OPHI MPI Methodological Note 60

A methodological note on the global Multidimensional Poverty Index (MPI) 2024 changes over time results for 86 countries

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Attribution

The global Multidimensional Poverty Index (MPI) harmonised level estimates and their changes over time, most recent four rounds (2021 – 2024), are produced by Professor Sabina Alkire, Dr Usha Kanagaratnam and Dr Nicolai Suppa for *over* 80 countries using over 200 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 & 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 & 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 & 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 & Seth (2015).

2014. Alkire & Vaz (2014) documented the changes over time results for 34 countries and 338 subnational regions. The methodological specifications were highlighted in Alkire, Conconi & Seth (2014). The harmonised estimates were based on comparable DHS datasets across two time points, while for two countries (Ethiopia and Peru) the comparison included three time points. Alkire, Roche & Vaz (2017) presented the changes estimates for 34 countries and its subnational regions.

2016-2017. Alkire, Jindra, Robles & Vaz (2016) extended the harmonised estimates to 50 countries (16 new countries, in addition to the previously harmonised 34 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 points. This was followed by a publication that focused on changes in multidimensional poverty among countries in Sub-Saharan Africa (Alkire, Jindra, Robles & 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 233 survey datasets used to produce the harmonised level estimates and their changes over time in multidimensional poverty for **86 countries** and **863 subnational regions**. 40 of the 86 countries have trends for two points in time, while poverty trends in 36 countries are based on three points in time. Six countries (Benin, Eswatini, Nigeria, Philippines, Tanzania, and Thailand) have results for four points in time, three countries (Ghana, Mexico and Peru) for five time periods and Nepal have trends for six time periods.

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. Indicator standardisation is detailed in Alkire, Kanagaratnam and Suppa (2024a), while indicator harmonisation is detailed in this and earlier publications by the authors (2023, 2022, 2021).

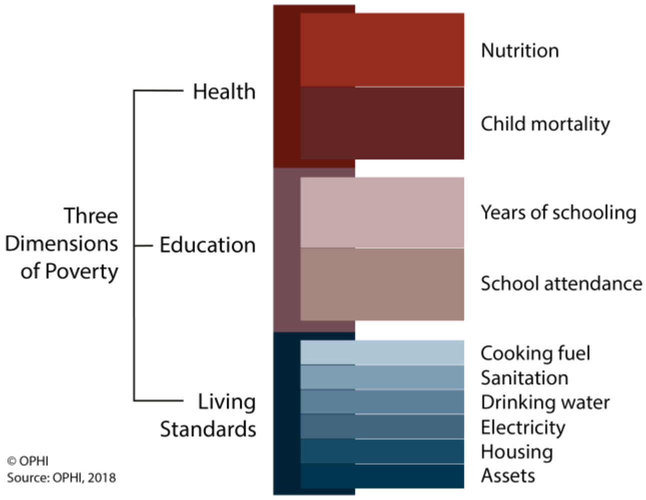
The global MPI harmonised level estimates and their changes over time remains an on-going work. The number of harmonised countries, its datasets and survey periods will increase as we continue to harmonise earlier surveys, alongside with upcoming surveys. As the survey time points grow longer, we may review the methodology and policies that underlie the harmonisation principles. This is because a few of the policies for harmonisation may be more relevant for surveys with two time points, but less with longer survey time points.

This document, focused on harmonisation methodology and principles of the 2024 round, 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 key highlights of the work implemented in this round.

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 analysis 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).

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.

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

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.

4.1 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.

4.2 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:

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

4.3 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:

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

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. 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.

Table 2. Comparing alternative approaches to estimating annualised change for India

		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.

4.4 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.

4.5 Disaggregation by 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 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 (2023). \`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. Suppa and Kanagaratnam (2023) present selected aspects related to the estimation procedures of the global MPI.

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. Harmonised survey time periods and datasets

The global MPI trends over time is released on an annual basis since 2021. The number of harmonised countries, its datasets and survey periods will increase as we continue to harmonise earlier surveys, alongside with upcoming surveys.

6.1 Survey time periods

For this 2024 round, the analysis of changes in multidimensional poverty draws on *233 survey microdata sets* from 86 countries.[1] 40 of these countries have two points in time, and 36 countries have trends for three points in time. Changes in multidimensional poverty in six countries (Benin, Eswatini, Nigeria, Philippines, Tanzania and Thailand) cover four points in time, three countries (Ghana, Mexico and Peru) cover five points in time and Nepal has trends for six points in time.

Table 3 provides an overview of the coverage in terms of countries and subnational regions for each of the releases since 2021.

Table 3. Harmonised survey details for each publication round, 2001-2024

Publication year	Country coverage	Countries with subnational regions	Country coverage in terms of survey time points	Survey microdata sets
2024	86	78 (863 regions)	46 (three or more points in time) 40 (two points in time)	233
2023	84	77 (814 regions)	39 (three or more points in time) 45 (two points in time)	211
2022	84	76 (810 regions)	36 (three or more points in time) 48 (two points in time)	205
2021	84	77 (793 regions)	28 (three points in time) 56 (two points in time)	196

Collectively, for this 2024 round, we standardised and harmonised 233 survey datasets [(40*2) + (36*3) + (6*4) + (3*5) + (1*6)] to produce harmonised MPI estimates for 86 countries at the national level; and by age groups, and by rural and urban areas.

[1] 26 countries – Angola, Argentina, Barbados, Bhutan, Botswana, Brazil, Costa Rica, Cuba, El Salvador, Fiji, Georgia, Guatemala, Kiribati, Libya, Maldives, Myanmar, Papua New Guinea, Paraguay, Saint Lucia, Samoa, Seychelles, South Africa, Sri Lanka, Tonga, Tuvalu and Uzbekistan – have surveys for one period, and so are part of the countries covered in our current release (Alkire, Kanagaratnam and Suppa, 2024a; see results in OPHI's Data Table 1). However, these countries are not part of the harmonisation and changes over time analysis because we have yet to identify relevantly comparable surveys from earlier time period. We continue to explore survey options for these countries, with the aim of including these countries into the Global MPI Harmonised Level Estimates and their Changes over Time database.

In addition, we produced harmonised MPI estimates for 863 subnational regions in 78 of the 86 countries using 209 of the 233 harmonised survey datasets.

6.2 Survey datasets

In 28 countries, we harmonised DHS datasets across all time points, while in 21 countries, we used only MICS dataset. For four countries (China, Ecuador, Jamaica and Mexico), the harmonisation work is exclusively based on national datasets, while for Morocco we have used PAPFAM across two time points. For Bolivia and Peru, the harmonised datasets include a combination of DHS surveys and national surveys. For 30 countries we have used a mix of DHS and MICS across time points, namely Afghanistan, Bangladesh, Benin, Cameroon, Chad, Comoros, Congo, Côte d'Ivoire, Democratic Republic of Congo, Dominican Republic, Eswatini, 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 have comparable sample designs and survey questionnaires (Khan and Hancioglu, 2019).

It is not unusual for survey providers to change sampling design of long running surveys over time. In such cases, we are then presented with an issue where the older and newer surveys have incomparable sample designs. For example, the sample design for the Jamaica Survey of Living Conditions (JSLC) 2018 was revised by survey providers and therefore, direct comparisons with previous survey rounds, namely JSLC 2010 and 2014, are not recommended (PIOJ and STATIN, 2021, p.139). However, we continue to include JSLC 2010 and 2014 as part of our harmonised estimates. In turn, JSLC 2018 is restricted to the non-harmonised recent estimates that are presented in OPHI's Data Table 1 (Alkire, Kanagaratnam and Suppa, 2024a). In other words, while it is not possible to use the recent 2018 survey data to understand most recent poverty trends in Jamaica, we continue to understand changes in MPI estimates in earlier periods of the country.

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 aligning the indicator definitions as close as possible. The next section describes the indicator-specific decisions required in the harmonisation process.[2]

7.1 Indicator-specific harmonisation decisions

7.1.1 Nutrition

It is useful to note that in recent surveys, there are often two variables – children's age in days and age in months – which can be used to compute the child under five nutrition statistics, while many earlier surveys, notably DHS, do not include the age-in-days variable. We continue to use children's age in days for surveys that have this information given its accuracy for nutrition statistics. For surveys that lack information on 'age in days', we use the 'age in months' variable when calculating the nutrition statistics for children. We do not harmonise this information between surveys.

Most MICS surveys used in this analysis collect anthropometric measurements only for children under five 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 five years.

Following this principle, adult nutrition is excluded from the harmonised nutrition indicator for 28 of the 86 countries, involving 46 of the datasets.[3]

For surveys of which we used information from children and adults to construct the nutrition indicator, if the reference populations were changed, the harmonised estimates follow the year with the more limited eligibility conditions.[4] 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.

[2] Indicator specific decisions is also concisely summarised in Suppa and Kanagaratnam (2023).

[3] 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, Comoros DHS 2012, Congo Republic DHS 2005, Congo Democratic Republic DHS 2007 and 2013-2014, Eswatini DHS 2006-2007, Ethiopia DHS 2011 and 2016, Gambia DHS 2013 and 2019-2020, Guinea DHS 2018 and 2018, Ghana DHS 2008, 2014 and 2022, 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, Moldova Republic DHS 2005, Mauritania DHS 2019-2021, Malawi DHS 2010 and 2015-2016, Nepal DHS 2006, 2011, 2016 and 2022, 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.

[4] For example, in Peru ENDES 2018, 2019, 2021 and 2022 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.

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 restricted data. In our sample of 86 countries, five countries dropped the nutrition indicator from one year to match the year that did not collect anthropometric measurements.[5]

7.1.2 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. Few 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 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.[6]

However, the issue of missing birth history information is usually limited to a single survey, largely the first survey period. It may not be reasonable to continue to exclude birth history information from more recent datasets as we continue to increase the survey period coverage of a given country. In this case, we may review the restricted condition principle. A sensitivity analysis may be conducted by comparing estimates between two specifications. The first specification may apply the restricted condition principle across the datasets if at least one survey has missing birth history information. The second specification retains the birth history information in all datasets that have the information despite its unavailability in a single survey year. If there are significant differences in the levels of MPI and H estimates between both specifications, then a decision may be made to exclude the single dataset with missing birth history information from the analysis of poverty trends of the given country.

[5] This includes Afghanistan, Colombia, Dominican Republic, Nigeria, and Trinidad and Tobago.

[6] For example, birth history information is excluded from the harmonised child mortality indicator for 10 of the 86 countries, involving 15 of the datasets. These include Belize MICS 2015-2016, Central African Republic MICS 2019, Chad DHS 2014-2015 and MICS 2019, Ecuador ENSANUT 2018, Kyrgyzstan MICS 2014 and 2018, Morocco PAPFAM 2017-2018, Mongolia MICS 2013 and 2018, Turkmenistan MICS 2019 and 2015-2016, Togo MICS 2017 and DHS 2013-2014, and Trinidad and Tobago MICS 2022.

Birth history information was consistently not collected across all survey datasets of five countries. For these countries, we applied the 2010 global MPI specifications, which considers whether any child has died in the household.[7]

In addition, attention was paid to which individuals provide information on child mortality to ensure the applicable populations match between survey 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 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.

If one year the surveys did not collect the information needed to construct the child mortality 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 restricted data. In our sample of 86 countries, two countries (North Macedonia and Suriname) dropped the child mortality indicator from one year to harmonise with the other dataset.

7.1.3 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).

[7] These datasets are Kazakhstan MICS 2010-2011 and 2015, Montenegro MICS 2013 and 2018, Serbia MICS 2019, 2014 and 2010, and Thailand MICS 2022, 2019, 2015-2016 and 2012.

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.

7.1.4 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 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.

Additionally, we construct school age eligibility using information on age at the beginning of school year, if surveys have this information. For example, most MICS datasets have the 'schage' variable which represents this information. For surveys that lack information on age at the beginning of school year, we use information on age that was collected from the household roaster to construct the school age eligibility. We do not harmonise school age eligibility across survey years in order to reduce the bias we usually observe with the general age variable from the household roaster, compared to the more accurate variable on age at the beginning of school year.

7.1.5 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.

7.1.6 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 years does have that information, the principle of restricted condition may be considered. Going forward, if data on sharing facility, as indicated by survey provider, are not collected in recent surveys because almost 100 percent of the households in the country use private toilet facilities, then we may consider all households do not share toilet facilities.

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.

7.1.7 Drinking water

For the drinking water indicator, there are two conditions to consider in defining a household's access to basic drinking water. First, whether the main drinking water source is considered an improved or unimproved source. Second, how long it takes the respondent to fetch water from the main drinking water source of the household.

In cases, where different main drinking water sources are considered improved between the two years, we follow the standard in the more recent survey. For example, in surveys released since 2020, bottled water and water delivered via truck is considered as improved source of 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 may be dropped to accord with the year that has the more limited information.[8] Alternatively, we may also review the restricted condition principle to consider variables that may inform whether access to drinking water is within dwelling premises or outside of the premises.

[8] At present, we adopt the restricted principle, where 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.

7.1.8 Cooking fuel

If in one year, there is no information on type of fuel used for cooking, but the other year does have that information, that information may be dropped to accord with the year that has the more limited information.[9] Going forward, if data on cooking fuel, as indicated by survey provider, are not collected in recent surveys because almost 100 percent of the households in the country use clean fuel, then we may consider all households not deprived in cooking fuel.

7.1.9 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 as natural or rudimentary and the 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.[10] However, the issue of missing components is usually limited to a single survey, largely the first survey period. It may not be reasonable to continue to exclude housing components from more recent datasets as we continue to increase the survey period coverage of a given country.

In this case, we may review the restricted condition principle. A sensitivity analysis may be conducted by comparing estimates between two specifications. The first specification excludes information on missing housing components across all survey datasets of a given country if it has missing component in at least one survey period. The second specification retains the components in all datasets that have the information despite its unavailability in a single survey year. If there are significant differences in the levels of MPI and H estimates between both specifications, then a decision may be made to exclude the single dataset with missing housing component from the analysis of poverty trends of the given country.

[9] We removed the cooking fuel indicator in four countries, namely Afghanistan, Eswatini, Lesotho and Turkmenistan.

[10] This restricted condition principle was applied on the harmonised housing indicator for eight countries involving 14 datasets, namely Democratic Republic of the Congo DHS 2013-2014 and 2017-2018, Mali MICS 2015 and DHS 2018, Mozambique DHS 2022 and 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.

7.1.10 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 28 countries across 41 datasets, we excluded computer from the harmonised assets indicator because this information was not available in at least one of the surveys.[11]

However, the principle of restricted condition in the case of asset related items must be reviewed as the survey period coverage of each country increases. In future rounds, sensitivity analysis should be applied to ascertain whether there is value in excluding asset items from a series of survey years simply because the data was not collected in an earlier survey. The sensitivity analysis may show that there are no significant differences in estimates either by excluding or retaining items in the aggregated asset indicator if these items are consistently available in newer surveys but missing in one or two of the older surveys.

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.

[11] These datasets are Afghanistan MICS 2022-2023 and 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, Comoros MICS 2022, Colombia DHS 2015-2016, Eswatini MICS 2021-2022, 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, Kenya DHS 2022, Madagascar MICS 2018 and 2021, Malawi DHS 2015-2015 and MICS 2019-2020, Mozambique DHS 2022-2023, Namibia DHS 2013, Niger DHS 2012, Suriname MICS 2006 and 2018, Tanzania DHS 2022 and 2015-2016, Timor-Leste DHS 2016, Togo DHS 2013-2014 and MICS 2017, Uganda DHS 2016, Zambia DHS 2013-2014 and 2018 and Yemen MICS 2022-2023.

7.2 Principles for subnational disaggregation

The principle for subnational disaggregation using harmonised datasets builds on the principles discussed in Alkire, Kanagaratnam and Suppa (2024b) 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. Two countries – Armenia and Bosnia and Herzegovina – have surveys in one or both of the years that did not satisfy this principle according to their survey reports. Hence, these two countries are excluded from subnational analysis; while the remaining 84 countries met this principle.

The second criterion required subnational units to be comparable across harmonised surveys. In four countries – Côte d'Ivoire, Morocco, Nepal and Sudan – the subnational regions have changed boundaries or have been split into new regions over the years. We exclude subnational disaggregations for 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 a high share of population, we exclude the harmonised dataset for Montenegro from the subnational analysis and limit the estimates to national level.

In summary, although subnational disaggregation is theoretically possible for 84 of the 86 countries, only 79 countries satisfy the principles for subnational disaggregation. Of the 79 countries, we restricted the subnational estimation for one country – Mexico – because of an issue with the subnational variable identifier in the microdata.[12] So, while we could have included Mexico for subnational disaggregation, this was not possible at the time of publication. As such, in this round of global MPI, only 78 countries with 863 regions satisfy the principles for subnational disaggregation 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.

8.1 Afghanistan

The most recent survey for this country is MICS 2022-2023. This survey is harmonised with an earlier survey, DHS 2015-2016.[13]

The 2015-2016 DHS dataset lacks anthropometric data. For harmonisation purposes, we remove data on nutrition to accord with the DHS 2015-2016 data and re-weight the child mortality indicator to one-third, to assure equal weighting among the three dimensions.

[12] The region of Edo México was part of ENSANUT 2021. But Edo México was no longer part of ENSANUT 2022. It was not evident from the microdata and related survey documents if Edo México was excluded from ENSANUT 2022 sampling or was merged with neighbouring subnational region. This required cross-checks with microdata provider, which is on-going.

[13] At the time of publication, the survey report for Afghanistan DHS 2015-2016 has been temporarily removed from the DHS website. As such, we do not reference the survey report in our notes.

For harmonisation purposes, we have removed the cooking fuel information from the earlier survey to match the MICS 2022-2023 dataset, which did not include questions on energy use in the household questionnaire. Hence the remaining five indicators (sanitation, drinking water, electricity, housing and assets) of the living standards are re-weighted to receive one-fifteenth of the indicator weight each, which sums to one-third of the dimension weight.

The earlier survey does not include information on whether the household owns a computer, and likewise the harmonised assets indicator does not include this item despite the availability of this information in the recent survey. For future rounds, when additional new surveys are available for Afghanistan, a sensitivity analysis will be essential to ascertain whether there is value in excluding computer ownership from the harmonised assets indicator. If sensitivity analysis indicates that there is no significant change in MPI estimates, then we may conclude there is no reason to exclude items from the aggregated asset indicator if these items are consistently available in newer surveys even if these were not collected in one or two of the older surveys.

At the subnational level, we estimated MPI and its partial indices for 34 provinces of the country since the samples across the harmonised datasets are representative at this level (UNICEF, 2023).

An earlier survey – Afghanistan MICS 2010-2011 of MICS4 round – was excluded from our harmonised estimates because of data limitations. Namely, the quality of the anthropometric data for 2010-2011 was problematic and as such was not made available by the survey provider. There is no data on birth history in this survey. In contrast, there is good quality data on birth history for MICS 2022-2023 and DHS 2015-2016. This means, by excluding the MICS 2010-2011 dataset from the harmonised estimates, this allowed for the construction of the child mortality indicator following the global MPI definition (see Table 1 of this publication).

8.2 Benin

The most recent survey for this country is MICS 2021-2022. This survey is harmonised with three earlier surveys, DHS 2017-2018, MICS 2014, and DHS 2006.

The DHS datasets have anthropometric information from children aged under five years and women aged 15 to 49 years. However, for harmonisation purposes, we only use the anthropometric information from children, to accord with the MICS datasets.

DHS 2006 lacked a direct question on access to electricity. We used data from source of lighting to identify access to electricity. The response to the question on source of lighting had the following categories: electricity, petroleum, gas, oil, solar energy, community generator, private generator, and other.

The categories – electricity and solar energy – is identified as having access to electricity. This follows the DHS and MICS definition of access to electricity from the national grid or solar. The remaining categories was identified as not having access to electricity. The grouping of these categories showed that some 26 percent of the population had access to electricity in 2006. This corresponds closely to numbers published by the World Bank, that is, some 28 percent of the population in Benin had access to electricity in 2006 (IEA, IRENA, UNSD, World Bank, and WHO, 2023).

The DHS 2006 survey does not include information on whether the household owned an animal cart, while the information was collected in the later three surveys. However, the empirical implication for MPI value and headcount ratio (H) estimates are negligible between excluding or retaining information on animal cart, as shown in Table 4. A t-test comparing the aggregate H between both specifications showed that the differences are not significant. As such, we retained animal cart in the construction of the assets indicator for the later three surveys, even if this information was missing from DHS 2006.

At the subnational level, we estimated MPI and its partial indices for 12 departments of the country since the samples across all four harmonised datasets are representative at this level (INStaD, 2023, INSAE and ICF, 2019; INSAE, 2015; INSAE and Macro International, 2007).

Table 4. A comparison of MPI estimations for Benin with and without data on animal cart

Country	Survey	Year	Specification	MPI value	H (%)	A (%)
Benin	MICS	2014	animal cart excluded	0.342	63.17	54.17
			animal cart retained	0.342	63.17	54.16
Benin	DHS	2017-2018	animal cart excluded	0.362	65.96	54.88
			animal cart retained	0.362	65.96	54.84
Benin	MICS	2021-2022	animal cart excluded	0.290	55.93	51.81
			animal cart retained	0.290	55.92	51.77

8.3 Burkina Faso

The most recent survey for this country is DHS 2021. This survey is harmonised with an earlier survey, DHS 2010. No indicator-specific harmonisation was applied across both datasets.

We present the harmonised MPI results and its partial indices by 13 administrative regions of the country since the samples across the harmonised datasets are representative at this level (INSD and ICF, 2023; INSD and ICF, 2012).

An earlier survey – MICS 2006 of MICS3 round – was excluded from the harmonised estimates. This dataset lacked birth history module, affecting the definition of child mortality indicator. The exclusion of this survey from the pool for harmonised surveys allowed us to retain the complete child mortality definition since detailed birth history information was collected in the newer surveys.

An earlier survey – DHS 2003 of DHS-IV phase – was also excluded from the harmonised estimates because of data limitations. Namely, the dataset lacked information on materials used to construct the roof and walls of the dwelling. A sensitivity analysis was conducted by comparing estimates between two specifications. The first specification excluded information on roof and walls across all datasets. The second specification retained the data on roof and walls in the recent datasets despite its unavailability in the 2003 survey. There are significant differences in the levels of MPI and H estimates between both specifications suggesting for the exclusion of DHS 2003 dataset from the analysis of poverty trends for Burkina Faso. This also allowed for computing poverty trends over time for Burkina Faso to be based on the complete ten global MPI indicator definition as presented in Table 1 of this publication.

8.4 Comoros

The most recent survey for this country is MICS 2022. This survey is harmonised with an earlier survey, DHS 2012.

The DHS dataset has anthropometric information from children under five years of age and women aged 15 to 49 years. However, for harmonisation purposes, we only use the anthropometric information from children, to accord with the MICS dataset.

The initial survey does not include information on whether the household owns a computer, and likewise the harmonised assets indicator does not include this item despite the availability of this information in the later survey. For future rounds, when additional new surveys are available for Comoros, a sensitivity analysis will be essential to ascertain whether there is value in excluding computer ownership from the harmonised assets indicator.

If sensitivity analysis indicates that there is no significant change in MPI estimates, then we may conclude there is no reason to exclude items from the aggregated assets indicator if these items are consistently available in newer surveys even if these were not collected in one or two of the older surveys.

The harmonised MPI estimates are disaggregated by the three major islands of the country since the samples across all the harmonised datasets are representative at this level (INSEED, 2023; DGSP and ICF International, 2014).

8.5 Cote d'Ivoire

The most recent survey for this country is DHS 2021. This survey is comparable with two earlier surveys, MICS 2016, and DHS 2011-2012.

The MICS and DHS datasets have anthropometric information from children aged under five years and women aged 15 to 49 years. As such, no indicator-specific harmonisation was applied across the three datasets.

Côte d'Ivoire is divided into 12 districts and 2 autonomous districts (Abidjan and Yamoussoukro) (INS and ICF, 2023). However, in the earlier two surveys, Cote d'Ivoire was divided into 11 departments which since have been abolished (Ministry of Planning and Development, UNICEF, and INS, 2017; INS and ICF, 2012). As such, the subnational units are comparable between MICS 2016 and DHS 2011-2012 but these are meaningless subnational definition for present day and not comparable to the districts presented in the most recent survey. As such, MPI disaggregation by subnational region is not possible for Cote d'Ivoire due to incomparable subnational regions across survey datasets.

8.6 Eswatini

The most recent survey for this country is MICS 2021-2022. This survey is harmonised with three earlier surveys, MICS 2014, MICS 2010 and DHS 2006-2007.

The DHS datasets have anthropometric information from children aged under five years, women and men aged 15 to 49 years. However, for harmonisation purposes, we only use the anthropometric information from children, to accord with the MICS datasets.

For harmonisation purposes, we have removed the cooking fuel information from the earlier surveys to match the MICS 2021-2022 dataset, which treated this indicator as missing.[14] Hence the remaining five indicators (sanitation, drinking water, electricity, housing and assets) of the living standards are re-weighted to receive one-fifteenth of the indicator weight each, which sums to one-third of the dimension weight.

In the MICS 2010 questionnaire, women 15-49 years who reported they had never been pregnant did not answer the birth history module. As such, all women who did not have a history of pregnancy was replaced as zero mortality for the child mortality indicator. In contrast, birth history modules were applied to all women aged 15-49 years in the subsequent MICS surveys. A harmonised decision was not applied in this context because the number of women who reported never being pregnant but with a potential birth history is usually very small and this do not affect aggregate numbers.

The toilet category for DHS 2006-2007 included country-specific categories, that is, 'ordinary pit latrine' and 'ventilated improved privy'. The former was categorised as a non-improved facility, while the latter is considered as an improved facility, following the SDG definition.

The initial three surveys do not include information on whether the household owns a computer, and likewise the harmonised assets indicator does not include this item despite the availability of this information in the most recent survey. For future rounds, when additional new surveys are available for Eswatini, a sensitivity analysis will be essential to ascertain whether there is value in excluding computer ownership from the harmonised assets indicator. A sensitivity analysis may show that there are no significant differences in estimates either by excluding or retaining items in the aggregated asset indicator if these items are consistently available in newer surveys but missing in one or two of the older surveys.

At the subnational level, we estimated MPI and its partial indices for four regions of the country since the survey sample across all four harmonised datasets are representative at this level (CSO Eswatini, 2024; CSO and UNICEF, 2016, 2011; CSO Swaziland and Macro International, 2008).

[14] In Eswatini MICS 2021-2022, the questions related to 'household energy use' was administered in half of the households sampled (CSO Eswatini, 2024). As such, the core questions – EU4 and EU1 – used to construct the cooking fuel indicator in the global MPI were not answered by 46.5 percent of the 4,675 households interviewed in this survey. The questions were not administered universally to reduce the overall burden of the survey on interviewers and households given that several non-standard country-specific modules was incorporated into the questionnaires, and this resulted in longer than usual questionnaires. Due to the limited coverage of the cooking fuel data in MICS 2021-2022, we have treated this indicator as missing.

8.7 Gabon

The most recent survey for this country is DHS 2019-2021. This survey is harmonised with an earlier survey, DHS 2012.[15] Both surveys do not include information on whether the household owns an animal cart and so the assets indicator does not include this item. No indicator-specific harmonisation was applied across both datasets.

The 2012 DHS survey is representative for 10 regions of the country (DGS and ICF International, 2013), and the 2019-2021 survey is representative for 11 regions (DGS and ICF, 2023). This is because in the earlier survey, the port city of Port-Gentil was grouped with the capital city of Libreville. For comparability over time, we grouped the port city and capital city in the 2019-2021 dataset, so it is comparable with the 2012 dataset. We present the harmonised MPI results and its partial indices by 10 administrative regions of the country.

8.8 Ghana

The most recent survey for this country is DHS 2022. This survey is harmonised with four earlier surveys, MICS 2017-2018, DHS 2014, MICS 2011, and DHS 2008.

The DHS datasets have anthropometric information from children under five years of age, and from women and men of reproductive age. However, for harmonisation purposes, we only use the anthropometric information from children, to accord with the MICS datasets.

The survey sample for DHS 2022 is representative for 16 regions (GSS and ICF, 2024); while the survey sample of the earlier four surveys are representative for 10 regions of the country (GSS, 2018; GSS, GHS and ICF International, 2015; GSS, 2011; GSS and ICF Macro, 2009)., The number of administrative regions in Ghana increased from 10 to 16 regions following a constitutional reform in 2020. The six new regions were created from four existing regions. First, the Brong Ahafo region was split into the regions of Ahafo, Bono and Nono East. Second, the Northern region was split into the regions of Northern, North East and Savannah. The region of Volta was divided into Oti and Volta. The Western region was divided into Western North and Western. For comparability over time, we grouped the six new regions in the 2022 dataset into the original four regions, so it is comparable with the earlier datasets. We present the harmonised MPI results and its partial indices by 10 administrative regions of the country across the five survey datasets.

[15] An earlier survey – Gabon DHS 2000 of phase IV recode III – was harmonised but requires further quality checks. The survey could be included in poverty trends over time if no data issues are identified.

An earlier survey – DHS 2003 of DHS-IV phase – was excluded from the harmonised estimates because of data limitations. Namely, the dataset lacked information on materials used to construct the roof and walls of the dwelling. A sensitivity analysis was conducted by comparing estimates between two specifications. The first specification excluded information on roof and walls across all datasets. The second specification retained the data on roof and walls in all five datasets despite its unavailability in the 2003 survey. There are significant differences in the levels of MPI and H estimates between both specifications suggesting for the exclusion of DHS 2003 dataset from the analysis of poverty trends for Ghana. This also allowed for estimations of poverty trends over time for Ghana to be based on the complete ten global MPI indicators as presented in Table 1 of this publication.

8.9 Kenya

The most recent survey for this country is DHS 2022. This survey is harmonised with two earlier DHS surveys, 2014 and 2008-2009.

For the housing indicator, the material iron sheets/metal used to construct the roof that is reported in the DHS 2022 corresponds to iron sheets and corregated iron/mabati as reported in the DHS 2014 and DHS 2008-2009 datasets, respectively. We identify these materials as finished (improved) material across all datasets.

The two earlier DHS surveys do not include information on whether the household owns a computer, and likewise the harmonised assets indicator does not include this item despite the availability of this information in the most recent survey. For future rounds, when additional new surveys are available for Kenya, a sensitivity analysis will be essential to ascertain whether there is value in excluding computer ownership from the harmonised assets indicator. A sensitivity analysis may show that there are no significant differences in estimates either by excluding or retaining items in the aggregated asset indicator if these items are consistently available in newer surveys but missing in one or two of the older surveys.

The 2008-2009 survey sample is representative for eight provinces (KNBS and ICF Macro, 2010), while the sample for DHS 2022 (KNBS and ICF, 2023) and 2014 (KNBS and ICF Macro, 2015) was designed to provide estimates for each Kenya's 47 counties. For harmonisation over time, the 47 counties are grouped into eight provinces, to accord with the earlier survey. The provinces are no longer official administrative areas; and so, the results across the eight provinces are only for academic comparison.

An earlier survey – DHS 2003 of DHS-IV phase – was excluded from the harmonised estimates because of data limitations. Namely, the dataset lacked information on materials used to construct the walls of the dwelling. A sensitivity analysis was conducted by comparing estimates between two specifications. The first specification excluded information on walls across all datasets. The second specification retained the data on walls in the later three datasets despite its unavailability in the 2003 survey. There are significant differences in the levels of MPI and H estimates between both specifications suggesting for the exclusion of DHS 2003 dataset from the analysis of poverty trends for Kenya. This also allowed for estimations of poverty trends over time for Kenya to be based on the complete ten global MPI indicators as presented in Table 1 of this publication.

8.10 Mexico

The most recent survey for this country is ENSANUT 2022. This survey is harmonised with four earlier ENSANUT surveys, 2021, 2020, 2016 and 2012. These are national surveys that is open access. There is difference in sample design of between the three most recent surveys 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; 2022).

For harmonisation purposes, we only use the anthropometric information from children under five to construct the nutrition indicator across all datasets. Anthropometric data was collected from individuals aged five years and older across the datasets, but not used because of high non-response rate and potential biased estimates particularly in the 2020, 2021 and 2022 datasets. For example, in the 2021 dataset, if the nutrition indicator was constructed using a combination of child under five and selected individuals who are five 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 male, between 18-59 years of age, living in the urban areas, living in the central regions of the country and are in a male-headed household. 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 five consistently across the Mexico datasets, which resulted in a much lower sample drop and bias analysis indicates the missing is random.

All five surveys lack information on time to collect water, hence the definition of drinking water indicator is limited to source of drinking water.

All five surveys do not collect information on whether the household owns a bicycle or an animal cart, and so the assets indicator for Mexico does not include these two items.

We do not report estimates for Mexico's subnational regions due to an issue with the regional variable identifier in the microdata. This requires cross-checks with microdata provider, which are on-going. As such, Mexico was excluded from subnational estimation for the 2024 round.

8.11 Mozambique

The most recent survey for this country is DHS 2022-2023. This survey is harmonised with two earlier DHS surveys, 2011 and 2003.

The 2003 survey does not include information on whether the household owns an animal cart. The 2003 and 2011 surveys lack information on computer ownership. As such, the harmonised assets indicator does not include these two items despite the availability of this information in the most recent survey. For future rounds, when additional new surveys are available for Mozambique, a sensitivity analysis will be essential to ascertain whether there is value in excluding computer and animal cart from the harmonised assets indicator. A sensitivity analysis may show that there are no significant differences in estimates either by excluding or retaining items in the aggregated asset indicator if these items are consistently available in newer surveys but missing in one or two of the older surveys.

At the subnational level, we estimated MPI and its partial indices for 11 administrative areas of the country since the samples across all three harmonised datasets are representative at this level (INE and ICF, 2024; MISAU, INE and ICFI, 2011).

8.12 Nepal

The most recent survey for this country is DHS 2022. This survey is harmonised with five earlier surveys, MICS 2019, DHS 2016, MICS 2014, DHS 2011 and DHS 2006.

The DHS datasets have anthropometric information from children aged under five years and collected weight and height data from adults. However, for harmonisation purposes, we only use the anthropometric information from children, to accord with the MICS datasets.

In March 2017, structural changes were made in the classifications of urban and rural locations (Ministry of Health Nepal, New ERA, and ICF, 2017, p.2). The 2016 DHS results are based on the updated urban-rural classification. This suggest urban-rural classification is comparable for surveys from 2016 onwards but may be less comparable with pre-2016 surveys. As such, readers should cautiously interpret the comparability of urban-rural poverty results between surveys from 2016 and pre-2016.

Nepal's provinces were created in late 2015 through a constitutional statute, which provided for the division of the country into seven provinces. The survey sample of DHS 2022, MICS 2019 and DHS 2016 is representative for seven provinces of the country (MOH, New Era, and ICF, 2023; 2017; CBS, 2020). These seven provinces replaced the previous 14 Administrative Zones which were grouped into five development regions in DHS 2006 (MOHP, New ERA, and ICF, 2007), and 13 development regions in DHS 2011 (MOHP, New ERA, and ICF, 2012); while it was expanded into 15 development regions in MICS 2014 (CBS, 2015). It is not possible to recode these development regions into the current seven provinces because this requires district-level data that is not provided in the data

sets. Theoretically it is possible to produce harmonised subnational estimates for the seven provinces of the most recent three surveys. However, this is not possible through the current global MPI technical workline. A constraint of the current workline is that the subnational estimates are only possible if a comparable subnational region variable is present in all survey datasets. As such, Nepal is excluded from harmonised subnational estimation.

8.13 Peru

The most recent survey for this country is ENDES 2022. This survey is harmonised with the 2021, 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 five years of age across the 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 from 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 2022, 2021 and the 2012 DHS covered women aged 15 to 49 years. The harmonised child mortality indicator across the surveys only considers data from women aged 15 to 49.

The survey sample for each of the survey period is representative for the 24 administrative regions and the capital district of Callao. We estimated MPI and its partial indices for all 25 regions of the country across the surveys.

8.14 Philippines

The most recent survey for this country is DHS 2022. This survey is comparable with three earlier DHS surveys – 2017, 2013 and 2008.

The DHS datasets for the Philippines specifically do not collect data on anthropometrics. We re-weight the child mortality indicator to one-third weight, to assure equal weighting among the three dimensions.

The standard questions that are used to construct the school attendance indicator is not present in the 2013 and 2008 datasets. We generated the school attendance indicator in both datasets by identifying all school-aged children (6-14 years) and their level of attained education (hv106). We assume all school-aged children who reported no education (hv106==0) is out of school except those who are 6 years old. The starting age for formal schooling is 6 years. However, children of this age are only likely to join school with the start of the new school year. Since both surveys were fielded before the start of school year, we assumed all children who are 6 years are in school. This is a lower bound assumption, to avoid overestimating deprivation in school attendance indicator.

We present the harmonised MPI results and its partial indices by 17 regions of the country across the four survey datasets since the survey sample is representative at this level (PSA and ICF, 2023; 2018; 2014; NSO Philippines and ICF Macro, 2009).

8.15 Tanzania

The most recent survey for this country is DHS 2022. This survey is harmonised with three earlier DHS surveys – 2015-2016, 2010 and 2004-2005.

Across all three earlier DHS surveys, anthropometric measurements were collected from women aged 15-49 years and children under five years; with an exception in the recent 2022 survey that also collected this data from a subsample of adult men. However, for harmonisation purposes, we only include nutrition information from women and children in the harmonised nutrition indicator across the four survey periods.

The earlier two DHS surveys do not include information on whether the household owns a computer or an animal cart, and likewise the harmonised assets indicator does not include these items despite the availability of this information in the latter two surveys. For future rounds, when additional new surveys are available for Tanzania, a sensitivity analysis will be essential to ascertain whether there is value in excluding computer and animal cart ownership from the harmonised assets indicator. A sensitivity analysis may show that there are no significant differences in estimates either by excluding or retaining items in the aggregated asset indicator if these items are consistently available in newer surveys but missing in one or two of the older surveys.

The 2010 and 2004-2005 surveys are representative for eight major zones of the country (NBS Tanzania and ICF Macro, 2011; NBS Tanzania and ORC Macro, 2005). The 2022 and 2015-2016 DHS surveys are representative for nine major zones of the country (DGS and ICF, 2023; MoHCDGEC Tanzania Mainland, MOH Zanzibar, NBS, OCGS, and ICF, 2016). This is because the South West Highlands and Southern Highlands was sampled as separate zones. For comparability over time, we grouped both the zones in the recent two datasets, so it is comparable with the earlier datasets. We present the harmonised MPI results and its partial indices by 8 major zones of the country.

8.16 Thailand

The most recent survey for this country is MICS 2022. This survey is harmonised with three earlier MICS surveys, 2019, 2015-2016 and 2012.

All four surveys lack birth history module. So, the child mortality indicator for Thailand considers individuals deprived if there is any child who died in the household.

All four surveys do not collect information on whether the household owns an animal cart, and so the assets indicator for Thailand does not include this item.

The most recent survey does not include information on whether the household owns a radio, and likewise the harmonised assets indicator does not include this item despite the availability of this information in the earlier three surveys. In the case of Thailand, it was practical to exclude radio from the harmonised assets indicator because, as confirmed by the survey provider, future surveys will no longer include radio in the list of assets. This is because very few households' own radio and is observed as no longer a relevant asset item for the society.

In the 2012 dataset, the area (hh6) variable consisted of two categories: municipal and non-municipal areas. Following advice received from data provider, we identified municipal as urban areas, and non-municipal as rural areas.

We present the harmonised MPI results and its partial indices by five major regions of the country across the four survey datasets since the survey sample is representative at this level (NSO Thailand, 2023; 2020; 2016; NSO, UNICEF, et al, 2013).

8.17 Trinidad and Tobago

The most recent survey for this country is MICS 2022. This survey is harmonised with MICS 2011.

Anthropometric data was not collected as part of the recent MICS 2022 survey. In MICS 2011, anthropometric measurements were collected from children aged under five years living in all of the households sampled. However, for harmonization purposes, we remove all data on nutrition to accord with the MICS 2022 data. This means the child mortality indicator is the only indicator within the health dimension, and as such it receives one-third of the dimensional weight.

The 2011 survey does not include information on whether the household owns a bicycle, a motorcycle, or an animal cart, and likewise the harmonised assets indicator does not include these items despite the availability of this information in the recent survey.

We present the harmonised MPI results and its partial indices by five major regions of the country for both survey period since the survey sample is representative at this level (CSO Trinidad and Tobago, 2023; Ministry of Social Development and Family Services, CSO and UNICEF, 2017).

For future rounds of update, a careful review should be undertaken in relation to harmonised decisions that are applied in the survey datasets of Trinidad and Tobago. For example, if future round of surveys collects anthropometric data, then retaining nutrition indicator as part of the harmonised datasets, may provide accurate poverty trends in Trinidad and Tobago.

8.18 Tunisia

The most recent survey for this country is MICS 2023. This survey is harmonised with two earlier MICS surveys, 2018 and 2011-2012. No indicator-specific harmonisation was applied across both datasets.

We present the harmonised MPI results and its partial indices by seven governorates of the country across both survey datasets since the survey sample is representative at this level (MDCI, NIS and UNICEF, 2013).

8.19 Yemen

The most recent survey for this country is MICS 2022-2023. This survey is harmonised with an earlier survey, DHS 2013.

The DHS dataset have anthropometric information from children aged under 5 years, and from women aged 15-49 years; the MICS collected anthropometric measurements from all eligible children under five years. However, for harmonisation purposes, we only use the anthropometric information from children, to accord with the recent MICS dataset.

For harmonisation purposes, we have removed the housing indicator from the earlier survey to match the MICS 2022-2023 dataset which had missing housing data.[16] Hence the remaining five indicators (sanitation, drinking water, electricity, housing and assets) of the living standards are re-weighted to receive one-fifteenth of the indicator weight each, which sums to one-third of the dimension weight.

The earlier survey does not include information on whether the household owns a computer, and likewise the harmonised assets indicator does not include this item despite the availability of this information in the later survey. For future rounds, when additional new surveys are available for Yemen, a sensitivity analysis will be essential to ascertain whether there is value in excluding an asset item simply because it is not available in the earlier survey. A sensitivity analysis may show that there is no significant differences in estimates either by excluding or retaining items in the aggregated asset indicator if these items are consistently available in newer surveys but missing in one or two of the older surveys.

The MICS 2022-2023 survey is representative for 22 governorates (DGS and ICF, 2023), and the DHS 2013 survey is representative for 21 governorates of the country (MOPHP, CSO et al., 2015).

16 In Yemen MICS 2022-2023, housing data was not collected from households in Yemen's northern highlands - where the conflict is active. Due to the limited coverage of the housing data, we have treated this indicator as missing.

This is because in the earlier survey, the governorate of Socotra Archipelago was part of the Hadramout governorate. For comparability over time, we grouped both governorates in the recent dataset, so it is comparable with the earlier dataset. We present the harmonised MPI results and its partial indices by 21 governorates of the country.

An earlier survey – MICS 2006 of MICS3 round – was excluded from the harmonised estimates due to lack of nutrition data, and birth history module. The exclusion of this survey from the pool for harmonised surveys allowed us to retain the complete health indicators for Yemen.

9. Concluding remarks

The global MPI 2024 includes harmonised levels and changes over time estimates for 86 countries. We 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 86 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. At the subnational level, we reported the changes in MPI estimates by 863 subnational regions in 78 countries.

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