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Revising the Global Multidimensional Poverty Index: Empirical Insights and Robustness

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Abstract

The global Multidimensional Poverty Index, published annually since 2010, captures acute multidimensional poverty in the developing regions of the world. In 2018, five of its ten indicators were revised with the purpose of aligning the index to the SDGs insofar as current data permit. This paper provides comprehensive analyses of the consequences of this revision from three perspectives. First, we offer new empirical insights available from the revised specification. Second, we analyse its robustness to changes in some key parameters, including the poverty cutoff and dimensional weights. Third, we compare the revised and the original specifications by implementing both on the same 105 national datasets. The country orderings in the revised specification are found to be robust to plausible parametric alternatives. Largely, these country orderings are at least as robust as the original one. Additional research on robustness standards is suggested.

Keywords: Multidimensional poverty, poverty measurement, poverty comparisons, joint distribution of deprivations, robustness.

JEL classification: D63, I32, O57

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1. Introduction

It is widely agreed in both academia and practise that poverty is multidimensional (e.g., Narayan et al., 2000; Atkinson, 2003, 2019; Bourguignon & Chakravarty, 2003; Alkire & Foster, 2011; Ferreira, 2011; Ravallion, 2011; Whelan et al., 2014; World Bank 2017, 2018). This consensus is reflected in the most influential contemporary development paradigms globally, including *Transforming our world* the 2030 Agenda for Sustainable Development and the Third United Nations Decade for Eradication of Poverty (2018-2027). For example, the 2030 Agenda document highlights the need to reduce poverty in all its forms and dimensions.[1] The first principle of the Plan of Action for the Third Decade states that "poverty is multidimensional in the forms it takes and its underlying causes..."[2] Importantly, a full account of the multidimensional nature of poverty is not merely concerned with its manifold manifestations, but also their intrinsic interconnections (Atkinson, 2019).

The global Multidimensional Poverty Index (MPI) systematically implements the most comprehensive counting-based measure of multidimensional poverty possible for developing regions given current data resources. The global MPI developed by Alkire and Santos (2010; 2014) in collaboration with the United Nations Development Program's Human Development Report Office was first published in its 20th anniversary flagship report (UNDP 2010). The aim of the measure is to offer a global account of acute multidimensional poverty that is transparent, disaggregated, and to the largest extent possible, comparable across countries in the developing world. Relying methodologically on the dual-cutoff counting approach pioneered by Alkire & Foster (2011), which draws on much earlier work (Atkinson, 2003; Chakravarty & D'Ambrosio 2006, among others), the global MPI is recognized as a useful complement of the more traditional notion of monetary poverty by directly measuring the simultaneous shortfall in manifold dimensions of human wellbeing (see e.g. Atkinson, 2019; Report of the UN Secretary General, 2018; and Global Sustainable Development Report[3], 2019). The methods applied in this paper could easily be extended to other counting-based measures using discrete data (e.g. Chakravarty & D'Ambrosio 2006; Bossert et al., 2013).

[1] See United Nations 2015a.

[2] United Nations General Assembly 2018: 9.

[3] The authors of the report are acknowledged as the Independent Group of Scientists appointed by the Secretary-General.

In 2018, the first major revision of the global MPI since its inception was undertaken, in order to take into account improvements in survey microdata, and to better align to the 2030 development agenda and related international strategies and policy actions (Alkire & Jahan, 2018). Formally, the 2018 revision consisted of adjustments in the definition of five out the ten indicators (Alkire et al., 2018; OPHI, 2018). Indicators related to child mortality, nutrition, years of schooling, housing and asset ownership, were revisited in light of theoretical foundations, data availability and policy relevance, and the detailed normative and empirical considerations underlying their revision is available in Alkire & Kanagaratnam (2020) and Vollmer & Alkire (2019).

This paper studies the empirical insights offered by the revised global MPI, fills a gap in the literature regarding how to assess the robustness of revised MPIs, and how to compare them with original MPIs – a topic which is of importance for national as well as internationally comparable measures. A vigorous assessment is useful because the global MPI is one of the development indices that simultaneously appears in the international media[4], as well as academic studies and policy discourse. Hence, the consequences of revising such an influential development index justify a careful empirical analysis and documentation. The global MPI's theoretical and methodological underpinnings are often taken as benchmarks for analysis in numerous academic studies about the causes and consequences of a broad notion of poverty (see e.g. Jindra & Vaz, 2019 for governance and poverty; Ogutu & Qaim, 2019 for the impact of commercialization on poverty; Espinoza-Delgado & Klasen, 2018 for intra-household poverty disparities; Alkire et al, 2017 for a cross-country analysis of changes over time; Pasha, 2017 for the consequences of alternative dimensional weights in MPI on country orderings; Rogan, 2016 for a gendered approach to poverty; and Alkire and Seth 2015 for analyses of over time in India), as well as country-specific poverty analyses (see e.g. Datt, 2019a for the Philippines, Suppa, 2018 for Germany, Hanandita & Tampubolon, 2016 for Indonesia; Angulo et al., 2016 for Colombia, Trani et al., 2016 for Afghanistan).

While the value of reflecting the joint distribution of deprivations was generally acknowledged, some proposed non-measurement strategies (Ferreira & Lugo 2013). Others criticised the household as unit of identification (Chzhen & Ferrone, 2017; Vijaya et al., 2014) as well as the selection of parameters, particularly the weights (Ravallion, 2011, Pasha, 2017 among others) and poverty cutoff (Ferreira, 2011; Pattanaik & Xu, 2018; Aaberge & Brandolini, 2015; Datt, 2019b).

[4] Wide circulating newspapers such as The Guardian, and more specialized magazines such as The Economist cover certain findings from the global MPI. For instance see: https://www.theguardian.com/global-development/2013/sep/25/new-ways-measure-poverty ; https://www.economist.com/graphic-detail/2018/09/14/life-in-developing-countries-continues-to-improve

Such concerns undergirded the rise of empirical assessments of the extent to which policy relevant comparisons were robust to modifications of parameters or even different approaches to multidimensional poverty measurement (e.g. Deutsch & Silber, 2005).

This paper makes a contribution by providing answers to the following questions: i) What novel insights about interlinkages among poverty-related indicators in the developing world do we gain from the revised global MPI? ii) How robust is the revised specification to changes in some of its fundamental parameters? iii) What are the empirical consequences of the revision for the way we understand poverty in light of the global MPI?

Providing rigorous answers to these questions entails data-intensive empirical analyses. We build upon the same data that was used to produce the results of the revised global MPI in 2018. It consists of a unique dataset that includes 105 strictly standardized microdata surveys (see Alkire et al., 2018), each of them being nationally representative of the population in a country located in one of six developing world regions as defined by UNDP: the Arab States, East Asia & the Pacific, Europe & Central Asia, Latin America & the Caribbean, South Asia and Sub-Saharan Africa. The overall pooled sample results in 8.78 million individual observations that represent around 5.7 billion people. This corresponds to nearly 77% of the global population and 91% of the population living in the developing world. Given that levels of acute multidimensional poverty are expected to be low outside the developing world, our analysis is close to having a global scale. To the best of our knowledge, there is no study about multidimensional poverty that builds on such an extensive and recent microdata. Only Alkire & Santos (2014) and Robles & Sumner, (2020) come close to such an ambitious endeavour by investigating multidimensional poverty based, however, on the 2010 specification of the global MPI.

To tackle the first question we perform a thorough assessment of the joint distribution of deprivations prior to a multidimensional poverty analysis focusing on an array of aggregate measures. Thus we align our paper with scholarship emphasizing the practical importance of the *joint* distribution of deprivations to understand the many facets of poverty (e.g. Atkinson, 2003, 2019; Robles & Sumner, 2020; Wolff & de-Shalit, 2007; Duclos et al., 2006). To uncover heterogeneities, we also disaggregate the overall aggregate poverty measures by world region, rural-urban areas and age groups.

Addressing the second question, we analyse the robustness of the revised global MPI to changes in the multidimensional poverty cutoff and the dimensional weights within a counting framework to measure multidimensional poverty (see Alkire & Foster, 2011). One way in which we do this consists of examining the effects of shifts in the specification of the global MPI on the *absolute* position of each country in a global poverty ordering. We build on analyses conducted in previous research about the robustness of pairwise comparisons applied in Alkire & Santos (2010, 2014), Yalontzky (2014), Santos & Villatoro (2016, 2018), Chen et al., (2019) and Gallardo (2019), among others, which relies on statistical tests to assess country poverty orderings, taking them two by two. This approach allows to assess an array of alternative MPI specifications simultaneously and involves computing the proportion of orderings that are preserved across these different specifications to summarize the test results. Essentially, this method compares the *relative* order between two countries. In addition to the robustness analysis of the MPI value (as in Alkire & Santos, 2010, 2014), we also assess the robustness of the poverty headcount ratio.

Finally, to address the third question we perform a detailed empirical comparison of the poverty patterns arising in light of the original and revised versions of the global MPI. Feeding the same data into both specifications of the index, we first analyse differences in the key aggregate poverty measures by world regions, as well as the deprivation rates suffered by the whole population and the subset of poor people. Also, we perform a country pairwise comparison analysis (with hypothesis tests) to assess the robustness of relative orderings between the two versions of the index.

The paper is structured as follows. Section 2 briefly presents methods and data underlying the global MPI. Section 3 contains results of the revised MPI at the global level, by world regions, rural-urban areas and age groups. Section 4 analyses robustness of the revised global MPI to changes in dimensional weights and the poverty cutoff. Section 5 compares the poverty figures of the original and the revised versions of the global MPI. Finally, Section 6 offers concluding remarks.

2. The revised global MPI: methods and data

The global MPI is arguably the most well-known application of the dual cutoff counting approach to poverty developed by Alkire & Foster (2011, AF method henceforth). Whereas the innovation of the dual cutoff approach was general and methodological, the innovation of the global MPI lies, precisely, in selection and empirical application of indicators and deprivation values. Given that the defining feature of the global MPI is its indicators and weights, and given that the revision adjusted the former, it is paramount to consider how to assess the revised global MPI, as this points out exercises that could also be useful when other established measures adjust their parameters. Hence, in this section, let us make a formal presentation of the method, which will allow us to put the main elements of the revision in a formal context, the data that we use as well as explaining our empirical methods.

2.1 The Alkire-Foster (AF) method

Let us consider a country for which we have a nationally representative dataset containing n individuals and $j = 1, \dots, d$ relevant indicators. Let X be a ($n \times d$)-sized matrix containing the achievement levels of these indicators. These data can be transformed into matrix g^0 containing defined binary deprivation indicators for all the individuals in each one of the indicators. If individual i falls short of the minimum achievement level in indicator j that is necessary for them to be considered non-deprived, then $g_{ij}^0 = 1$. Otherwise, $g_{ij}^0 = 0$. Each deprivation may have a different relative importance, which is reflected in the vector of weights $w = (w_1 \dots w_d)$ such that $w_j > 0$ and $\sum_{j=1}^{d} w_j = 1$. Each element w_j reflects the relative value or importance of each deprivation to poverty. Aggregating across indicators, we can obtain individual deprivation scores as $c_i = \sum_{j=1}^{d} w_j \, g_{ij}^0, \forall i$. These scores represent the number of weighted deprivations experienced by each individual.

An individual is identified as poor if their deprivation score equals or exceeds the poverty cutoff k. Formally, an individual is considered to be poor using an identification function that we define as $\rho(g_i^0, w, k) = \mathbb{I}(c_i \geq k)$, where g_i^0 is the row of the deprivation matrix containing all the deprivation indicators of person i. The identification function equals 1 if the individual is poor and 0 otherwise. In this notation, we explicitly state the set of parameters that define the specification of the poverty measure. Note that the deprivation matrix reflects the definition of indicators, whereby it is easy to see that the revision modifies the identification the poor, even though w and k remain unchanged.

After the identification step of poverty measurement, we aggregate across individuals to obtain the poverty headcount ratio as $H = \frac{1}{n}\sum_{i=1}^{n} \rho(g_i^0, w, k)$, which represents proportion of poor people. Second, the rate of multidimensional poverty intensity can be computed as $A = \frac{1}{q}\sum_{i=1}^{n}(\rho(g_i^0, w, k) \times c_i)$, where $q = \sum_{i=1}^{n} \rho(g_i^0, w, k)$ is the number of poor people. Thus A represents the average number of weighted deprivations *experienced by the poor*. Third, the *adjusted* poverty headcount ratio, denoted as M_0, combines H and A in a multiplicative form, such that $M_0 = H \times A = \frac{1}{n}\sum_{i=1}^{n}(\rho(g_i^0, w, k) \times c_i)$. This rate represents the number of weighted deprivations experienced by the poor as a proportion of the number of individuals in the whole sample. The adjusted headcount ratio is the level of the MPI, so M_0 and MPI are interchangeable notations. Note that every specification of an MPI and its subindices requires a specific choice of i) indicator definitions, ii) dimensional weights and iii) a poverty cutoff. This shows how and why the revision of indicators affects these aggregate poverty measures.

2.2 The original and the revised global MPI

The original and the revised versions of the global MPI share many common elements in their specifications. They both comprise three dimensions, namely health, education and living standards. The index includes ten indicators, two of them pertaining to health, two to education and six to living standards. Both global MPI specifications have a nested weight structure: reflecting their equal importance, each dimension is given the same weight (one-third) and every indicator is given the same weight within dimensions. The poverty cutoff is $k = \frac{1}{3}$ in both specifications signifying that a person is identified as being multidimensionally poor if they suffer deprivations in one-third or more of the weighted indicators. Both specifications are complemented with two additional headcount ratios: severity and vulnerability. People suffering deprivations in half or more of the weighted indicators are considered severely poor. Individuals are identified as vulnerable to multidimensional poverty if their weighted deprivation score is between one-fifth and one-third.

The revision of the global MPI modified five out of the ten indicators. Table 1 summarizes these revisions. We limit ourselves here to state that in the revised version, the nutrition status for children under five includes the union between weight-for-age (underweight) and height-for-age (stunting). The original specification was limited to only underweight. The inclusion of stunting better aligns with the SDG framework towards zero hunger.[5] In addition, for 51 countries where there is nutrition data for adults, we applied the BMI-for-age measure for individuals age 15-19 and the BMI measure for adults 20 years and older. The original specification applied the BMI measure for all individuals 15 years and older. The BMI-for-age measure better accommodates the sporadic growth experience of youth than a BMI measure.

In the revised specification, a child death is considered in the child mortality indicator only if it took place five years prior to the survey. This avoids capturing past mortality stocks and allows to better capture policy success in reducing it. The deprivation cut-off in years of schooling was

[5] Specifically indicator 2.2.1 of Goal 2 of the SDGs (https://sustainabledevelopment.un.org/sdg2).

Table 1: A comparison between original and revised (highlighted) global MPI indicators

Dimensions of poverty	**Indicator**	**Original global MPI Deprived if…**	**Revised global MPI Deprived if…**
Health	**Nutrition**	Any adult under 70 years of age have **low BMI** or any child under 5 is **underweight**.	Any adults have **low BMI** or persons aged 5 to 19 have **low BMI-for-age** or any child under 5 is **underweight** or **stunted**.
	Child mortality	Any **child** has **died** in the household.	Any **child*** has **died** in the household in the **five-year** period preceding the survey.
Education	**Years of schooling**	No household member aged 10 years or older has completed **five** years of schooling.	No household member aged 10 years or older has completed **six** years of schooling.
	School attendance	Any school-aged child is not attending school up to the age at which he/she would complete class 8.	
Living Standards	Cooking fuel	The household cooks with dung, wood or charcoal.	
	Sanitation	The household's sanitation facility is not improved, or it is improved but shared with other households.	
	Drinking water	The household does not have access to improved drinking water or safe drinking water is at least a 30-minute walk from home, roundtrip.	
	Electricity	The household has no electricity.	
	Housing	The household has a dirt, sand, dung or other unspecified type of **floor**.	The household has inadequate housing: the **floor** is of natural materials or the **roof** or **walls** are of rudimentary materials.
	Assets	The household does not own more than one **radio**, **TV**, **telephone**, **bike**, **motorbike** or **refrigerator** and does not own a car or truck.	The household does not own more than one of these assets: radio, TV, telephone, **computer**, **animal cart**, bicycle, motorbike, or refrigerator, and does not own a car or truck.

***Note: In 2019, the definition of child mortality was further revised to include age criteria. Individuals are deprived in child mortality if any child **under 18** has died in the household in the five-year period preceding the survey.

revised from five to six years in order to reflect the international standard duration of primary schooling. The flooring indicator is now coupled with walls and roof, allowing for a comprehensive housing indicator. The assets indicator was expanded to include computer and animal cart and thus reflect urban and rural deprivations more adequately (Vollmer & Alkire, 2018).

2.3 Data

We use the same data that were used to produce the revised global MPI following Alkire et al., (2018) and published in OPHI (2018). These data are based on 105 nationally representative datasets drawn from five major sources: the Demographic and Health Surveys (DHS), the Multiple Indicator Cluster Surveys (MICS), the combined DHS-MICS survey, the Pan Arab Project for Family Health (PAPFAM) surveys, and six national surveys.[6] Among these 105 countries, subnational disaggregation was possible for 88 countries. The vast majority of the countries (90) had surveys that were fielded between 2011 and 2016, and this represents 97% of the population covered in the 2018 global MPI. Details of the standardisation of the indicators for each survey can be found in Alkire et al., (2018).

In 87 countries, the results were based on all 10 indicators of the global MPI.[7] In 17 countries, the results were based on nine indicators, while Philippines was the only country that lacked two indicators. The countries lacking one indicator mainly lacked information on nutrition or child mortality, with Egypt lacking cooking fuel, Honduras lacking electricity and China not having information on housing. To account for these special cases, weights within the dimension of the missing indicator are equally increased such that they sum up to one-third. This procedure amounts to maintaining equal weights across the three dimensions, while making best use of the limited available information. Thus it is aimed at preserving the theoretical rationale of the global MPI since it was conceived in 2010.

2.4 Aggregating and disaggregating the global MPI

When estimating the global MPI and its component indices, each one of the underlying national surveys has a specific complex survey design, by which each household is assigned a sampling weight. In each national survey, these weights are inversely proportional to the probability of selection within the specified sampling frame (ICF International, 2012; Khan & Hancioglu, 2019).

[6] See Alkire et al., (2018) for details on the country, region, survey and year in Appendix 1, p. 29.

[7] This is a visible improvement from 2010 in which only 63 of the 104 countries had all 10 indicators.

Thus they expand the sample in each country to the corresponding population size at the moment of the survey. Hence, each national survey allows, in principle, to obtain unbiased estimators of M_0, H and A for each country.[8] Thus it is possible to obtain poverty estimates for subnational regions (such as provinces, departments or states), urban and rural areas, for instance.

Formally, as the global MPI relies on the AF method, the value of the MPI of country $u = \{1 \dots U\}$, denoted as $MPI(X_u)$, can be disaggregated by subgroups $\ell = 1, \dots, m$ (e.g. subnational regions, urban-rural) as:

$$MPI(X_u) = \sum_{\ell} \frac{n_u^{\ell}}{n_u} MPI(X_u^{\ell}) \tag{1}$$

where n_u is the population in country u, and $MPI(X_u^{\ell})$ denotes the MPI of subgroup ℓ in country u with a population sized n_u^{ℓ}. For notational convenience, we omit the parameters of the poverty identification function in the above equation to highlight on which data a particular estimate depends. Equation (1) states that country level MPI can also be obtained as population weighted average of the disaggregated subgroup-specific MPIs. In turn, H can be disaggregated following the same procedure. Moreover, A can also be disaggregated in a similar way replacing the country and subgroup population sizes by the number of poor people in the corresponding levels.

Starting from the country level, the H, A and MPI values can be *aggregated* into a supranational level. This could be world regions or the developing world level as represented by our 105 countries. Essentially, aggregation follows a similar logic as the disaggregation procedure that we just described. For instance, the MPI value of the supranational level of interest, denoted as $MPI(X_S)$, can computed as:

$$MPI(X_S) = \sum_{\ell} \frac{n_u}{n_S} MPI(X_u) \tag{2}$$

where X_S refers to the pooled data representing the supranational level, which has a population of size n_S. This means that $MPI(X_S)$ can be obtained as population weighted average of the country level MPIs. Consequently, subgroup estimates from the different countries are related to $MPI(X_S)$ as follows:

$$MPI(X_S) = \sum_u \frac{n_u}{n_S} \sum_{\ell} \frac{n_u^{\ell}}{n_u} MPI(X_u^{\ell}) \tag{3}$$

[8] Note that this statement holds true in the absence of sample drop. If sample drop occurs generating a pattern of missing values that is completely at random (MCAR, see e.g. Heitjan & Basu, 1996), the national representativity of the sample is preserved.

Note that the above equation shows that $MPI(X_u^\ell)$ can in fact be conceived as the result of a two-level *disaggregation* of $MPI(X_S)$ with the appropriate population weights.

This procedure emphasizes the vital role of population weights in order to obtain meaningful supranational multidimensional poverty estimates. On the one hand, population weighting aligns with the global MPI's core conceptual underpinning, namely A. Sen's people-centered approach to human development (Sen, 2009). A simple unweighted average of all country-level MPIs would assign a life in India, for instance, a much lower importance than a life in, say, the Maldives. On the other hand, a more technical way to understand the need of population weighting, is to view our pooled data as one stratified sample representing the supranational region of interest. In order to adequately reflect this population, sampling weights have to be rescaled using the country-specific ratio n_u/n_S.

The explanation that we offer for the aggregation procedure allows us to discuss a key data constraint that is currently impossible to circumvent with the existing data. It is related to the fact that not all the national datasets are collected in the same timespan. The survey used ranges between 2006 to 2016. Thus, the 'raw' pooled dataset expands to an abstract population size that hardly has a meaningful interpretation, as it is a mixture of national population sizes at different times. So, differences between world regions or countries, for instance, could be attributable to a) different survey years or b) different levels of measured poverty. This creates challenges in interpreting cross-regional differences. To recover the logic of our analysis, we operationalize the population weighting procedure by computing population shares in a common time period using known real population sizes. This amounts to rescaling the sampling weights for each national survey so that they add up to the population of that country in the chosen common time period. Based on data availability, we thus rescaled the weights to add up to the 2016 population size as reported in UNFPA (UNDESA, 2017). This facilitates international comparisons, it is a convention used in the global MPI reports to aggregate using a common population year (Alkire et al., 2018). As a result, if the population date post-dates the survey, and if population has grown, and if poverty is declining, this convention will overstate the number of poor persons. Our results have to be interpreted keeping this in mind.

3. The revised global MPI: What insights do we really gain?

Let us begin our analysis by discussing the prevalence of deprivations one by one, and the extent to which they overlap. Subsequently, we will assess the patterns of multidimensional poverty in the developing world highlighting heterogeneities between world regions, urban and rural areas and age groups.

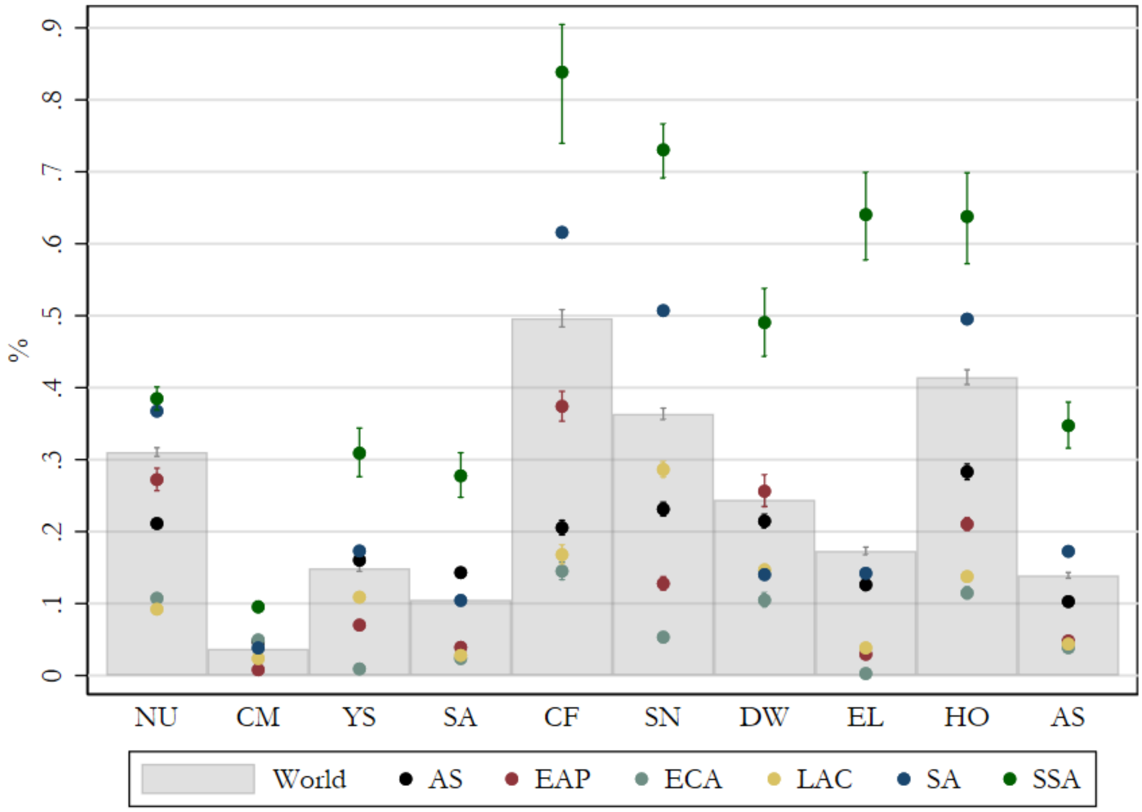
3.1 A dashboard of deprivation indicators

An analysis of deprivation headcount ratios one at a time is the simplest way to start a description of poverty patterns in the developing world. This is akin to taking a dashboard approach to multidimensional poverty, which focuses on the marginal indicator distributions (Ravallion, 2011). These ratios are termed as *uncensored headcount ratios* (Alkire et al., 2015) and they correspond to the column-wise mean of the deprivation matrix g^0. While analysing these headcount ratios, however, one has to keep in mind that these figures result from an estimation performed prior to the identification and aggregation steps, so they do not correspond to a fully-fledged poverty analysis. The focus is not on the poor population, but on the society as a whole, and the interconnections between the indicators are cast aside, for now.

Globally, the highest overall uncensored headcount ratios correspond to *cooking fuel* (44.8%), *housing* (39.6%) and *sanitation* (37.0%) (Figure 1). Deprivations in these indicators afflict large portions of the population, regardless if and how one gauges their poverty status, but there are stark differences between world regions. Deprivations in almost every indicator are unambiguously higher in Sub-Saharan Africa. Considering 95% confidence intervals, the uncensored deprivation headcount ratio in this world region is over two-thirds in cooking fuel, housing, sanitation and electricity. This goes on to show the extent of geographical concentration of these deprivations.

The uncensored headcount ratios in South Asia and Sub-Saharan Africa are highest among all world regions in almost every indicator. This is a clear pattern that regularly emerges even through a purely monetary approach to poverty (World Bank, 2018; Ravallion, 2016). The only exception is *child mortality* for which we observe very low poverty headcount ratios even in highly populated regions such as East Asia & the Pacific. This is related to the progress made in terms under-5 mortality globally in recent years (UN, 2015; You et al., 2015). This is also aligned with Bishai et al. (2016) who make a case for improvements in coverage of health determinants as a main driver of fast reductions in child (and maternal) mortality in the developing world.

Figure 1. Uncensored headcount ratios by indicator and world region



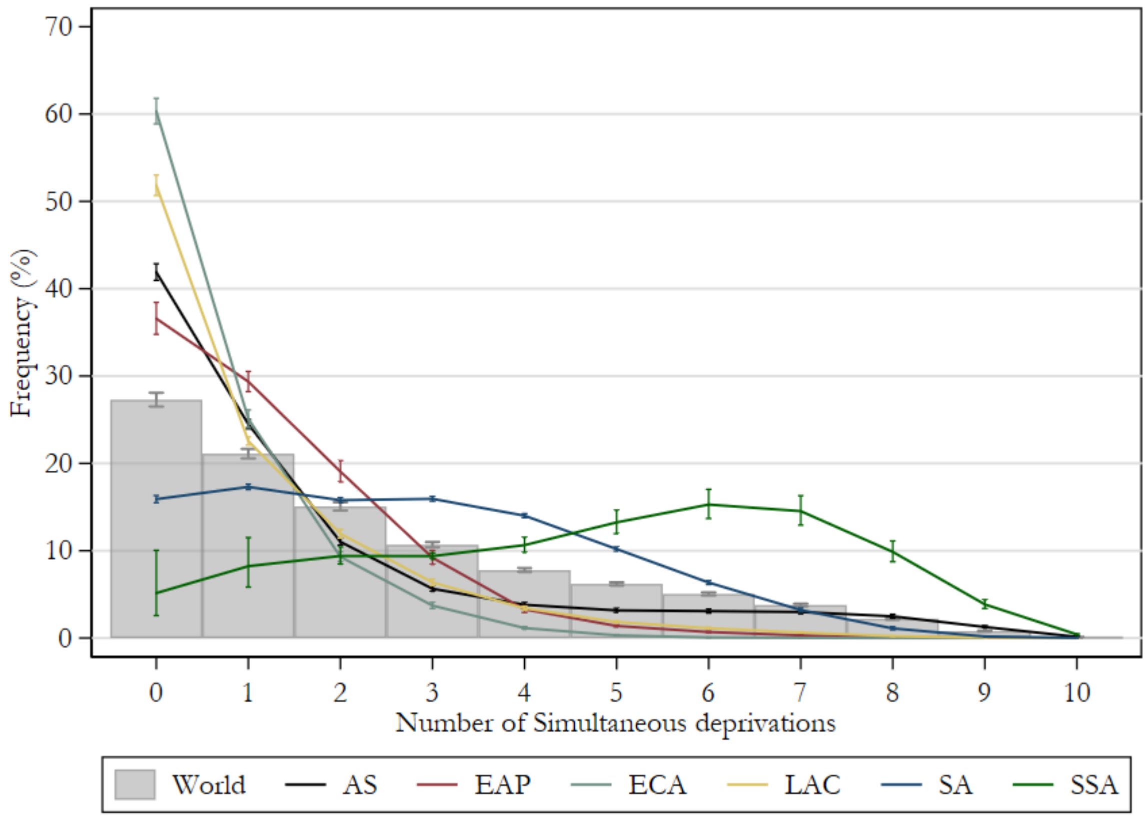
Notes: a) AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa. b) NU: nutrition; CM: child mortality; YS: years of schooling; SA: school attendance; CF: cooking fuel; SN: sanitation; DW: drinking water; E: electricity; HO: housing; AS: assets c) Vertical lines represent 95% confidence intervals.

3.2 Joint distribution of deprivations

The analysis of each indicator one by one provides useful insights but considering them as separate entities overlooks their interlinkages or natural interconnections. People who suffer one deprivation are very likely to face *other* deprivations at the same time. As shown in Figure 2, at a global level, around 27% of the population do not suffer any deprivation and 21% face exactly one single deprivation.

The majority of the population (52%) are deprived in multiple ways; they face two or more deprivations. However, there is a high level of heterogeneity by world region around this global pattern. In South Asia, people are most likely to face one deprivation and there is a similar chance of facing two or three simlutanous deprivations. This means, for instance, that multisectoral policies with unified targeting mechanisms have more chances of being effective in the battle against these joint deprivations. In Sub-Saharan Africa, however, the most likely situation is to suffer five, six or seven simultaneous deprivations. The likelihood of living deprivation-free is the lowest in this region. This depicts much larger, more complex challenges for policymaking. More actors and institutions need to align efforts in the form of multisectoral programs, which risk to face obstacles linked to persisting institutional fragility in the region (Deléchat et al., 2018; McKay & Thorbecke, 2019).

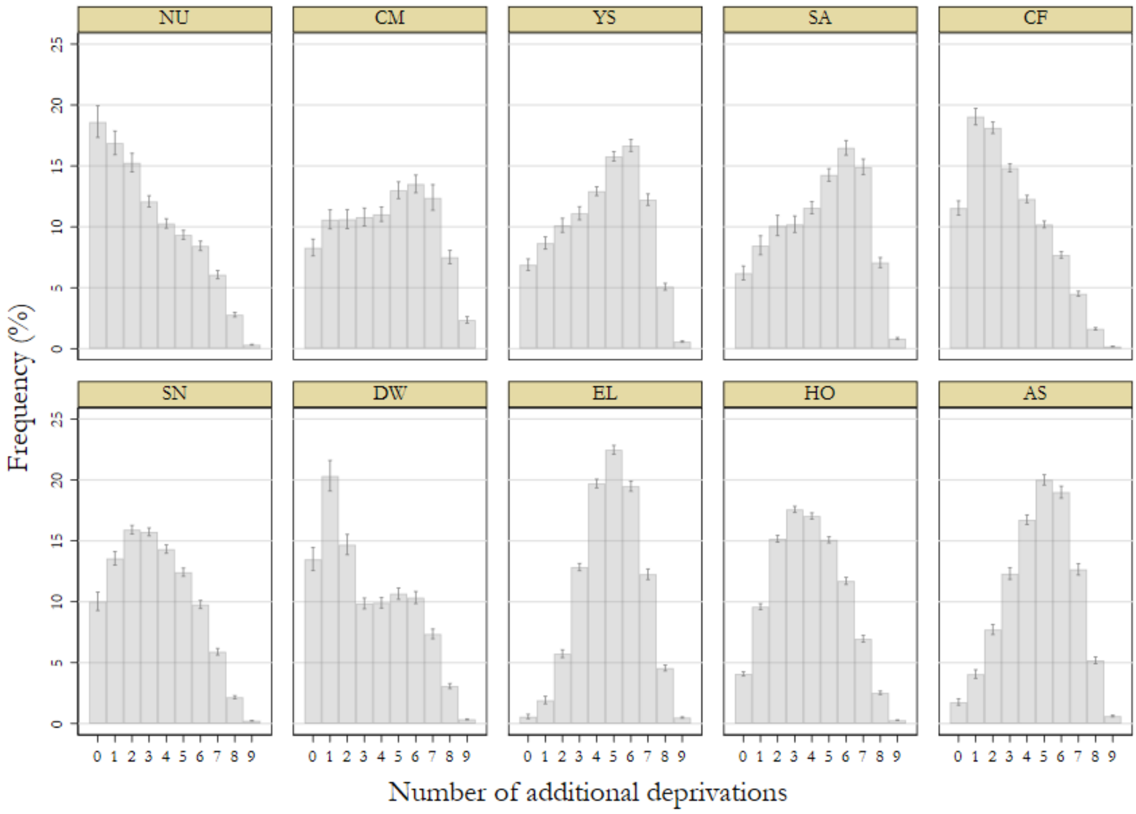
Figure 2 Number of simultaneous deprivations by world region



Notes: a) AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa. b) Vertical lines represent 95% confidence intervals.

The higher number of simultaneous deprivations experienced by individuals has important consequences for policymaking. The challenges that they raise for policymaking in South Asia and South Africa may not be faced without accepting that poverty is multidimensional and that no one-proxy will do to fully grasp the livelihood of poor people. To see this, let us consider the distribution of the number of deprivations conditional on being deprived in each indicator. Figure 3 considers 100% of the persons who are deprived in a given indicator such as child mortality and plots the percentage of them who are deprived in differing numbers of other indicators simultaneously. Implicitly, indicators are here equally weighted. Taking into account the confidence intervals of these conditional frequencies, facing one single deprivation alone is never the most likely situation (Figure 3).[9]

Figure 3 Distribution of additional deprivations by indicator



Notes: a) Bars sum up to 100% of the deprived population in each indicator. b) NU: nutrition; CM: child mortality; YS: years of schooling; SA: school attendance; CF: cooking fuel; SN: sanitation; DW: drinking water; E: electricity; HO: housing; AS: assets; c) Vertical lines represent 95% confidence intervals.

Figure 3 is a graphical representation of the information presented in Table 2, which shows only the mean point estimates. We can see that the proportion of persons who are only deprived in electricity or assets are less than one and two percent, respectively. We also see that those deprived only in housing are around four percent, those deprived only in child mortality, school attendance, years of schooling and sanitation are between 5-10%. Only in three indicators out of the ten that are included in the global MPI, more than one in ten persons *only* deprived in that indicator: water, cooking fuel, and nutrition. Thus, across all ten indicators, between 81% and 99% of the

[9] Nutrition behaves differently with respect to the other indicators. Based on point estimates, it is the only indicator for which no additional deprivations is the most likely situation. But considering the 95% confidence intervals we find the likelihood of facing that deprivation alone or one additional deprivation to be statistically indistinguishable.

population in the developing world deprived in that indicator experience one or more additional deprivations. At the bottom of Table 2, we can also see for every one of the ten indicators, the average number of additional deprivations is between 3 (nutrition and cooking fuel) and 5 (electricity and assets).

Table 2. Frequency of additional deprivations by indicator

	Frequency by indicator (%)									
Nb. of additional Deprivations	**NU**	**CM**	**YS**	**SA**	**CF**	**SN**	**DW**	**EL**	**HO**	**AS**
0	18.6	8.3	6.9	6.2	11.5	10.0	13.5	0.6	4.1	1.7
1	16.9	10.6	8.7	8.5	19.0	13.5	20.3	1.9	9.6	4.1
2	15.3	10.6	10.1	10.1	18.1	15.9	14.7	5.7	15.2	7.7
3	12.1	10.8	11.1	10.2	14.8	15.7	9.9	12.8	17.6	12.3
4	10.3	11.0	12.9	11.6	12.3	14.3	9.9	19.7	17.0	16.7
5	9.3	13.0	15.8	14.3	10.2	12.4	10.7	22.5	15.1	20.0
6	8.4	13.5	16.7	16.5	7.7	9.8	10.3	19.5	11.7	19.0
7	6.1	12.4	12.2	14.9	4.5	5.9	7.4	12.3	7.0	12.7
8	2.8	7.5	5.1	7.1	1.6	2.2	3.1	4.6	2.5	5.2
9	0.3	2.3	0.6	0.8	0.2	0.2	0.3	0.5	0.3	0.6
Total	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Average number of additional deprivations	4.2	2.9	4.4	4.2	4.9	3.1	3.3	3.8	2.9	4.7

Note: cm: child mortality; nutr: nutrition; satt: school attendance; educ: years of schooling; elct: electricity; wtr: drinking water; sani: sanitation; hsg: housing; ckfl: cooking fuel; asst: assets.

Based on this, we argue that the global MPI is a useful way to account for the direct interlinkages across these deprivations. This index summarizes the multidimensional nature of poverty as measured by the manifestation of manifold deprivations, while accounting for their interlinkages.

3.3 The global MPI, its components and related measures

The overall incidence of multidimensional poverty in the developing world is around 23.2%, and the average poor person experiences around 49.5% of the weighted deprivations. The population-weighted average value of the global MPI is 0.115. To delve deeper, we present the regional heterogeneities (see Table 3).

It is statistically unambiguous that Sub-Saharan Africa followed by South Asia have the largest proportions of their population living in poverty (57.7% and 31.3%, respectively). However, there is not a direct relationship between the incidence and the intensity of poverty. In Sub-Saharan Africa and in the Arab States we find that the average poor person experiences more than half of the weighted deprivations (54.9% and 50.8% respectively). Balancing incidence and intensity and including 95% confidence intervals the adjusted headcount ratio depicts a clear regional poverty ordering with Sub-Saharan Africa (0.317) as the poorest region, followed by South Asia (0.143) and the Arab States (0.098).

When it comes to *severe* multidimensional poverty, Sub-Saharan Africa is undoubtedly the most affected region, with 35.3% of this population facing extreme hardships. However, one may not rule out that the incidence of severe poverty is similar in South Asia and the Arab States, as their 95% confidence intervals overlap. Around 10% of the population in these regions live in severe multidimensional poverty.

So far we have focused on people who are poor, with varying intensity, by the global MPI. We also want to stress that South Asia has the largest incidence of *vulnerability* to poverty in the developing world (see Table 3). It is also noticeable that a large proportion of the population are vulnerable to poverty in Sub-Saharan Africa (17.3%), which confirms the marked challenges for policymaking in this region. Not only is it home to the highest proportion of the poor population in the developing world, but those who are not poor are very close to multidimensional poverty cutoff. On average, three out of every four persons in Sub-Saharan Africa are either poor or vulnerable to multidimensional poverty.

Table 3. Poverty incidence (%) for different poverty cutoffs by world region

	H(%) Acute			**H(%) Severe**			**H(%) Vulnerable**		
	mean	**lb**	**ub**	**mean**	**lb**	**ub**	**mean**	**lb**	**ub**
World	23.24	22.57	23.90	10.66	10.26	11.07	15.56	15.15	15.98
AS	19.23	18.42	20.03	9.65	9.05	10.25	9.72	9.35	10.09
EAP	5.85	5.20	6.50	1.23	1.06	1.40	15.57	14.47	16.67
ECA	2.37	2.12	2.61	0.26	0.19	0.33	5.85	5.42	6.27
LAC	7.69	7.44	7.95	2.13	1.99	2.28	7.64	7.32	7.96
SA	31.28	30.69	31.86	11.48	10.97	11.98	18.90	18.61	19.19
SSA	57.79	51.82	63.77	35.32	31.27	39.37	17.30	16.80	17.79

Notes: a) AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa. b) lb and ub denote, respectively, lower bound and upper bounds of the 95% confidence intervals.

After identifying the part of the population suffering multidimensional poverty across various poverty cutoffs, naturally the question arises as to how they are poor. For this, we take a step further with respect to our previous analysis of uncensored headcount ratios and identify the proportion of the population who are poor and deprived in each indicator. These proportions are called the censored headcount ratios (Alkire et al., 2015). They are denoted as $h_j, j = 1 \dots 10$ and they can be computed as the mean of corresponding column of matrix g^0: $h_j = \frac{1}{N}\sum_{i=1}^{N} g_{ij}^0, \forall j$. Unlike their uncensored counterparts, the censored headcount ratios depend on the poverty cutoff and thus they allow to lay focus on the prevalence of each deprivation only among the poor.

Table 4. MPI and Intensity (A) by world region

	Intensity (A, %)			MPI		
	mean	**lb**	**ub**	**mean**	**lb**	**ub**
World	49.50	49.27	49.73	0.115	0.111	0.119
AS	50.82	50.29	51.35	0.098	0.093	0.102
EAP	43.06	42.44	43.68	0.025	0.022	0.028
ECA	38.25	37.72	38.79	0.009	0.008	0.010
LAC	43.19	42.76	43.62	0.033	0.032	0.034
SA	45.76	45.37	46.14	0.143	0.139	0.147
SSA	54.88	54.54	55.21	0.317	0.283	0.351

Notes: a) AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa. b) lb and ub denote, respectively, lower bound and upper bounds of the 95% confidence intervals.

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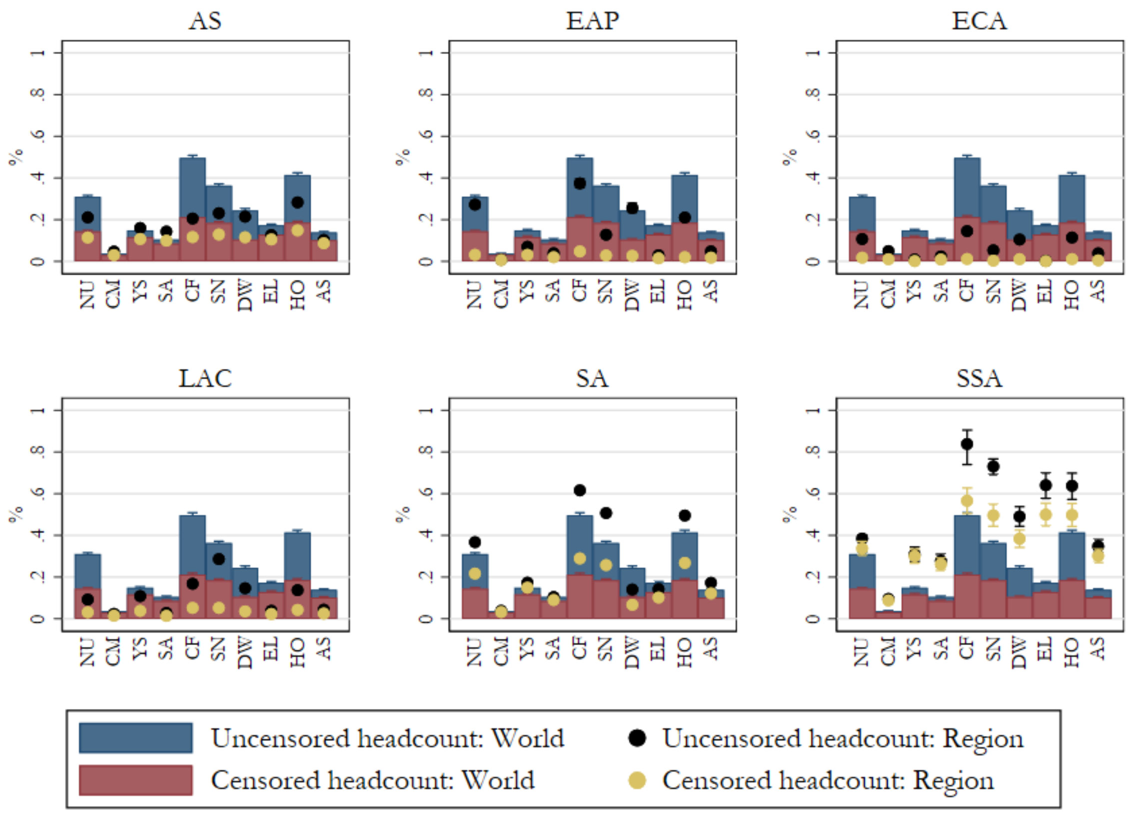
Compared to South Asia and Sub-Saharan Africa, the censored headcount ratios are very low in East Asia & the Pacific, Europe & Central Asia and Latin America & the Caribbean (see Figure 4). In contrast, the censored headcount ratios in Sub-Saharan Africa are highest for every single indicator, followed by those in South Asia.

There are some stark differences between the uncensored and censored headcount ratios in different regions. These differences denote that some deprivations are prevalent among the entire population, but are not necessarily a condition of the poor, because people deprived in those indicators are not deprived in at least one-third of the weighted indicators overall. This may be due to non-sampling measurement issues, preferences, or pervasive singleton deprivations. Empirically, the indicators which are most often censored are *nutrition, water, housing and cooking fuel* in East Asia & the Pacific; *sanitation* in Latin America & the Caribbean; and s*anitation, housing and cooking fuel* in South Asia.

Figure 4. Censored and uncensored headcount ratios by world region

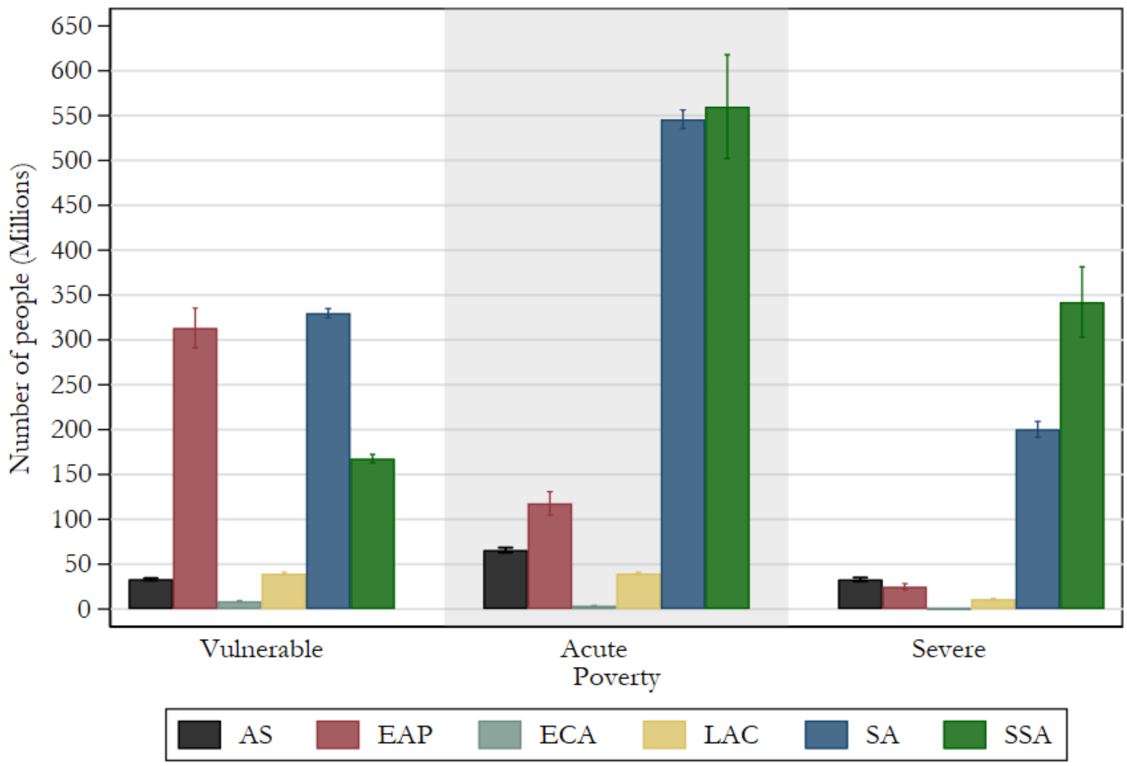


Notes: a) AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa. b) NU: nutrition; CM: child mortality; YS: years of schooling; SA: school attendance; CF: cooking fuel; SN: sanitation; DW: drinking water; E: electricity; HO: housing; AS: assets. c) Vertical lines represent 95% confidence intervals.

So far, our assessment of the revised global MPI results has focused on proportions of the population. However, the actual number of people suffering poverty and deprivation is also important. Whereas South Asia and Sub-Saharan Africa are home to the largest number of poor people (546 and 560 million, respectively), the number of people vulnerable to poverty is highest in South Asia and East Asia & the Pacific (330 and 313 million, respectively) (see Figure 5).

Although on average there are more MPI-poor people in Sub-Saharan Africa than in South Asia, if we take into account the standard error of these estimates, the number of MPI-poor people in these regions is actually undistinguishable.[10] In contrast, the number of people suffering severe multidimensional poverty (defined as those deprived in 50% or more of the weighted indicators) is unambiguously highest in Sub-Saharan Africa (342 million), followed by South Asia (200 million).

Figure 5 Number of poor, severely poor and vulnerable



Notes: a) AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa. b) Vertical lines represent 95% confidence intervals.

3.4 Poverty in selected population subgroups

We will close out this section by scrutinizing two key disaggregations of the global MPI values at the country level, which can then be aggregated into the regional level using the appropriate

[10] To check that this important result is robust to the year selected for the known population size (i.e. 2016), we also compared the number of poor people in Sub-Saharan Africa and South Asia taking a) 2015 and b) the country-varying survey year for the known population sizes. In both cases we confirm that the estimated number of poor people in both regions are statistically undistinguishable. Taking 2015 population sizes and 95% confidence levels, the number of poor people in South Asia is between 314 and 380 million, while that in South Asia is between 346 and 362 million. Taking the country-varying survey year population sizes, these bounds are 313-379 million people in Sub-Saharan Africa and 346-364 million people in South Asia.

population weights. The first one distinguishes urban and rural poverty[11] (see Table 5), and the second disaggregates by age groups (see Table 6).

Table 5 Disaggregation of H, A and MPI by urban-rural area and world regions

	H (%)					
	Urban			Rural		
	mean	Lb	ub	mean	lb	ub
World	8.01	7.59	8.46	35.50	34.52	36.49
AS	8.24	7.64	8.88	29.98	28.52	31.48
EAP	2.43	1.81	3.25	9.52	8.48	10.68
ECA	0.73	0.61	0.88	4.05	3.62	4.51
LAC	3.28	3.04	3.53	21.11	19.28	23.07
SA	12.01	11.43	12.61	40.50	39.79	41.22
SSA	26.44	21.55	31.98	73.20	68.96	77.05
	A (%)					
	Urban			**Rural**		
	mean	**lb**	**ub**	**mean**	**lb**	**ub**
World	44.01	43.64	44.37	50.50	50.26	50.73
AS	43.47	42.67	44.27	52.79	52.19	53.40
EAP	39.33	38.38	40.29	44.08	43.46	44.69
ECA	35.72	35.16	36.28	38.73	38.13	39.33
LAC	40.23	39.51	40.96	44.59	44.19	45.00
SA	43.12	42.62	43.62	46.13	45.71	46.55
SSA	46.83	46.33	47.33	56.30	55.97	56.64
	MPI					
	Urban			**Rural**		
	mean	**lb**	**ub**	**mean**	**lb**	**ub**
World	0.035	0.033	0.037	0.179	0.174	0.185
AS	0.036	0.033	0.039	0.158	0.150	0.167
EAP	0.010	0.007	0.013	0.042	0.037	0.047
ECA	0.003	0.002	0.003	0.016	0.014	0.018
LAC	0.013	0.012	0.014	0.094	0.086	0.103
SA	0.052	0.049	0.055	0.187	0.182	0.192
SSA	0.124	0.101	0.151	0.412	0.388	0.437

Notes: a) lb and ub denote, respectively, lower bound and upper bounds of the 95% confidence intervals. b) AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa.

[11] In the global MPI, we adopt the definition of 'urban' and 'rural' areas as provided in the datasets. The DHS surveys, for example, use national census definitions for most datasets, and these vary across countries. Unfortunately, it is not possible at this time to use a consistent definition of rurality, and this may affect the interpretation of results.

Table 6 Disaggregating H, A and MPI over age groups by world regions

	H (%)											
	Age 0-9			Age 10-17			Age 18-59			Age 60+		
	mean	lb	ub	mean	ub	lb	mean	lb	ub	mean	lb	ub
World	38.14	37.20	39.08	28.32	27.60	29.05	17.73	17.17	18.30	17.38	16.76	18.02
AS	28.06	27.00	29.14	21.65	20.72	22.61	14.79	14.14	15.45	13.95	13.14	14.80
EAP	9.86	8.51	11.40	7.30	6.54	8.13	4.45	3.94	5.02	7.21	6.44	8.05
ECA	4.86	4.40	5.36	2.46	2.16	2.81	1.95	1.75	2.18	1.25	1.09	1.43
LAC	12.52	12.09	12.96	9.13	8.72	9.56	6.00	5.82	6.18	6.88	6.43	7.35
SA	44.97	44.09	45.85	31.34	30.68	32.00	26.75	26.25	27.25	28.49	27.95	29.02
SSA	67.18	62.87	71.22	58.53	53.93	62.98	50.51	43.40	57.59	55.93	47.94	63.63

	A (%)											
	Age 0-9			Age 10-17			Age 18-59			Age 60+		
	mean	lb	ub	mean	ub	lb	mean	lb	ub	mean	lb	ub
World	52.46	52.19	52.73	50.28	50.03	50.53	47.88	47.67	48.09	44.45	44.21	44.70
AS	52.76	52.16	53.37	51.05	50.47	51.63	49.32	48.82	49.81	47.64	47.07	48.21
EAP	45.27	44.36	46.19	44.17	43.44	44.91	42.60	41.96	43.24	40.70	40.02	41.38
ECA	38.93	38.30	39.56	38.14	37.47	38.81	37.99	37.46	38.52	37.28	36.56	38.02
LAC	45.01	44.44	45.58	44.17	43.73	44.61	42.60	42.15	43.06	39.53	39.22	39.85
SA	48.20	47.68	48.72	46.22	45.81	46.64	44.69	44.37	45.01	42.55	42.20	42.91
SSA	56.93	56.58	57.27	54.77	54.41	55.13	53.57	53.22	53.92	50.16	49.83	50.49

	MPI											
	Age 0-9			Age 10-17			Age 18-59			Age 60+		
	mean	lb	ub	mean	ub	lb	mean	lb	ub	mean	lb	ub
World	0.200	0.195	0.206	0.142	0.138	0.146	0.085	0.082	0.088	0.077	0.074	0.080
AS	0.148	0.142	0.155	0.111	0.105	0.116	0.073	0.069	0.077	0.066	0.062	0.071
EAP	0.045	0.038	0.052	0.032	0.029	0.036	0.019	0.017	0.021	0.029	0.026	0.033
ECA	0.019	0.017	0.021	0.009	0.008	0.011	0.007	0.007	0.008	0.005	0.004	0.005
LAC	0.056	0.054	0.059	0.040	0.038	0.042	0.026	0.025	0.026	0.027	0.025	0.029
SA	0.217	0.211	0.223	0.145	0.141	0.149	0.120	0.117	0.122	0.121	0.118	0.124
SSA	0.382	0.358	0.408	0.321	0.295	0.347	0.271	0.233	0.312	0.281	0.242	0.323

Note: a) lb and ub denote, respectively, lower bound and upper bounds of the 95% confidence intervals. b) AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa.

For policy purposes, it is useful to compare the poverty measures of each subgroup with the global aggregate. We find that some 36% of the global rural population are MPI poor. In contrast, only 8% of the global urban population are MPI poor. The subgroup disaggregation also shows that only in two world regions, namely South Asia and Sub-Saharan Africa, poverty exceeds the global average. In South Asia and Sub-Saharan Africa, 41% and 73% of the rural population, respectively, are MPI poor. The Sub-Saharan Africa figure is twice higher when compared to the global average.

In terms of age group, we find that a higher share of younger children live in MPI poor households. In 105 countries covered by the global MPI, some 38% of the children under 10 and 28% of children between 10-17 years are MPI poor. This finding is in line with other studies that have concluded that the poor tend to live in large households with more children (World Bank, 2018).

4. Robustness of the revised global MPI

As we mentioned earlier, one particular MPI specification underlies all the results that we have discussed so far. When the MPI was first released in 2010, there was some scepticism about its robustness to alternative parametrizations in the academic and policy-making spheres (see Ferreira 2011 for a discussion on this matter). However, this index was found to be robust to changes in (a) the dimensional weights and (b) the poverty cutoff in Alkire & Santos (2010, 2014). For comparison purposes, we revisit the latter paper to evaluate the robustness of the revised index to the same parameters.

4.1 Shifting the poverty cutoff

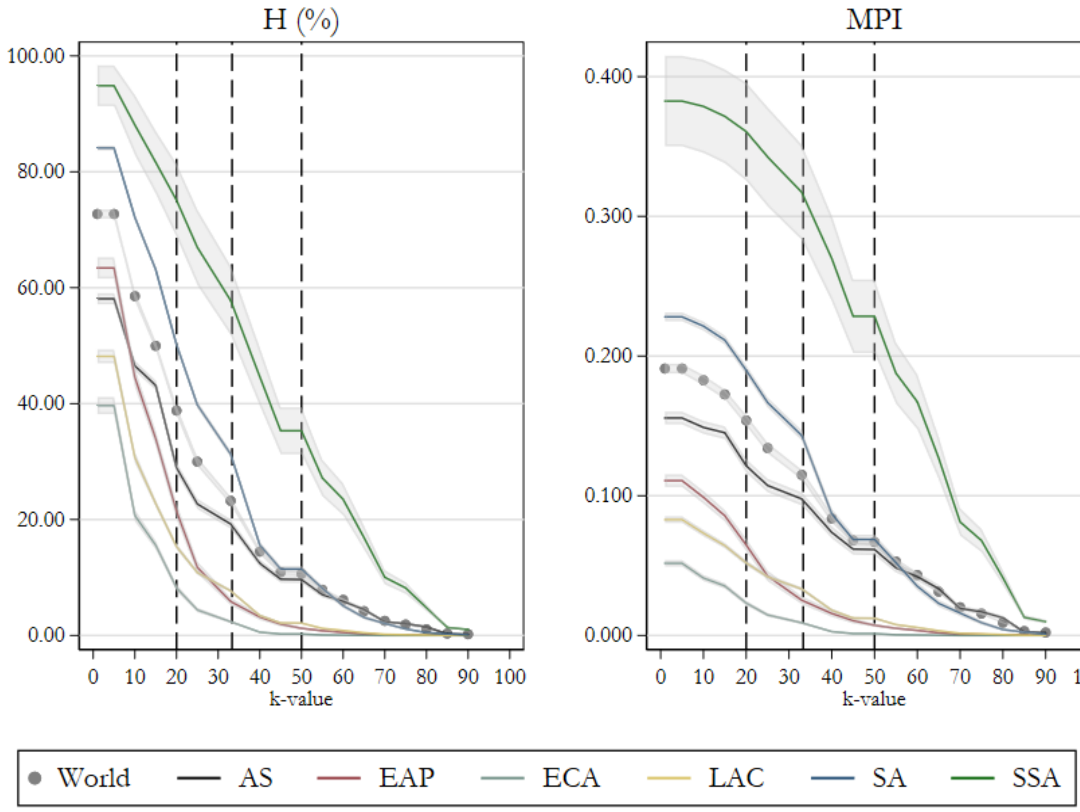
Let us first visually describe some robustness patterns by assessing the H and MPI complementary CDFs over different poverty cutoffs k. In Figure 6, we can see that H and MPI for Sub-Saharan Africa are the highest, and conversely, they are the lowest in Europe & Central Asia. These are powerful results in that they hold true over the entire set of possible poverty cutoffs.

In an inspection of the pattern of MPI levels, one can identify three groups of world regions. Sub Saharan Africa is undoubtedly the poorest region, followed by South Asia and the Arab States as regions with middle MPI levels. East Asia & the Pacific, Latin America & the Caribbean and Europe & Central Asia are the least poor world regions.

In a general way, results that hold true over the *entire range* of k are the exception. Since both H and MPI are monotonic decreasing functions of k, different population subsets are effectively identified as multidimensionally poor by adopting distinct k-values. Each one of these subsets regroups people that experience joint deprivations to different extents and with varying intensity.

Their livelihoods are different, and the types of policies required to improve their situation should build upon these differences in order to be effective. Thus, we argue that if changes arise due to shifts in k, they have a meaningful interpretation and they may usefully point towards distinct poverty analyses and policy actions against different patterns and intensities of joint deprivations.

Figure 6. Complementary cumulative distribution functions of H and MPI by world region



Notes: a) AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa. b) Grey-shaded regions represent 95% confidence intervals.

Thus, instead of delving deeper into a *general* robustness analysis of H and MPI distributions, it may be more informative to focus on *local* robustness within a relevant neighbourhood of k (World Bank, 2017). One useful way to establish this neighbourhood is to build upon the difference made between the poor population, those living in severe poverty and those who are vulnerable to poverty. Let us recall that the multidimensionally poor people were identified with the cutoff $k = \frac{1}{3}$, the severely multidimensionally poor people with $k = \frac{1}{2}$ (which is a subset of the former group), and people that are vulnerable to multidimensional poverty are identified if $\left(\frac{1}{3} > c_i \geq \frac{1}{5}\right)$. These definitions implicitly define the range $k \in \left[\frac{1}{5}; \frac{1}{2}\right]$ as the relevant neighbourhood to assess the local robustness of H and MPI around the baseline cutoff $k = \frac{1}{3}$.

Restricting our visual analysis of Figure 6 to $k \in \left[\frac{1}{5}; \frac{1}{2}\right]$, we can also affirm that the H and MPI distributions of South Asia are the second highest in the world, followed by the ones of the Arab States. We cannot establish clear differences between East Asia & the Pacific and Latin America

& the Caribbean, as their complementary CDFs cross each other. For k-values close to $\frac{1}{5}$ (i.e. vulnerability), Latin America & the Caribbean tend to be less poor by H and the MPI. This means that the likelihood of being vulnerable to poverty is lower in this region. However, this relative advantage is not preserved for k-values closer to $\frac{1}{2}$ (i.e. severe poverty), meaning that the likelihood of suffering severe poverty tends to be similar in both regions.

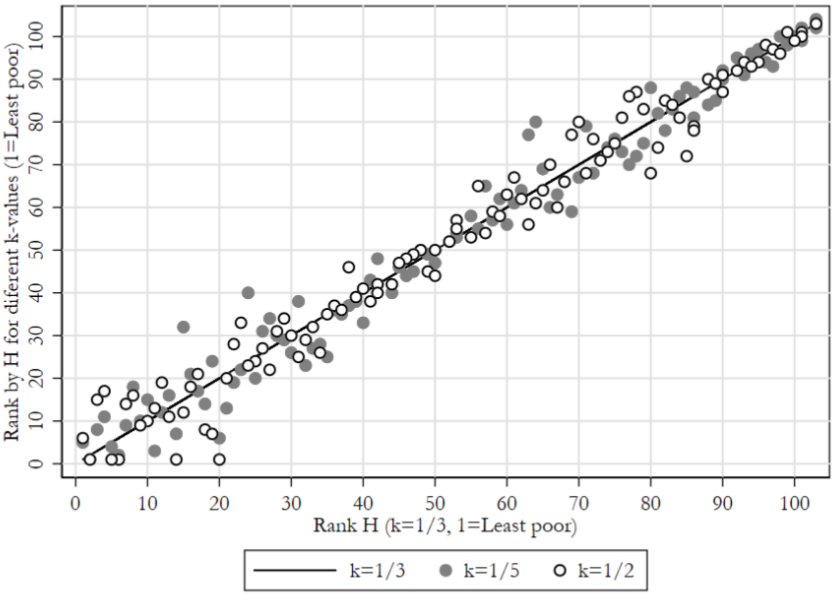
To start describing the robustness of H and MPI to changes in k-values within the relevant neighbourhood, let us discuss the extent to which the *absolute* country poverty orderings shift. We focus on rank changes corresponding to shifts in the position of each country in the poverty ordering. In Figure 7, we plot the country rank by H (panel a) and MPI (panel b) for different k-values against the rank at the baseline (k=1/3)[12]. The closer the points are to the diagonal, the closer the country rank under the alternative k-value is to the rank at the baseline. We can clearly see that MPI orderings are more stable than H orderings, and that this is particularly true for the least poor countries (upper-right side of the plots). The median Euclidean distance of country ranks by H is 3.74, while it is 2.89 for rankings by the MPI. Thus, the adjustment of H by the average intensity of the poor (A) to yield the MPI endows the latter with a higher absolute country rank stability. Partly, this is a consequence of the monotonic nature of H (decreasing) and A (increasing) with respect to k, which attenuates the responsiveness of MPI with respect to k shifts compared to H. But more than a purely technical result, we also argue that this points to the practical superiority of MPI compared to H as for international poverty comparisons.

Going beyond single-country descriptions, let us now focus on country pairwise comparisons following the approach of (Alkire & Santos, 2010, Alkire et al., 2015). We evaluate the extent to which the ordering between pairs of countries established at the baseline specification is preserved if the poverty cutoff shifts *across* the relevant neighbourhood $\left[\frac{1}{5};\frac{1}{2}\right]$, i.e. several different MPI specifications simultaneously. Establishing the order of two countries in terms of their poverty

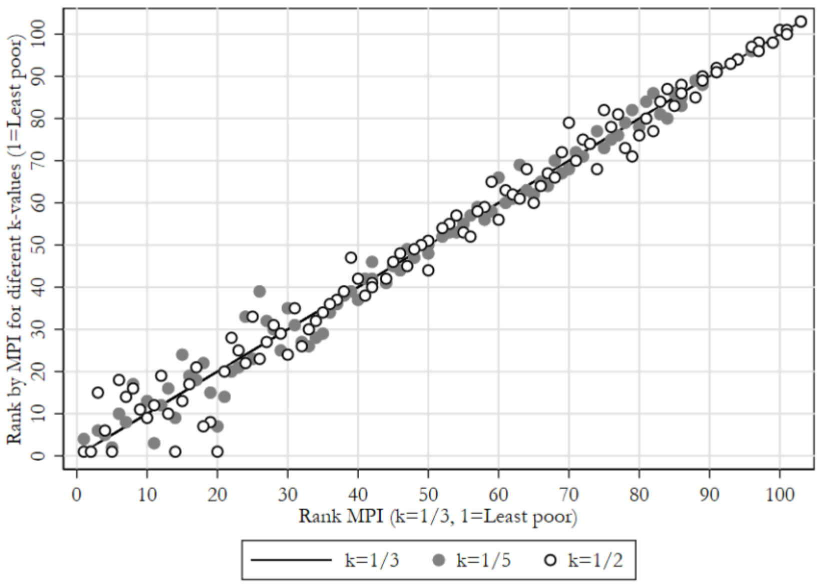
[12] All the rankings for each k value take into account ties detected by hypothesis tests comparing the values of H and MPI for the different countries.

Figure 7. Absolute country poverty orderings by H and MPI for different k-values

Panel (a): H



Panel (b): MPI



relies on statistical hypothesis testing to take sampling error into account. Therefore, we can distinguish three possible outcomes: poverty is significantly higher in one country, the other country, or they are not significantly different from each other. We consider a pairwise comparison to be robust if the pairwise poverty order is preserved across all alternative specifications. One way to summarize the results of these hypotheses tests is to compute the proportion of robust pairwise country orderings of all possible pairwise comparisons, denoted as R_{pwc}. In a variant of this approach we only consider those pairwise comparisons, which we found to be significantly different under baseline, denoted R^{*}_{pwc}. The motivation for this is that significant differences between countries are of particular interest to policy makers.[13] These figures are presented in Table 7.

It is important to consider how to interpret all analyses of pairwise comparisons in what follows. As should be self-evident, it is not possible to assess the extent of robustness across world regions based on the percent of pairwise comparisons alone. Such assessments must consider, in addition, the number of countries being compared, as well as their mean poverty level and the dispersion around it. We thus interpret our results keeping this in mind and take an empirical approach to it. Further research may develop refined methods, which explicitly address these issues.

First, for the pairwise comparisons between the entire set of countries ('Developing world' line in Table 7), around 95% of country pairwise orderings by H and MPI are found to entail significant differences at the baseline. Moreover, we find R^{*}_{pwc} of around 94% for the entire developing world. Alkire & Santos (2014) found a similar rate (95.7%) in a comparable robustness analysis of the 2010 version of the MPI. However, they considered $k = \frac{1}{5}$ and $k = \frac{2}{5}$ as alternative poverty cut-offs, so finding a similar robustness rate even if the upper-limit alternative cut-off is pushed to $k = \frac{1}{2}$ depicts a higher level of robustness of the revised index.

In an analysis by world regions, we find that the overall robustness figures mask stark differences between world regions. R^{*}_{pwc} by MPI is above 90% for every world region except for Europe & Central Asia and South Asia, where it is just over 66% and 80%, respectively although as mentioned above this is not decisive because of the lower number of countries. Overall, the robustness of H as measured by the proportion of robust pairwise comparisons restricted to the significantly different under baseline is lower compared to the MPI (See Table 7).

Having compact summary measures of robustness is undeniable useful, but to be clear, let us stress two elements need to be taken into account to meaningfully interpret the ratios presented in Table 7 (see Alkire & Santos, 2014). The first is that regions with a high number of countries (such as Sub-Saharan Africa) may tend to show higher robustness due to the larger number of comparisons

[13] The formalisation of the ratio is explained in Appendix A.

Table 7. Pairwise comparisons using alternative poverty cutoffs

Region	Countries	Possible Comparisons	Simple mean at baseline	Std. Dev. at baseline	Significant comparisons at baseline		Same ordering: Sig. and non-sig. at Baseline		Same ordering: only sig. at Baseline	
					Number	%	Number	R_{pwc}	Number	R_{pwc}^{*}
					$\boldsymbol{MPI}$					
Dev. World	104	5356	0.160	0.161	5072	94.70	4847	90.50	4765	93.95
AS	13	78	0.110	0.155	73	93.59	70	89.74	69	94.52
EAP	11	55	0.098	0.086	50	90.91	46	83.64	46	92.00
ECA	14	91	0.009	0.013	69	75.82	50	54.95	46	66.67
LAC	20	190	0.047	0.056	163	85.79	166	87.37	149	91.41
SA	7	21	0.165	0.085	21	100.00	17	80.95	17	80.95
SSA	39	741	0.307	0.138	687	92.71	672	90.69	652	94.91
					$\boldsymbol{H}$					
Dev. World	104	5356	30.46	27.90	5065	94.57	4673	87.25	4615	91.12
AS	13	78	20.81	25.84	74	94.87	68	87.18	68	91.89
EAP	11	55	21.20	18.05	49	89.09	43	78.18	43	87.76
ECA	14	91	2.38	3.19	70	76.92	50	54.95	47	67.14
LAC	20	190	10.43	11.49	164	86.32	164	86.32	148	90.24
SA	7	21	34.72	16.93	19	90.48	14	66.67	14	73.68
SSA	39	741	55.88	21.77	683	92.17	603	81.38	591	86.53

Notes: a) AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa. b) R_{pwc} denotes the proportion of country pairwise poverty orderings that are similar in all the alternative k-values. In this proportion, countries that have similar levels of poverty at the baseline specification are taken into account. R_{pwc}^{*} is similar to R_{pwc}, but omits country poverty orderings at the baseline that show undistinguishable poverty levels. c) The publically available data for South Africa (NIDS 2014-15) lacks information about the primary sampling unit and the strata, so standard errors of the estimates for this country cannot be computed.

that are possible. The second element is that regions where the differences between countries in terms of H and MPI are high will tend to show a higher stability because the common range between poverty levels is wider. Our results have to be interpreted taking this into account. Notefor instance, that Europe & Central Asia is the least poor region in the developing world (with simple mean incidence of 2.38% and MPI value of 0.009), and it is *also* the region where the levels of H and MPI are relatively less disperse (with a standard deviations of 3.19% and 0.013, respectively). Thus, the overall low levels of inequality across countries in this region make it difficult to arrive at a stable pairwise ordering by H and the MPI. We stress that is not necessarily a negative result, as it reflects the fact that poverty levels in this region are 'clustered' in the lower extreme, depicting a favourable state of affairs in terms of poverty *and inequality* between countries.

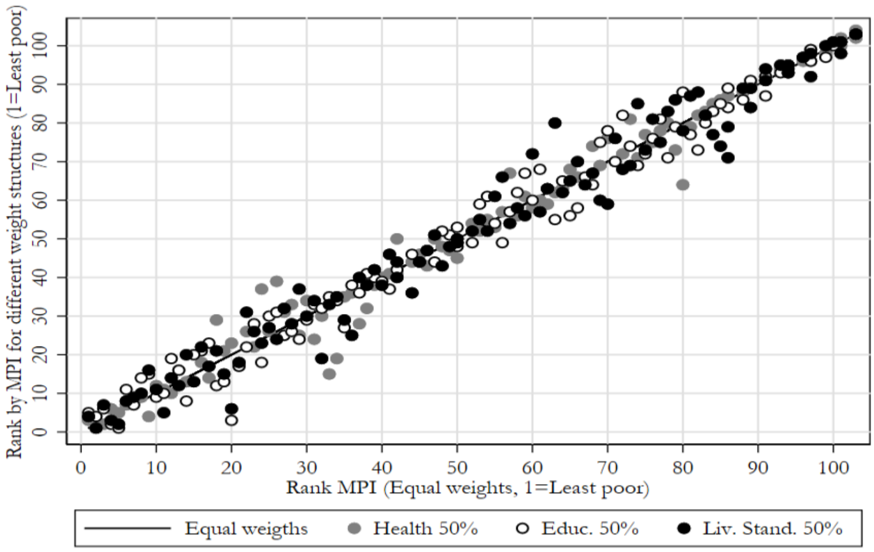
4.2 Shifting the weighting structure

Let us now focus on a robustness analysis to changes in the dimensional weights. In a strict sense, there is an infinite combination of alternative weighs, so a full robustness evaluation is beyond the scope of this paper. We follow Alkire & Santos (2014) and limit ourselves to three sets of plausible weights that could make sense in the practical academic and policy-making spheres, while also being easy to comprehend widely. They consist of considering, in turn, one dimension to be twice as important as the other two. Effectively, these alternative weights are computed based on different arrangements of the trio (25%, 25%, 50%) (see Foster et al., 2013).

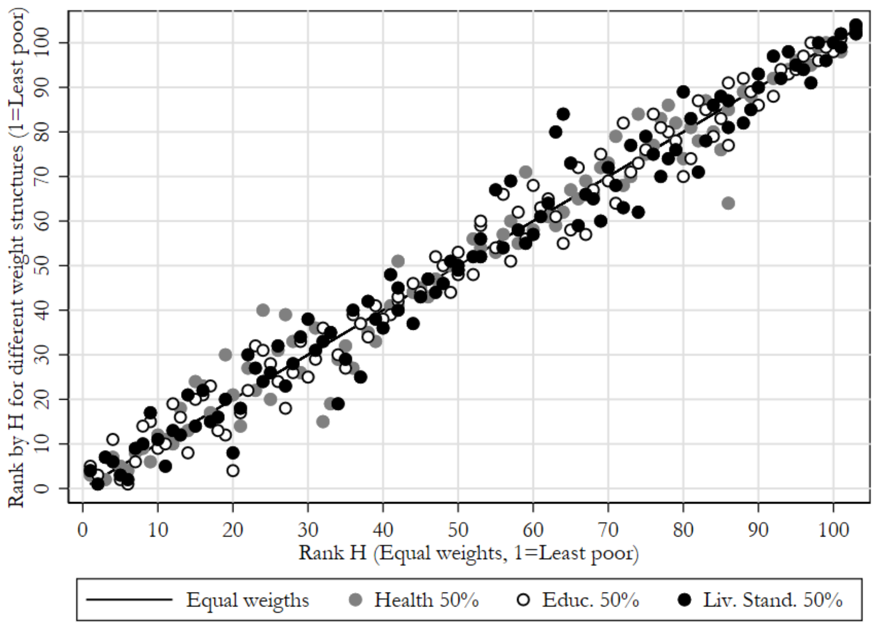
Let us first conduct a robustness analysis of each country's absolute positions in the poverty orderings by H and MPI. Figure 8 depicts absolute rank shifts due to changes in the weight structure and it is interpreted in the same way as Figure 7. This time, however, we do not observe a dissimilar response of H and MPI to changes in the weight structure. Largely, we can see that the absolute country ranks by H and MPI are preserved under alternative weight structures. The average Euclidian distance with respect to each country's mean rank is 36.08 for H and 35.80 for MPI. This corroborates that absolute rank shifts by both H and MPI are similar in magnitude. Furthermore, we do not observe distinct rank shift patterns arising from giving a 50% weight to any particular dimension, nor do we detect a clear relationship between rank shifts and the country rank at the baseline. These results are important in that they confirm that the absolute country orderings by the global MPI aggregate poverty figures are robust to the relative importance of each dimension in the index.

Figure 8. Absolute country poverty orderings by H and MPI for different weight structure

Panel (a): H



Panel (b): MPI



Let us now turn to a country pairwise comparisons analysis. Following the same approach introduced above, we now assess the robustness of the baseline measure of pairwise poverty orderings across the four weighting structures simultaneously.

We find that 88% of the strict ordering by H at the baseline are preserved across the three alternative weighting structures. In all the world regions, this rate is over 70%, with pairwise country orderings in the Arab States (96%) and Sub-Saharan Africa (81%) being the most robust.

The least robust orderings are found in South Asia (63%), but as mentioned above, that will to some extent be influenced by the small numbers of countries being compared.

Table 8. Pairwise comparisons using alternative dimensional weights

Region	Countries	Possible Comparisons	Simple mean $P(\theta)$ at baseline	Std. Dev. $P(\theta)$ at baseline	Significant comparisons at baseline		Same ordering: Sig. and non-sig. at baseline		Same ordering: only sig. at Baseline	
					Number	%	Number	R_{pwc}	Number	R^*_{pwc}
					MPI					
Dev. World	104	5356	0.160	0.161	5072	94.70	4571	85.34	4553	89.77
AS	13	78	0.110	0.155	73	93.59	70	89.74	70	95.89
EAP	11	55	0.098	0.086	50	90.91	38	69.09	38	76.00
ECA	14	91	0.009	0.013	69	75.82	57	62.64	53	76.81
LAC	20	190	0.047	0.056	163	85.79	133	70.00	130	79.75
SA	7	21	0.165	0.085	21	100.00	14	66.67	14	66.67
SSA	39	741	0.307	0.138	687	92.71	579	78.14	576	83.84
					H					
Dev. World	104	5356	30.46	27.90	5065	94.57	4485	83.74	4475	88.35
AS	13	78	20.81	25.84	74	94.87	71	91.03	71	95.95
EAP	11	55	21.20	18.05	49	89.09	36	65.45	36	73.47
ECA	14	91	2.38	3.19	70	76.92	58	63.74	55	78.57
LAC	20	190	10.43	11.49	164	86.32	131	68.95	130	79.27
SA	7	21	34.72	16.93	19	90.48	12	57.14	12	63.16
SSA	39	741	55.88	21.77	683	92.17	553	74.63	553	80.97

Notes: a) AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa. b) R_{pwc} denotes the proportion of country pairwise poverty orderings that are similar in all the alternative weight structures. In this proportion, countries that have similar levels of poverty at the baseline specification are taken into account. R^*_{pwc} is similar to R_{pwc}, but omits country poverty orderings at the baseline that show undistinguishable poverty levels. c) We can only perform pairwise comparisons between 104 out of the 105 considered countries. The publically available data for South Africa (NIDS 2014-15) lacks information about the primary sampling unit and the strata, so standard errors of the estimates for this country cannot be computed.

Similar robustness patterns for all the world regions are found among the strict orderings by the $\boldsymbol{MPI}$ at the baseline (Table 8). Almost 90% of all pairwise comparisons that are significant at the baseline are preserved across all the considered alternative weighting structures. A directly comparable analysis was conducted in Alkire & Santos (2014) for the 2010 global MPI specification, where they found a rate of 88.9%. We can thus affirm that the country ordering by the 2018 specification of this index is no less stable as the original one to changes in the dimensional weights.

5. The revised and original global MPI: an empirical comparison

To empirically evaluate the consequences of the revision, we produced estimates for the original version with the exact same data used for the estimation of the revised version. In that sense, our figures do not actually reflect the original MPI values reported in 2010 (UNDP, 2010; Alkire & Santos, 2014), but rather a set of counterfactual estimations that are useful only for evaluative purposes. We compare actual (revised specification) and counterfactual (original specification) figures in three ways. First, we focus on differences between aggregate MPI figures, then we assess differences in indicator deprivation headcount ratios and finally, we perform a country pairwise comparison analysis between the 2010 and 2018 indicator specifications using the 2018 datasets.

In a nutshell, we find that the range of the overall, global proportion of people who live in multidimensional poverty (H) is very similar after the revision. With 95% confidence, the level of H level ranges between 22.6% - 23.9% in the revised specification and 23.4% - 24.7% in the original one. In that sense, the differences induced by the revision are certainly small; however given the large sample at hand (and the ensuing small standard errors for our estimates), proper hypothesis tests on the difference of H between both specifications show that the difference, although small, is statistically significant (see Table 9). Importantly however, even this strict way of assessing robustness results in a *non-statistically significant* difference for the proportion of poor people in Sub Saharan Africa, the poorest region in the world. This is also true for Europe & Central Asia if we take a 1% significance level. The similar range of poverty incidence in these regions directly implies a similarly stable nature of the number of people identified as poor in both specifications.

Turning now to the intensity of poverty, A, we find that it has significantly shifted in every region due to the revision. It ranges between 49.3% - 49.7%, in the revised specification, and between 45.3% - 45.9% in the original one. The biggest intensity shift is found in Europe & Central Asia (+15.3 percentage points), followed by Latin America & the Caribbean (+10.4 pp).

Finally, the MPI levels for the whole developing world range between 0.112-0.119 in the revised specification and 0.116-0.123 in the original one. The level of the index is around the same range after the revision, although the statistically significant shifts in A (and in H for some regions) yields statistically significant differences for the MPI as well. (see Table 9).

Table 9. MPI and its components by world region and specification

	H (%)						
	2010 specif.		2018 specif.				
	Mean	SE	Mean	SE	Diff	SE	p value
World	24.08	0.33	23.24	0.33	0.84	0.06	0.000
AS	17.93	0.40	19.23	0.41	-1.30	0.09	0.000
EAP	7.63	0.34	5.85	0.33	1.78	0.14	0.000
ECA	2.17	0.12	2.37	0.13	-0.19	0.08	0.020
LAC	6.84	0.14	7.69	0.16	-0.86	0.08	0.000
SA	32.43	0.29	31.28	0.30	1.15	0.10	0.000
SSA	57.91	2.97	57.73	3.04	0.18	0.13	0.169
	A (%)						
	2010 specif.		**2018 specif.**				
	Mean	**SE**	**Mean**	**SE**	**Diff**	**SE**	**p value**
World	45.62	0.16	49.50	0.12	-3.88	0.07	0.000
AS	44.86	0.39	50.82	0.27	-5.96	0.17	0.000
EAP	36.88	0.47	43.06	0.31	-6.18	0.41	0.000
ECA	22.91	0.78	38.25	0.27	-15.34	0.66	0.000
LAC	32.76	0.36	43.19	0.18	-10.43	0.32	0.000
SA	41.92	0.24	45.76	0.20	-3.83	0.10	0.000
SSA	52.21	0.24	54.87	0.17	-2.66	0.10	0.000
	MPI						
	2010 specif.		**2018 specif.**				
	Mean	**SE**	**Mean**	**SE**	**Diff**	**SE**	**p value**
World	0.120	0.002	0.115	0.002	0.005	0.000	0.000
AS	0.092	0.002	0.098	0.002	-0.006	0.000	0.000
EAP	0.033	0.001	0.025	0.001	0.008	0.001	0.000
ECA	0.008	0.000	0.009	0.001	-0.001	0.000	0.021
LAC	0.030	0.001	0.033	0.001	-0.003	0.000	0.000
SA	0.150	0.002	0.143	0.002	0.007	0.000	0.000
SSA	0.321	0.017	0.317	0.017	0.004	0.001	0.000

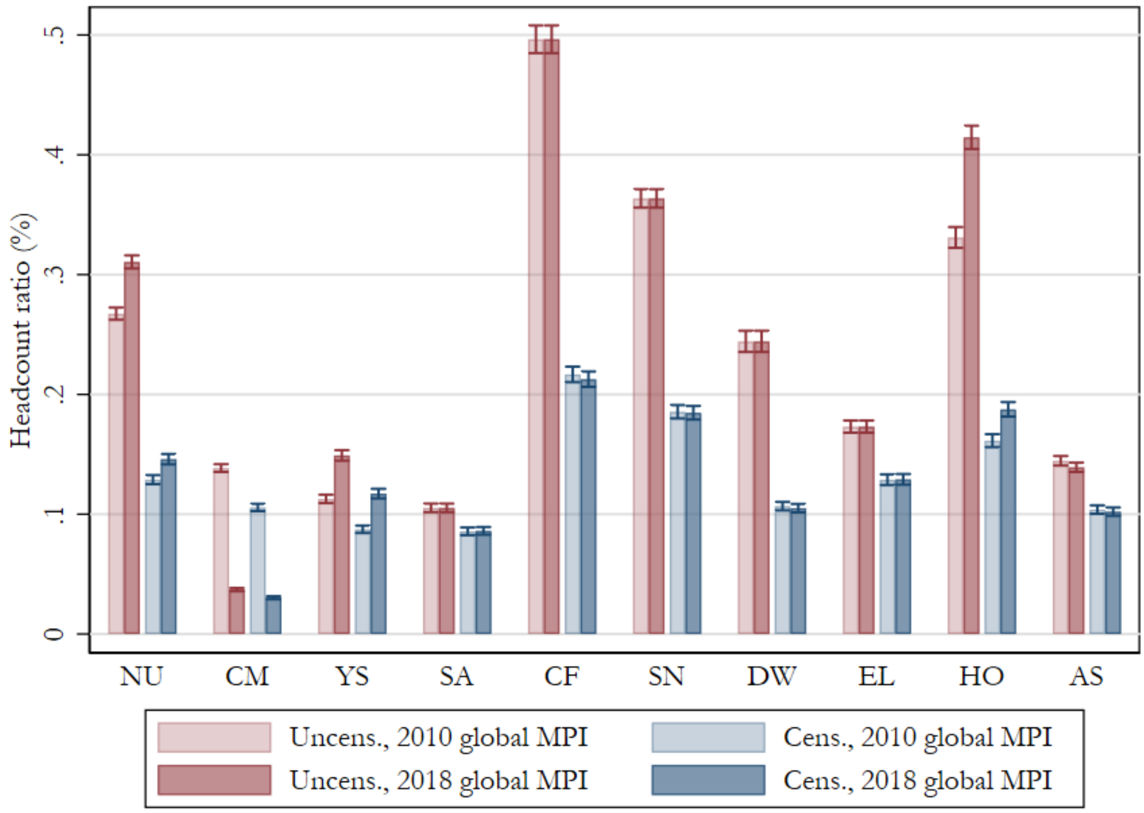
Note: AS: Arab States; EAP: East Asia & the Pacific; ECA: Europe & Central Asia; LAC: Latin America & the Caribbean; SA: South Asia; SSA: Sub-Saharan Africa.

In order to gain a more in-depth insight about changes in the intensity of poverty, let us present a disaggregated analysis by indicator. Not only will we present how the revision modified the prevalence of deprivations among the poor (censored headcount ratios), but also among the entire population (uncensored headcount ratios).

The deprivation headcount ratios corresponding to four out of the five revised indicators have significantly increased in the revised specification. The only exception is the *assets* indicator, for which censored and uncensored headcount ratios remained unchanged, despite the inclusion of two items - computer and animal cart in the revision. This result is aligned with Vollmer & Alkire (2018) who found that these two items have relatively low difficulty and discrimination parameters in an Item-Response Theory analysis. This reflects that they are likely to be associated with the other items included in the assets indicator.

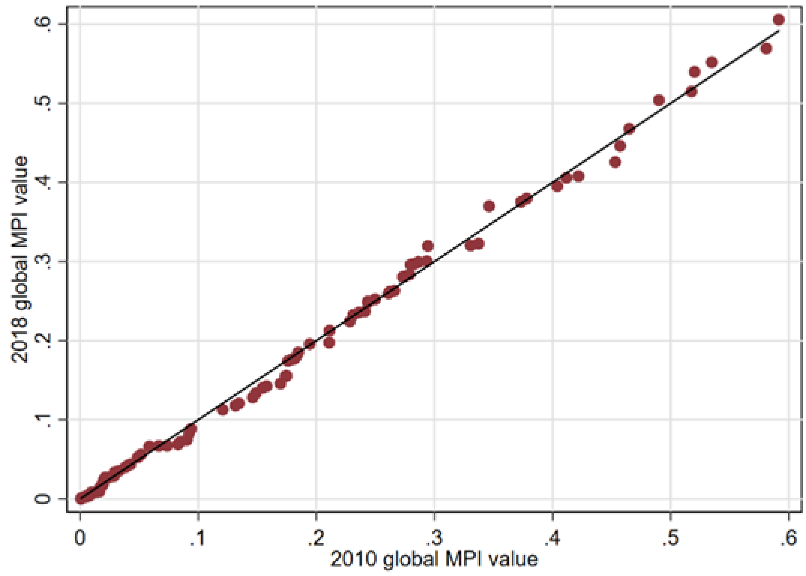
The censored and uncensored deprivations in *child mortality* are dramatically lower in the revised global MPI – by around 10 percentage points (see Figure). This is because the revised indicator only considers deaths occurred during the last five years preceding the survey – as opposed to the household ever having suffered the death of a child in the original version of the global MPI. The lower headcount ratios observed in the revised index are more accurate as well as policy-salient. This is in line with the success in reducing the global under-five mortality rate by more than half between 1990 and 2015 (90 to 43 per 1000 children) (UN, 2015). Similarly, You et al. (2015) have estimated that around 94 million children would die before they are 5 years old by 2030 if each country maintains their observed mortality rate in 2015. However, they also estimate that more than one-fourth of these could be prevented if each country manages to keep the average 2000-2015 average annual reduction pace between 2016 and 2030.

Figure 9. Censored and uncensored headcount ratios by specification



Note: a) NU: nutrition; CM: child mortality; YS: years of schooling; SA: school attendance; CF: cooking fuel; SN: sanitation; DW: drinking water; E: electricity; HO: housing; AS: assets. b) Vertical lines represent 95% confidence intervals.

Figure 10. Quintile-quintile plot: Global distributions of MPI



Conversely, the censored and uncensored deprivation headcount ratios corresponding to *nutrition, education* and *housing* are all higher in the new version of the MPI – by around 4 pp., 3pp. and 8pp., respectively. In the revision, these indicators have been assigned more demanding deprivation cut-offs, which better align with the new international standards evinced in the SDG indicators.

In a more detailed cross-country analysis, we find that the MPI distribution across the 105 considered countries has remained largely unchanged. As depicted in the quantile-quantile plot in Figure 10, the shape of both MPI structures' distributions is similar. Their corresponding quantiles match closely and no systematic differences can be detected across the entire observed range of MPI values. Such a close distributional resemblance probably translates into a highly robust country ordering by the MPI (Alkire et al., 2015). To explore this, we performed a pairwise comparison analysis where the alternative specification is defined as the original definition of indicators.

Taking into account both significant and non-significant poverty orderings at the baseline (i.e. the revised specification), 93.02% of the possible country pairwise comparisons are identical in both MPI versions (4982 out of 5356). This rate can be interpreted a summary figure of the overall robustness of the MPI to the revision. To gauge the robustness of strict poverty orderings only, we can focus on 86.07% of the possible pairwise comparisons (4610 out of 5356) that are found to be strict in the 2018 MPI specification. Practically all of them (99.15%) are identical in the 2010 specification (4571 out of 4610). In our view, this is a quite powerful result showing that MPI revision manages to better identify deprivations, while maintaining country poverty orderings largely unchanged.

6. Concluding remarks

In 2018, the definitions of five of the ten global MPI indicators were revised. The motivation for the revision was to align the global MPI closer to the 2030 development agenda, and this was made possible by improvement and expansion in indicator availability in surveys.

This is the first paper to provide comprehensive analyses of the poverty pattern in the developing regions of the world using the revised global MPI. The empirical assessment is focused on three aspects. First, we assess the extent to which people experience overlapping deprivations across indicators and provide insights on the state of multidimensional poverty across world regions, and by their urban-rural locations and age groups. Second, we test the robustness of the revised global MPI to changes in poverty cutoffs and dimensional weights. Third, we extend the robustness analyses by comparing the poverty patterns and country poverty ranking between the original and revised global MPI.

Considering the global MPI indicators, between 81% and 99% of the population in the developing world who are deprived in one indicator experience one or more additional deprivations. This striking finding confirms the interlinkages across deprivations and the need to view them jointly. However joint distributions vary: the proportion of persons who are only deprived in one indicator, or in two, three or up to nine additional indicators, varies greatly across the ten considered indicators.

The global MPI identification strategy censors the deprivations of non-poor persons. Exploration of the patterns by indicator across all major world regions and using different poverty cutoffs reveals stark regional differences in terms of the prevalence of indicators and extent of censoring. This underscores the value added of a counting approach in bringing different patterns of interlinkages across deprivations into a common framework.

Across the entire set of countries, 94% to 95% of country pairwise orderings by H and MPI are robust for poverty lines from 20% to 50%, and almost 90% of country pairwise comparisons for MPI (88% for H) are robust across the weighting scheme of 25% to 50% per dimension. Comparing these results to the original MPI we find that revised global MPI country orderings across a plausible set of poverty cutoffs and weights are no less stable than the original MPI.

Estimating the global MPI is not short of challenges. One sustained challenge is basing the estimates on a more recent data. For the revised global MPI data applied in this paper, the most recent surveys that were available for Azerbaijan, Djibouti, Somalia and Uzbekistan were carried out in 2006; and in Vanuatu it was 2007. We recognise that the population in these countries is small, as such, unlikely to change the global poverty pattern presented in this paper. However, poverty measurement must strive to capture people's most recent lived experience. The second challenge is the limited indicator availability within the surveys used. We had hoped to augment the revised global MPI with additional dimensions such as on work, security, to name a few. This proved challenging as data related to these dimensions at a global scale is non-existing. These remain as missing dimensions. We recognize that quantity and quality of internationally comparable multi-topic household surveys have improved significantly in the last decade. The DHS is typically updated, on average every, five years while MICS increasingly has coverage for every three years. Yet, there is scope for a continuous call on reducing the gap between survey releases and improving data.

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Appendix A

In this paper we consider several different MPI specifications $\theta_s = \{\theta_0, \dots, \theta_S\}$, where each generic element θ_s represents a vector containing all information needed to define an MPI: the matrix of defined deprivation indicators, the weighting structure, and the poverty cutoff. θ_0 represents the baseline specification with the poverty cutoff $k = 1/3$ and equal dimensional weights. The other remaining specifications only deviate in one particular way from our baseline (i.e. they either apply a different poverty cutoff, a different set of weights or indicator definitions). In order to systematically assess poverty ordering of countries across specifications, we follow Alkire & Santos (2014) (cf. Alkire et al., 2015) in calculating the share of robust pairwise comparisons, which explicitly takes sampling errors into account.

We first assess the poverty levels differences for each possible distinct unordered pair of countries (u, v) (with $u \neq v$), for a given MPI specification θ_s. Taking the MPI value as the poverty measure defining the country orderings, we apply *one* of the following tests depending on the sign of the difference of the point estimates:

- If we observe $\widehat{MPI}(u|\theta_s) - \widehat{MPI}(v|\theta_s) > 0$, we test the null hypothesis $\mathcal{H}_0: MPI(X_u|\theta_s) \leq MPI(X_v|\theta_s)$ against the alternative $\mathcal{H}_a: MPI(X_u|\theta_s) > MPI(X_v|\theta_s)$
- If we observe $\widehat{MPI}(u|\theta_s) - \widehat{MPI}(v|\theta_s) < 0$, we test the null hypothesis $\mathcal{H}_0: MPI(X_u|\theta_s) \geq MPI(X_v|\theta_s)$ against the alternative $\mathcal{H}_a: MPI(X_u|\theta_s) < MPI(X_v|\theta_s)$

Note that these tests can be evaluated using a z-statistics and that we can safely assume independent samples between any pair of countries. Similar tests can be conducted in the same way for other poverty measures such as H.

The same tests are carried out for every (alternative) parametrization θ_s. We call a pairwise comparison between countries u and v robust if we observe the same ordering for all alternative parameter choices considered. We record our results as follows:

$$r_{pwc}(u, v) = \begin{cases} 1 \text{ if } (\mathcal{H}_0 \text{ is not rejected } \forall \theta_s) \vee (\mathcal{H}_0\ is \text{ rejected } \forall \theta_s) \\ 0\ otherwise \end{cases}$$

One way to summarise our test results is then to count all pairwise robust comparisons, denoted as n_r, and normalise this count using the number of possible pairwise comparisons, n_p. The number of possible pairwise comparisons can be obtained as $0.5U(U - 1)$, which in our case is

$0.5 \times 104 \times (104 - 1) = 5356$ possible pairwise comparisons. We can then express the share of pairwise robust comparison as:

$$R_{pwc} = \frac{n_r}{n_p}$$

A variation of this approach is to disregard tied ranks and take only those pairwise comparisons into account, which were significantly different for the baseline specification θ_0. In this case we consider a pairwise comparison to be robust only if we can reject the respective $\mathcal{H}_0$ for all θ_s. The motivation for this approach is that from a policy perspective significant differences tend to receive particular attention. We record our test results as:

$$r^*_{pwc}(u,v) = \begin{cases} 1 \text{ if } \mathcal{H}_0 \; is \text{ rejected } \forall \theta_s \\ 0 \; otherwise \end{cases}$$

Moreover, for this variation, the maximum number of possible pairwise comparison corresponds to those that were significantly different under the baseline MPI specification θ_0, which we denote as n^*_p. Finally, we write the respective share as:

$$R^*_{pwc} = \frac{n^*_r}{n^*_p}$$