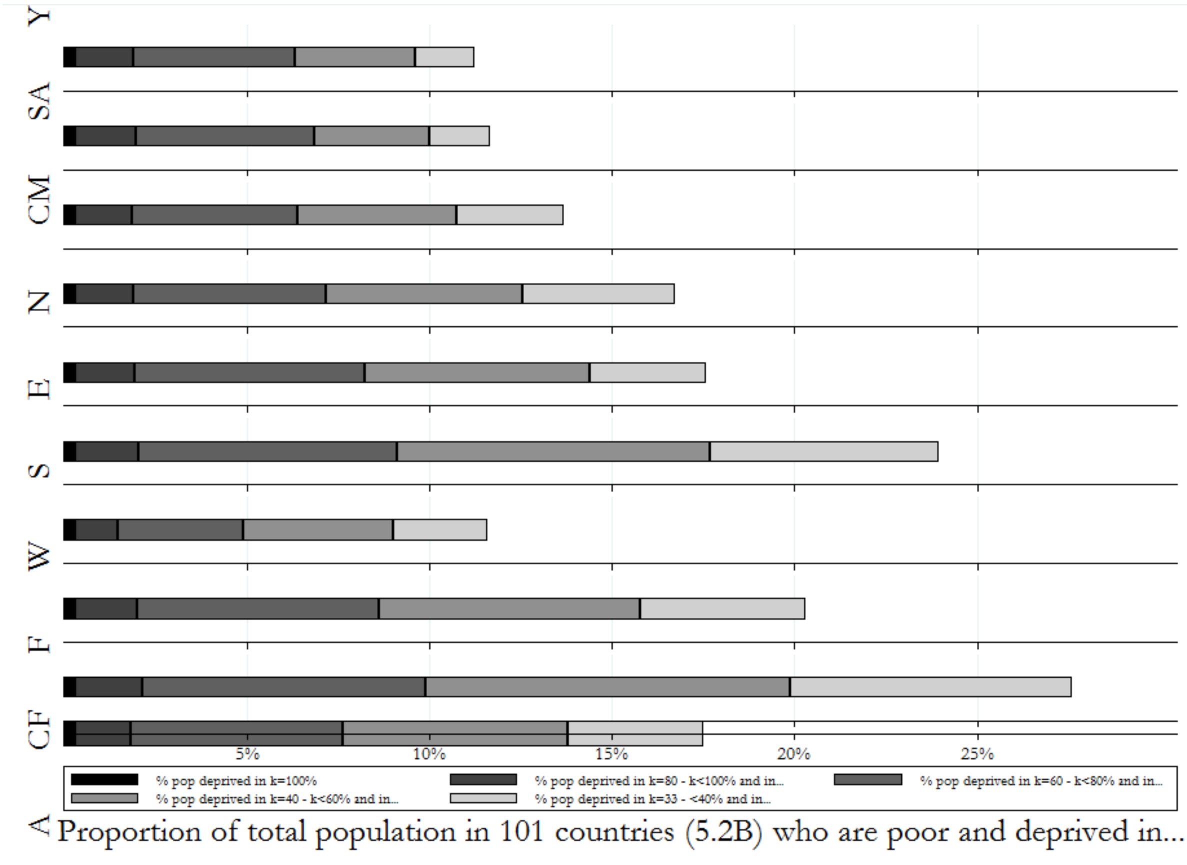


In the above pie-charts, each successively darker segment shows the proportion of the MPI poor who are deprived in different shares of indicators.[7] We can see that Niger has many more people in high-intensity poverty of 90-100%.

One of the features of the MPI is that we can closely monitor the censored headcount ratios that compose it. A censored headcount ratio of an indicator reports the proportion of the population who are identified as poor and are deprived in that indicator. Figure 6 below provides a summary of the distribution of simultaneous deprivations among those identified as poor. The length of each bar indicates the population-weighted censored headcount ratio, and each segment of the bar indicates the share of people who are MPI poor and are deprived in that indicator, and, simultaneously, deprived in differing percentages of the weighted indicators.

[7] This diagramme has been published for every country since 2010 in the MPI country briefings.

Figure 6: Panel of MPI Censored Headcount Ratios among the Poor, for k Poverty Thresholds between 33% and 0%.



4. And the Union MPI? Possibilities and challenges

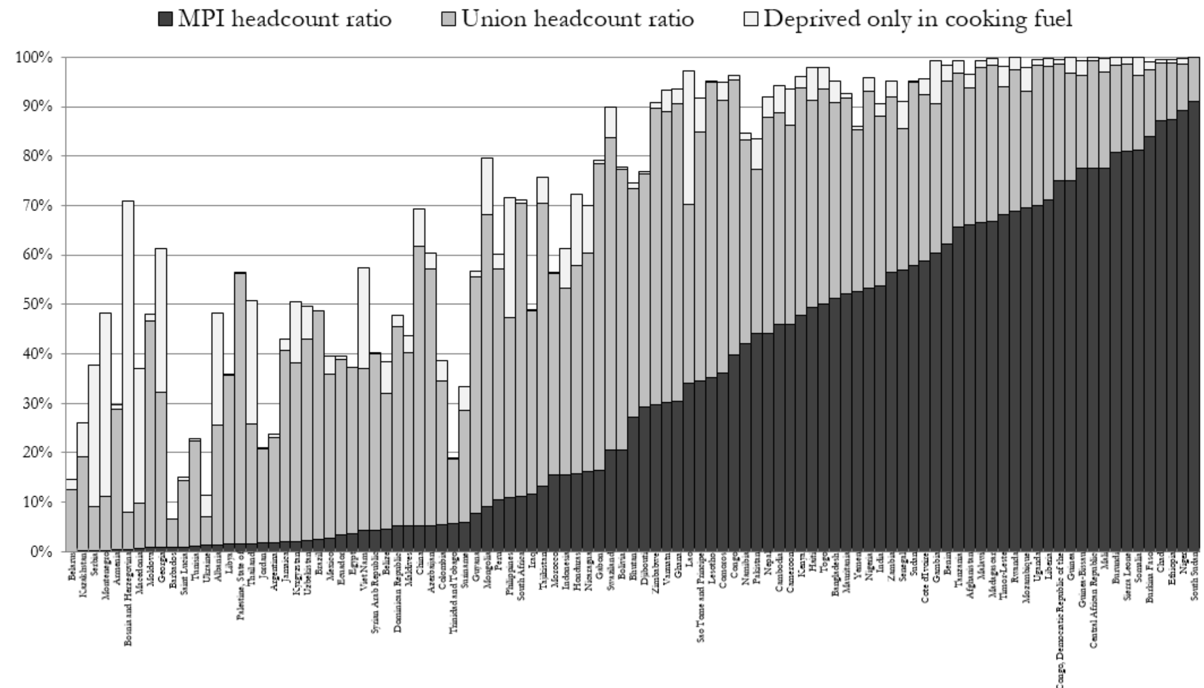
A natural question from the previous discussion is whether it might be possible to have a compromise, namely to implement a global MPI using the Union approach with explicit weights. Recall that in the Union MPI, the raw and censored headcount ratios are identical because no deprivations are censored. Above we clarified conceptually some concerns regarding the exacting level of data accuracy required for the union approach to be accurate.

To illustrate this empirically we use a clear example of a survey and data imperfection, which is the measure of cooking fuel. In the global MPI, the largest differences between uncensored and censored headcount ratios occur in the indicator of cooking fuel. In 63 countries out of 99 countries with information on cooking fuel[8], the absolute difference between uncensored and censored headcount ratios is bigger than it is for any other indicator. The top of the bars in Figure 7 show the proportion of people who are 'union poor'. The uppermost white section gives

[8] Egypt DHS 2014 and Brazil PNDS 2006 do not have information on cooking fuel.

the proportion of the population who are deprived solely in cooking fuel for 99 countries and are not deprived in any other indicators. This proportion is largest in Bosnia and Herzegovina (63 percentage points).

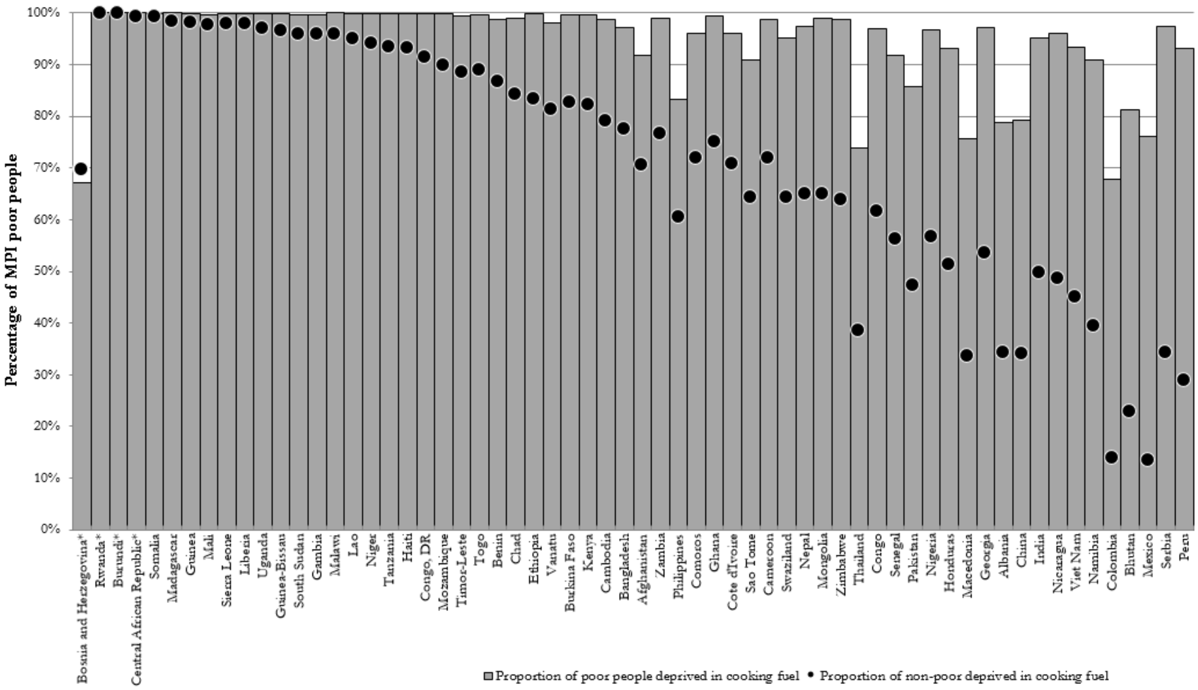
Figure 7 Comparing Union and multidimensional Headcount Ratios, and proportion of people deprived only in cooking fuel



Yet, as figure 7 shows, a 63% of those 69% deprived in cooking fuel in Bosnia and Herzegovina are only deprived in that single indicator, hence they are not identified as poor. In fact, in Bosnia and Herzegovina, poor and non-poor persons are equally likely to be deprived in cooking fuel – a situation which is generally avoided in indicator selection. But this is not the case in other countries. To illustrate this, the height of the bars in the following figure show the proportion of global MPI poor people in each country who are deprived in cooking fuel. The horizontal lines plot the proportion of non-poor people who are deprived in cooking fuel (by definition these are union poor but not poor by the global MPI). We see some countries like Rwanda and Burundi in which deprivation levels are similar – because the deprivations are near universal. In no country are deprivations of non-poor persons statistically significantly higher than those of poor persons, and in many they are significantly lower.

Improvements in surveys could improve the accuracy of this indicator by clarifying situations in which the use of solid cooking fuel is likely to create indoor air pollution and health risks. For example, a follow-up survey question on ventilation could improve its accuracy. However, we also see that this change would still leave many people who only experience precisely one deprivation in some *other* indicator.

Figure 8 Proportion of MPI poor and non-poor people deprived in cooking fuel: 63 countries in which cooking fuel is the largest deprivation



The indicator that witnesses largest differences between uncensored and censored headcount ratios in the second highest number of countries is sanitation. The difference is highest in 24 of 101 countries analysed. A follow up question on the circumstances under which sanitation is shared, and clarification of 'other' categories could improve the accuracy of this indicator. In five countries, drinking water has the largest difference between uncensored and censored headcount ratios in Tunisia, Libya, Palestine, Azerbaijan and Morocco. Otherwise, the mismatch between uncensored and censored headcount ratios is rarely the largest in the case of years of schooling (only for Argentina), school attendance (only for Iraq and Yemen), child mortality (only for Maldives), nutrition (only for Jordan and Ecuador) and electricity (only Guyana and Lesotho). This is also natural given that cooking fuel and sanitation deprivations tend to have the highest incidence overall.

An MPI using an intermediate poverty cutoff, that is, identifying a person as poor if they experience some proportion of deprivations higher than just one, can reduce errors of inclusion and have greater confidence that people are in fact *multidimensionally* poor, "cleaning" the data for non-sampling measurement errors, preferences, spurious deprivations or particular circumstances, and focusing resources on prioritized groups. Naturally improvements in data quality are vital and will make the original data more precise. But given that they are unlikely to completely eradicate errors, and also in situations in which the concerned populations have a wide diversity of preferences and cultural and climactic conditions, a Union MPI will still reflect deprivations that are not directly related to poverty.

The policy implications of analysing either censored or uncensored headcount ratios are also important. The difference is not between universal versus targeted policies necessarily. The silo approach of the MDGs appealed to reduce deprivations in sanitation universally, for the whole population. By focusing on the censored headcount ratios, policy makers would seek to reduce the deprivations of those identified as muldimensionally poor, rather than of the whole population. In the case of those countries that face the largest censoring of cooking fuel deprivation due to the poverty cut-off, is it irrelevant to focus on cooking fuel censored headcount ratios? Not necessarily. As mentioned, deprivations cooking fuel are more prevalent among the multidimensionally poor in all but a handful of cases, and even so, it is still the most frequent deprivation among the poor. What the multidimensional poverty index adds is a vision of the world outside the silos, which can inform an integrated (and often more effective) approach to tackling cooking fuel and other deprivations that may occur simultaneously. Also, and very importantly, to 'leave no one behind' and get to zero poverty, extra effort will be required in the regions and population groups who experience multiple and overlapping deprivations. They will benefit by the integrated and coordinated policies discussed in the SDG document cited above. Who and where are they? A dashboard that treats all persons deprived in one indicator equivalently, cannot show us.

Conclusion

In measuring multidimensional poverty, multiple strategies will be used. In this paper we have clarified some reasons for not using solely a dashboard, nor a union based MPI when identifying poverty in different dimensions. Conceptually, a measure that is called 'multidimensional' might be expected to refer only to situations in which a person experiences multiple deprivations. Empirically, a union approach often identifies a large proportion of the population as poor. Given fiscal constraints, resources need to be prioritized, and the share of people identified as poor by a union approach may be unmanageable, so prioritising those who experience overlapping deprivations has an ethical appeal and also is arguably more precise. Also, survey and data imperfections mean that some measured deprivations are not accurate (for example 80% of Bosnians cook with wood, but for many this is not a deprivation causing indoor air pollution: they have chimneys, but the survey does not include this information; in other cases the age of the child was incorrectly remembered by a parent, making the apparent stunting or underweight data incorrect). Furthermore, some deprivations may reflect individual or cultural preferences or climactic conditions (for example indigenous flooring may be natural, but in that climate it is not a deprivation; a professional actor may have a low BMI in order to play a particularly gaunt role. Finally, some may reflect deprivations that are not poverty: a tragic death of a child from an accident.

OPHI always report the uncensored headcount ratios – that is, the percentage of persons who are deprive din that indicator across society, regardless of whether or not they are poor – in our Interactive Databank. We also always analyse this data when interpreting changes over time. This is important because 'universal' programmes – such as water/sanitation – may find these figures to be useful.

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Country	Survey	Year	Global MPI k>=33%: Headcount ratio in multidimensional poverty (H)	Global MPI k>=33%: Multidimensional Poverty Index (MPI)	Global MPI k>=33%: Intensity of deprivation among the poor (A)	Union k>=1%: Headcount ratio in union poverty (uH)	Union k>=1%: Population deprived in only 1 indicator	Union k>=1%: Union MPI (uMPI)	Union k>=1%: Intensity among the union poor (uA)	Vulnerable to poverty (20% intensity of deprivations)	Severe poverty (intensity higher than 50%)	Population 2011
			% Population	Range 0 to 1	Average % of weighted deprivations	% Population	% Population	Range 0 to 1	Average % of weighted deprivations	% Population	% Population	thousands
Barbados	MICS	2012	**0.9**	0.003	34.2	**6.6**	**6.0**	0.0	11.1	1.0	0.0	281.8
Ukraine	MICS	2012	**1.2**	0.004	34.8	**11.4**	**10.4**	0.0	10.3	1.5	0.0	45802.7
Belarus	MICS	2005	**0.0**	0.000	35.1	**14.7**	**13.4**	0.0	9.9	0.8	0.0	9450.4
Saint Lucia	MICS	2012	**1.0**	0.003	35.4	**15.1**	**11.2**	0.0	10.6	1.9	0.0	179.3
Trinidad and Tobago	MICS	2006	**5.6**	0.020	35.1	**18.7**	**15.4**	0.0	16.1	6.0	0.3	1333.1
Jordan	DHS	2012	**1.7**	0.006	35.0	**20.7**	**18.3**	0.0	17.7	2.4	0.1	6731.2
Tunisia	MICS	2012	**1.2**	0.004	38.5	**22.5**	**16.5**	0.0	14.8	4.5	0.1	10753.1
Argentina	ENNyS	2005	**1.8**	0.007	38.0	**23.9**	**15.4**	0.0	15.8	5.4	0.1	40728.7
Kazakhstan	MICS	2011	**0.2**	0.001	36.2	**26.2**	**20.5**	0.0	10.9	2.8	0.0	16098.0
Armenia	DHS	2010	**0.3**	0.001	35.2	**29.7**	**22.3**	0.0	10.3	3.3	0.0	2964.1
Suriname	MICS	2010	**5.9**	0.024	40.8	**33.4**	**20.2**	0.1	16.3	10.2	1.1	529.8
Libya	PAPFAM	2007	**1.5**	0.006	37.0	**35.7**	**28.8**	0.0	12.3	5.4	0.1	6103.2
Macedonia	MICS	2011	**0.7**	0.002	35.7	**37.1**	**30.4**	0.0	8.6	3.5	0.0	2103.9
Egypt	DHS	2014	**3.6**	0.014	38.1	**37.3**	**27.2**	0.1	16.7	9.0	0.4	79392.5
Serbia	MICS	2014	**0.2**	0.001	40.5	**37.8**	**32.0**	0.0	8.0	3.1	0.1	9597.4
Belize	MICS	2011	**4.6**	0.018	39.6	**38.4**	**20.8**	0.1	16.4	10.9	0.7	316.3
Colombia	DHS	2010	**5.4**	0.022	40.9	**38.7**	**21.6**	0.1	18.4	11.8	1.1	47078.8
Ecuador	ECV	2014	**3.5**	0.013	38.5	**39.5**	**25.4**	0.1	16.4	10.0	0.4	15246.5
Mexico	ENSANUT	2012	**2.8**	0.011	38.8	**39.6**	**23.4**	0.1	14.7	8.9	0.4	119361.2
Syrian Arab Republic	PAPFAM	2009	**4.4**	0.016	37.4	**40.1**	**26.9**	0.1	16.3	10.7	0.4	21804.4
Jamaica	JSLC	2010	**2.0**	0.008	39.4	**43.0**	**25.0**	0.1	12.2	8.7	0.2	2754.7
Maldives	DHS	2009	**5.2**	0.018	35.6	**43.6**	**33.4**	0.1	17.8	9.9	0.3	332.0
Dominican Republic	DHS	2013	**5.1**	0.020	39.0	**47.8**	**29.6**	0.1	16.4	13.2	0.5	10147.6
Moldova, Republic of	MICS	2012	**0.8**	0.003	35.9	**48.0**	**30.8**	0.0	9.9	4.9	0.0	3542.9

Albania	DHS	2009	**1.4**	0.005	37.7	**48.2**	**34.8**	0.1	11.5	8.8	0.1	3153.9
Montenegro	MICS	2013	**0.3**	0.001	46.4	**48.4**	**40.2**	0.0	7.9	3.6	0.1	620.6
Brazil	PNDS	2006	**2.5**	0.010	38.4	**48.7**	**37.5**	0.1	13.1	8.7	0.2	196935.1
Iraq	MICS	2011	**11.6**	0.045	38.5	**48.8**	**30.9**	0.1	21.3	17.2	1.9	31837.0
Uzbekistan	MICS	2006	**2.3**	0.008	36.2	**49.6**	**30.8**	0.1	13.5	10.4	0.1	28151.8
Kyrgyzstan	DHS	2012	**2.0**	0.007	36.4	**50.5**	**30.8**	0.1	13.2	10.3	0.1	5403.4
Thailand	MICS	2006	**1.6**	0.006	38.5	**50.8**	**34.9**	0.1	12.0	11.5	0.2	66576.3
Palestine, State of	MICS	2010	**1.5**	0.006	38.3	**56.4**	**42.3**	0.1	11.4	11.5	0.1	4114.2
Morocco	PAPFAM	2011	**15.4**	0.067	43.7	**56.5**	**23.5**	0.1	23.3	27.5	4.6	32059.4
Guyana	DHS	2009	**7.7**	0.030	39.2	**56.8**	**30.3**	0.1	18.3	20.0	1.0	790.9
Viet Nam	MICS	2011	**4.2**	0.017	39.5	**57.4**	**28.9**	0.1	13.4	12.1	0.7	89914.0
Peru	DHS-Cont	2012	**10.5**	0.043	41.0	**60.2**	**17.5**	0.1	19.2	23.4	2.0	29614.9
Azerbaijan	DHS	2006	**5.3**	0.021	39.4	**60.5**	**32.5**	0.1	15.4	17.8	0.6	9202.4
Georgia	MICS	2005	**0.8**	0.003	35.2	**61.2**	**35.5**	0.1	10.1	6.1	0.0	4374.2
Indonesia	DHS	2012	**15.5**	0.066	42.9	**61.4**	**24.6**	0.1	19.6	22.5	4.2	243801.6
China	CFPS	2012	**5.2**	0.023	43.2	**69.4**	**32.0**	0.1	17.8	25.1	1.0	1368440
Nicaragua	DHS	2012	**16.1**	0.072	45.0	**69.9**	**20.4**	0.1	21.3	30.1	5.3	5905.1
Bosnia and Herzegovina	MICS	2012	**0.5**	0.002	37.3	**70.9**	**64.4**	0.1	7.1	4.4	0.0	3839.3
South Africa	NIDS	2012	**11.1**	0.044	39.5	**71.1**	**32.8**	0.1	18.5	29.0	1.3	51949.0
Philippines	DHS	2013	**11.0**	0.052	47.3	**71.5**	**31.5**	0.1	16.0	17.0	4.7	95053.4
Honduras	DHS	2012	**15.8**	0.072	45.7	**72.3**	**25.5**	0.2	22.2	36.9	5.0	7776.7
Bhutan	MICS	2010	**27.2**	0.119	43.9	**74.5**	**20.3**	0.2	26.4	44.4	8.5	729.4
Tajikistan	DHS	2012	**13.2**	0.054	40.8	**75.8**	**28.7**	0.2	19.9	34.0	2.5	7814.9
Djibouti	MICS	2006	**29.3**	0.139	47.3	**76.8**	**22.7**	0.2	28.0	45.4	12.5	846.6
Bolivia, Plurinational State of	DHS	2008	**20.5**	0.089	43.7	**77.8**	**26.1**	0.2	22.1	39.2	5.8	10324.5
Gabon	DHS	2012	**16.5**	0.070	42.5	**79.1**	**31.9**	0.2	20.6	38.8	3.8	1594.0
Mongolia	MICS	2010	**9.2**	0.037	40.7	**79.7**	**19.5**	0.1	17.6	28.5	1.4	2754.2
Pakistan	DHS	2013	**44.2**	0.230	52.1	**83.4**	**16.3**	0.3	35.5	59.2	23.7	176166.4
Namibia	DHS	2013	**42.0**	0.193	46.0	**84.5**	**12.9**	0.3	31.9	60.6	15.0	2217.6
Yemen	MICS	2006	**52.5**	0.283	53.9	**86.1**	**19.5**	0.3	39.5	65.5	31.9	23304.2
Swaziland	MICS	2010	**20.4**	0.086	41.9	**89.9**	**17.3**	0.2	21.8	43.6	4.5	1212.2

India	DHS	2006	**53.7**	0.283	52.7	**90.6**	**10.9**	0.3	38.5	70.2	28.6	1221156
Zimbabwe	MICS	2014	**29.7**	0.127	42.7	**90.8**	**12.4**	0.2	26.0	58.7	7.9	13358.7
Senegal	DHS Cont.	2014	**56.9**	0.309	54.3	**91.1**	**12.5**	0.4	40.3	72.9	33.4	13330.7
Sao Tome and Principe	DHS	2009	**34.5**	0.154	44.7	**91.7**	**15.1**	0.2	27.2	58.8	10.7	183.2
Nepal	DHS	2011	**44.2**	0.217	49.0	**92.1**	**11.6**	0.3	32.1	61.6	20.8	27156.4
Mauritania	MICS	2011	**52.2**	0.285	54.6	**92.7**	**10.6**	0.4	38.2	69.6	31.7	3702.8
Vanuatu	MICS	2007	**30.1**	0.129	42.7	**93.3**	**7.8**	0.2	26.6	63.8	6.5	241.8
Ghana	MICS	2011	**30.4**	0.139	45.8	**93.5**	**11.8**	0.2	25.4	50.5	10.4	24820.7
Cameroon	DHS	2011	**46.0**	0.248	53.8	**93.6**	**13.9**	0.3	34.6	64.9	25.1	21156.3
Cambodia	DHS	2010	**45.9**	0.212	46.1	**94.2**	**9.6**	0.3	31.6	67.3	17.0	14605.9
Comoros	DHS-MICS	2012	**36.0**	0.173	47.9	**95.0**	**10.4**	0.3	28.5	57.5	14.9	700.2
Sudan	MICS	2010	**57.8**	0.321	55.6	**95.1**	**8.1**	0.4	40.6	74.7	36.2	36430.9
Zambia	DHS	2014	**56.6**	0.281	49.8	**95.1**	**7.0**	0.4	37.2	77.1	26.7	13633.8
Lesotho	DHS	2009	**35.3**	0.156	44.1	**95.2**	**9.1**	0.3	27.7	61.9	11.1	2029.5
Bangladesh	DHS	2011	**51.3**	0.253	49.4	**95.3**	**8.1**	0.3	34.9	71.7	21.7	152862.4
Cote d'Ivoire	DHS	2012	**58.7**	0.310	52.8	**95.5**	**7.9**	0.4	39.7	78.1	33.0	19390.0
Nigeria	DHS	2013	**53.2**	0.303	56.8	**95.8**	**11.0**	0.4	38.9	70.8	32.8	164192.9
Kenya	DHS	2009	**47.8**	0.229	48.0	**96.1**	**5.7**	0.3	33.6	75.2	19.8	42027.9
Congo, Republic of	DHS	2012	**39.7**	0.181	45.7	**96.3**	**10.7**	0.3	29.0	64.0	15.0	4225.4
Afghanistan	MICS	2011	**66.2**	0.353	53.4	**96.5**	**7.6**	0.4	42.2	80.3	39.1	29105.5
Lao People's Democratic Republic	MICS/DHS	2012	**34.1**	0.174	50.9	**97.2**	**27.6**	0.3	26.7	54.8	16.8	6521.3
Togo	DHS	2014	**50.1**	0.252	50.4	**97.9**	**6.6**	0.3	34.5	71.9	24.0	6472.3
Mozambique	DHS	2011	**69.6**	0.389	55.9	**98.0**	**5.7**	0.4	45.1	85.3	45.0	24581.4
Haiti	DHS	2012	**49.4**	0.248	50.3	**98.0**	**7.7**	0.3	34.1	72.0	24.7	10032.9
Timor-Leste	DHS	2010	**68.1**	0.360	52.9	**98.3**	**5.7**	0.4	42.6	86.3	38.7	1096.3
Benin	DHS	2012	**62.2**	0.307	49.3	**98.4**	**5.3**	0.4	38.2	81.7	30.5	9779.8
Burkina Faso	DHS	2010	**84.0**	0.535	63.7	**99.1**	**3.0**	0.6	56.7	91.1	65.7	15995.3
Tanzania, United Republic of	DHS	2010	**65.6**	0.332	50.7	**99.3**	**3.2**	0.4	40.4	86.5	33.4	46354.6
Malawi	DHS	2010	**66.7**	0.334	50.1	**99.4**	**1.8**	0.4	40.8	90.0	31.4	15457.5
Guinea-Bissau	MICS	2006	**77.5**	0.462	59.6	**99.4**	**3.1**	0.5	50.6	89.0	55.5	1624.2
Gambia	DHS	2013	**60.4**	0.323	53.4	**99.4**	**9.1**	0.4	39.3	79.4	36.9	1735.0

Chad	MICS	2010	**87.2**	0.554	63.5	**99.4**	**1.2**	0.6	58.2	95.3	68.3	12080.0
Uganda	DHS	2011	**69.9**	0.367	52.5	**99.5**	**1.5**	0.4	43.0	89.0	38.2	35148.1
Ethiopia	DHS	2011	**87.3**	0.564	64.6	**99.6**	**1.6**	0.6	59.0	94.2	71.1	89393.1
Congo, Democratic Republic of the	DHS	2014	**75.1**	0.401	53.4	**99.6**	**2.0**	0.5	45.4	91.2	44.9	63931.5
Madagascar	DHS	2009	**66.9**	0.357	53.3	**99.7**	**1.6**	0.4	42.2	84.7	35.4	21678.9
Niger	DHS	2012	**89.3**	0.605	67.7	**99.8**	**1.4**	0.6	62.7	95.5	74.3	16511.5
Liberia	DHS	2013	**71.2**	0.374	52.5	**99.8**	**1.6**	0.4	43.3	87.7	39.5	4079.7
Mali	DHS	2013	**77.7**	0.457	58.9	**99.8**	**2.8**	0.5	49.9	88.7	54.5	14416.7
Guinea	DHS-MICS	2012	**75.1**	0.459	61.1	**99.9**	**3.3**	0.5	50.6	88.2	54.3	11161.5
Somalia	MICS	2006	**81.2**	0.514	63.3	**99.9**	**3.5**	0.5	54.8	90.6	65.6	9907.9
Sierra Leone	DHS	2013	**81.0**	0.464	57.3	**99.9**	**1.4**	0.5	50.4	92.9	54.7	5865.5
Burundi	DHS	2010	**80.8**	0.454	56.2	**100.0**	**1.6**	0.5	49.5	94.9	50.5	9540.4
Central African Republic	MICS	2010	**77.6**	0.430	55.5	**100.0**	**0.6**	0.5	47.9	93.1	49.9	4436.2
Rwanda	DHS	2010	**69.0**	0.350	50.8	**100.0**	**2.6**	0.4	41.3	88.3	34.7	11144.3
South Sudan	MICS	2010	**91.1**	0.557	61.2	**100.0**	**0.1**	0.6	57.8	98.0	71.1	10381.1