OPHI MPI METHODOLOGICAL NOTE 53

The global Multidimensional Poverty Index (MPI) 2022 disaggregation results and methodological note

Sabina Alkire*, Usha Kanagaratnam* and Nicolai Suppa*

October 2022

Acknowledgements

We are truly grateful to the teams at the Demographic Health Surveys (under Sunita Kishor) and the Multiple Indicator Cluster Surveys (under Attila Hancioglu) for their continuous dedication, advice and support. We are also thankful to colleagues at the Planning Institute of Jamaica for their generous support and sharing the Jamaica Survey of Living Conditions for this work. We warmly acknowledge the advice received from Roberto Castillo, Executive Director of the National Institute of Statistics and Censuses (Instituto Nacional de Estadística y Censos) in relation to the Ecuador dataset. We acknowledge the technical assistance we received from Dyah Savitri Pritadrajati and Rolando Gonzales in the global MPI 2022 work. All errors remain our own.

* The Oxford Poverty and Human Development Initiative (OPHI), Oxford Department of International Development, University of Oxford. Contact details: ophi@qeh.ox.ac.uk Tel +44 1865 271915.

This note has been prepared within the OPHI theme on multidimensional poverty measurement.

Attribution

The estimates of MPI and its partial indices are disaggregated by several different population groups: age groups (OPHI's Table 3), urban and rural areas (Table 4), subnational regions (Table 5) and gender of household head (Table 7). All Tables based on disaggregated analysis are produced by Sabina Alkire, Usha Kanagaratnam and Nicolai Suppa.

Suggested citation of this methodological note

Alkire, S., Kanagaratnam, U., and Suppa, N. (2022). 'The global Multidimensional Poverty Index (MPI) 2022 disaggregation results and methodological note', OPHI MPI Methodological Note 53, Oxford Poverty and Human Development Initiative (OPHI), University of Oxford.

Contents

1. Overview

This Methodological Note presents the methodology and technical decisions that underlie the published **disaggregation** results (age groups, rural and urban areas, subnational regions and gender of household head) of the global Multidimensional Poverty Index (MPI) 2022. The 2022 MPI **disaggregation** results are based on the most recent data from 111 countries, covering 6.1 billion people. We estimate the MPI and its associated statistics by four age categories (0 to 9 years, 10 to 17 years, 18 to 59 years, and over 60 years) as well as two broad age categories covering children aged 0 to 17 years and adults 18 years and older, by rural and urban areas, and gender of the household head. In addition, the MPI is also computed for 1,287 subnational regions to show disparities in poverty within countries. Subnational disaggregations are published when the survey used for the global MPI is representative at the subnational level and the retained sample permits.

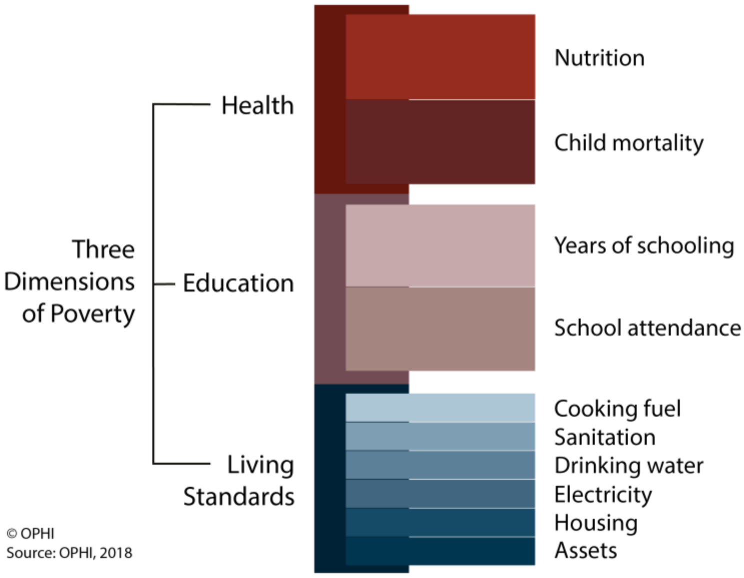
This document is structured as follows. Section 2 presents the global MPI structure and indicator definitions. Section 3 provides an outline of the global MPI and its partial indices that we estimate and publish. Section 4 outlines the disaggregation methodology. Section 5 outlines the principles and decisions that underlie our disaggregation work. Section 6 summarises the country-specific decisions that were applied for the new or updated datasets in this round. We conclude with brief closing summary.

2. The global MPI structure[1]

The global MPI, published annually since 2010, captures acute multidimensional poverty in developing regions of the world (Alkire and Santos, 2014 & 2010). This measure is based on the dual-cutoff counting methodology developed by Alkire and Foster (2011). The global MPI is composed of three dimensions (health, education, and living standards) and ten indicators (Figure 1). Each dimension is equally weighted, and each indicator within a dimension is also equally weighted. In 2018, the first major revision of the global MPI, that is, the adjustments in the definition of five out of the ten indicators was undertaken (see Alkire, Kanagaratnam, Nogales and Suppa, 2022a; Alkire and Kanagaratnam, 2021; Vollmer and Alkire, 2022).

[1] The text in this section draws on methodological notes published for previous rounds of the global MPI and the book by Alkire, Foster, Seth et al. (2015). It is useful to include similar text in each methodological note, in order to provide an overview of the global MPI structure, as well as MPI and its partial indices to first-time users of the global MPI data.

Figure 1. Composition of the Global MPI – Dimensions and Indicators



The global MPI begins by establishing a deprivation profile for each person, showing which of the 10 indicators they are deprived in. Each person is identified as deprived or non-deprived in each indicator based on a deprivation cutoff (Table 1). In the case of health and education, each household member may be identified as deprived or not deprived according to available information for other household members. For example, if any household member for whom data exist is undernourished, each person in that household is considered deprived in nutrition. Taking this approach – which was required by the data – is intuitive and assumes shared positive (or negative) effects of achieving (or not achieving) certain outcomes. Next, looking across indicators, each person's deprivation score is constructed by adding up the weights of the indicators in which they are deprived. The indicators use a nested weight structure: equal weights across dimensions and an equal weight for each indicator within a dimension.

Table 1. Global MPI – Dimensions, Indicators, Deprivation Cutoffs, and Weights

Dimensions of poverty	Indicator	Deprived if...	SDG area	Weight
Health	Nutrition	Any person under 70 years of age for whom there is nutritional information is **undernourished**.[1]	SDG 2	1/6
	Child mortality	A child **under 18** has **died** in the household in the five-year period preceding the survey.[2]	SDG 3	1/6
Education	Years of schooling	**No** eligible household member has completed **six years** of **schooling**.[3]	SDG 4	1/6
	School attendance	Any school-aged child is **not attending** school **up to** the age at which he/she would complete **class 8**.[4]	SDG 4	1/6
Living Standards	Cooking fuel	A household cooks using **solid fuel**, such as dung, agricultural crop, shrubs, wood, charcoal, or coal.[5]	SDG 7	1/18
	Sanitation	The household has **unimproved** or **no** sanitation **facility** or it is improved but **shared** with other households.[6]	SDG 6	1/18
	Drinking water	The household's source of **drinking water** is **not safe** or safe drinking water is a **30-minute** or **longer walk** from home, roundtrip.[7]	SDG 6	1/18
	Electricity	The household has **no electricity**.[8]	SDG 7	1/18
	Housing	The household has **inadequate** housing materials in **any** of the three components: **floor**, **roof**, or **walls**.[9]	SDG 11	1/18
	Assets	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.	SDG 1	1/18

Notes: The global MPI is related to the following SDGs: No Poverty (SDG 1), Zero Hunger (SDG 2), Health and Well-being (SDG 3), Quality Education (SDG 4), Clean Water and Sanitation (SDG 6), Affordable and Clean Energy (SDG 7), and Sustainable Cities and Communities (SDG 11).

[1] Children under 5 years (60 months and younger) are considered undernourished if their z-score of either height-for-age (stunting) or weight-for-age (underweight) is below minus two standard deviations from the median of the reference population. Children 5–19 years (61–228 months) are identified as deprived if their age-specific BMI cutoff is below minus two standard deviations. Adults aged 20 to 70 years (229–840 months) are considered undernourished if their Body Mass Index (BMI) is below 18.5 m/kg^2.

[2] The child mortality indicator of the global MPI is based on birth history data provided by mothers aged 15 to 49. In most surveys, men have provided information on child mortality as well but this lacks the date of birth and death of the child. Hence, the indicator is constructed solely from mothers. However, if the data from the mother are missing, and if the male in the household reported no child mortality, then we identify no child mortality in the household.

[3] If all individuals in the household are in an age group where they should have formally completed 6 or more years of schooling, but none have this achievement, then the household is deprived. However, if any individuals aged 10 years and older reported 6 years or more of schooling, the household is not deprived.

[4] Data source for the age children start compulsory primary school: DHS or MICS survey reports; and http://data.uis.unesco.org/.

[5] If the survey report uses other definitions of solid fuel, we follow the survey report.

[6] A household is considered non-deprived in sanitation if it has some type of flush toilet or latrine, or ventilated improved pit or composting toilet, provided that they are not shared. If the survey report uses other definitions of improved sanitation, we follow the survey report

[7] A household is considered non-deprived in 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. It must also be within a 30-minute walk, round trip. If the survey report uses other definitions of improved drinking water, we follow the survey report.

[8] A small number of countries do not collect data on electricity because of 100% coverage. In such cases, we identify all households in the country as non-deprived in electricity.

[9] Deprived if floor is made of natural materials or if dwelling has no roof or walls or if either the roof or walls are constructed using natural or rudimentary materials. The definition of natural and rudimentary materials follows the classification used in country-specific DHS or MICS questionnaires.

3. The global MPI and its partial indices

The global MPI person is identified as multidimensionally poor or MPI poor if they are deprived in at least one-third of the weighted MPI indicators. After the poverty identification step, we aggregate across individuals to obtain the **incidence** of poverty or headcount ratio (H) which represents the percentage of poor people in the population. We then compute the **intensity** of poverty (A), representing the average percentage of weighted deprivations experienced by the *poor*. We then compute the adjusted poverty headcount ratio (M_0) or **MPI** by combining H and A in a multiplicative form (MPI = H x A). A headcount ratio is also estimated using two other poverty cutoffs. Individuals are identified as **vulnerable** to poverty if they are close to the one-third threshold, that is, if they are deprived in 20 to 33.33 percent of weighted indicators. The tables also apply a higher poverty cutoff to identify those in **severe poverty**, meaning those deprived in 50 percent or more of the dimensions.

The AF methodology has a property that makes the global MPI even more useful—dimensional breakdown. This property makes it possible to consistently compute the percentage of the population who are multidimensionally poor and simultaneously deprived in each indicator. This is known as the **censored headcount ratio** of an indicator. The weighted sum of censored headcount ratios of all MPI indicators is equal to the MPI value.

The censored headcount ratio shows the extent of deprivations among the poor but does not reflect the weights or relative values of the indicators. Two indicators may have the same censored headcount ratios but different contributions to overall poverty, because the contribution depends both on the censored headcount ratio and on the weight assigned to each indicator. As such, a complementary analysis to the censored headcount ratio is the **percentage contribution** of each indicator to overall multidimensional poverty.

4. Subgroup disaggregation or decomposability

A component of the AF method is the link between overall poverty and poverty in different subgroups of the population. Decomposable and subgroup-consistent poverty measures (Foster Greer and Thorbecke, 1984, Foster and Shorrocks 1991) fulfil the property that the change in overall (national) poverty is consistent with the change in subgroup poverty (examples of subgroups: age groups, urban-rural areas, subnational regions, gender of household head, ethnicity, special abled, to name a few). For example, assuming the entire society is divided into three population subgroups (e.g. subnational regions): region 1, region 2, and region 3. Poverty in region 1 remains unchanged while poverty in region 2 and region 3 decreases. The overall poverty, that reflects subgroup poverty, must decrease. Population subgroup decomposability specifies that overall poverty (national level) is a population-share weighted sum of subgroup poverty levels. This principle is useful for monitoring progress in different subgroups of the population in a country and comparing it with aggregate national poverty.

Using the same procedure for national estimates, we disaggregate the country-level **MPI**, **H**, **A**, **vulnerable** to poverty and **severe poverty** by each population subgroup: age groups, urban-rural areas, subnational regions, and gender of household head. The population share for each subgroup is obtained by applying the sampling weight in the respective survey dataset to the final sample used for the computation of the reported statistics.

We compute the **censored headcount ratios of each subgroup** to show the extent of deprivation among the poor in the subgroup. In addition, we compute the weighted **contribution of each indicator** to poverty for each subgroup.

The survey datasets used in global MPI 2022 are collected in different years. The survey used ranges between 2010 to 2020-2021. We rescale the sampling weights for each national survey so that they add up to the population of that country in the chosen common time period or reference year. This round, we rescaled the weights to add up to the 2020 population size as reported in the World Population Prospects 2022 (UNDESA, 2022). We compute population size for subgroups using a combination of the population share and the 2020 population size to facilitate comparisons of the number of poor in a given subgroup.

All disaggregated estimates are based on the global MPI specification outlined in Alkire, Kanagaratnam and Suppa (2022b). The global MPI disaggregation estimates are produced using the Stata package 'mpitb' developed by Suppa (2022).

5. Disaggregation principles and decisions[2]

Disaggregation by age groups

We disaggregate the MPI and its partial indices by these age groups: 0 to 9 years, 10 to 17 years, 18 to 59 years, and 60+ years, children aged 0 to 17 years and for adults 18 years and older. We use information on 'age of household members' from the household roster to categorise the age information into groups. Age is a self-reported category across most surveys. An exception is the survey for China where age was constructed using birth month and year information. In cases where respondents in the dataset have missing age information, we then exclude these respondents from the computation by age group, though they are included in the national MPI. The number of observations that are missing age data is less than

[2] The principles and decisions for disaggregation estimates of subgroups over time is not a focus of this document. This is detailed in Alkire, Kanagaratnam and Suppa (2022c).

100 across the 111 countries. In this sense, this issue does not affect the population-share weighted sum of age group poverty levels when compared to overall poverty.

Disaggregation by urban-rural areas

We disaggregate the MPI and its partial indices by urban and rural areas in 110 countries. The definition of 'rural' and 'urban' are taken directly from the surveys used to construct the MPI; these definitions may vary across countries. The stratification used in the sample design of the datasets defines the geographic units within which the sample was designed. This determine the possibility for disaggregation by urban and rural areas. Across 109 country surveys, the sample was designed to be self-weighting within urban areas and rural areas. The area variable in the datasets would define the urban and rural areas and we have used this variable for our disaggregation work. In addition, we refer to survey reports produced by data providers to ascertain the sample stratification.

In cases where the sample design was stratified beyond the urban-rural units, we make use of the additional information for disaggregation. In the case of Palestine MICS 2019-2020 dataset, the sample was designed to be self-weighting within urban, rural and camp areas. The MPI estimation at the area level in this country is based on these three categories. In cases where the sample design is stratified to certain areas, we restrict the disaggregation to the area that was sampled. The sample for Argentina MICS 2019-2020 did not cover rural areas mainly due to the cost of survey of these areas, as well as the low share of rural population in Argentina (9% of the total population) (UNICEF and SIEMPRO, 2021). The MPI estimation at the area level in this country is restricted to urban areas.

In the case of Seychelles, the sample is self-weighting at the national level. This means any estimation based on this country sample is restricted to the national level. Following this, information on urban-rural areas are also not made available in Seychelles QFLS 2019 dataset by the survey providers.

Subnational disaggregation

We disaggregate the MPI and its partial indices by 1,287 subnational regions in 100 countries. The decision whether national estimates could be disaggregated at the subnational level was determined by two criteria that were established in our earlier work.[3] These criteria were (1) the sample was representative of subnational regions; and (2) the sample size after the treatment of missing data was reasonably high.

An additional criterion was specified in earlier rounds of the global MPI: the national poverty headcount ratio (H) and the MPI must be large enough (H more than 1.5 percent and MPI greater than 0.005) to

[3] See Alkire and Santos (2014); Alkire, Roche, Santos and Seth (2011).

allow for a meaningful subnational analysis. Since 2018, our estimates are reported along with standard errors estimates and confidence intervals. Poverty measures should be accompanied by standard errors to evaluate their precision and properly rank regions of a country. In cases where the subnational estimates are zero, the standard errors establish whether these are true zeros. As such this criterion is no longer required. We disaggregate by subnational regions of countries with low H and MPI.

The first criterion for disaggregation is that the survey report must establish that the sample is representative at the subnational level following the survey metadata on sample design. In 2022, 106 country surveys fulfilled this criterion. Five countries – Armenia, Bosnia and Herzegovina, Saint Lucia, Seychelles and Tuvalu – have sample sizes that are representative at the national level but not at the subnational level. Hence, these five countries were excluded at this stage.

The second criterion emphasises that the sample size after the treatment of missing data must be reasonably high at the national and subnational levels. For borderline cases, bias analyses are conducted to exclude those cases where the sample reduction leads to statistically significant bias. We specify the second criterion in three ways.

First, the national sample size must be at least 85 percent of the original sample after dropping observations that had missing data in any of the 10 global MPI indicators. This is because a lower sample size may affect accurate comparability across subnational estimations. Following this specific criterion, we identified six countries that did not meet this cutoff (Table 2). The sample drop across these six countries ranges between 17 to 29 percent. Collectively these six countries represent 3 percent of the 6.1 billion people covered in global MPI 2022.

Table 2. Global MPI countries with national sample size below 85 percent of the original sample after missing data is treated

Country	Survey	Year	Total sample size used to compute MPI (weighted)	Total sample drop (weighted)
Georgia	MICS	2018	82%	18%
Maldives	DHS	2016-2017	83%	17%
Mexico	ENSANUT	2020	74%	26%
Montenegro	MICS	2018	80%	20%
South Africa	DHS	2016	78%	22%
South Sudan	MICS	2010	71%	29%

Source: Alkire, S., Kanagaratnam, U., and Suppa, N. (2022b). The global Multidimensional Poverty Index (MPI) 2022 country results and methodological note. *OPHI MPI Methodological Note 52*, Oxford Poverty and Human Development Initiative, University of Oxford.

Second, every subnational region in a country must have a retained sample size of at least 75 percent of the original sample. A smaller sample creates a problem of representativeness for that particular subnational region, which may distort the subnational comparisons. Our analyses indicate that a total of 17 subnational regions across five countries fall short with respect to this sub-criterion (Table 3). The retained sample size across these 17 regions ranges from 56 percent to 75 percent.

Table 3. Subnational regions of five countries with sample size below 75 percent of the original sample after missing data is treated

Country	Survey	Year	Subnational region	Population share of region	Total sample size used to compute MPI (weighted)	Total sample drop (weighted)
Maldives	DHS	2016-2017	Malé	41%	75%	25%
Maldives	DHS	2016-2017	Central Region	7%	74%	26%
Mexico	ENSANUT	2020	Edo México	13%	72%	28%
Mexico	ENSANUT	2020	Frontera	13%	74%	26%
Mexico	ENSANUT	2020	Mexico City	7%	67%	33%
Mexico	ENSANUT	2020	Pacífico-Sur	13%	73%	27%
Mexico	ENSANUT	2020	Península	10%	68%	32%
Montenegro	MICS	2018	Central	55%	73%	27%
South Africa	DHS	2016	Gauteng	26%	71%	29%
South Africa	DHS	2016	Western Cape	11%	56%	44%
South Sudan	MICS	2010	Central Equatoria	13%	64%	36%
South Sudan	MICS	2010	Eastern Equatoria	11%	75%	25%
South Sudan	MICS	2010	Jonglei	15%	70%	30%
South Sudan	MICS	2010	Lakes	8%	66%	34%
South Sudan	MICS	2010	Unity	7%	60%	40%
South Sudan	MICS	2010	Upper Nile	12%	68%	32%
South Sudan	MICS	2010	Warap	14%	67%	33%

Source: Author's computation.

Third, a bias analysis test is carried out for each of the 17 region whose sample size is lower than 75 percent and whose national sample size is lower than 85 percent of the original. We identify the major cause of the sample reduction (in this case, nutrition for all five countries listed above) and divide the entire sample into two groups based on this cause and check the headcount ratios of the other indicators across these two groups. Suppose there is a systematic and statistically significant difference (at a significance level of 1%) between the headcount ratios across these two groups. In that case, that region does not satisfy the bias analysis test. If a region with a large population share (more than 20 percent) within a country does not pass the test, we exclude the country from our subnational analysis.

Following this sub-criterion, we carried out the bias test for the 17 regions with a low retained sample, as well as for regions in Georgia. The results for the regions in Maldives, Montenegro, South Africa, and South Sudan indicate that the likelihood of being deprived in child mortality (as well in other indicators) is not the same for those who are missing the nutrition indicator and those who are not missing this indicator. Those without a missing nutrition indicator are systematically more likely to be deprived in child mortality (or in other indicators). This suggests that the sampling structure would need to be revised to assure representativity as those who are dropped from the sample are likely the non-poor.

Further, Malé and the Central Region collectively account for almost half of the population in Maldives. Across the three major regions of Montenegro, the region of Central is the most populated – 55 percent of the population live in this region. The regions of Gauteng and Western Cape are home to one-third of South Africa's population. In South Sudan, four-fifth of the population live in seven of the regions listed in Table 3. Following the bias observed, we exclude these countries from our subnational analysis.

In the case of Mexico, in the absence of child mortality data, similar results was observed when the bias test was implemented between nutrition and cooking fuel indicators (and other living standard indicators). Five of the regions in Mexico with high sample drop also account for three-fifth of the country's population (Table 3). Thus, Mexico is also excluded from the subnational analysis.

Georgia has a weighted sample loss of 18 percent at the national level, leaving it at the borderline. Two of the 10 subnational regions within the country (Kakheti and Shida Kartli) had a retained sample of 77 percent each. Both regions had the highest missing values for nutrition and child mortality. Those without missing nutrition indicators are systematically more likely to be deprived in child mortality, suggesting that non-poor people are being excluded. Given that the national sample loss is more than 15 percent and two of its subnational regions, home to 45 percent of the population, indicate biased estimates, we exclude Georgia from subnational disaggregation.

In summary, although subnational disaggregation is theoretically possible for 106 of the 111 countries, only 100 countries with 1,287 regions satisfy the principles for subnational disaggregation and are thus used for our subnational analysis.

Disaggregation by gender of household head

Out of the 111 countries included in the 2022 global MPI, disaggregated results by female-headed and male-headed households were produced for 110 countries – all except China. Information on household head and relationship to head of household based on the household listing was not available in China CFPS 2014 data sets. Across all the surveys, household head is a self-reported category. The selection of a household head by householders may be based on a person's economic status (main provider), age hierarchy (older), or cultural preference (men). However, despite the variation in the definition of household head, the value of presenting a global account of multidimensional poverty by the gender of household head is considerable despite the limitation by the mixed definition of headship.

In our microdata work, we constructed the 'gender of household head' variable using information drawn from two variables in the data sets - sex and relationship to household head. It is useful to summarise a couple of data decisions that we made. In a small number of cases, the category 'household head' is not assigned to any household members. In such cases, if information of spouse was available (male or female), we replace them as household head. The number of replacements made was less than 50 observations across the 111 countries. The replacement to the missing value made no difference to the final aggregate numbers.

In the region of Haa of Bhutan, 10 households (home to 84 people) reported two heads: one male head within the economically active age group and one elderly female head. We recoded these households as headed by the male from the economically active age group. The justification for this is that the majority of households in that cluster reported heads in the economically active age group. In the same region, one household (home to 5 members) reported 2 female heads, one from the economically active group and the other an elderly female head. We likewise recoded the household as headed by the female from the economically active age group. However, the number of observations with this particular issue is small that it does not affect the final results observed for Bhutan.

6. Country-specific considerations

This section details the country-specific disaggregation decisions for each of the 15 new or updated countries included in the global MPI 2022.

Argentina (MICS 2019-2020): The sample for Argentina MICS 2019-2020 did not cover rural areas mainly due to the cost of survey of these areas, as well as the low share of rural population in Argentina (9% of the total population) (UNICEF and SIEMPRO, 2021). The MPI estimation at the area level in this country is restricted to urban areas. The MPI estimates are disaggregated by six regions since the survey sample is representative at this level.

Dominican Republic (MICS 2019): The MPI estimates are computed for 10 geographic regions since the survey sample is representative at this level (ONE and UNICEF, 2021). Our estimates at the area level cover urban and rural areas.

Ecuador (ENSANUT 2018): The survey sample was designed to produce representative estimates for the urban and rural areas and to facilitate disaggregation at the province level (Valdivieso, Albán, and

Nabernegg, 2019). We estimate the MPI and its associate statistics for 25 provinces since the survey sample is representative at this level; as well as for urban and rural areas.

Gambia (DHS 2019-2020): The survey sample is representative for the urban and rural areas, two urban municipalities (Banjul and Kanifing) and six Local Government Areas (GBoS and ICF, 2021). We publish the MPI estimate and its associate statistics for all eight regions and urban and rural areas.

Honduras (MICS 2019): The sample design of this dataset was designed to produce reliable estimates for urban and rural areas, for the two main cities of the departments of Cortés and Francisco Morazán, and for the 18 departments (National Institute of Statistics and the Secretary of Health of Honduras, 2021). As such, our subnational estimates cover 20 regions of this country since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

India (DHS 2019-2021): The sample for this dataset was designed to provide estimates for urban and rural areas, and for each of the 707 districts, 28 states, and 8 union territories (IIPS and ICF, 2021, p.2). Our subnational estimates cover 36 regions of this country (28 states and 8 union territories) since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

Jamaica (JSLC 2018): The sample design of this dataset was designed to produce reliable estimates for urban and rural areas, and to facilitate disaggregation at the parish level (PIOJ and STATIN, 2021). Our subnational estimates cover 14 parish of this country since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

Malawi (MICS 2019-2020): The sample for this dataset was designed to provide statistically reliable estimates for urban and rural areas, and for the 28 districts (National Statistical Office, 2021, p.355). We estimate the MPI and its associate statistics by districts since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

Mauritania (DHS 2019-2021): This survey was designed to produce representative estimates for urban and rural areas, and for each of the wilayas. The sample for northern wilayas – Inchiri and Tiris Zemour – are grouped into one domain given their small population size (ONS, MS, and ICF, 2021). The capital Nouakchott is subdivided into three wilayas: West Nouakchott, North Nouakchott and South Nouakchott. Our subnational estimates cover all 14 wilayas of this country since the survey sample is representative at this level. Our estimates at the area level cover urban and rural areas.

Mexico (ENSANUT 2020): We do not report estimates for Mexico's nine major subnational regions. This is because the estimates were biased at the subnational level.

Peru (ENDES 2019): The survey sample is representative for the urban and rural areas, 24 administrative regions and the capital district of Callao. We publish the MPI estimate and its associate statistics for all 25 regions; as well as urban and rural areas.

Rwanda (DHS 2019-2020): The survey sample was designed to produce representative estimates for the urban and rural areas, and for each of the five provinces (NISR, MOH, and ICF, 2021). We produced our urban-rural estimates and subnational estimates accordingly.

Samoa (MICS 2019-2020): The sample of this dataset was designed to provide statistically reliable estimates at the national level, for urban and rural areas, and for the four regions of the country (Samoa Bureau of Statistics, 2021). Our urban-rural estimates and subnational estimates are based on the specification of the survey report.

Tuvalu (MICS 2019-2020): The survey sample was designed to produce representative estimates at the national level and for urban and rural areas. This country data was excluded from subnational estimation because the sample is not representative at the subnational level.

Viet Nam (MICS 2020-2021): The sample this dataset was designed to provide statistically reliable estimates for urban and rural areas, and for the six regions (General Statistics Office and UNICEF, 2021). We publish the MPI estimate and its associate statistics for all regions as stated in the survey report; as well as urban and rural areas.

Concluding remarks

This methodological note outlines the principles that underlie poverty estimation in different subgroups of the population, going beyond a national aggregate. The global MPI 2022 covers 111 countries, of which 15 countries have new or updated surveys. We compute estimates of MPI and its partial indices by six major age groups, by rural and urban areas for 110 countries (excluding Seychelles due to lack of data on rural-urban area), by 1,287 subnational regions across 100 countries (excluding 11 countries due to constraints in sample representation or bias in regional estimates) and by the gender of the household head for 110 countries (excluding China due to lack of information on household head). 13 of the 15 countries with new or updated surveys was included in our estimation at the subnational level. Collectively, these 13 countries accounted for 201 subnational regions – now with new or updated estimates.

References

Alkire, S., Kanagaratnam, U., Nogales, R., & Suppa, N. (2022a). Revising the global Multidimensional Poverty Index: Empirical insights and robustness. *Review of Income and Wealth*, DOI 10.1111/roiw.12573.

Alkire, S., Kanagaratnam, U., and Suppa, N. (2022b). The global Multidimensional Poverty Index (MPI) 2022 country results and methodological note. *OPHI MPI Methodological Note 52*, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., Kanagaratnam, U., and Suppa, N. (2022c). A methodological note on the global Multidimensional Poverty Index (MPI) 2022 changes over time results for 84 countries. *OPHI MPI Methodological Note 54*, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., & Kanagaratnam, U. (2021) Revisions of the global multidimensional poverty index: indicator options and their empirical assessment. *Oxford Development Studies*, 49:2, 169-183, DOI: 10.1080/13600818.2020.1854209

Alkire, S., Foster, J.E., Seth, S., Santos, M.E., Roche, J.M. and Ballon, P. (2015). *Multidimensional Poverty Measurement and Analysis: A Counting Approach.* Oxford: Oxford University Press.

Alkire, S. and Santos, M.E. (2014). Measuring acute poverty in the developing world: Robustness and scope of the Multidimensional Poverty Index. *World Development,* vol. 59, pp. 251–274.

Alkire, S. and Foster, J.E. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics*, vol. 95(7–8), pp. 476–487.

Alkire, S., Roche, J.M., Santos, M.E., Seth, S. (2011). Multidimensional Poverty Index 2011: Brief methodological note. *OPHI MPI Methodological Note 05*, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S. and Santos, M.E. (2010). Acute multidimensional poverty: A new index for developing countries. *OPHI Working Paper 38*, Oxford Poverty and Human Development Initiative, University of Oxford.

Foster, J.E., Greer, J., and Thorbecke, E. (1984). A class of decomposable poverty measures. *Econometrica*, 52 (3): 761-766.

Foster, J. E., and Shorrocks, A. F. (1991). Subgroup consistent poverty indices. *Econometrica*, 687-709.

Gambia Bureau of Statistics (GBoS) and ICF. (2021). *The Gambia Demographic and Health Survey 2019-20.* Banjul, The Gambia and Rockville, Maryland, USA: GBoS and ICF.

General Statistics Office and UNICEF. (2021). *Survey measuring Viet Nam Sustainable Development Goal indicators on Children and Women 2020-2021, Survey Findings Report.* Ha Noi, Viet Nam: General Statistics Office

International Institute for Population Sciences (IIPS) and ICF. (2021). *National Family Health Survey (NFHS-5) 2019-21 India*. Mumbai: IIPS.

National Statistics Office (ONE) and UNICEF. (2021). *Multiple Indicator Cluster Survey 2019*, Survey results report. Santo Domingo, Dominican Republic: ONE-UNICEF.

National Institute of Statistics and the Secretary of Health of Honduras. (2021). *National Demographic and Health Survey / Survey of Multiple Indicators by Conglomerates Honduras 2019*. Tegucigalpa: National Institute of Statistics.

National Statistical Office. (2021). *Malawi Multiple Indicator Cluster Survey 2019-20, Survey Findings Report*. Zomba, Malawi: National Statistical Office.

National Office of Statistics (ONS), Ministry of Health (MS), and ICF. (2021). *Mauritania Demographic and Health Survey 2019-2021*. Nouakchott, Mauritania and Rockville, Maryland, USA: ONS, MS, and ICF.

National Institute of Statistics of Rwanda (NISR), Ministry of Health (MOH), and ICF. (2021). *Rwanda Demographic and Health Survey 2019-20 Final Report*. Kigali, Rwanda, and Rockville, Maryland, USA: NISR and ICF.

OPHI. (2018). Global Multidimensional Poverty Index 2018: The Most Detailed Picture to Date of the World's Poorest People. Oxford Poverty and Human Development Initiative (OPHI), University of Oxford. ISBN 978-1-912291-12-0.

Planning Institute of Jamaica (PIOJ) and Statistical Institute of Jamaica (STATIN). (2021). *Jamaica Survey of Living Conditions 2018*. Kingston, Jamaica: A Joint Publication of the Planning Institute of Jamaica and the Statistical Institute of Jamaica.

Samoa Bureau of Statistics. (2021). *Samoa Demographic and Health – Multiple Indicator Cluster Survey 2019-20*, Survey Findings Report. Apia, Samoa: Samoa Bureau of Statistics.

Suppa, N. (2022). mpitb: A toolbox for multidimensional poverty indices. *OPHI Research in Progress 62a*, Oxford Poverty and Human Development Initiative (OPHI), University of Oxford.

United Nations, Department of Economic and Social Affairs, Population Division (UNDESA) (2022). *World Population Prospects 2022*, Online Edition.

UNICEF and SIEMPRO. (2021). *National Survey of Girls, Boys and Adolescents Argentina (MICS) 2019-2020*. Argentina: SIEMPRO.

Valdivieso, K., Alban, A., and Nabernegg, M. (2019). Historical evolution of the National Health and Nutrition Survey 2018. Retrieved from https://www.ecuadorencifras.gob.ec/institucional/home/

Vollmer, F. and Alkire, S. (2022). Consolidating and improving the assets indicator in the global Multidimensional Poverty Index. *World Development*, No. 158, 105997.