OPHI MPI Methodological Note 57

A methodological note on the global Multidimensional Poverty Index (MPI) 2023 changes over time results for 84 countries

Sabina Alkire*, Usha Kanagaratnam**, Nicolai Suppa***

July 2023

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 warmly acknowledge the insights shared by Ivan Gonzalez de la Alba and Herizo Andrianandrasana in regards to the changes over time results for Cambodia and Madagascar respectively. All errors remain our own.

* Sabina Alkire, OPHI, Department of International Development, University of Oxford, sabina.alkire@qeh.ox.ac.uk.

** Usha Kanagaratnam, OPHI, Department of International Development, University of Oxford, usha.kanagaratnam@qeh.ox.ac.uk.

*** Nicolai Suppa, Center for Demographics Studies (a CERCA institute), Autonomous University of Barcelona, Spain and EQUALITAS and OPHI, nsuppa@ced.uab.es.

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

Suggested citation of this methodological note

Alkire, S., Kanagaratnam, U., and Suppa, N. (2023). 'A methodological note on the global Multidimensional Poverty Index (MPI) 2023 changes over time results for 84 countries', OPHI MPI Methodological Note 57, Oxford Poverty and Human Development Initiative.

Attribution

The global Multidimensional Poverty Index (MPI) harmonised level estimates and their changes over time are produced by Sabina Alkire, Usha Kanagaratnam and Nicolai Suppa using 211 harmonised survey datasets. The harmonised level and changes over time results – covering national estimates, and disaggregated estimates by age groups, rural and urban areas, and subnational regions – are published in excel Database labelled as 'Table 6' on OPHI website. Since 2021, a new and well-conceived production process was implemented to provide transparent and user-friendly access which was not possible in earlier work. The authors continue to reference and acknowledge all earlier work.

2011. The changes over time estimates using global MPI specifications was first published by Alkire, Roche and Seth (2011) that compared changes in MPI for ten countries and 158 subnational regions using the DHS data across two periods of time.

2013. Alkire and Roche (2013) published harmonised levels and changes estimates for 22 countries using comparable DHS data across two periods. The methodological specifications were discussed in Alkire, Conconi and Roche (2013). In addition, a country specific analysis on the change in multidimensional poverty in India between 1998-99 and 2005-06 was published by Alkire and Seth (2015).

2014. Alkire and Vaz (2014) published a briefing on the changes over time results for 34 countries and 338 subnational regions. The methodological specifications were highlighted in Alkire, Conconi and Seth (2014). The harmonised estimates were based on comparable DHS datasets across two time periods; for two countries (Ethiopia and Peru) the comparison included three time periods. A paper discussing the descriptive results of the changes estimates for 34 countries and subnational regions was published by Alkire, Roche and Vaz (2017).

2016-2017. Alkire, Jindra, Robles and Vaz (2016) extended the harmonised estimates to include 16 countries, in addition to the previously harmonised 34 countries, extending the publication of harmonised estimates to 50 countries. This round included comparisons using DHS and MICS and for three countries (Nigeria, Senegal and Zimbabwe), the analysis was extended from two to three time periods. This was followed by a special publication that focused on changes in multidimensional poverty among countries in Sub-Saharan Africa (Alkire, Jindra, Robles and Vaz, 2017).

2018. A country specific analysis on the change in multidimensional poverty in India between 2005-2006 and 2015-2016 was published by Alkire, Oldiges and Kanagaratnam (2021).

2019. The 2019 global MPI covered harmonised intertemporal estimations using two data points for 10 countries (Alkire, Kovesdi, Mitchell and others, 2019).

2020. The 2020 global MPI covered harmonised intertemporal estimations using two data points for 80 countries (Alkire, Kovesdi, Mitchell and others 2020).

Table of Contents

1. Overview

This Methodological Note presents the methodology and policies that underlie the harmonised level estimates and their changes over time in multidimensional poverty for 84 countries. 35 of the 84 countries have trends for three points in time; while poverty trends in 45 countries are based on two points in time. Four countries, Gambia, Mexico, Nigeria and Peru, have results for four points in time.

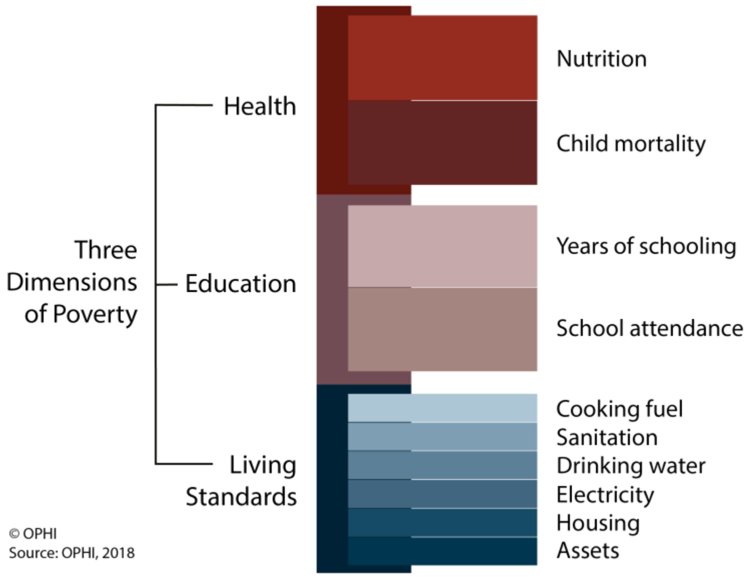
We also estimate how multidimensional poverty changed by four major age categories (0 to 9 years, 10 to 17 years, 18 to 59 years, and over 60 years) and by two age categories covering children aged 0 to 17 years and adults 18 years and older in all countries. Our results also show poverty trends by rural-urban area and by 814 subnational regions. We standardised and harmonised 211 survey datasets to estimate the harmonised levels and changes in multidimensional poverty. Indicator standardisation is detailed in Alkire, Kanagaratnam and Suppa (2023a).

This document, focused on harmonisation methodology and principles, 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 summarises the changes over time methodology. Section 5 provides a summary of the harmonised surveys. Section 6 outlines the principles and decisions that underlie our harmonisation work. Section 7 summarises the country-specific decisions that were applied for the datasets harmonised in this round. We conclude with brief reflections.

2. The global MPI structure

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.

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



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. Alkire, Kanagaratnam, Nogales and Suppa (2022) provide a comprehensive analyses of the consequences of the 2018 revision. The normative and empirical decisions that underlie the revision of the global MPI, and adjustments related to the child mortality, nutrition, years of schooling and housing indicators are discussed in Alkire and Kanagaratnam (2021). The revision of assets indicator is detailed in Vollmer and Alkire (2022).

The global MPI begins by establishing a deprivation profile for each person, showing in which of the 10 indicators they are deprived. 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	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 (mud/clay/earth, sand or dung) or if dwelling has no roof or walls or if either the roof or walls are constructed using natural or rudimentary materials such as such as carton, plastic/ polythene sheeting, bamboo with mud/stone with mud, loosely packed stones, uncovered adobe, raw/reused wood, plywood, cardboard, unburnt brick or canvas/tent. 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

In the global MPI, a 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 (M0) or **MPI** by combining H and A in a multiplicative form (MPI = H x A).

Both the incidence and the intensity of these deprivations are highly relevant pieces of information for poverty measurement. The incidence of poverty is intuitive and understandable by anyone. Yet, the proportion of poor people as the headline figure, does little to shed light on the poorest of the poor. For example, the trends of multidimensional poverty for India between 2005-2006 and 2015-2016 indicate that the poorest states within India had a slower progress by incidence of poverty. However, by MPI value, the poorest states showed the fastest reduction, because the intensity of deprivations experienced by the poorest people in these states reduced much faster compared to those who are less poor (Alkire, Oldiges and Kanagaratnam, 2021). By combining the two pieces of information – the change in intensity of deprivations and the change in proportion of poor people – the MPI captures the progress observed among those in poverty. The MPI puts a spotlight on the poorest of the poor, affirming that they are not left behind in poverty reduction efforts.

A headcount ratio is also estimated using two other poverty cutoffs. The global MPI identifies individuals as **vulnerable** to poverty if they are close to the one-third threshold, that is, if they are deprived in 20 to 33.32 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.

4. Changes over time methodology

Trends are estimated using indicators in the global MPI that are harmonised across the time periods. Harmonisation is necessary to ensure that any differences observed are due to changes in the conditions of poverty in the country rather than changes in the questionnaire. We estimate the harmonised levels of MPI and its partial indices using the harmonised indicators. This is important: in poverty analysis, the headline of interest is often the overall change in poverty measures. People want to know whether poverty has reduced, increased, or remained unchanged over time. Therefore, a prominent component of poverty comparisons is the absolute pace of change across periods or points in time.

Absolute rate of change

The absolute rate of change is the simple difference in poverty levels between two periods. We denote the initial period by t^1 and the final period by t^2. The corresponding achievement matrices for these two periods by X_{t^1} and X_{t^2}, respectively. Note that the parameters of the poverty measure – deprivation cutoffs $\boldsymbol{z}$, weights $\boldsymbol{w_j}$ and poverty cutoff k – used in each period remain unchanged. The absolute rate of change (Δ) is the difference in MPIs between two periods and is computed as (and similarly for H and A, which are not presented):

$$\Delta MPI = MPI(X_{t^2}) - MPI(X_{t^1}).$$

The significance of the difference is determined by t-tests and is reported at 90% (*), 95% (**), and 99% (***) confidence levels in Table 6 on OPHI website.

The absolute rate of change is indifferent to the initial level. For example, a 10-percentage point reduction could mean that the headcount ratio decreased from 80 to 70 percent or from 15 to 5 percent. To look at the proportion of the change with respect to the initial level we use a relative measure.

Relative rate of change

The relative rate of change is the difference in poverty as a percentage of the initial poverty level. Interpreting the analysis of absolute and relative changes together provides a clear sense of overall progress. The relative rate of change $(\delta)$is computed for the MPI (and similarly for H and A, which are not presented) as:

$$\delta MPI = \frac{MPI(X_{t^2}) - MPI(X_{t^1})}{MPI(X_{t^1})} \times 100.$$

Annualised change

However, the absolute and relative changes are not comparable for different countries when the reference periods (duration between survey years) are of different length. To compare the rates of poverty reduction across countries that have different periods of reference, annualised changes are used. The annualised absolute rate of change $(\bar{\Delta})$ is computed for the MPI as:

$$\bar{\Delta}MPI = \frac{MPI(X_{t^2})-MPI(X_{t^1})}{t^2-t^1}.$$

The annualised relative rate of change $\left(\bar{\delta}\right)$ is computed for the MPI as:

$$\bar{\delta}MPI = [(\frac{MPI(X_{t^2})}{MPI(X_{t^1})})^{\frac{1}{t^2-t^1}} - 1] \times 100.$$

We have used the same formula to compute and report annualised changes in the other partial indices, namely H, A, and censored headcount ratios.

For surveys that are fielded between two or more years, the analysis takes the average of the years for calculating annualised change (Alkire, Kovesdi, Mitchell and others, 2020). For instance, in the case of India, we compute changes in poverty using harmonised data from three survey datasets, namely DHS 2005-2006, 2015-2016 and the most recent survey, 2019-2021. The annualised change between 2005-2006 and 2015-2016 is then 2015.5 – 2005.5 = 10 years; while the annualised change between 2015-2016 and 2019-2021 is 2020-2015.5 = 4.5 years.

As a measure of robustness, we also computed annualised change using two alternative approaches in the case of India (Table 2). We assess the implications of two alternative year policies on the change in the headcount ratio, as it is the most sensitive result. The first alternative approach is counting the mean of the month and year of the interviews to produce the annualised change; while the second alternative approach is counting the median instead of the mean. The current approach of the changes over time methodology which takes the average across the survey years shows we are going with a lower bound of possible absolute annual reduction.

Changes in deprivations among the poor

The reductions in MPI can be broken down by indicators. An analysis of changes in MPI considers both changes in the raw or uncensored headcount ratios and in the censored headcount ratios. The changes in censored headcount ratios depict changes in deprivations among the poor.

Table 2. Comparing alternative approaches to estimating annualised change

		t1 initial year		**t2 final year**				Duration between t1 & t2	Multidimensional Headcount Ratio (H_T)		
		Survey	Year	Survey	Year				t_1	t_2	Abs annualised change
Current approach: For surveys fielded between survey years, the analysis takes the average of the years for calculating annualised change.	India	DHS	2005-2006	DHS	2015-2016	2005.5	2015.5	10.0	55.07	27.68	-2.74
	India	DHS	2015-2016	DHS	2019-2021	2015.5	2020	4.5	27.68	16.39	-2.51
Mean approach: The average of the interview months and years used to compute the annualised changes.	India	DHS	2005-2006	DHS	2015-2016	Mar-06	Dec-15	9.7	55.07	27.68	-2.83
	India	DHS	2015-2016	DHS	2019-2021	Dec-15	May-20	4.3	27.68	16.39	-2.60
Median approach: The median of the interview months and years used to compute the annualised changes.	India	DHS	2005-2006	DHS	2015-2016	Mar-06	Dec-15	9.8	55.07	27.68	-2.81
	India	DHS	2015-2016	DHS	2019-2021	Dec-15	Feb-20	4.1	27.68	16.39	-2.76

Note: DHS survey contain only year and month of interview. Date of interview is not available.

Disaggregation of subgroups over time

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. 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. In the harmonised global MPI, we have estimated changes in the MPI and its partial indices by age groups, rural-urban areas and subnational regions. Our analyses of poverty changes by population subgroups allows us to identify if the poorest subgroups reduced poverty faster than less poor subgroups and to see the dimensional composition of reduction across subgroups. Note that the population shares for each period must always be analysed alongside subgroup trends in order to consider demographic shifts such as migration or population growth, as these can significantly influence the interpretation of results.

5. Tool to estimate MPI

The global MPI harmonised level estimates and their changes over time estimates are produced using the Stata package `mpitb` which is documented in Suppa (2022). `mpitb` facilitates the estimation of measures such as the MPI (adjusted headcount ratio), the H (headcount ratio), the A (intensity), the censored and uncensored headcount ratios for each time period. It supports the estimation of change between time periods for each of the measure. The level and change estimates are computed at national level, subnational regions, age groups, and rural and urban areas and could include other subgroup disaggregations. `mpitb` also simplifies estimations and analyses in cross-country settings.

The package is available at the Statistical Software Components (SSC) Archive and on gitlab. The MPI toolbox is distributed free of charge under an MIT license. The package may be installed by issuing `ssc install mpitb` in Stata. To access its comprehensive help files issue `help mpitb` after the installation. `mpitb` requires Stata 16 or higher.

6. Survey details

The analysis of changes in multidimensional poverty draws on datasets from 84 countries. We also estimated how multidimensional poverty changed by four major age categories: 0 to 9 years, 10 to 17 years, 18 to 59 years, and over 60 years in 84 countries using harmonised datasets. In addition, we also publish the disaggregation by two major age groups: for children aged 0 to 17 years and adults 18 years and older. At the area level, we were able to produce changes in multidimensional poverty by rural-urban area for all countries except for Trinidad and Tobago, as the initial survey period (MICS 2006) lacked this information.

35 of these countries have three points in time, 45 two points in time and changes in multidimensional poverty in Gambia, Mexico, Nigeria and Peru covers four points in time. Collectively, we standardised and harmonised 211 survey datasets [(35*3) + (45*2) + (4*4)] across these 84 countries.

Harmonised survey datasets

In 27 countries, we harmonised DHS datasets across all time points, and used only MICS datasets in 22 countries. For three countries (China, Ecuador and Mexico), the harmonisation work is exclusively based on national datasets, while for Morocco we have used PAPFAM across time points. For Bolivia and Peru, the harmonised datasets include a combination of DHS surveys and national surveys. For 29 countries we have used a mix of DHS and MICS across time points, namely Afghanistan, Bangladesh, Benin, Burkina Faso, Cameroon, Chad, Congo, Côte d'Ivoire, Democratic Republic of Congo, Dominican Republic, Gambia, Ghana, Guinea, Guyana, Honduras, Lesotho, Madagascar, Malawi, Mali, Mauritania, Moldova, Nepal, Nigeria, Sao Tome and Principe, Sierra Leone, Togo, Ukraine, Yemen, and Zimbabwe. The decision to use mixed data sources between time points was possible because MICS and DHS usually have comparable sample designs and questionnaires.

Countries excluded from data harmonisation

These 29 countries – Angola, Argentina, Barbados, Bhutan, Botswana, Brazil, Comoros, Costa Rica, Cuba, El Salvador, Fiji, Georgia, Guatemala, Jamaica, Kiribati, Libya, Maldives, Myanmar, Papua New Guinea, Paraguay, Saint Lucia, Samoa, Seychelles, South Africa, South Sudan, Sri Lanka, Tonga, Tuvalu and Uzbekistan – are currently or were part of the previous rounds of the global MPI. However, these countries are excluded from the harmonisation and changes over time analysis. This is because these countries (1) lack surveys for earlier time period or (2) the older and newer surveys have incomparable sample designs. For example, in 2018, the sample design for the Jamaica Survey of Living Conditions (JSLC) was revised. As such, direct comparisons with previous survey rounds – namely JSLC 2010 and 2014 are not recommended (PIOJ and STATIN, 2021, p.139).

7. Harmonisation principles and decisions

It is common for indicator definitions to vary across survey years because it may be the case that survey providers may have changed how questions are asked, from whom these are collected or the response categories. Another reason may be that we are using different survey sources with comparable sampling design to capture changes over time in a country, and as such indicator definitions may require adjustment across these survey sources (e.g., comparing DHS and MICS). Harmonisation seeks to make two or more MPI estimations comparable by exactly aligning the indicator definitions. In other words, harmonisation, where necessary, re-creates the indicators in the global MPI so that they are using the same information and deprivation cutoffs across survey years.

General harmonisation principles

Several general principles are applied in the global MPI harmonisation process. In cases of differences between available indicators between the two surveys, we resort to the most restricted condition. For example, if one year the surveys did not collect the information needed to construct the nutrition indicator and the other year did, the indicator was dropped from the year that includes the information, and the indicators within the dimensions were re-weighted to maintain equal weights across dimensions and match the survey with the more restricted data. In our sample of 84 countries, five countries dropped the nutrition indicator from one year to match the year that did not collect anthropometric measurements (Colombia, Dominican Republic, Nigeria, Trinidad and Tobago, and Yemen). Two countries (North Macedonia and Suriname) dropped the child mortality indicator from one year. Furthermore, we removed the school attendance indicator from one year in one country (Philippines) and cooking fuel indicator in two countries (Lesotho and Turkmenistan) to harmonise with the other dataset. The next section builds on these general principles to describe the indicator-specific decisions required in the harmonisation process.

Indicator-specific decisions

Nutrition

Most MICS surveys used in this analysis collect anthropometric measurements only for children under 5 years of age. In comparisons where in one year the survey is a DHS and in the other the survey is a MICS, the nutrition indicator is harmonised to include anthropometric information only for children under 5 years. Following this principle, adult nutrition is excluded from the harmonised nutrition indicator for 26 of the 84 countries, involving 40 of the datasets. These countries and datasets are: Armenia DHS 2015-2016, Bangladesh DHS 2014, Burkina Faso DHS 2010, Benin DHS 2017-2018, Cameroon DHS 2011 and 2018, Republic of Congo DHS 2005, Democratic Republic of the Congo DHS 2007 and 2013-2014, Ethiopia DHS 2011 and 2016, Gambia DHS 2013 and 2019-2020, Guinea DHS 2018 and 2018, Ghana DHS 2014, Guyana DHS 2009, Honduras DHS 2005-2006 and 2011-2012, Lesotho DHS 2009 and 2014, Madagascar DHS 2008-2009 and 2021, Mali DHS 2006 and 2018, Republic of Moldova DHS 2005, Mauritania DHS 2019-2021, Malawi DHS 2010 and 2015-2016, Nepal DHS 2011 and 2016, Senegal DHS 2005, Sao Tome and Principe DHS 2008-2009, Sierra Leone DHS 2019 and 2013, Togo DHS 2013-2014, Zambia DHS 2007 and 2013-2014, Zimbabwe DHS 2010-2011 and 2015.

In addition, for the nutrition indicator, if the reference populations were changed, the harmonised estimates follow the year with the more limited eligibility conditions. For example, in Peru ENDES 2018, 2019 and 2021 surveys, eligible women for height and weight measurement included all women aged 12 to 49 years, whereas in Peru DHS 2012, eligible women included all women aged 15 to 49 years. As a result, in Peru, only women aged 15 to 49 years are considered as eligible for nutrition measurement for both years. This restricted condition principle also applies when one year includes nutrition information from men and the other year does not; in that case, men's nutritional information would be excluded from the harmonised indicator.

Child mortality

The child mortality indicator was constructed using birth history information – whether the mother gave birth in the last five years preceding the survey and how old the child was when they died. Often, the older surveys do not include a birth history questionnaire and thus do not have information on the age and time of passing of the child. When one year includes birth history information and the other does not, the more restricted condition principle is followed, and information on age and year of death are removed from the survey that has them. In this case, the child mortality indicator then takes on the deprivation cutoff from the 2010 global MPI specifications, which considers whether any child has died in the household. Following this principle, birth history information is excluded from the harmonised child mortality indicator for 12 of the 84 countries, involving 19 of the datasets. These datasets are: Afghanistan DHS 2015-2016, Belize MICS 2015-2016, Burkina Faso DHS 2010, Central African Republic MICS 2019, Chad DHS 2014-2015 and MICS 2019, Ecuador ENSANUT 2018, Gambia DHS 2013, MICS 2018 and DHS 2019-2020, Kyrgyzstan MICS 2014 and 2018, Morocco PAPFAM 2017-2018, Mongolia MICS 2013 and 2018, Turkmenistan MICS 2019 and 2015-2016, and Togo MICS 2017 and DHS 2013-2014.

Birth history information was consistently not available across 12 survey datasets of five countries. As such, we applied the 2010 global MPI specifications, which considers whether any child has died in the household. These datasets are Kazakhstan MICS 2010-2011 and 2015, Montenegro MICS 2013 and 2018, Serbia MICS 2019, 2014 and 2010, Thailand MICS 2019, 2015-2016 and 2012, and Trinidad and Tobago MICS 2011 and 2006.

In addition, attention was paid to which individuals provide information on child mortality to ensure the applicable populations match between the two years. For instance, in the Bolivia 2016 dataset, women who are eligible to provide child mortality information are all women aged 14 to 49 years, and in the 2008 and 2003 datasets, eligible women were aged 15 to 49 years. Therefore, only child mortality information from women aged 15 to 49 years is included in the indicator for all three years, following the more restricted condition principle. However, child mortality information from eligible men was not excluded even when not present in the other year, as it is only used to identify zero child mortality at the household level in the absence of information from eligible women.

Years of schooling

For the years of schooling indicator, DHS data contains a variable that states the total number of years of education for the individual. In contrast, the MICS data does not provide an equivalent variable. Instead, when using MICS data, the total number of years of schooling is computed by combining the education level and highest-grade variables, taking into consideration the country's national education system, as described in the survey report. In cases where this information is not included in the survey report, we refer to the UNESCO Institute for Statistics (UIS) databank. In cases of mismatch between the survey report and the national guidance, we investigate this issue with respective national statistical offices or the survey providers. For the DHS and MICS comparisons, the DHS variable was treated as equivalent to the MICS composite variable (e.g. six years of schooling in the DHS variable corresponds to the first six years of education in MICS). All adults are eligible for the years of schooling indicator; while the youngest eligible persons are specified using country-specific age cutoffs that correspond to the age at which they are expected to complete class six (Alkire, Kanagaratnam, and Suppa, 2020). For example, in India, children start school at the age of six years so we would expect a child aged 12 years to have completed six years of schooling. Hence the minimum age of eligibility for years of schooling indicator for India is from 12 years old. On the other hand, in Indonesia, children start school at the age of seven years and so would complete six years of schooling at the age of 13. Hence the minimum eligibility for years of schooling indicator in Indonesia is 13 years.

School attendance

The eligibility for school attendance indicator is computed using the age range for the indicator based on the national entry age to compulsory schooling. The official national entry age to compulsory schooling is selected using either the survey report (where possible) or the UNESCO Institute for Statistics data (if not available in the survey report). In cases of mismatch between the report and the UNESCO guidance, we consult the national statistical offices or the survey providers. For most countries included in the changes over time analysis, the official entry age for primary schooling is six years, although this differs for a few countries. For example, the official entry age is 7 years for Indonesia, and for Pakistan, the official entry age is five years. When the official entry age changes between the two surveys, often due to education policy changes, we retain the exact official entry age in each survey and do not harmonise across the years in order to fully capture the range of eligible children.

Electricity

The electricity indicator does not have any indicator-specific harmonisation decisions, beyond the general principles of only using information that is available in datasets from both survey years.

Sanitation

For the sanitation indicator, two conditions are used – whether other households share the toilet facility and whether the toilet facility is considered an improved or unimproved facility – to define a household's access to improved sanitation. If, there is no information on whether the facility is shared in one year, but the other year does have that information, the more limited information is considered in both years. This principle was only applied for Central African Republic MICS 2019 and 2010 where the shared toilet facility is excluded from the harmonised sanitation indicator because the initial survey – MICS 2000 – lacked this information.

Regarding categorising labelled types of toilet facilities as improved or unimproved, if survey report classifications differ between the two years, we consider the more recent data's definition of improved facilities for both years. If a first-year survey specifies a category for sanitation facilities that the second year does not; we would leave the category labelled as is in the first year.

Drinking water

For the drinking water indicator, there are two conditions to consider – how long it takes the respondent to fetch water from the main drinking water source of the household and whether the main drinking water source is considered an improved or unimproved source – to define a household's access to basic drinking water. If in one year, there is no information on how long it takes to fetch water, but the other year does have that information, that information is dropped to accord with the year that has the more limited information. Following this principle, information on time to collect water is excluded from the harmonised drinking water indicator for three countries involving four datasets, namely Jordan DHS 2017-2018, Republic of Moldova MICS 2012, and the State of Palestine MICS 2019-2020 and 2014.

Further, when different main drinking water sources are considered improved between the two years, we follow the standard in the more recent survey. Lastly, unless directly specified otherwise by the report, because the quality of bottled water is unknown, households that use bottled water for drinking are classified as using an improved source only if the water they use for cooking and hand washing comes from an improved source. This information exists in a non-drinking water variable, which often is not present in the earlier surveys. When there is no information on non-drinking water in one year, as in Tajikistan DHS 2012, but the second year does have that information, as in Tajikistan DHS 2017, the condition is dropped to accord with the year that has the more limited information. Often, when this is the case, the reports specify that bottled water is an improved source, and, consequently, it is coded as such. In surveys released since 2020, bottled water is considered as improved source of drinking water. The information on non-drinking water is no longer considered to determine the quality of bottled water. This is consistent with the SDG definition of safe drinking water. In such case, we consider bottled water as improved source of drinking water across survey years even if older surveys applied the non-drinking water criterion.

Cooking fuel

For the cooking fuel indicator, households are defined as deprived when they cook with solid fuels: dung, agricultural crop, shrubs, wood, charcoal, or coal. For surveys where there is information on type of stove, we have used this additional data to determine whether the category of 'other' cooking fuel is improved or non-improved. For example, if household used stove that are meant for solid fuel but reported using 'other' type of fuel, then we identify householders as using deprived sources. However, for households who reported using electric stove and indicated using 'other' types of fuel, then we code this group as using non-deprived sources.

Housing

For the housing indicator, the household is considered as deprived if they live in inadequate housing, where the floor is of natural materials, or the roof or walls are of natural or rudimentary materials. Following the principle of differing classifications reverting to the more recent standard, when the first year considers a housing material (constituting the dwelling's floor, roof, or walls) as natural or rudimentary and the second (more recent) year does not, both years are coded to consider that housing material as an improved housing material.

Further, when information on one or two of the three housing components (floor, roof, walls) is missing in one year, the information from the year where it exists is removed to match the missing year. This restricted condition principle was applied on the harmonised housing indicator for eight countries involving 13 datasets, namely Democratic Republic of the Congo DHS 2013-2014 and 2017-2018, Mali MICS 2015 and DHS 2018, Mozambique DHS 2011, Niger 2012, the State of Palestine MICS 2014 and 2019-2020, Sao Tome and Principe MICS 2014 and 2019, Senegal DHS 2017 and 2019, Yemen DHS 2013.

Assets

The assets indicator considers whether a household owns a radio, television, telephone, computer, animal cart, bicycle, motorbike, refrigerator, or car/truck. When in one year there is no information on certain assets, those assets are dropped from the assets indicator in the later years to accord with the more limited information available. The most common asset item that is missing in one year is computer, followed by animal cart. For example, in 24 countries across 35 datasets, we excluded computer from the harmonised assets indicator because this information was not available in at least one of the surveys. These datasets are: Afghanistan DHS 2015-2016, Bosnia and Herzegovina MICS 2011-2012, Burkina Faso DHS 2010, Cambodia DHS 2021-2022, Central African Republic MICS 2010 and 2019, Chad MICS 2019, Colombia DHS 2015-2016, Democratic Republic of the Congo DHS 2013-2014 and 2017-2018, Republic of Congo DHS 2005, Ethiopia DHS 2016 and 2019, Gabon DHS 2012, Gambia DHS 2013, MICS 2018 and DHS 2019-2020, Guinea MICS 2016 and DHS 2018, Indonesia DHS 2017, Madagascar MICS 2018 and 2021, Malawi DHS 2015-2015 and MICS 2019-2020, Namibia DHS 2013, Niger DHS 2012, Suriname MICS 2006 and 2018, Tanzania DHS 2015-2016, Timor-Leste DHS 2016, Togo DHS 2013-2014 and MICS 2017, Uganda DHS 2016, and Zambia DHS 2013-2014 and 2018.

Our definition of telephone ownership includes information on whether a household owns a landline or mobile telephone. In earlier surveys, as is the case in Mozambique DHS 2003, the questionnaire did not include a question on whether the household owned a mobile telephone (as they were not as common a telecommunications device as they are today). In these cases, for the second year, as in the case of Mozambique DHS 2011, we kept the telephone information from both the landline and mobile phone questions (as opposed to excluding the information on whether the household owns a mobile phone), as we believe the changes in phone ownership are best reflected with the inclusion of all available information on telephone devices because individuals may own a mobile phone instead of, rather than in addition to, a landline.

Principles for subnational disaggregation

The principle for subnational disaggregation using harmonised datasets builds on the principles discussed in Alkire, Kanagaratnam and Suppa (2023b) for standardised datasets. The decision whether a country qualifies for a harmonised subnational disaggregation was determined by three criteria. These criteria were (1) the sample was representative at the subnational level across harmonised surveys; (2) the subnational unit definitions are comparable across harmonised surveys; and (3) the sample size after the treatment of missing data was reasonably high across harmonised surveys.

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. Four countries – Armenia, Bosnia and Herzegovina, Burkina Faso and Yemen – have surveys in one or both of the years that did not satisfy this principle according to their survey reports. Hence, these four countries are excluded from subnational analysis; while the remaining 80 countries met this principle.

The second criterion required subnational units to be comparable across harmonised surveys. In two countries – Morocco and Sudan – the subnational regions have changed boundaries or have been split into new regions over the years. We exclude subnational disaggregations for both these countries where changes in the subnational unit definitions between time periods are incomparable.

Besides these cases, a number of countries had regional changes between the time points that did not violate the principle of comparability, and we were therefore able to harmonise and obtain subnational estimates for these countries. To ensure comparable estimates are derived across time periods, where possible, regions were aggregated to recreate the region(s) presented in the survey with the more limited regional classification. For instance, in the cases of India DHS 2019-2021 and DHS 2015-2016, we aggregated regions of Andhra Pradesh and Telangana to recreate the Andhra Pradesh region; as well as aggregated the regions of Punjab and Chandigarh to recreate Punjab presented in the DHS 2005-2006. Similarly, we aggregated regions of Jammu and Kashmir and Ladakh in the most recent survey to recreate the Jammu and Kashmir region that is present in DHS 2015-2016 and 2005-2006.

In a few exceptional cases, a different number of regions were surveyed across survey years due to accessibility, physical security, or cost issues. For example, India DHS 2015-16 and 2019-2021 surveyed additional regions (union territories) that are not available in the earlier survey – DHS 2005-2006. This presented a problem for the estimation of trends over time as we aimed to preserve the national estimates while ensuring that subnational estimates are comparable between the two times. Our approach was to estimate national poverty using all available regions in both years (even if some were not present earlier) in order to preserve the weighting scheme for obtaining the national estimates. Subnational estimates utilise the individual regional weights, and, in cases where additional regions were surveyed in one year compared to those in the other, our analysis omits the extra region(s) in its estimation of the regional results, but the weights and sample are retained for national analyses.

The third and final 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 third criterion in three ways.

First, the national sample size for all surveys must be at least 85 percent of the original sample after missing data is treated. This is because a lower sample size may affect accurate comparability across subnational estimations. Following this specific criterion, we identified two datasets representing two countries that did not meet this cutoff. In the Montenegro MICS 2018 dataset, we retained 80 percent of the weighted sample for estimation after dropping observations that had missing data in any of the 10 global MPI indicators.

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 the region of Centre in Montenegro MICS 2018 dataset recorded a sample drop of 27 percent, falling short with respect to this sub-criterion.

Third, a bias analysis test is carried out for each 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, child mortality for Montenegro) 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 region of Centre in the case of Montenegro. Results indicate that the likelihood of being deprived in child mortality 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. This suggests that the sampling structure would need to be revised to assure representativity. In addition, some 55 percent of the population live in the region of Centre. Following the bias observed for the Montenegro MICS 2018 dataset, and that the region account for high share of population, we exclude the harmonised dataset for Montenegro from the subnational analysis and limit the estimates to national level.

In summary, 77 countries with 814 regions satisfy all three criteria and are thus used to estimate changes in poverty over time at the subnational level.

8. Country specific considerations

This section details the country-specific harmonised decisions concerning indicator availability and data treatment for each country with updated survey.

Cambodia. The most recent survey for this country is DHS 2021-2022. This survey is harmonised with two earlier surveys, DHS 2010 and DHS 2014. The earlier two survey datasets – DHS 2010 and 2014 – reported the main source of drinking water across two seasons, the dry and wet. Households using non-improved sources in any season was identified as deprived. Drinking water obtained from tanker truck and cart are harmonised as improved following the most recent survey. Bottled water is considered as an improved source of drinking water over time. The 2010 and 2014 datasets do not include information on whether the household owns a computer; likewise, the harmonised over time assets indicator does not include this item. The 2021-2022 survey has six additional provinces compared to the earlier DHS surveys. This is because larger provinces in earlier years have been divided into smaller regions at present day. For harmonisation purposes, we re-grouped the 25 provinces in the 2021-2022 survey to match the 19 provinces in the earlier DHS datasets. Specifically, Tboung Khmum was merged into Kampong Cham because Tboung Khmum was formed when Kampong Cham province was split in two by a royal decree signed in December 2013. In addition, in the most recent survey, the province of Battambang was grouped into Pailin; Kampot into Kep; Koh Kong into Preah Sihanouk; Mondul Kiri into Ratanak Kiri; and Preah Vihear into Stung Treng to match the earlier two surveys.

Madagascar. The most recent survey for this country is DHS 2021. This survey is harmonised with two earlier surveys, MICS 2018 and DHS 2008-2009. The DHS datasets have anthropometric information from children aged under 5 years and women aged 15 to 49 years; however, for harmonisation purposes, we only use the anthropometric information from children, to accord with the 2018 MICS dataset. In addition, the harmonised child nutrition indicator was limited to stunting to accord with the DHS 2008-2009 dataset. The data on weight measurement was not available in the DHS 2008-2009 microdata due to inaccuracy and quality issue (INSTAT and ICF, 2010). Following this, the definition of the harmonised nutrition indicator was limited to whether children under 5 were stunted or not across all three surveys. The earlier two surveys – DHS 2008-09 and MICS 2018 – included a specific category for type of toilet, that is, the pit latrine with slab that cannot be washed. This category was identified as non-improved sanitation following the survey reports by INSTAT and UNICEF (2019) and INSTAT and ICF (2010). Drinking water obtained from tanker truck and cart are harmonised as improved following the two most recent survey – MICS 2018 and DHS 2021. Bottled water is considered as an improved source of drinking water over time. The 2008-2009 dataset do not include information on whether the household owns a computer; likewise, the harmonised over time assets indicator does not include this item. The 2008-2009 DHS survey and 2018 MICS survey are representative for 22 regions of the country, while the 2021 survey is representative for 23 regions. This is because in the earlier surveys, the capital city of Antananarivo was presented as part of the Analamanga region. For the purpose of comparability over time, we group the capital city of Antananarivo and Analamanga in the 2021 dataset so it is comparable with the earlier two datasets.

Mexico. The most recent survey for this country is ENSANUT 2021. This survey is harmonised with three earlier ENSANUT surveys, 2020, 2016 and 2012. These are national surveys that is open access. There is difference in sample design of between the two most recent survey to the earlier two surveys, but the estimates defined on geographic regions (rural localities, and urban localities) are comparable because the sampling is probabilistic and the survey questions are comparable (Shamah-Levy, Romero-Martinez, Barrientos-Gutierrez and others, 2021, p.28).

For harmonisation purposes, we only use the anthropometric information from children under 5 to construct the nutrition indicator across all four data time period. Anthropometric data was collected from individuals 5 years and older across the datasets, but not used because of high non-response rate and potential biased estimates particularly in the 2020 and 2021 dataset. For example, in the 2021 dataset, if the nutrition indicator was constructed using a combination of child under 5 and selected individuals 5 years and older, then the sample size after the treatment of missing data is quite low at the national level – only 64 percent. The bias test compared whether those with missing nutrition and those without missing nutrition experience other deprivations similarly. If this is the case, then we may assume missing is distributed randomly. However, if those with missing nutrition and those without missing nutrition experience other deprivations significantly differently, then estimates are potentially biased. The bias analysis based on the 64 percent retained sample using the 2021 dataset indicate that the likelihood of being deprived in housing, sanitation and living in urban areas is not the same for those who have missing nutrition indicator and those who do not have missing in this indicator. In addition, a probit regression (dependent variable: 1=missing nutrition; 0=no missing nutrition) show that there are observable exogenous variables that are significant predictors of the risk of having a missing value in the nutrition indicator. Those that are most likely to have missing nutrition significantly increases if they are a man, between 18-59 years of age, living in the urban areas, living in the central regions of the country and are maleheaded. This suggests that the missing values of the nutrition indicator are not distributed completely at random and there is a high risk of bias in the national-level estimates. As such, we opted to construct the nutrition indicator using anthropometric data from only children under 5 consistently across the Mexico datasets, which resulted in a much lower sample drop and bias analysis indicates the missing is random.

All four surveys lack information on time to collect water, hence the definition of drinking water indicator is limited to source of drinking water. The surveys do not include information on whether the household owns a bicycle or an animal cart, and likewise the assets indicator does not include these items across all four surveys.

Nigeria. The most recent survey for this country is MICS 2021. This survey is harmonised with three earlier surveys, DHS 2018, MICS 2016-2017 and DHS 2013. The most recent survey lacks anthropometric information. The DHS datasets have anthropometric information from children aged under 5 years and women aged 15 to 49 years; while this data is limited to children under 5 in MICS 2016-2017. For harmonization purposes, we remove all data on nutrition to accord with the most recent data and re-weight the child mortality indicator to assure equal weighting among the three dimensions. In the 2016-2017 MICS survey dataset, we find that some 10 percent of the school-aged children, specifically 6-14 years, attended non-formal school. We count these children as attending school even if it is non-formal schooling. Sachet water is considered as an improved source of drinking water over time.

Peru. The most recent survey for this country is ENDES 2021. This survey is harmonised with the 2019, 2018 ENDES and 2012 DHS survey datasets. The ENDES are national surveys that is open access. Anthropometric measurement was collected from all children under 5 years across the four surveys. In addition, anthropometric measurement was also collected from women aged 12 to 49 years in the ENDES surveys, while in the DHS survey, data collection covered women aged 15 to 49 years. The harmonised nutrition indicator only considers data from children and women aged 15 to 49. Similarly, child mortality information was provided by women aged 12 to 49 in the 2019 and 2018 ENDES surveys while the most recent ENDES 2021 and the 2012 DHS covered women aged 15 to 49 years. The harmonised child mortality indicator across the four surveys only considers data from women aged 15 to 49.

9. Concluding remarks

The global MPI 2023 includes harmonised levels and changes over time estimates for 84 countries. We estimate changes in MPI and its partial indices by age groups for all countries, rural-urban areas for 83 countries (excluding Trinidad and Tobago due to lack of data on rural-urban area in earlier survey) and by 814 subnational regions across 77 countries (excluding 7 countries due to constraints in sample representation, incomparability across regional units over time or bias in regional estimates).

10. References

Alkire, S., Kanagaratnam, U., and Suppa, N. (2023a). The global Multidimensional Poverty Index (MPI) 2023 country results and methodological note. OPHI MPI Methodological Note 55, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., Kanagaratnam, U., and Suppa, N. (2023b). The global Multidimensional Poverty Index (MPI) 2023 disaggregation results and methodological note. OPHI MPI Methodological Note 56, Oxford Poverty and Human Development Initiative, University of Oxford.

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

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., Oldiges, C., and Kanagaratnam, U. (2021). Examining multidimensional poverty reduction in India 2005/6–2015/16: Insights and oversights of the headcount ratio. World Development, 142, DOI https://doi.org/10.1016/j.worlddev.2021.105454

Alkire, S., Kanagaratnam, U., and Suppa, N. (2020). The global Multidimensional Poverty Index (MPI) 2020. OPHI MPI Methodological Note 49, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., Kanagaratnam, U. and Suppa, N. (2019). The Global Multidimensional Poverty Index (MPI) 2019. OPHI MPI Methodological Note 47, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., Kovesdi, F., Mitchell, C., Pinilla-Roncancio, M. and Scharlin-Pettee, S. (2020). Changes over Time in the Global Multidimensional Poverty Index. OPHI MPI Methodological Note 50, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., Kanagaratnam, U. and Suppa, N. (2018). The Global Multidimensional Poverty Index (MPI): 2018 revision. OPHI MPI Methodological Note 46, Oxford Poverty and Human Development Initiative, University of Oxford.

Alkire, S., Jindra, C., Robles, G., and Vaz, A. (2017). Multidimensional poverty reduction among countries in Sub-Saharan Africa. Forum for Social Economics, 46:2 178-191.

Alkire, S., Roche, J. M., and Vaz, A. (2017). Multidimensional poverty dynamics: methodology and results for 34 countries, World Development, 94: 232-249.

Alkire, S., Jindra, C., Robles, G., and Vaz, A. (2016). 'Multidimensional Poverty Index – Summer 2016: Brief methodological note and results', OPHI MPI Methodological Note 42 (OPHI Briefing 42), Oxford Poverty and Human Development Initiative (OPHI), University of Oxford.

Alkire, S., and Seth, S. (2015). Multidimensional poverty reduction in India between 1999 and 2006: where and how? World Development, 72: 93-108.

Alkire, S., Conconi, A. and Seth, S. (2014). 'Multidimensional Poverty Index 2014: Brief methodological note and results', OPHI MPI Methodological Note 19 (OPHI Briefing 19), Oxford Poverty and Human Development Initiative (OPHI), University of Oxford.

Alkire, S. and Vaz, A. (2014). 'Reducing Multidimensional Poverty and Destitution: Pace and Patterns', OPHI Briefing 23, Oxford Poverty and Human Development Initiative (OPHI), University of Oxford.

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., Conconi, A. and Roche, J.M. (2013). Multidimensional Poverty Index 2013: Brief Methodological Note and Results. OPHI MPI Methodological Note 12 (OPHI Briefing 12), Oxford Poverty and Human Development Initiative (OPHI), University of Oxford.

Alkire, S. and Roche, J.M. (2013). How Multidimensional Poverty Went Down: Dynamics and Comparisons. OPHI Briefing 16, Oxford Poverty and Human Development Initiative (OPHI), University of Oxford.

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 and Seth, S. (2011). 'Sub-national Disparities and Inter-temporal Evolution of Multidimensional Poverty across Developing Countries', OPHI Research in Progress 32a, Oxford Poverty and Human Development Initiative (OPHI), 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.

National Institute of Statistics (INSTAT) and ICF. (2022). Demographic and Health Survey in Madagascar 2021. Antananarivo, Madagascar and Rockville, Maryland, USA: INSTAT and ICF.

INSTAT and UNICEF. (2019). Multiple Indicator Cluster Survey MICS Madagascar, 2018, Final Report. Antananarivo, Madagascar: INSTAT and UNICEF.

National Institute of Statistics (INSTAT) and ICF Macro. (2010). Madagascar Demographic and Health Survey 2008-2009. Antananarivo, Madagascar: INSTAT and ICF Macro.

National Bureau of Statistics (NBS) and United Nations Children's Fund (UNICEF). (2022). Multiple Indicator Cluster Survey 2021: Survey Findings Report. Abuja, Nigeria: NBS and UNICEF.

National Bureau of Statistics (NBS) and United Nations Children's Fund (UNICEF). (2017). Multiple Indicator Cluster Survey 2016-17, Survey Findings Report. Abuja, Nigeria: National Bureau of Statistics and United Nations Children's Fund.

National Institute of Statistics. Cambodia (NIS), Ministry of Health Cambodia (MoH), and ICF. (2023). Cambodia Demographic and Health Survey 2021–22 Final Report. Phnom Penh, Cambodia, and Rockville, Maryland, USA: NIS, MoH, and ICF.

National Institute of Statistics (NIS), Directorate General for Health, and ICF International. (2015). Cambodia Demographic and Health Survey 2014. Phnom Penh, Cambodia, and Rockville, Maryland, USA: National Institute of Statistics, Directorate General for Health, and ICF International.

National Institute of Statistics (NIS), Directorate General for Health, and ICF Macro. (2011). Cambodia Demographic and Health Survey 2010. Phnom Penh, Cambodia and Calverton, Maryland, USA: National Institute of Statistics, Directorate General for Health, and ICF Macro.

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.

Shamah-Levy, T., Romero-Martinez, M., Barrientos-Gutierrez, T., Cuevas-Nasu, L., Bautista-Arredondo, S., Mattress, M.A., Gaona-Pineda, E.B., Lazcano-Ponce, E., Martinez-Barnetche, J., Alpuche-Arana, C., and Rivera-Dommarco, J. (2022). National Health and Nutrition Survey 2021 on Covid-19 National results. Cuernavaca, Mexico: National Institute of Public Health.

Shamah-Levy, T., Romero-Martinez, M., Barrientos-Gutierrez, T., Cuevas-Nasu, L., Bautista-Arredondo, S., Mattress, M.A., Gaona-Pineda, E.B., Lazcano-Ponce, E., Martinez-Barnetche, J., Alpuche-Arana, C., and Rivera-Dommarco, J. (2021). National Health and Nutrition Survey 2020 on Covid-19 National results. Cuernavaca, Mexico: National Institute of Public Health.

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

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.

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