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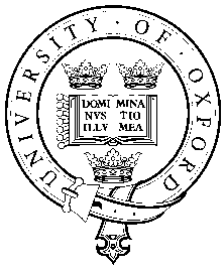

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Changes over Time in the Global Multidimensional Poverty Index and Other Measures: Towards National Poverty Reports.

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Abstract
This paper compares trends in multidimensional and monetary poverty systematically across developing regions. The trends in multidimensional poverty draw on the global Multidimensional Poverty Index (MPI) and related sub- and partial-indices in 80 countries and 647 subnational regions, covering roughly 5 billion people, for which there is a recent MPI estimation and comparable datasets for two time periods. This paper uses two main techniques to assess the pro-poorness of multidimensional poverty reduction and triangulate monetary and nonmonetary poverty measures. First, utilizing the properties of subgroup decomposability and dimensional breakdown, it examines changes in the MPIT and its consistent sub-indices over time across sub-national regions and urban–rural regions. The decomposition analysis identifies relevant national patterns, including those in which the pace of poverty reduction is higher for the poorest subgroups. Next, it assesses overall annualized changes in the incidence of multidimensional poverty, compares this with changes in $1.90 poverty trends, and evaluates the pace and direction of various international poverty lines for monetary poverty, with national monetary and multidimensional measures, and for the family of global MPIT measures. This extensive empirical analysis illustrates how to assess the extent and patterns of reduction of multidimensional poverty, as well as whether it is inclusive or whether some people or groups are left behind, and triangulates various poverty measures to evaluate the reliability and credibility of their purposes. Naturally, some further research questions emerge.

Keywords: Multidimensional Poverty, Monetary Poverty, Intertemporal Poverty Trends, Poverty measurement, Rural Poverty, Urban Poverty, Subnational Disaggregation, Destitution, Atkinson

JEL classification: I3, I32, D63, O1

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1. Introduction

The aim of this paper is to compare trends in multidimensional and monetary poverty systematically across developing regions. Tracking the relationships and variations of distinct poverty measures for different countries allows us to investigate the congruence and contribution of each method and their implications for poverty eradication. As we advance in the Third Decade on Poverty, track the SDG deadline of halving poverty in all its forms and dimensions, and countenance the poverty impacts of the current pandemic, Sir Tony Atkinson's call to triangulate poverty trends by different measurement approaches resonates louder than ever (Atkinson 2019).

Methodologically, this paper extends the intertemporal multidimensional poverty analysis of the global multidimensional poverty index (MPI)[1] to the largest number of countries to date, documenting how multidimensional poverty and its incidence and intensity have changed in 80 countries representing nearly 5 billion people.[2] To assess whether the poorest are progressing the fastest, it further assesses the pro-poorness of those changes across 647 subnational regions, urban and rural areas of residence, and also introduces destitution. To measure multidimensional poverty, we use the global Multidimensional Poverty Index (MPI). We also explore the changes over time in a destitution measure, which identifies the subset of MPI poor who are destitute according to more severe deprivation cutoffs (e.g. severe undernutrition instead of undernutrition).

The contribution of this paper is two-fold. First, never before has intertemporal multidimensional poverty analysis been extended to a critical mass of countries. Building on earlier work by Alkire, Roche, and Vaz (2017) and Alkire, Jindra, et al (2017), we select 80 countries with available data and conduct a rigorous harmonization procedure to ensure comparability of the MPI values and associated statistics over time. As with earlier accounts, such a systematic review is an essential step towards clarifying the Sustainable Development Goal's (SDGs) aim of Target 1.2 to halve the proportion of people who are poor in many dimensions, using datasets ranging from 2000 for the Central African Republic (MICS) and Gabon (DHS) to the most recent datasets from 2019 for Bangladesh (MICS) and 2018 for Madagascar (MICS), Nigeria (DHS), and Peru (ENDES).

[1] The MPI, an internationally comparable measure of acute poverty in over 100 developing countries, was developed by the Oxford Poverty and Human Development Initiative (OPHI) at the University of Oxford with the Human Development Report Office of the United Nations Development Programme (Alkire and Santos, 2014; Alkire, Kanagaratnam, and Suppa 2020).

[2] The population of these countries is about 5 billion. The population was 4.7 billion in the first time period, 5.1 billion in the second and 5.3 billion in 2018. When analyzing trends in multidimensional poverty, the population in the survey years is used to estimate the number of multidimensional poor people. If a survey was conducted between two years, we present the average of the two survey years.

Second, neither has triangulation of poverty trends across time been initiated at this scale between monetary and nonmonetary poverty measures for developing countries. This analysis interrogates the credibility and implications of varied poverty measurement approaches to find that, indeed, monetary and nonmonetary poverty trends differ. By comparing the $1.90 a day and national monetary poverty headcount trends with the incidence of multidimensional poverty, and assessing the variety of multidimensional poverty measures applied by the global MPI – destitution, vulnerability, and severity – we paint a picture of the shape of poverty reduction for a slice of time per country and illustrate how such analyses add value.

We begin the paper in Section 2 by describing the counting-based measurement methodology of the MPI, detailing the intertemporal analysis, and defining the associated statistics used to analyze changes over time and disaggregated analysis. Section 3 details the data used in this study and the harmonization process to obtain comparable poverty estimates for a country across multiple time periods. Section 4 presents the key results of the 80-country study, from the national level to the subnational regions, rural and urban areas of residence, and breakdown by indicator; it ends by evaluating the impact of population growth on intertemporal poverty analysis and the complementarity of the MPI measure to the World Bank's income classifications and $1.90 a day methodology. Section 5 takes up the mantle of Atkinson's call for poverty triangulation, evaluating $1.90 a day trends, $3.20 a day trends, national poverty line headcount ratios, National MPI trends, and the 80-country multidimensional poverty trends for MPI$_T$, destitution, severity, and vulnerability. Section 6 concludes.

2. Methodology

2.1 Counting-based measurement methodology

The global MPI is a measure of acute global poverty developed by the Oxford Poverty and Human Development Initiative (OPHI) with the UNDP's Human Development Report Office (Alkire, Kanagaratnam, and Suppa 2020; Alkire and Santos 2014). The index is an application of the method developed by Sabina Alkire and James Foster (2011; cf Alkire et al., 2015).

The online Table 6 of the 2020 global MPI data tables[3] presents harmonized intertemporal estimations using 160 datasets from 80 countries.[4] As summarized in Table 1 below, the MPI uses

[3] Table 6 contains 14 worksheets with full country, indicator, and disaggregated details, is cited as Alkire, Kovesdi, et al 2020, and can be downloaded from https://ophi.org.uk/multidimensional-poverty-index/data-tables-do-files/.

[4] Afghanistan, Albania, Armenia, Bangladesh, Belize, Benin, Bolivia, Bosnia and Herzegovina, Burkina Faso, Burundi, Cambodia, Cameroon, Central African Republic, Chad, China, Colombia, Congo, Côte d'Ivoire, Democratic

Table 1: Global MPI 2020: Dimensions, Indicators, Deprivation Cutoffs, and Weights

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

Notes:

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 older than 19 to 70 years (229–840 months) are considered undernourished if their Body Mass Index (BMI) is below 18.5 kg/m².

2 The child mortality indicator of the global MPI is based on birth history data provided by mothers aged 15–49. In most surveys, men have provided information on occurrence of 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 occurrence of 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 age children start compulsory primary school: DHS/MICS survey reports and UIS.Stat.

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

6 A household is considered to have access to improved sanitation if it has some type of flush toilet or latrine, or ventilated improved pit or composting toilet, provided that they are not shared. If a survey report uses other definitions of adequate sanitation, we follow the survey report.

Republic of the Congo, Dominican Republic, Egypt, eSwatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guyana, Haiti, Honduras, India, Indonesia, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kyrgyzstan, Lao PDR, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mexico, Moldova, Mongolia, Montenegro, Mozambique, Namibia, Nepal, Nicaragua, Niger, Nigeria, North Macedonia, Pakistan, Peru, Philippines, Rwanda, Sao Tome and Principe, Senegal, Serbia, Sierra Leone, State of Palestine, Sudan, Suriname, Tajikistan, Tanzania, Thailand, Timor-Leste, Togo, Trinidad and Tobago, Turkmenistan, Uganda, Ukraine, Vietnam, Yemen, Zambia, and Zimbabwe.

[7]A household has access to clean drinking water if the water source is any of the following types: piped water, public tap, borehole or pump, protected well, protected spring or rainwater, and it is within 30 minutes' walk (round trip). If a survey report uses other definitions of clean or safe drinking water, we follow the survey report.

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

Source: Alkire, Kanagaratnam and Suppa (2020).

information from 10 indicators that are organized into three dimensions: health, education, and living standards, following the same dimensions and weights as the UNDP's Human Development Index (HDI). Each person is identified as deprived or non-deprived in each indicator based on a deprivation cutoff (See Table 1 as well as Alkire, Kanagaratnam, and Suppa 2020). Each person's deprivation score is the sum of the weighted deprivations they experience, using a nested weight structure: equal weight across dimensions and equal weight for each indicator within dimensions. Finally, a poverty cutoff of 33.33% identifies those people as multidimensionally poor whose deprivation score meets or exceeds this threshold.

The MPI reflects both the **incidence** or headcount ratio (H) of poverty – the proportion of the population that is multidimensionally poor – and the average **intensity** (A) of their poverty – the average proportion of indicators in which poor people are deprived. The MPI is calculated by multiplying the incidence of poverty by the average intensity across the poor ($H \times A$).

Table 1 presents the dimensions, indicators, deprivation cutoffs, and weights used in the global MPI 2020. For a more detailed look at the specifications of the global MPI 2020, please refer to Alkire, Kanagaratnam, and Suppa (2020), and for a more detailed look at the specifications of the intertemporal changes over time of the global MPI, please refer to 'Methodological Note 50', Alkire, Kovesdi, et al. (2020).

2.2 Intertemporal trends

A strong motivation for computing multidimensional poverty is to track and analyze changes over time. This section describes how to compare the MPI and its associated partial indices over time using repeated cross-sectional data.

The basic component of poverty comparisons is the absolute pace of change across periods. The absolute rate of change is the simple difference in poverty levels between two periods. We denote the initial period by $t1$ and the final period by $t2$, and the corresponding achievement matrices for these two periods by $Xt1$ and $Xt2$, respectively. The same set of parameters – deprivation cutoff

vector z, weight vector w and poverty cutoff k – are used in each period. The **absolute rate of change** (Δ)[5] is the difference in MPIs between two periods and is computed as

$$\Delta MPI = MPI(X_{t2}) - MPI(X_{t1}).$$

Similarly, for H and A:

$$\Delta H = H(X_{t2}) - H(X_{t1}).$$

$$\Delta A = A(X_{t2}) - A(X_{t1}).$$

The absolute rate of change is indifferent to the initial level. For example, a 5-percentage point reduction of H could mean that H decreased from 75% to 70% or from 10% to 5%.

Changes (increases or decreases) in poverty across two time periods are also evaluated using relative rates. The **relative rate of change** is the difference in poverty as a percentage of the initial poverty level. It shows the percentage of the distance to zero poverty that was covered in the period concerned. Interpreting the analysis of absolute and relative changes together provides a clear sense of overall progress. The **relative rate of change** (δ) is computed for the MPI (and similarly for H, and A which are not presented) as

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

The absolute and relative changes, however, are not comparable for different countries when the reference periods are of different length. To compare the rates of poverty reduction across countries that have different periods of reference, annualized changes are used. The **annualized absolute rate of change** ($\bar{\Delta}$) is the difference in the MPI between two periods divided by the difference in the two time periods ($t_2 - t_1$) and is computed for the MPI as

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

The **annualized relative rate of change** ($\bar{\delta}$) is the compound rate of reduction in the MPI per year between the initial and the final periods, and is computed for the MPI as

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

[5] This section draws on Chapter 9 of Alkire et al. (2015) and the papers by Alkire et al. (2016) and Alkire, Roche and Vaz (2017).

The same formula can be used to compute and report annualized changes in the other partial indices, namely H, A, or censored headcount ratios. And all of these formulas may be used for MPI or for destitution measures.

The reductions in MPI can be broken down by indicators to see how change happened. An analysis of changes in MPI considers both changes in the raw or uncensored headcount ratios (h_j) and in the censored headcount ratios ($h(k)$). The changes in censored headcount ratios depict changes in deprivations among the poor.

Changes in the MPI at the national level can be decomposed by subnational regions, age groups, or other population subgroups. That is, poverty in each period can be expressed as

$$MPI = \sum_{\ell=1}^{m} v^{\ell} MPI(X^{\ell}),$$

where $MPI(X^{\ell})$ denotes the MPI of subgroup ℓ and $v^{\ell} = n^{\ell}/n$ denotes the population share of subgroup ℓ, respectively. It can be extremely useful to analyze poverty changes by population subgroups, to see if the poorest subgroups reduced poverty faster than less poor subgroups, and to see different patterns in the dimensional composition of changes across subgroups (Alkire and Roche 2013; Alkire and Seth 2015; Alkire, Roche, and Vaz 2017). Note that population shares for each period must be analyzed alongside subgroup trends in order to take into account demographic shifts such as migration or population growth.

3. Data

As mentioned above, harmonized intertemporal estimations were performed for 80 countries to facilitate rigorous comparisons of changes in the MPI and its associated statistics over time. Strict harmonization requires using the same information from both the older and newer datasets to ensure that any differences observed are due to changes in the conditions of the country rather than changes in the questionnaire.[6]

The 80 countries in this study span all developing regions (East Asia and the Pacific, Europe and Central Asia, Latin America and the Caribbean, South Asia, and Sub-Saharan Africa), various World Bank income categories (e.g. upper-middle income, lower-middle income, and low income), all four categories of human development according to their country's HDI status in 2018 (Low, Medium, High, and Very High), and include six of the top ten most populated countries in the

[6] The harmonization process is treated with far greater detail in Alkire, Kovesdi, et al. (2020), Methodological Note 50, Section 3, 'Harmonization Principles and Decisions'.

world (Bangladesh, China, India, Indonesia, Nigeria, and Pakistan). They contain more than 4.7 billion people in the first time period considered and 5.1 billion people in the second, around two-thirds of the world's population as per population estimates from 2019. Their GNI per capita in 2010 ranged from $233 in Burundi to $15,781 in Trinidad and Tobago. The simple average time span between the two surveys are 5.7 years for the 80 countries included, and the population-weighted average time span is 6 years. The effective sample size ranges from 5,193 for Jamaica in 2010 to 2,702,677 in India in 2015/16, while the average sample size is 58,284 in Year 1 and 92,742 in Year 2. Appendix A describes the time period, survey, and sample size for the two periods in each country. Appendix B describes the countries, population, GNI, and HDI category for the analysis of changes over time. These 80 countries were selected from the 101 countries estimated in the global MPI 2019, based on the availability of multiple comparable datasets.

This study presents harmonized intertemporal estimations following the same basic principles as previous harmonization of the original MPI over time (Alkire & Roche 2013; Alkire & Seth 2016; Alkire, Jindra, et al. 2017; Alkire, Roche, and Vaz 2017; Alkire, Kovesdi, et al. 2020). The harmonization process guarantees rigorous comparisons of changes in MPI and its associated statistics and invites us to analyze trends in poverty over time. Unlike *standardization* – the process used to compute the global MPI for over 100 countries by obtaining the same (or as similar as possible, following defined rules) general indicator definitions from different datasets – *harmonization* seeks to make two or more MPI estimations comparable by exactly aligning the indicator definitions. In other words, harmonization, where necessary, re-creates the indicators in the global MPI so that they are using precisely the same information and deprivation cutoffs in both years. Comparable MPI values are denoted by MPI_T as their values may differ from published global MPI values. We have information on the 10 MPI indicators for 62 countries; nine countries lack information on nutrition only,[7] six countries lack information on child mortality,[8] Egypt lacks information on cooking fuel, Honduras lacks information on electricity, and the Philippines lacks information on both nutrition and school attendance. It is important to emphasize that these surveys cover different time periods; therefore, direct cross-country comparisons using annualized changes should be made with caution.

[7] Afghanistan, Colombia, Dominican Republic, Indonesia, Philippines, Trinidad and Tobago, Ukraine, Vietnam, and Yemen.

[8] Bosnia and Herzegovina, Jamaica, Mexico, Montenegro, North Macedonia, and Suriname.

Further, for countries that have retained samples of less than 85% of the original sample, or a sample size of less than 75% for one or more of the subnational regions, we conduct a bias analysis using hypothesis tests of differences in means (Alkire and Santos 2014) to identify whether we are able to obtain meaningful and non-biased estimates at the subnational level. We conducted bias analyses for three countries that did not meet this criterion on sample size, and, after interpreting the results, the decision was made to exclude the countries of Guinea-Bissau, Maldives, and South Africa, as they did not meet the 85% retained national sample criteria. Greater detail on the MPI adjustment for comparability and differences with the published figures is provided in 'Methodological Note 50', Alkire, Kovesdi, et al. (2020).

4. Results

4.1 Overview of National trends

The fastest progress in absolute annualized reduction of MPI_T was in Sierra Leone (2013-2017), Mauritania (2011-2015), Liberia (2007-2013), and Timor-Leste (2009/10-2016), whereas in relative terms, North Macedonia (2005/06-2011), China (2010-2014), Armenia (2010-2015/16), and Kazakhstan (2010/11-2015) reduced their poverty the most. Overall, 67 of the 80 countries had significant reductions in MPI at the α=0.05 significance level, with 60 countries at α=0.01. These 67 countries were home to 98% of the poor people living in all 80 countries in the first time period and 97% of the poor living in all 80 countries in the second.

Ranking developing regions by average MPI reveals that while South Asia and Sub-Saharan Africa are the poorest in both time periods, averaging across the survey years, they also had the largest annualized absolute reductions. The fastest country in each region in terms of the annualized absolute MPI_T reductions are Sudan (2010-2014) in the Arab States, Timor-Leste (2009/10-2016) in East Asia and the Pacific, Mongolia (2010-2013) in Europe and Central Asia, Honduras (2005/06-2011/12) in Latin America and the Caribbean, India (2005/06-2015/16) in South Asia, and Sierra Leone (2013-2017) in Sub-Saharan Africa. The countries leading their region in annualized relative MPI_T reductions include Egypt (2008-2014) in the Arab States, China (2010-2014) in East Asia and the Pacific, North Macedonia (2005/06-2011) in Europe and Central Asia, Honduras (2005/06-2011/12) in Latin America and the Caribbean, Bangladesh (2014-2019) in South Asia, and Sao Tome and Principe (2008/09-2014) in Sub-Saharan Africa.

The multidimensional headcount ratio and its annualized rates of change are presented in Table 6.2. The headcount ratio (H_T) can be seen as the multidimensional equivalent to the $1.90 a day poverty headcount, as it focuses on the number of people who experience deprivations due to

poverty in their everyday lives. While H_T is valuable for comparisons between multidimensional poverty measurement and the $1.90 a day measure, the MPI_T remains a more complete account of poverty due to its inclusion of the average intensity of deprivations experienced by the individual (Alkire, Kanagaratnam and Suppa 2020). The $1.90 a day poverty headcount measure and its annualized rates of change are presented in Appendix C and discussed later in this section.

Of the 67 countries with significant changes in MPI_T, 63 countries observed significant changes in the headcount ratio, in addition to Thailand, which only had a significant change in MPI_T at the α=0.10 significance level. Those countries that were most successful in reducing the MPI_T in absolute terms – Sierra Leone, Mauritania, Liberia, Timor-Leste, and Guinea – also strongly reduced the incidence of multidimensional poverty, both in absolute and relative terms. Sierra Leone, the fastest country, reduced incidence from 74.1% to 58.3% in a four-year period (2013-2017), a yearly decrease of 3.9 percentage points, made all the more remarkable by its experience of the Ebola crisis during that period. The other top performing countries registered annualized reductions between 2.4 and 3.5 percentage points.

Meanwhile, almost two-thirds of the countries experience a significant annualized reduction (absolute or relative) in their intensity of poverty, A_T, between their two time periods. Mauritania, Ghana, and Guinea had the fastest absolute annualized reductions among the countries, both in relative and absolute terms. Jordan had a significant increase in intensity, indicating those in poverty experienced more deprivations, on average, in the second time period, although Jordan's MPI_T and H_T changes are insignificant. Of the 15 countries with an overall reduction in poverty but a higher number of poor[9], only Nigeria does not see a significant reduction of the average intensity of deprivations. Thus, this story is not entirely pessimistic: although the number of poor may be increasing in some populations, those in poverty nearly always face fewer global MPI deprivations on average in the latest year.

While many of the stories presented here describe hard-won victories in the fight against poverty, for a few countries, the narrative remains complex. Although no country significantly increased poverty, thirteen countries saw no significant change in their MPI_T during the time periods studied.[10] Ten of those countries were low poverty already and had MPI_T values less than 0.050 in

[9] Burkina Faso, Burundi, Central African Republic, Chad, Democratic Republic of the Congo, Ethiopia, Gambia, Madagascar, Mali, Mozambique, Niger, Nigeria, Senegal, Sudan, and Zambia.

[10] Armenia, Benin, Cameroon, Jamaica, Jordan, Montenegro, Serbia, State of Palestine, Thailand, Togo, Trinidad and Tobago, Ukraine, and Vietnam. Note that Thailand and Armenia are significant at the α=0.10 significance level.

their first survey year, making it difficult to have a significant change.[11] Benin, Cameroon, and Togo, however, still face large hurdles in their race to eradicate extreme poverty by 2030, as according to their recent data, nearly half or more than half of their populations live in multidimensional poverty – and that's not gone down.

4.2 Subnational MPI$_T$ Changes

In this section, we compare the MPI$_T$ reduction across subnational regions, as subnational patterns are vital to display regional disparities. Data representative at the regional level are available for 60 countries and 647 regions. In total, 405 regions containing 93% of the poor population in t_1 and 95% of the poor population in t_2 showed statistically significant reductions in MPI$_T$. Across the 405 subnational regions of the countries with significant reductions in poverty, 311 regions decreased multidimensional poverty at α=0.01 significance level and 94 regions only at α=0.05.

Most of the top performers in reducing poverty also decreased disparities across regions relatively well. Notably, of the top five national champions in annualized absolute reductions – Sierra Leone, Mauritania, Liberia, Timor-Leste, and Guinea – only Liberia did not have a subnational region in the fastest twenty of subnational reducers in terms of annualized absolute MPI$_T$ reductions. Sierra Leone's reduction in poverty was driven by powerful reductions in three regions: Kambia, Kenema, and Kono[12]; Mauritania's in five: Assaba, Gorgol, Hodh el Gharbi, Hosh ech Chargui, and Tagant; Timor-Leste's in two: Lautem and Viqueque; and Guinea's in one: Kindia. Furthermore, of the top five national champions in annualized relative reductions that qualified for subnational disaggregation – North Macedonia, China, Indonesia, Mongolia, and Sao Tome and Principe – only Sao Tome and Principe did not have a subnational region in the top twenty of subnational reducers in annualized relative reductions. North Macedonia's reduction in poverty was led by powerful reductions in four of its eight regions: Northeast, Pelagonia, Skopje, and Southeast; China's in one: East/Costal Region; Indonesia's in three: Bengkulu, Jambi, and West Sulawesi; and Mongolia's in one: Ulaanbaatar.

Hosh el Gharbi, a southern region in Mauritania, was the fastest subnational reducer with an annualized reduction rate of 0.051 percentage points in absolute terms between 2011 and 2015. Improvements in the education and living standards indicators drove progress in the region, where,

[11] Armenia, Benin, Cameroon, Jamaica, Jordan, Montenegro, Serbia, State of Palestine, Thailand, Togo, Trinidad and Tobago, Ukraine, and Vietnam.

[12] Unlike the other regions specified here, Kono had a high relative difference (≥40%) in the population share between the two periods, as a reflection of the sample drop in the first year. For more information on Kono's sample drop, please refer to Appendix D.

for example, the years of schooling indicator's censored headcount ratio dropped from 67.6% in 2011 to 18.2% in 2015, and the drinking water indicator's censored headcount ratio dropped from 76.2% in 2011 to 44.6% in 2015. The Southeast region of North Macedonia, meanwhile, was the fastest subnational reducer in relative terms between 2005/06 and 2011, and with an annualized relative reduction rate of 44.8 percent, almost double the national rate. A total of 32 subnational regions reduced their MPI_T values in absolute terms faster than Sierra Leone, our fastest national reducer, with 17 of them located in Sub-Saharan Africa.[13] The Lao PDR is also home to two such runaway regions – Phongsaly and Ouodomxay – which had an annual MPI_T reduction rate of over 0.030 in absolute terms, a rate higher than the fastest national reducer, Sierra Leone.

Any study of subnational poverty requires simultaneous consideration of the number and population share of the regions over time. For 12 countries,[14] we observed high relative differences (≥40%) in the population shares of a few subnational regions between the two periods, most of which could be attributed to population growth or internal migration patterns.[15] The Democratic Republic of the Congo, for instance, observed a near-doubling of the population shares between 2007 and 2013/14 for the Nord-Kivu and Sud-Kivu provinces, both of which took in many refugees and IDPs from neighboring countries (Norwegian Refugee Council 2014, UNHCR 2019). Meanwhile, the Tete province of Mozambique saw a rise in the population share from 0.09 and 0.013 between 2003 and 2011, likely due to economic migration into the province for the purposes of working on the Moatize coal project, where in 2011 alone, the Vale company, owner of the mine, relocated 5,000 workers to the province (Flak 2011, Murphy 2011). In Sierra Leone, internal and economic migration explains the atmospheric growth rate between 2013 and 2017 in Western Area Rural, whose population share jumped from 0.03 to 0.07 (Statistics Sierra Leone 2015a, Statistics Sierra Leone 2015b). Of these 12 countries, only two exist outside of Sub-Saharan Africa: Nicaragua (Latin America and the Caribbean) and Pakistan (South Asia). For greater

[13] In descending order of absolute annualized change: Hosh el Gharbi (Mauritania), Kono (Sierra Leone), Upper East (Ghana), Kindia (Guinea), Gorgol (Mauritania), Tagant (Mauritania), Phongsaly (Lao PDR), Assaba (Mauritania), Kambia (Sierra Leone), Lempira (Honduras), Olancho (Honduras), Upper West (Ghana), Oudomxay (Lao PDR), Hosh ech Chargui (Mauritania), Kenema (Sierra Leone), Takeo (Cambodia), Intibucá (Honduras), Lautem (Timor-Leste), Viqueque (Timor-Leste), Santa Bárbara (Honduras), Mondul Kiri & Ratanak Kiri (Cambodia), Northern (Ghana), Chitipa (Malawi), Rural Interior (Suriname), Kankan (Guinea), La Paz (Honduras), Centre (Côte d'Ivoire), Saravane (Lao PDRManica (Mozambique), Janjanbureh (Gambia), Svay Rieng (Cambodia), and Chuquisaca (Bolivia).

[14] Benin, Congo, Democratic Republic of Congo, Ethiopia, Kenya, Madagascar, Malawi, Mozambique, Nicaragua, Nigeria, Pakistan, and Sierra Leone.

[15] For a few countries, sample drop due to missing observations on the indicators contributes to the population share changes, though the bias testing procedures we have in place allow for comparability between the regions.

explication of subnational regions where sample drop explains the observed relative difference of ≥40% between the population shares, please refer to Appendix D.

That said, among the 67 countries with significant changes in MPIT, 15 countries saw progress in every one of its subnational regions[16], including China, Liberia, and Rwanda, which were three of our top-five fastest reducers (in absolute or relative terms). Out of the seven countries that did not observe a significant reduction in their MPIT between the two periods and had a subnational disaggregation,[17] two countries had at least one subnational region reduce their MPIT significantly. Further, of the 647 subnational regions, 47 regions reduced every indicator significantly, and these include all but five of India's 29 regions (Delhi, Goa, Himachal Pradesh, Mizoram, and Uttarakhand).

When comparing only the poorest and least poor subnational regions, we find that often the national MPIT hides large regional disparities. The country with the largest range of subnational MPIT values at the initial year was Nigeria. In 2013, Lagos, the most populous city in Nigeria, had an MPIT of 0.021, while the Yobe state, which has unfortunately been affected by violence due to Boko Haram's insurgency, had an MPIT of 0.612. Peru, meanwhile, was the country with the largest ratio considering the initial year. In 2012, the province Loreto had an MPIT of 0.186, more than 60 times higher than the MPIT of the small province Callao (0.003), using point estimates. There were countries, of course, with much smaller differences. For instance, in the initial year, Liberia observed an MPIT between 0.359 in South Central and 0.548 in the South Eastern A. In 16 countries, the MPIT of the poorest region was less than twice the MPIT of the richest region, in the initial year, considering point estimates.[18]

Even so, most countries are moving towards convergence; hence, the gap between the poorest and richest subnational regions is closing in absolute terms. Fifty-four of the 65 countries observed an absolute reduction in the gap between the poorest and richest subnational regions[19] – in

16 Bangladesh, Bolivia, China, Congo, eSwatini, Gabon, Gambia, Guyana, India, Liberia, Mozambique, Nepal, Nicaragua, Niger, and Rwanda.

17 The two: Extrême-Nord in Cameroon and North in Montenegro. The seven: Benin, Cameroon, Jamaica, Montenegro, Togo, Trinidad and Tobago, and Vietnam.

18 Afghanistan, Bangladesh, Central African Republic, eSwatini, Haiti, Lesotho, Liberia, Madagascar, Malawi, Montenegro, Nepal, Niger, Rwanda, Sao Tome and Principe, Togo, and Trinidad and Tobago.

19 Bangladesh, Belize, Benin, Bolivia, Cambodia, Cameroon, Central African Republic, China, Congo, Côte D'Ivoire, Democratic Republic of Congo, Dominican Republic, Egypt, eSwatini, Gabon, Gambia, Ghana, Guinea, Guyana, Haiti, Honduras, India, Indonesia, Jamaica, Kenya, Kyrgyzstan, Lao PDR, Lesotho, Madagascar, Malawi, Mauritania, Mexico, Moldova, Montenegro, Namibia, Nepal, Nicaragua, Niger, Nigeria, North Macedonia, Pakistan, Peru, Philippines, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Suriname, Tajikistan, Thailand, Timor-Leste, Turkmenistan, Ukraine, and Zimbabwe.

particular, Nicaragua saw its absolute gap drop from a 0.436 MPI_T difference between its poorest and richest regions in 2001 to a 0.194 MPI_T difference in 2011/12. The country with the largest increase in an absolute gap between its poorest and richest subnational regions was Mali, which observed a 0.395 MPI_T difference between its poorest and richest regions in 2005 that rose to a 0.461 MPI_T difference in 2015. Although the MPI_T range depends tightly upon the number and population share of the regions, the range can provide some indication of geographic variation. Despite the intricacies involved in cross-country comparisons, we disaggregate MPI_T reduction across regions, because the national averages do indeed hide very different regional paths.

4.3 Rural-Urban Disaggregation

Forty-four countries[20] reduced poverty in both urban and rural areas, and twenty-four – more than half – of those countries were located in Sub-Saharan Africa. Colombia significantly reduced its urban poverty, although its rural area saw no significant change in its levels of poverty. Of these 44 countries that significantly reduced poverty in both urban and rural areas, their urban poverty decreased more, on average, in relative terms.

Of the 78 countries that could be disaggregated by urban and rural areas, 45 had a significant reduction in urban poverty and 64 in rural poverty. Two countries – Madagascar and Nepal – observed a significant increase in urban poverty, although no country observed a significant increase in rural poverty. Rwanda and Mali showed the fastest annualized absolute reduction in MPI among urban areas, while poverty in rural areas decreased fastest in Bolivia, followed by Honduras, Mauritania, and Nicaragua. Meanwhile, the countries with the largest relative reduction in H_T, the percentage of the population living in poverty, were in the urban areas of North Macedonia, Mongolia, and Bolivia, with more than a 20% annual decrease relative to their starting level, and in the rural areas of the States of Palestine, North Macedonia, China, and Turkmenistan, where the incidence of poverty reduced by over 15% per year relative to their initial level of poverty. Naturally in-migration and rural-urban migration will also have affected these rates. Indeed, in North Macedonia, the Skopje region, which houses the capital, has been the only region with continuous positive migration balance in internal migration during the last two decades preceding the second year of the survey (Bornarova and Janeska 2012: 8); meanwhile, in China, atmospheric rural-urban migration rates are the result of economic reform and rapid urbanization,

[20] Afghanistan, Bangladesh, Bolivia, Burundi, Cambodia, Central African Republic, China, Colombia, Congo, Côte d'Ivoire, Democratic Republic of the Congo, Dominican Republic, Egypt, eSwatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Haiti, Honduras, India, Indonesia, Iraq, Kyrgyzstan, Lao PDR, Liberia, Madagascar, Malawi, Mali, Mauritania, Mongolia, Mozambique, Nepal, Nicaragua, Niger, North Macedonia, Peru, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Sudan, Suriname, Tanzania, Timor-Leste, and Zambia.

where over the last two decades, China has experienced the largest population flow in recorded human history (United Nations Population Fund 2015; Chen and Wang 2019). Sending communities may experience negative impacts on poverty as a result of young people leaving for cities' greater livelihood opportunities, but they may also benefit from remittances sent home by their urban relatives.

4.4 How MPI Changes: Reductions in Each Indicator

Twenty countries significantly reduced all indicators' censored headcount ratios,[21] and 11 of those countries were located in Sub-Saharan Africa. Nine countries significantly reduced all indicators' population-wide or uncensored headcount ratios.[22]

Over half of the 80 countries observed a significant reduction in each indicator, although these countries varied by indicator. Both indicators in the health dimension had a significant reduction in the censored headcounts of 51 countries, whereas the school attendance and years of schooling indicators significantly reduced in the censored headcounts of 49 and 53 countries, respectively. As for the living standards indicators, 61 of the 80 countries observed a significant reduction in the censored headcount for the cooking fuel indicator, 60 for the sanitation indicator, 58 for the drinking water indicator, 53 for the electricity indicator, 59 for the housing indicator, and 66 for the assets indicator. For all indicators, over half of the 80 countries also observed a significant reduction in their uncensored headcount ratios.

The child mortality indicator had the slowest annualized reductions among the indicators, and unfortunately, in Nigeria, the child mortality indicator significantly increased in terms of both its censored and raw headcount ratios, by 0.3 and 0.4 of a percentage point each year. The largest annualized reduction in a single indicator's censored headcount ratio was sanitation in Malawi, which improved from 64.3% in 2011 to 29.6% in 2015/16. The largest annualized reduction in electricity, the indicator with the greatest annualized reduction in censored headcount ratios on average, came from Timor-Leste, which improved from 54.8% in 2009/10 to 19.2% in 2016.

At the country level, the largest annualized reduction in nutrition's censored headcount ratio was in Rwanda, which improved from 41.3% in 2010 to 17.7% in 2014/15. In child mortality, Sierra Leone took the lead (from 15.9% in 2013 to 7.9% in 2017); in years of schooling, Mauritania (from

[21] Bangladesh, Bolivia, Ethiopia, Gabon, Guinea, Honduras, India, Indonesia, Lao PDR, Malawi, Mauritania, Mozambique, Nicaragua, Niger, Sao Tome and Principe, Sierra Leone, Suriname, eSwatini, Timor-Leste, and Zambia

[22] Bolivia, Guinea, Honduras, India, Indonesia, Lao PDR, Niger, Sierra Leone, and Timor-Leste.

43.8% in 2011 to 21.9% in 2015); in school attendance, Liberia (from 56.8% in 2007 to 23.6% in 2013); in cooking fuel, also Sierra Leone (from 74.0% in 2013 to 58.0% in 2017), in sanitation, Malawi (from 64.3% to 29.6%); in drinking water, Timor-Leste (from 40.8% in 2009/10 to 18.6% in 2016); in electricity, also Timor-Leste (from 54.8% to 19.2%); in housing, Guinea (from 50.9% in 2012 to 33.4% in 2016); and finally, in assets, also Liberia (from 64.6% in 2013 to 38.1% in 2017).

4.5 Changes in the Number of Poor

More complexities arise when we take the view towards the number of poor in these 80 countries. Fifteen of the countries – all located in Sub-Saharan Africa – have seen a rise in the number of poor people between their surveyed time periods despite statistically significant reduction in their MPIT, a consequence of rapid population growth.[23]

World Bank data shows that Sub-Saharan Africa observed a regional annual population growth rate of 2.72% on average between 2000 and 2018.[24] The two countries with the largest increase in the number of poor, the Democratic Republic of Congo and Ethiopia, saw an average annual population growth rate of 3.32% and 2.79% respectively between their survey years. As such, many countries in the region should be lauded for their impressive reductions in the value of MPIT, and indeed, many saw significant reductions in urban poverty despite atmospheric growth in cities (take Tanzania, for example, whose urban population increased by 5.32% annually between 2010 and 2015/16 and still saw a relative reduction of 3.3% in its MPI per year). Yet, the risks and vulnerabilities of population swells remain real.

In the age of COVID-19, these population expansions incur additional hazards. While population growth puts stress on social protection, insurance, and welfare systems at the best of times, when many people live in overcrowded, inadequate dwellings, must walk over thirty minutes to fetch their main source of drinking water, or share a sanitation facility among their neighbors, the ability to self-isolate or quarantine a household is remote. Food insecurity and famine persist as major concerns for much of Sub-Saharan Africa in the path of COVID-19,[25] as disrupted employment and supply chains could lead to chronic malnourishment throughout the region. The major gains

[23] Burkina Faso, Burundi, Central African Republic, Chad, Democratic Republic of the Congo, Ethiopia, Gambia, Madagascar, Mali, Mozambique, Niger, Nigeria, Senegal, Sudan, and Zimbabwe.

[24] World Development Indicators Databank. Accessed 5 May 2020.

[25] *2020 Global Report on Food Crises*, Food Security Information Network: 2020. (https://docs.wfp.org/api/documents/WFP-0000114546/download/). Accessed 5 May 2020.

in eradicating poverty made by these countries, despite the increased pressure on public infrastructure, spending, and policy due to population growth, could soon become unmanageable. To cement these successes will require concerted and preventative multi-sectoral policy responses from national governments and regional and global bodies.

4.6 Comparison with Monetary Poverty trends

a. Income groups

Of the 80 countries under study, 28 were classified as low income, 22 as lower-middle income, and nine as upper-middle income countries in both time periods, while 21 countries have changed classification between the two years studied.[26] Ten countries graduated from the low to lower-middle category, 10 moved from lower-middle to upper-middle, and one country moved from upper-middle to the high income classification. Of the 21 countries that graduated to a higher rank of income classification between their survey years, three halved their MPIT (India, Nicaragua, and North Macedonia).

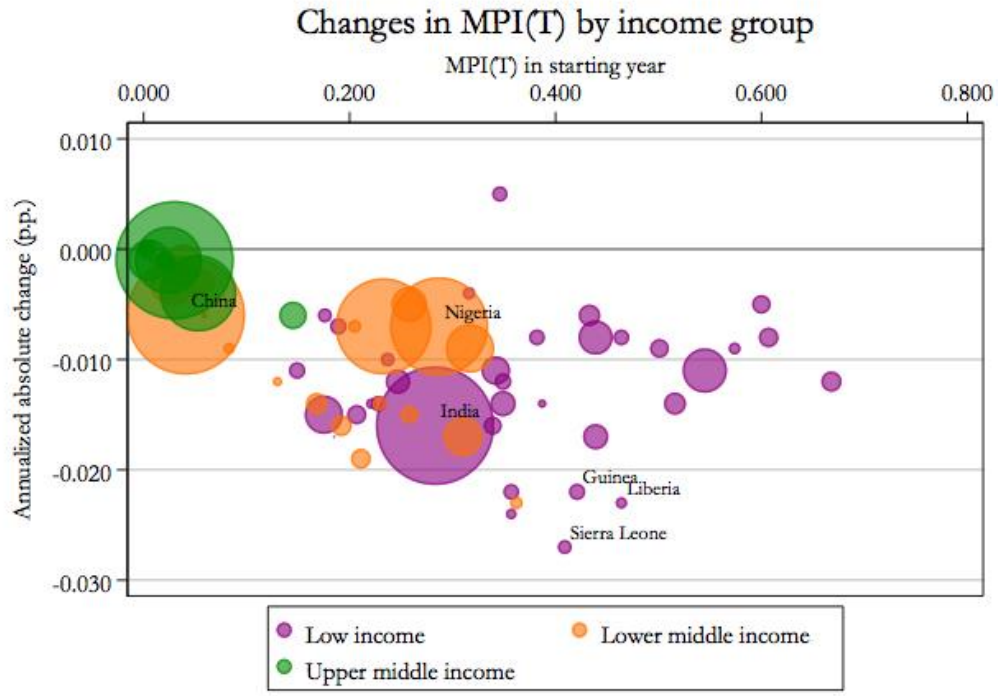
Ranking countries by their World Bank income classification explicates a complex pattern that does not cleanly match the multidimensional poverty trends over time. For instance, a large difference exists between the performance of post-Soviet states and former Yugoslav countries according to monetary and multidimensional measures. Kyrgyzstan, Moldova, and Tajikistan all have MPIT values below 0.049 in the starting year and MPIT values below 0.029 in the second year, signaling low levels of deprivation in non-monetary indicators; however, they are all classified as low income countries. Similarly, 16 countries (seven in Europe and Central Asia – of which three are post-Soviet states and three are former Yugoslav states, four in East Asia and Pacific, three in Latin America and Caribbean, and two in the Arab States) all have MPIT values below 0.041 in the first year and MPIT values of 0.036 or less in the second year and are considered to be lower-middle income countries at their starting period. Notably, 10 of these 19 countries had no change in its income classification group despite significant developments captured by the MPIT. In contrast, Gabon is classed as an upper-middle income country with an initial MPIT of 0.145, placing it above many of the countries classed as low income. Such disparities between the MPIT and income group classifications demonstrate the need for complementary measures of poverty

[26] Ten countries (Bangladesh, Ghana, India, Mauritania, Moldova, Nicaragua, Sao Tome and Principe, Tajikistan, Yemen, and Zambia) moved from low to lower middle income classification, 10 countries (Belize, Bosnia and Herzegovina, China, Dominican Republic, Iraq, Montenegro, Namibia, North Macedonia, Suriname, and Turkmenistan) moved from lower middle to upper middle income classification, and one country (Trinidad and Tobago) moved from upper middle to high income classification.

and development to capture the nuances of deprivation resulting from differing historical and political development.

Figure 1 below displays the starting level of MPIT and the annualized absolute reductions for each country, sorted by income groups. The Leaving No One Behind principle of the 2030 Sustainable Development Agenda highlights the need for progress across all groups to reduce inequality; thus, we would want to see the poorest countries reduce their MPIT the fastest – in this case, the low income countries situated on the right of the figure. The overall distribution of countries by initial level of MPIT and their level of progress shows an encouraging pattern with some poorer and low income countries (Sierra Leone, Liberia, Guinea, and Rwanda) reducing poverty faster than those in the lower- or upper-middle income group. Nevertheless, some of the poorest countries with the highest MPIT values experienced a slower rate of reduction in their poverty.

Figure 1. Annualized Changes in MPIT by Income Groups



Overall, the top ten fastest movers in annualized absolute reductions in their MPIT include seven countries who were classified as low income in their starting year. And of the top three fastest reducers, Sierra Leone and Liberia are low income countries in both time periods, and Mauritania is a low income country in the first time period and graduates to lower-middle income in its second survey year. On average, low income countries had an annual reduction rate of -0.012 for MPIT, while lower-middle income countries reduced by -0.07 per year and upper-middle income countries by -0.01. Considering population numbers, the weighted average shows that lower-

middle income countries reduced the fastest, with the change driven largely by China, which accounts for over half the population of lower-middle income countries in the first period.

Of the top three fastest movers in annualized relative reductions in their MPIT values, North Macedonia and China graduate from lower middle income to upper-middle income countries between 2005/06 and 2011 and 2010 and 2014 respectively, while Armenia is a lower-middle income country in both survey years.

Clearly, multidimensional poverty trends over time offer information about countries' poverty status that simply dividing the world's economies into income groups cannot reveal.

a. $1.90/day

An interesting question is whether changes over time in multidimensional poverty reflect or differ from changes in monetary poverty. The SDGs call for reduction in both multidimensional and monetary poverty, so if these trends do not move together, governments would require different policy responses to poverty. Comparing multidimensional poverty incidence and the $1.90 a day measure underscores the importance of these two measures as complements. The key limitation in comparing these two measures is the lack of frequently updated monetary poverty data. For countries where monetary poverty data was available for both years included in our analysis, those figures were used, and the analysis was straightforward.[27] Unfortunately, for the majority of countries included, this was not the case, as only 13 of the 80 countries under analysis had available $1.90 data in both survey years.[28]

When income poverty data was not available for the year(s) of a survey, we used linear interpolation or extrapolation between the two closest data points to estimate the level of income poverty at the year of the survey(s). We conducted simple linear interpolations using the available data closest to the MPIT survey year prior to the survey year and after the survey year. For instance, in Bolivia, the survey years for the MPIT are 2003 and 2008. We have monetary data for 2002, 2004, and 2008, so we used the data for 2008 and then took the average of the monetary poverty rates in 2002 and 2004 to estimate the $1.90/day rate of 2003. Where there were no monetary poverty figures for years both before and after the MPIT survey year, we used the two closest dates to the survey year, either both before or both after, and did extrapolations based on those. For example, in Pakistan, the most recent MPIT survey year is 2017/18, but the most recent monetary

[27] Where one of the surveys used in the MPI analysis spanned two different years, the average of the monetary poverty measures for those two years was taken.

[28] Armenia, China, Colombia, Dominican Republic, Honduras, Indonesia, Kazakhstan, Kyrgyzstan, Mexico, Moldova, Peru, Thailand, and Ukraine.

data is from the years 2013 and 2015. Thus, we extrapolated the $1.90/day headcount ratio for 2017/18 based on the information from 2013 and 2015. In total, we had information for one year of the MPIT survey years and interpolated/extrapolated for the other year in 19 countries[29], and we interpolated/extrapolated for both years in 43 countries[30], where there was no available monetary data for either survey years.

It is also worth noting that there are several countries in which the data for extrapolations exist immediately before or after the 2007/08 global financial crisis, and these should be understood with that caveat in mind[31]. For instance, in North Macedonia, the first survey year used in the MPIT estimations is 2005/06, but the earliest monetary data was from 2009 and 2010. This means that our extrapolation for monetary poverty in 2005/06 (before the financial crisis) was made using data from shortly after the crisis. We have reported these figures, because they use the only data available, but recognize that they are likely to be inaccurate. Further, there are a few countries where the only monetary poverty data were outdated. In Belize, Guyana, and Trinidad and Tobago, the only monetary poverty data available were from prior to 2000. In Nigeria, the most recent $1.90/day figures were from 2003 and 2009, but the MPIT survey years were 2013 and 2016/17. Finally, for five countries (Afghanistan, Cambodia, Haiti, Suriname, and Turkmenistan), there were either no years or only one year available for monetary poverty data, so it was not possible to calculate monetary poverty trends. Thus, the final comparison of $1.90 and headcount ratio covers 75 countries for which comparable income poverty data is available (or calculated), but the conclusions may be affected by the lack of matching data points.

In 50 of the 75 countries with comparable income data, multidimensional poverty reduced faster than monetary poverty in absolute terms. The difference was particularly striking in the Arab States, where every country experienced a reduction in multidimensional poverty, but only Egypt and Sudan saw a decrease in their monetary poverty, too.[32] In Zimbabwe (2010/11-2015), monetary poverty increased by an average of more than 2 percentage points a year, but multidimensional poverty decreased by approximately 1.4 percentage points a year. In Côte

[29] In eight countries (Bolivia, Cameroon, Montenegro, North Macedonia, Serbia, Sudan, Uganda, Vietnam) we have extrapolated for the first survey year, and in 11 countries (Congo, Egypt, Guinea, Liberia, Malawi, Mali, Mongolia, Nicaragua, State of Palestine, Rwanda, Senegal) we have extrapolated for the second survey year.

[30] Albania, Bangladesh, Belize, Benin, Bosnia and Herzegovina, Burkina Faso, Burundi, Central African Republic, Chad, Côte d'Ivoire, the Democratic Republic of the Congo, Ethiopia, Gabon, Gambia, Ghana, Guyana, India, Iraq, Jamaica, Jordan, Kenya, Lao PDR, Lesotho, Madagascar, Mauritania, Mozambique, Namibia, Nepal, Niger, Nigeria, Pakistan, Philippines, Sao Tome and Principe, Sierra Leone, eSwatini, Tajikistan, Tanzania, Timor-Leste, Togo, Trinidad and Tobago, Yemen, Zambia, and Zimbabwe.

[31] Albania, Central African Republic, Jamaica, Jordan, and North Macedonia.

[32] Incidence of monetary poverty did not change in Jordan and increased in Iraq and Yemen over the periods observed.

d'Ivoire (2011/12-2016), monetary poverty decreased slightly (an average of 0.1 percentage points a year), but incidence of multidimensional poverty decreased an average of 2.8 percentage points a year. By contrast, Niger (2006-2012) saw its share of people living on less than $1.90/day decrease by more than 25 percentage points over the period, while its headcount ratio (H_T) reduced by a more modest 3 percentage points over that same period. Ukraine (2007-2012) had nearly identical rates of monetary and multidimensional poverty reduction, with decreases of 0.02 per year, on average, in the percentages of poor. The significant degrees of difference between the monetary and multidimensional poverty trends suggest that these two measures are identifying different phenomena and different people as poor, meriting complementary analyses that identify the differing factors at play.

Multidimensional poverty incidence was larger than income poverty at the beginning of the comparison period in 60 of the 75 countries.[33] The gap between the multidimensional and income poverty incidence varies from slight differences in Ukraine (0.4% and 0.1%), Jordan (0.5% and 0.1%), Congo (53.8% and 53.4%), and Belize (7.4% and 7.9%), to dramatic differences in Ethiopia (88.4% and 33%), Mauritania (63% and 8.4%), or Moldova (1.5% and 13.9%). Figure 2 depicts the annualized absolute rates of change in the incidence of MPI_T and $1.90/day poverty for the 75 countries for which we have income data. 37 countries had a reduction in poverty according to both measures, with multidimensional poverty reducing faster.[34] In 12 countries, H_T reduced while incidence of monetary poverty increased.[35] Additionally, four countries had a reduction in the incidence of MPI_T but no change in $1.90/day figures.[36] Thus overall, 53 of the 75 countries reduced multidimensional poverty faster than income poverty. The reverse occurred in 20 countries, where multidimensional headcount ratios decreased slower than $1.90 a day incidence[37]. Additionally, in one country (Benin), multidimensional poverty increased while monetary poverty declined. In only one country (Serbia), did poverty increase according to both measures.

[33] Fifteen countries had higher income poverty at initial period: Armenia, Belize, China, Colombia, Democratic Republic of the Congo, Indonesia, Kyrgyzstan, Malawi, Moldova, Montenegro, Nigeria, Philippines, Serbia, eSwatini, and Trinidad and Tobago.

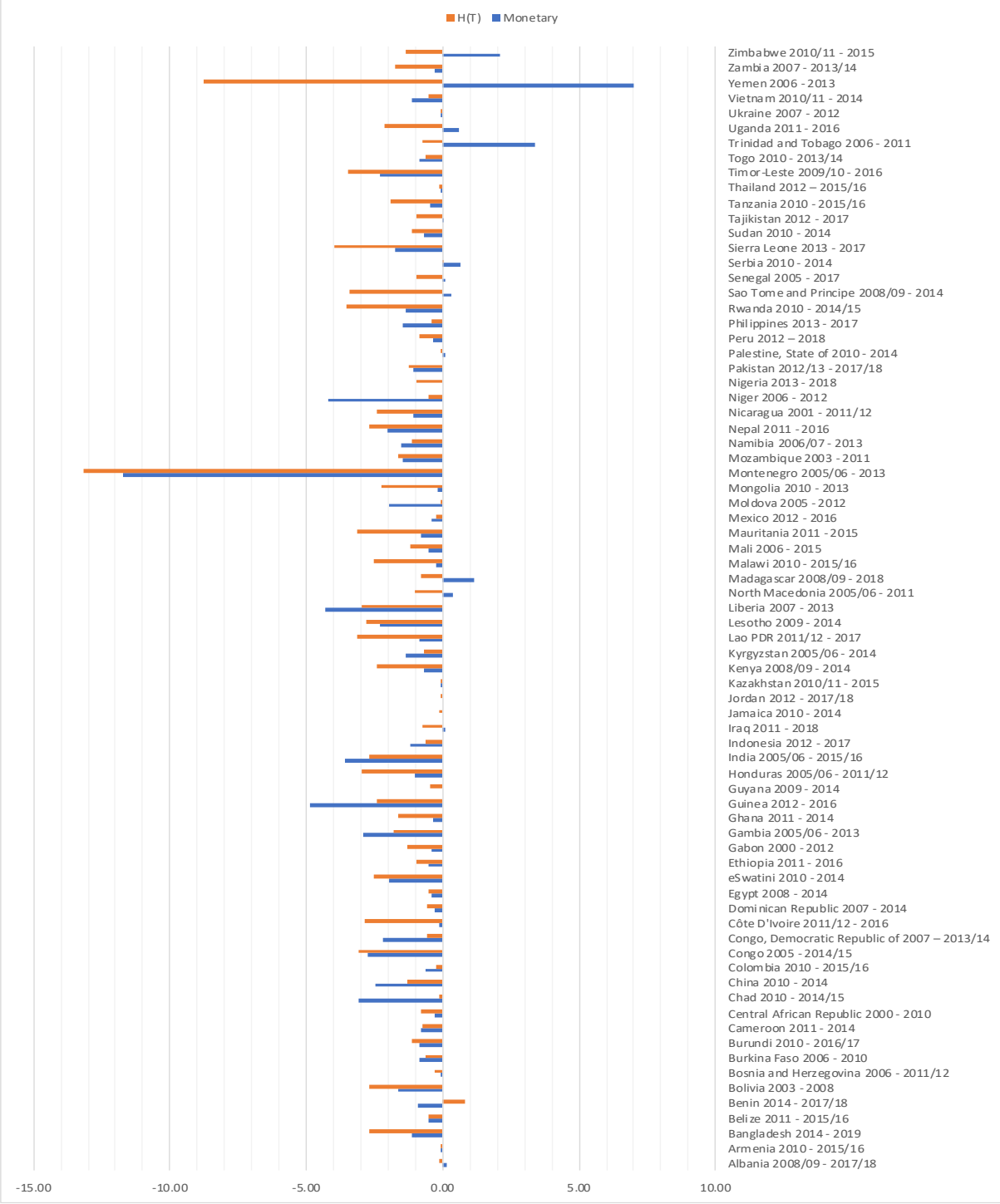
[34] Armenia, Bangladesh, Belize, Bolivia, Bosnia and Herzegovina, Burkina Faso, Burundi, Central African Republic, Congo, Cote d'Ivoire, Dominican Republic, Egypt, eSwatini, Ethiopia, Gabon, Ghana, Kazakhstan, Kenya, Lao PDR, Lesotho, Malawi, Mali, Mauritania, Mongolia, Mozambique, Nepal, Nicaragua, Pakistan, Rwanda, Sierra Leone, Sudan, Tanzania, Thailand, Timor-Leste, Ukraine, Zambia.

[35] Albania, Iraq, Madagascar, North Macedonia, Sao Tome and Principe, Senegal, State of Palestine, Tajikistan, Trinidad and Tobago, Uganda, Yemen, Zimbabwe.

[36] Guyana, Jamaica, Jordan, Nigeria.

[37] Cameroon, Chad, China, Colombia, Democratic Republic of the Congo, Gambia, Guinea, India, Indonesia, Kyrgyzstan, Mexico, Moldova, Montenegro, Namibia, Niger, Peru, Philippines, Togo, Vietnam.

Figure 2. Annualized Absolute Change in Incidence of H_T and $1.90



If progress were only measured by reducing income poverty, Guinea, Liberia, and Niger would be considered the leaders in poverty reduction for annualized absolute reduction, and Thailand, Kazakhstan, and China for relative annualized reduction. The gains of Sierra Leone, Rwanda, Timor-Leste, and North Macedonia would have been invisible. If income and multidimensional poverty measures were perfectly correlated, and if they both identified the same people as poor, there would be no need for two separate measures. While the issue of identification lies beyond

the scope of this paper, we do observe significant variations between both the rates and, at times, the direction of change of these two poverty measures. This suggests that MPI$_T$ trends are not tracking $1.90 trends, and we must look at both "sister" measures to understand the character of poverty around the world.

5. Triangulation of Monetary and Nonmonetary Poverty Trends

Sir Tony Atkinson's final book, *Measuring Poverty around the World* (published posthumously by Princeton University Press: 2019), issues a call for triangulation among monetary and nonmonetary poverty measures to analyze the reliability and credibility of their purposes. Atkinson argues that, in the diversity of poverty measures available, we have different portraits, distributions, and levels of poverty. Triangulation, then, allows us to interrogate these trends and evaluate the relationships between monetary and nonmonetary poverty indicators. The unfinished annex of his book details national reports of 60 countries, graphing PovCal estimates for the $1.90 a day line against other indicators of poverty: e.g., the Gini income %, incidence of households below the national poverty line, and the global MPI headcount ratio from the 2017/18 release. For most countries, the "changes over time" section is notably absent, and indeed, the editors themselves note that this section is often underdeveloped, missing altogether, or restricted to a monetary definition of poverty (Atkinson 2019: 248). This paper begins to take up the mantle of Atkinson's triangulation of poverty measures over time.

For our 80 countries, where applicable, we collect information on eight measures defined subsequently: 1) the monetary poverty headcount ratio of national poverty lines (the % of the population); 2) the $3.20 a day monetary poverty headcount ratio; 3) the $1.90 a day monetary poverty headcount ratio; 4) the official National MPI headcount ratio;[38] 5) the incidence of MPI$_T$; 6) the incidence of destitution; 7) the incidence of vulnerability; and 8) the incidence of severe multidimensional poverty, published for the first time for all 80 countries in this paper. By triangulating these eight measures, we may come to better understand the nature of poverty trends and the relationships between these measures. Appendix E includes the national poverty reports for 80 countries, with all available information.

[38] The official national MPI of a country is a permanent statistic of multidimensional poverty using the AF method that tailors the dimensions, indicators, and deprivation values to the national context and datasets. Unlike the global MPI, where careful comparisons can be feasible, National MPIs cannot be compared across countries because they define and measure poverty differently.

The national monetary poverty headcount ratio is the percentage of the population living below the national poverty lines. National estimates are based on population-weighted subgroup estimates from household surveys and extracted from the World Development Indicators.[39] The poverty headcount ratios at $3.20 and $1.90 a day, as a percentage of the population, are also based on primary household survey data obtained from government statistical agencies and World Bank country departments, extracted from the World Development Indicators.[40] The national MPI headcount ratios are drawn from the published incidence figures, for the 16 of our 80 countries that have an official national MPI.[41] The destitution measure is outlined in detail in Alkire, Kanagaratnam and Suppa (2020). The vulnerability and severity measures, meanwhile, use the same weights and indicators as the MPI_T but apply different cross-dimensional poverty ($\boldsymbol{k}$) cutoffs. We consider those vulnerable to multidimensional poverty the households that experience a 20-33.32% intensity of deprivations and those living in severe poverty to be households with an intensity higher than 50% – that is, the household must be deprived in one-half of the total weighted indicators.

5.1 Direction

Of the 72 countries that have information on both $1.90 a day and national poverty headcount trends,[42] three countries have multidimensional poverty trends that differ in direction from these two monetary trends: Albania, Uganda, and Yemen. While Albania's incidence of multidimensional poverty drops from 2.1% in 2008/09 to 0.7% in 2017/18, the monetary poverty measures describe an opposing trend. In 2008, 0.4% of Albania's population was living on less than $1.90 a day, but by 2017, that figure had risen to 1.7%; similarly, in 2008, 12.4% of the population were living below the national poverty line, but by 2012, that figure had risen to 14.3%. Uganda presents an exceptionally stark case, as the monetary poverty measures followed negative trends until 2012, when both the $1.90 a day and national poverty headcount ratios rose. Uganda's case interests us particularly because the time span for the monetary measures, 2012-2016, maps well onto our time periods for multidimensional poverty trends over time, 2011-2016. Uganda's incidence of multidimensional poverty drops from 67.7% in 2011 to 57.2% in 2016, whereas the

[39] Accessed April 7, 2020.

[40] Accessed April 7, 2020.

[41] Afghanistan, Armenia, Colombia, Dominican Republic, Honduras, Mexico, Mozambique, Nigeria, Nepal, Pakistan, Philippines, Rwanda, Sierra Leone, State of Palestine, Thailand, and Vietnam.

[42] The eight countries that do not have these three data points include Afghanistan, Belize, Cambodia, Guyana, State of Palestine, Suriname, Trinidad and Tobago, and Turkmenistan. Afghanistan, Cambodia, and the State of Palestine do, however, have information available for the population living below the national poverty line.

population living on less than $1.90 a day rises from 35.9% to 41.7% and the population living below the national monetary poverty line rises from 19.7% to 21.4% in 2012 and 2016, respectively. All three data points are outdated for Yemen, which has since experienced the largest humanitarian crisis of the last decade, but like the Ugandan case, the data points we do have match a similar time series. Yemen's incidence of multidimensional poverty drops from 38.0% in 2006 to 29.2% in 2013, whereas the population living on less than $1.90 a day rises from 9.8% to 18.8% and the population living below the national monetary poverty line rises from 34.8% to 48.5% in 2005 and 2014, respectively.

A similar situation occurs in Afghanistan, where the national monetary poverty headcount ratio describes an increase in poverty over time, whereas the family of global MPIT measures show a reduction. Afghanistan does not have available information for the $1.90 or $3.20 a day measure. This shows that trends may diverge; however, further analysis is required to understand the different drivers of change – for example, whether they are related to fiscal expenditure, development assistance, or to particular macroeconomic condition. It would also be useful to probe the robustness of monetary poverty trends to different datasets and specifications.

A few other countries present compelling stories. Zimbabwe, for instance, observed negative trends in both the changes over time headcount (from 40.1% to 34.0% between 2010/11 and 2015) and the national monetary poverty headcount (from 72.3% to 70.0% between 2011 and 2017), although the $1.90 a day headcount rose (from 21.4% to 33.9% between 2011 and 2017). Likewise, in Tajikistan, the $.190 a day headcount rose from 4.7% in 2009 to 4.8% in 2015, whereas the changes over time and national monetary poverty headcounts dropped, from 12.2% in 2012 to 7.4% in 2017 and 34.4% in 2013 to 27.4% in 2018, respectively. Further, in Gambia, the national monetary poverty headcount rose 48.1% in 2010 to 48.6% in 2015, even as the changes over time and $1.90 a day headcounts dropped, from 68.1% in 2005/06 to 54.7% in 2013 and 45.3% in 2003 to 10.1% in 2015, respectively. Likewise, in Gabon, the national monetary poverty headcount rose 32.5% in 2005 to 33.4% in 2017, even as the MPIT headcount and $1.90 a day headcounts dropped, from 30.9% in 2000 to 15.5% in 2012 and 8.0% in 2005 to 3.4% in 2017, respectively. Clearly, triangulation of these trends reveals tremendous variation among monetary and nonmonetary poverty measures, even in simple terms of increases or decreases in poverty.

5.2 Slope and initial poverty levels

At first glance, although we often observe that the direction of poverty trends over time matches for monetary and nonmonetary indicators, the slope and initial levels of poverty can be quite different. For example, in Burkina Faso, we observe that the incidence of those living in

multidimensional poverty in 2006 drops from 88.7% to 86.3% in 2010, compared to the $1.90 a day measure, which observes 57.3% of the population living on less than $1.90 a day in 2003 and 55.3% in 2009. Thus, depending on which measure one uses (and taking into account that the time periods are imperfectly aligned), nearly one-third of the Burkina Faso population would be considered either in poverty, as the MPIT issues, or out of it, following the $1.90 a day measure.

Similarly, in Niger, we observe that the incidence of those living in multidimensional poverty in 2006 drops from 92.9% to 89.9% of the population in 2012, but the $1.90 a day measure shows a steep decline from 74.9% of the population living on less than $1.90 a day in 2005 to only 50.3% in 2011. Niger's time periods allow us a better comparison of the two measures, as the multidimensional poverty trends span 2006 to 2012 and the $1.90 a day trends span 2005 to 2011. But indeed, the measures differ both in slope and initial poverty levels. Although Niger has annualized absolute and relative changes of only 0.51 and 0.55 respectively in its multidimensional poverty headcount, nearly one-quarter of the population moves out of extreme income poverty during the same time period, and by 2012, slightly over half of the population is considered poor by the $1.90 a day measure compared to the nearly nine-out-of-ten person incidence of multidimensional poverty.

The same general observation holds true for the comparison between MPIT incidence and the national monetary poverty line. In Tanzania, for example, we observe that the population incidence of those living in multidimensional poverty in 2010 drops from 67.8% to 57.1% of the population in 2015/16, compared to the national poverty line headcount ratio, which observes 34.4% of the population living below the national poverty line in 2007 and 28.2% in 2011. Taking 2010 and 2011 as a cross-sectional comparison, depending on which measure one uses, nearly two-thirds of the Tanzanian population included in the incidence of multidimensional poverty in 2010 could be considered non-poor according to the national poverty line in 2011. Ethiopia exhibits a similar trend. Ethiopia's time points offer a helpful comparison of the two measures, as the multidimensional time series covers the period between 2011 and 2016 and the national poverty line time series covers 2011 to 2015. In ostensibly the same time frame within Ethiopia, we observe the population incidence of those living in multidimensional poverty drops from 88.4% in 2011 to 83.5% in 2016, compared to the national poverty line headcount ratio, which observes 29.6% of the population living below the national poverty line in 2011 and 23.5% in 2015. What is clear from these examples is that the multidimensional poverty incidence often documents higher levels of poverty than the $1.90 a day and national poverty line monetary measures.

5.3 Destitution, vulnerability, severity

We extend Atkinson's call to triangulate different poverty measures not only to the monetary and nonmonetary comparison but also to different measures and gradations of multidimensional poverty. Like the global MPI, we compute three additional statistics of multidimensional poverty – destitution, vulnerability, and severity – and through our harmonization procedure, we have computed comparable estimates for the annualized absolute and relative changes for each of these three measures. The destitution, vulnerability, and severity measures are outlined above and in further detail in Alkire, Kanagaratnam, and Suppa (2020).

One of the more fascinating findings of this multidimensional poverty triangulation is that while more than half the countries reduce their incidence of multidimensional poverty, destitution headcount ratios, and percentage of the population living in severe poverty, 38 countries either increase the percentage of the population vulnerable to multidimensional poverty or see no significant change.[43] Of these 38 countries, 27 countries show a significant increase at either α=0.05 or α=0.01 significance in the population vulnerable to multidimensional poverty.[44] This finding carries additional weight in the era of COVID-19, as countries fear backsliding into greater poverty with the economic hit of closed borders, lockdowns, and unemployment. Among the ten MPI indicators, a lack of access to clean drinking water, undernutrition, and no clean cooking fuel also put people at high risk to COVID-19 (Alkire, Dirksen, et al. 2020).

Four of our top five fastest reducers in absolute terms – Liberia, Mauritania, Sierra Leone, and Timor-Leste – also rank in the top five countries with significant increases in annualized absolute changes within the population vulnerable to poverty. Rwanda, the country with the largest increase in the vulnerable population, observes a jump from 18.4% of the population in 2010 to 25.8% in 2014/15[45]. Liberia, the country with the second-largest increase, nearly doubles its vulnerable population from 11.2% in 2007 to 20.0% in 2013. Liberia, Rwanda, and Sierra Leone also make it into the top five countries with significant increases in annualized relative changes within the

[43] The 38 countries with a positive trend or no change in vulnerability are: Afghanistan, Belize, Burundi, Central African Republic, Chad, Democratic Republic of the Congo, Ethiopia, Gambia, Ghana, Guinea, Haiti, Honduras, India, Kenya, Lao PDR, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mexico, Mozambique, Nepal, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Sudan, Suriname, Tanzania, Timor-Leste, Togo, Trinidad and Tobago, Uganda, Zambia, and Zimbabwe.

[44] Afghanistan, Burundi, Central African Republic, Chad, Democratic Republic of Congo, Ethiopia, Gambia, Guinea, India, Kenya, Lao PDR, Liberia, Madagascar, Malawi, Mali, Mauritania, Mozambique, Nepal, Niger, Nigeria, Rwanda, Senegal, Sierra Leone, Tanzania, Timor-Leste, Trinidad and Tobago, and Zambia.

[45] Notably, Rwanda is the sixth fastest national reducer in absolute terms.

population vulnerable to poverty, although Ethiopia and Trinidad and Tobago replace Mauritania and Timor-Leste.

This finding reveals an important caution. While countries may be making strides in reducing the share of the population living in multidimensional poverty, it may be the case that these gains are fragile. Indeed, while the structure of our data does not allow for us to be certain,[46] it may be the case that these people who have entered the vulnerable population are the same people who left the multidimensionally poor population. If true, these poverty reductions remain laudable, but reversible.

Even still, 25 countries observed a significant decrease in their vulnerable population,[47] including Armenia, Serbia, the State of Palestine, and Thailand – all of which saw no significant overall change in their MPIT. Of the top five fastest national relative reducers, both China and Indonesia make the top five of fastest reducers in annualized absolute changes within their vulnerable populations, and Indonesia is the fourth-fastest reducer in annualized relative changes. China reduced its population vulnerable to poverty from 25.1% in 2010 to 18.5% in 2014, and Indonesia reduced its vulnerable population from 9.0% in 2012 to 4.6% in 2017. Considering both countries are in the top four most populous countries in the world, these achievements should not be overlooked.

With the fragility of these gains in mind, it is all the more remarkable that 59 of our countries saw significant reductions in their population experiencing severe multidimensional poverty.[48] Our top five fastest national reducers in absolute terms also saw the fastest annualized absolute reductions in severe MPIT, with Sierra Leone once again leading the charge. Sierra Leone reduced its population living in severe poverty from 47.3% in 2013 to 31.0% in 2017, while Timor-Leste more than halved its population living in severe poverty from 39.0% in 2009/10 to 16.9% in 2016, considering point estimates. China and North Macedonia, two of the fastest national reducers in relative terms, make the top three fastest annualized relative reductions in severity. China reduced

46 Indeed, if we had panel data, we could make this claim with certainty. The cross-sectional nature of our data does not allow us to verify whether the increased population who are vulnerable live in the same households who left poverty using the one-third $\boldsymbol{k}$ cutoff.

47 Albania, Armenia, Bangladesh, Bolivia, Bosnia and Herzegovina, China, Colombia, Dominican Republic, Egypt, Guyana, Indonesia, Iraq, Kazakhstan, Kyrgyzstan, Moldova, Mongolia, Peru, Philippines, Serbia, State of Palestine, Tajikistan, Thailand, Turkmenistan, Ukraine, and Yemen.

48 Afghanistan, Bangladesh, Bolivia, Bosnia and Herzegovina, Burundi, Cambodia, Central African Republic, Chad, China, Congo, Côte D'Ivoire, Democratic Republic of Congo, Dominican Republic, Egypt, eSwatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Haiti, Honduras, India, Indonesia, Iraq, Kenya, Kyrgyzstan, Lao PDR, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mexico, Mongolia, Montenegro, Mozambique, Namibia, Nepal, Nicaragua, Niger, Nigeria, North Macedonia, Peru, Philippines, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Sudan, Suriname, Tajikistan, Tanzania, Timor-Leste, Uganda, Yemen, Zambia, and Zimbabwe.

its population living in severe poverty from 1.9% in 2010 to 0.4% in 2014, and North Macedonia more than halved its population living in severe poverty from 1.1% in 2005/06 to 0.2% in 2011, considering point estimates.

Similarly, according to our harmonized destitution measure, 59 countries observed significant reductions in their destitute MPI_{T},[49] and of those countries, only three – Burkina Faso and Thailand – did not observe a significant reduction in their destitution headcount ratios. Sixteen countries nearly halved their destitute populations,[50] including China and India, which saw reductions in their destitute populations from 3.3% in 2010 to 1.2% in 2014 and from 29.7% in 2005/06 to 11.1% in 2015/16, respectively. Only Benin observed a significant increase in their destitute populations. These results show clear headway on the Leave No One Behind agenda, but nevertheless, policymakers must remain vigilant to avoid backslides into poverty.

6. Concluding Remarks

This paper presented trends in multidimensional poverty for 80 developing countries, then probed patterns by subnational regions as well as rural and urban areas to assess the pro-poorness of those results. Each of the 10 indicators drove the observed change, with 20 countries reducing every indicator. But despite strong reductions, in one quarter of countries the number of poor persons increased due to population increases.

Having presented trends in acute multidimensional poverty, the paper then added to it trends in three other multidimensional poverty measures drawn from the same datasets: destitution, severe multidimensional poverty, and vulnerability. These were mapped, with 95% confidence intervals, onto trend in national and international monetary poverty measures. The second part of the paper took a first cut at observing how trends differ across these countries, with four countries having opposite directions of change, and many others having differing speeds of poverty reduction.

Naturally this study raises a plethora of questions for further research.[51] Perhaps the most evident question is why did the observed changes happen – what were the determinants of

[49] Afghanistan, Bangladesh, Belize, Bolivia, Bosnia and Herzegovina, Burkina Faso, Burundi, Cambodia, Central African Republic, Chad, China, Congo, Côte D'Ivoire, Democratic Republic of Congo, Dominican Republic, Egypt, eSwatini, Ethiopia, Gabon, Gambia, Ghana, Guinea, Honduras, India, Indonesia, Iraq, Kenya, Lao PDR, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mongolia, Mozambique, Namibia, Nepal, Nicaragua, Niger, Nigeria, North Macedonia, Peru, Philippines, Rwanda, Sao Tome and Principe, Senegal, Sierra Leone, Sudan, Suriname, Tajikistan, Tanzania, Thailand, Timor-Leste, Turkmenistan, Uganda, Yemen, Zambia, and Zimbabwe.

[50] Bangladesh, Belize, Bolivia, China, Congo, Gabon, Honduras, India, Iraq, Lao PDR, Nepal, Nicaragua, North Macedonia, Sao Tome and Principe, Timor-Leste, and Turkmenistan.

[51] For a set of wider research questions related to MPI please see Alkire (2020).

multidimensional poverty reduction in terms of institutions, political leadership, public expenditure, development assistance, economic growth, NGO and private sector activities, remittances, social movements, and positive or negative shocks, and what explains the differences in the pro-poorness of poverty reduction patterns. Often such studies will look across regions in one country, or across a smaller block of countries, rather than including all of them. In addition to quantitative analyses the above research will also of necessity entail mixed methods and case studies to understand the policy activities during the periods of study.

In addition to this vitally important empirical work, a number of pivotal research questions remain. To name just a few, a core issue for further work is the analysis of intertemporal poverty trends when population shares change. MPIT trend analysis (and consideration of alternative ways to increase the retained sample) needs to be accompanied by analyses of demographic changes that interact both with the sampling frames of the surveys used and with contemporaneous patterns of domestic and international migration, fertility, and shocks. Naturally far more extensive analyses are required of the Atkinson graphics, including analyses of national and global MPIT trends, to ascertain how similar or distinct the trends of differently structured MPITs are; analyses of MPIT and monetary poverty data at the household level when both measures are built using the same surveys. Because the harmonized trends have not previously been available to this extent, it is naturally of interest to explore the extent to which the trends of the global MPI without harmonized indicator definitions differ from the harmonized trends. And while having merely one period of time is certainly a step forward, multiple periods will be vital to ascertain the variability or durability of trends at the national and subnational levels, both of the MPIT and of component indicators.

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Appendix

Countries, Time Periods, and Data Use for the Analysis of Changes over Time

Country	Time period	Surveys	Sample size (t_1)	Sample Size (t_2)
Afghanistan	2010/11–2015/16	MICS - DHS	101,240	200,132
Albania	2008/09–2017/18	DHS - DHS	30,453	51,317
Armenia	2010–2015/16	DHS - DHS	23,111	26,879
Bangladesh	2014–2019	DHS - MICS	73,995	248,068
Belize	2011–2015/16	MICS - MICS	16,070	18,177
Benin	2014–2017/18	MICS - DHS	71,903	72,098
Bolivia	2003–2008	DHS - DHS	76,935	73,563
Bosnia and Herzegovina	2006–2011/12	MICS - MICS	20,754	19,611
Burkina Faso	2006–2010	MICS - DHS	35,901	39,271
Burundi	2010–2016/17	DHS - DHS	20,053	37,759
Cambodia	2010–2014	DHS - DHS	36,895	46,805
Cameroon	2011–2014	DHS - MICS	35,348	44,814
Central African Republic	2000–2010	MICS - MICS	87,876	51,031
Chad	2010–2014/15	MICS - DHS	77,928	61,485
China	2010–2014	CFPS - CFPS	42,376	41,740
Colombia	2010–2015/16	DHS - DHS	191,719	152,688
Congo	2005–2014/15	DHS - MICS	27,970	51,872
Congo, Democratic Republic of	2007–2013/14	DHS - DHS	22,543	46,482
Côte D'Ivoire	2011/12–2016	DHS - MICS	23,860	55,108
Dominican Republic	2007–2014	DHS - MICS	115,086	116,159
Egypt	2008–2014	DHS - DHS	89,678	115,996
eSwatini	2010–2014	MICS - MICS	17,256	20,651
Ethiopia	2011–2016	DHS - DHS	72,938	69,889
Gabon	2000–2012	DHS - DHS	29,386	26,502
Gambia	2005/06–2013	MICS - DHS	44,765	49,363
Ghana	2011–2014	MICS - DHS	53,055	42,596
Guinea	2012–2016	DHS - MICS	22,098	45,220
Guyana	2009–2014	DHS - MICS	19,614	20,754
Haiti	2012–2016/17	DHS - DHS	38,458	58,054
Honduras	2005/06–2011/12	DHS - DHS	86,031	93,200
India	2005/06–2015/16	DHS - DHS	484,462	2,702,677
Indonesia	2012–2017	DHS - DHS	178,033	191,090
Iraq	2011–2018	MICS - MICS	234,442	130,155
Jamaica	2010–2014	JSLC - JSLC	5,357	5,193
Jordan	2012–2017/18	DHS - DHS	48,793	44,606
Kazakhstan	2010/11–2015	MICS - MICS	53,153	54,254
Kenya	2008/09–2014	DHS - DHS	36,840	69,538
Kyrgyzstan	2005/06–2014	MICS - MICS	24,285	30,141
Lao PDR	2011/12–2017	MICS - MICS	96,257	105,140
Lesotho	2009–2014	DHS - DHS	17,268	15,163
Liberia	2007–2013	DHS - DHS	32,734	22,637
Madagascar	2008/09–2018	DHS - MICS	39,223	77,651

Malawi	2010–2015/16	DHS - DHS	38,393	37,716
Mali	2006–2015	DHS - MICS	68,899	96,973
Mauritania	2011–2015	MICS - MICS	55,972	64,051
Mexico	2012–2016	ENSANUT - ENSANUT	194,143	29,759
Moldova	2005–2012	DHS - MICS	29,719	27,816
Mongolia	2010–2013	MICS - MICS	34,160	49,583
Montenegro	2005/06–2013	MICS - MICS	8,888	14,405
Mozambique	2003–2011	DHS - DHS	57,350	61,013
Namibia	2006/07–2013	DHS - DHS	39,007	18,292
Nepal	2011–2016	DHS - DHS	22,511	22,796
Nicaragua	2001–2011/12	DHS - DHS	57,245	81,378
Niger	2006–2012	DHS - DHS	22,371	28,148
Nigeria	2013–2018	DHS - DHS	171,853	65,667
North Macedonia	2005/06–2011	MICS - MICS	25,629	15,907
Pakistan	2012/13–2017/18	DHS - DHS	30,034	27,831
Peru	2012–2018	DHS-Cont. - ENDES	71,761	51,757
Philippines	2013–2017	DHS - DHS	98,453	139,822
Rwanda	2010–2014/15	DHS - DHS	70,215	118,069
São Tomé and Príncipe	2008/09–2014	DHS - MICS	27,623	53,666
Senegal	2005–2017	DHS - DHS-Cont.	12,102	13,055
Serbia	2010–2014	MICS - MICS	20,121	74,012
Sierra Leone	2013–2017	DHS - MICS	21,580	20,410
State of Palestine	2010–2014	MICS - MICS	34,674	73,906
Sudan	2010–2014	MICS - MICS	78,025	87,675
Suriname	2006–2010	MICS - MICS	20,499	25,735
Tajikistan	2012–2017	DHS - DHS	37,694	44,020
Tanzania	2010–2015/16	DHS - DHS	46,869	60,765
Thailand	2012–2015/16	MICS - MICS	85,502	103,602
Timor–Leste	2009/10–2016	DHS - DHS	65,390	59,978
Togo	2010–2013/14	MICS - DHS	29,354	22,446
Trinidad and Tobago	2006–2011	MICS - MICS	18,190	17,164
Turkmenistan	2006–2015/16	MICS - MICS	24,733	28,651
Uganda	2011–2016	DHS - DHS	13,396	28,480
Ukraine	2007–2012	DHS - MICS	32,659	33,631
Vietnam	2010/11–2014	MICS - MICS	44,057	38,785
Yemen	2006–2013	MICS - DHS	25,318	118,071
Zambia	2007–2013/14	DHS - DHS	33,436	78,059
Zimbabwe	2010/11–2015	DHS - DHS	38,717	40,769

Appendix B

Countries, Population, GNI, and Income and HDI Category for the Analysis of Changes over Time[52]

Country (t_1 - t_2)	World Region	Pop. (t_1) 1,000s	Pop. (t_2) 1,000s	GNI per capita in USD (t_1)[1]	GNI per capita in USD (t_2) [1]	Income category (t_1)[2]	Income category (t_2) [2]	HDI category (2018)
Afghanistan 2010/11 - 2015/16	South Asia	29,651	34,898	544	544	L	L	Low
Albania 2008/09 - 2017/18	Europe and Central Asia	2,988	2,883	3,829	4,877	LM	LM	High
Armenia 2010 - 2015/16	Europe and Central Asia	2,877	2,931	3,378	4,018	LM	LM	High
Bangladesh 2014 - 2019	South Asia	154,517	163,046	1,014	1,258	L	LM	Medium
Belize 2011 - 2015/16	Latin America and Caribbean	330	365	3,957	4,001	LM	UM	High
Benin 2014 - 2017/18	Sub-Saharan Africa	10,287	11,330	829	874	L	L	Low
Bolivia 2003 - 2008	Latin America and Caribbean	8,906	9,721	1,565	1,820	LM	LM	Medium
Bosnia and Herzegovina 2006 - 2011/12	Europe and Central Asia	3,765	3,633	4,309	4,792	LM	UM	High
Burkina Faso 2006 - 2010	Sub-Saharan Africa	13,829	15,605	529	560	L	L	Low
Burundi 2010 - 2016/17	Sub-Saharan Africa	8,676	10,658	233	217	L	L	Low

[52] Population figures correspond to years of survey and are in thousands. GNI is GNI per capita, PPP (constant US $2010). Income category refers to the World Bank income category classification for the year of survey. For more details, please see Table 6.12 of Alkire, Kovesdi, et al. (2020).

Cambodia 2010 - 2014	East Asia and the Pacific	14,312	15,275	750	921	L	L	Medium
Cameroon 2011 - 2014	Sub-Saharan Africa	20,906	22,682	1,289	1,389	LM	LM	Medium
Central African Republic 2000 - 2010	Sub-Saharan Africa	3,640	4,387	470	490	L	L	Low
Chad 2010 - 2014/15	Sub-Saharan Africa	11,952	13,887	862	925	L	L	Low
China 2010 - 2014	East Asia and the Pacific	1,368,811	1,399,454	4,531	6,105	LM	UM	Very High
Colombia 2010 - 2015/16	Latin America and Caribbean	45,223	47,848	6,095	7,509	UM	UM	High
Congo 2005 - 2014/15	Sub-Saharan Africa	3,623	4,856	1,551	3,538	LM	LM	Medium
Congo, Democratic Republic of 2007 – 2013/14	Sub-Saharan Africa	58,454	73,767	304	348	L	L	Low
Côte D'Ivoire 2011/12 - 2016	Sub-Saharan Africa	20,781	23,823	1,136	1,494	LM	LM	Low
Dominican Republic 2007 - 2014	Latin America and Caribbean	9,339	10,165	4,856	6,002	LM	UM	High
Egypt 2008 - 2014	Arab States	79,636	90,425	2,518	2,583	LM	LM	Medium
eSwatini 2010 - 2014	Sub-Saharan Africa	1,065	1,095	3,956	4,592	LM	LM	Medium
Ethiopia 2011 - 2016	Sub-Saharan Africa	90,140	103,603	340	340	L	L	Low
Gabon 2000 - 2012	Sub-Saharan Africa	1,228	1,750	8,870	8,254	UM	UM	High
Gambia 2005/06 - 2013	Sub-Saharan Africa	1,568	1,964	780	763	L	L	Low

Ghana 2011 - 2014	Sub-Saharan Africa	25,388	27,224	1,400	1,571	L	LM	Medium
Guinea 2012 - 2016	Sub-Saharan Africa	10,652	11,738	708	800	L	L	Low
Guyana 2009 - 2014	Latin America and Caribbean	748	763	3,016	3,630	LM	LM	Medium
Haiti 2012 - 2016/17	Latin America and Caribbean	10,251	10,911	707	734	L	L	Low
Honduras 2005/06 - 2011/12	Latin America and Caribbean	7,547	8,561	1,728	1,841	LM	LM	Medium
India 2005/06 - 2015/16	South Asia	1,156,548	1,317,335	1,066	1,792	L	LM	Medium
Indonesia 2012 - 2017	East Asia and the Pacific	248,452	264,651	3,326	3,990	LM	LM	Medium
Iraq 2011 - 2018	Arab States	30,725	38,434	4,711	4,711	LM	UM	Medium
Jamaica 2010 - 2014	Latin America and Caribbean	2,810	2,875	4,528	4,605	UM	UM	High
Jordan 2012 - 2017/18	Arab States	8,090	9,876	3,445	3,249	UM	UM	High
Kazakhstan 2010/11 - 2015	Europe and Central Asia	16,371	17,572	7,947	10,188	UM	UM	Very High
2008/09 - 2014	Sub-Saharan Africa	40,347	46,700	899	1,046	L	L	Medium
Kyrgyzstan 2005/06 - 2014	Europe and Central Asia	5,100	5,845	729	956	L	L	Medium
Lao PDR 2011/12 - 2017	East Asia and the Pacific	6,396	6,953	1,169	1,547	LM[3]	LM	Medium
Lesotho 2009 - 2014	Sub-Saharan Africa	1,990	2,043	1,436	1,548	LM	LM	Low

Liberia 2007 - 2013	Sub-Saharan Africa	3,462	4,248	453	538	L	L	Low
Madagascar 2008/09 - 2018	Sub-Saharan Africa	20,283	26,262	496	476	L	L	Low
Malawi 2010 - 2015/16	Sub-Saharan Africa	14,540	16,975	471	497	L	L	Low
Mali 2006 - 2015	Sub-Saharan Africa	13,203	17,439	652	706	L	L	Low
Mauritania 2011 - 2015	Sub-Saharan Africa	3,599	4,046	1,215	1,290	L	LM	Low
Mexico 2012 - 2016	Latin America and Caribbean	117,274	123,333	9,504	9,942	UM	UM	High
Moldova 2005 - 2012	Europe and Central Asia	4,159	4,076	1,845	2,258	L	LM	High
Mongolia 2010 - 2013	Europe and Central Asia	2,720	2,882	2,430	3,456	LM	LM	High
Montenegro 2005/06 - 2013	Europe and Central Asia	617	626	6,178	7,078	LM[3]	UM	Very High
Mozambique 2003 - 2011	Sub-Saharan Africa	19,331	24,188	339	486	L	L	Low
Namibia 2006/07 - 2013	Sub-Saharan Africa	1,989	2,234	5,045	5,848	LM	UM	Medium
Nepal 2011 - 2016	South Asia	27,041	27,263	615	741	L	L	Medium
Nicaragua 2001 - 2011/12	Latin America and Caribbean	5,145	5,943	1,250	1,571	L	LM	Medium
Niger 2006 - 2012	Sub-Saharan Africa	14,144	17,795	333	360	L	L	Low
Nigeria 2013 - 2018	Sub-Saharan Africa	171,766	195,875	2,362	2,327	LM	LM	Low
North Macedonia 2005/06 - 2011	Europe and Central Asia	2,062	2,072	3,807	4,565	LM	UM	High

Pakistan 2012/13 - 2017/18	South Asia	189,270	210,067	1,069	1,240	LM	LM	Medium
Palestine, State of 2010 - 2014	Sub-Saharan Africa	4,056	4,429	552	452	L	L	Low
Peru 2012 – 2018	Arab States	27,863	31,989	2,512	2,905	LM	LM	Medium
Philippines 2013 - 2017	Latin America and Caribbean	98,872	105,173	5,281	6,143	UM	UM	High
Rwanda 2010 - 2014/15	East Asia and the Pacific	10,039	11,226	2,902	3,471	LM	LM	Medium
Sao Tome and Principe 2008/09 - 2014	Sub-Saharan Africa	173	196	578	692	L	L	Low
Senegal 2005 - 2017	Sub-Saharan Africa	11,090	15,419	1,098	1,098	L	LM	Medium
Serbia 2010 - 2014	Sub-Saharan Africa	8,991	8,898	1,226	1,447	L	L	Low
Sierra Leone 2013 - 2017	Europe and Central Asia	6,864	7,488	5,613	5,787	UM	UM	High
Sudan 2010 - 2014	Arab States	34,545	37,978	1,373	1,657	LM	LM	Low
Suriname 2006 - 2010	Latin America and Caribbean	505	529	8,059	8,059	LM	UM	High
Tajikistan 2012 - 2017	Europe and Central Asia	7,875	8,880	1,029	1,093	L	LM	Medium
Tanzania 2010 - 2015/16	Sub-Saharan Africa	44,347	52,266	730	869	L	L	Low
Thailand 2012 – 2015/16	East Asia and the Pacific	67,836	68,843	5,194	5,539	UM	UM	High
Timor-Leste 2009/10 - 2016	East Asia and the Pacific	1,084	1,219	3,064	3,125	LM	LM	Medium
Togo 2010 - 2013/14	Sub-Saharan Africa	6,422	7,046	530	605	L	L	Low

Trinidad and Tobago 2006 - 2011	Latin America and Caribbean	1,303	1,336	15,871	15,871	UM	H	High
Turkmenistan 2006 - 2015/16	Europe and Central Asia	4,810	5,614	4,067	4,067	LM	UM	High
Uganda 2011 - 2016	Sub-Saharan Africa	33,477	39,649	650	679	L	L	Low
Ukraine 2007 - 2012	Europe and Central Asia	46,366	45,454	3,181	3,097	LM	LM	High
Vietnam 2010/11 - 2014	East Asia and the Pacific	88,420	91,714	1,297	1,297	LM[3]	LM	Medium
Yemen 2006 - 2013	Arab States	20,688	25,147	1,256	1,256	L	LM	Low
Zambia 2007 - 2013/14	Sub-Saharan Africa	12,503	15,163	1,389	1,389	L	LM	Medium
Zimbabwe 2010/11 - 2015	Sub-Saharan Africa	12,796	13,815	878	1,102	L	L	Low

Notes:

1 The year of GNI corresponds to the survey year where possible, the average of the split year when possible, and otherwise to the nearest available data year.

2 In the first year of the split year, the country was considered low income, but graduated to lower middle income in the latter year. We present the more recent classification.

3 The L refers to "low income," LM to "lower-middle income," UM to "upper-middle income," and H to "high income."

Appendix C

Countries, $1.90/day Extrapolations, and Annualized Changes

Country (t1 - t2)	World Region	Extrapolations		Monetary Poverty Trends		MPI Trends		MPI-Monetary Diff	
		$1.90/day (t1)	$1.90/day (t2)	Absolute Change	Relative Change	Absolute Change	Relative Change	Absolute	Relative
Afghanistan 2010/11 - 2015/16	South Asia			0.00	0.00	-11.75	-0.15		
Albania 2008/09 - 2017/18	Europe and Central Asia	0.49	2.00	1.51	3.10	-1.36	-0.66	-2.88	-3.76
Armenia 2010 - 2015/16	Europe and Central Asia	1.90	1.85	-0.05	-0.03	-0.23	-0.57	-0.18	-0.55
Bangladesh 2014 - 2019	South Asia	27.52	16.40	-11.12	-0.40	-28.06	-0.41	-16.94	-0.01
Belize 2011 - 2015/16	Latin America and Caribbean	7.90	5.65	-2.25	-0.28	-2.41	-0.33	-0.16	-0.04
Benin 2014 - 2017/18	Sub-Saharan Africa	50.40	47.25	-3.15	-0.06	2.77	0.04	5.92	0.11
Bolivia 2003 - 2008	Latin America and Caribbean	19.20	11.00	-8.20	-0.43	-13.51	-0.39	-5.31	0.03
Bosnia and Herzegovina 2006 - 2011/12	Europe and Central Asia	0.13	0.10	-0.03	-0.25	-1.76	-0.45	-1.73	-0.20
Burkina Faso 2006 - 2010	Sub-Saharan Africa	56.30	52.98	-3.32	-0.06	-2.42	-0.03	0.90	0.03
Burundi 2010 - 2016/17	Sub-Saharan Africa	74.33	68.85	-5.48	-0.07	-7.20	-0.09	-1.72	-0.01
Cambodia 2010 - 2014	East Asia and the Pacific			0.00	0.00	-10.51	-0.22		
Cameroon 2011 - 2014	Sub-Saharan Africa	26.16	23.80	-2.36	-0.09	-2.20	-0.05	0.15	0.04

Central African Republic 2000 - 2010	Sub-Saharan Africa	70.12	66.90	-3.22	-0.05	-8.12	-0.09	-4.90	-0.04
Chad 2010 - 2014/15	Sub-Saharan Africa	41.46	27.68	-13.78	-0.33	-0.63	-0.01	13.15	0.33
China 2010 - 2014	East Asia and the Pacific	7.70	4.50	-3.20	-0.42	-1.11	-0.19	2.09	0.23
Colombia 2010 - 2015/16	Latin America and Caribbean	87.54	73.32	-14.22	-0.16	-3.88	-0.05	10.34	0.11
Congo 2005 - 2014/15	Sub-Saharan Africa	28.65	28.07	-0.58	-0.02	-12.81	-0.22	-12.23	-0.20
Congo, Democratic Republic of 2007 – 2013/14	Sub-Saharan Africa	4.30	2.10	-2.20	-0.51	-3.95	-0.50	-1.75	0.01
Côte D'Ivoire 2011/12 - 2016	Sub-Saharan Africa	3.90	1.30	-2.60	-0.67	-3.13	-0.39	-0.53	0.28
Dominican Republic 2007 - 2014	Latin America and Caribbean	40.06	32.29	-7.77	-0.19	-10.05	-0.34	-2.28	-0.15
Egypt 2008 - 2014	Arab States	32.96	30.26	-2.70	-0.08	-4.84	-0.05	-2.14	0.03
eSwatini 2010 - 2014	Sub-Saharan Africa	9.92	5.32	-4.60	-0.46	-15.37	-0.50	-10.77	-0.03
Ethiopia 2011 - 2016	Sub-Saharan Africa	38.09	16.10	-21.99	-0.58	-13.40	-0.20	8.59	0.38
Gabon 2000 - 2012	Sub-Saharan Africa	13.79	12.65	-1.14	-0.08	-4.96	-0.16	-3.82	-0.08
Gambia 2005/06 - 2013	Sub-Saharan Africa	35.30	15.78	-19.52	-0.55	-9.67	-0.14	9.85	0.42
Ghana 2011 - 2014	Sub-Saharan Africa	60.50	73.70	13.20	0.22	-10.71	-0.13	-23.91	-0.34
Guinea 2012 - 2016	Sub-Saharan Africa	0.00	0.00	0.00	0.00	-2.23	-0.41	-2.23	-0.41

Guyana 2009 - 2014	Latin America and Caribbean			0.00	0.00	-8.52	-0.18		
Haiti 2012 - 2016/17	Latin America and Caribbean	24.50	18.35	-6.15	-0.25	-17.86	-0.47	-11.71	-0.22
Honduras 2005/06 - 2011/12	Latin America and Caribbean	36.07	0.00	-36.07	-1.00	-27.18	-0.49	8.89	0.51
India 2005/06 - 2015/16	South Asia	2.43	2.90	0.47	0.19	-5.07	-0.35	-5.53	-0.54
Indonesia 2012 - 2017	East Asia and the Pacific	0.00	0.00	0.00	0.00	-0.62	-0.12	-0.62	-0.12
Iraq 2011 - 2018	Arab States	0.10	0.10	0.00	0.00	-0.09	-0.18	-0.09	-0.18
Jamaica 2010 - 2014	Latin America and Caribbean	0.05	0.00	-0.05	-1.00	-0.43	-0.48	-0.38	0.52
Jordan 2012 - 2017/18	Arab States	41.29	37.49	-3.80	-0.09	-13.37	-0.26	-9.57	-0.16
Kazakhstan 2010/11 - 2015	Europe and Central Asia	12.60	1.30	-11.30	-0.90	-5.93	-0.64	5.37	0.26
2008/09 - 2014	Sub-Saharan Africa	23.13	18.40	-4.73	-0.20	-17.37	-0.43	-12.64	-0.23
Kyrgyzstan 2005/06 - 2014	Europe and Central Asia	45.25	33.78	-11.47	-0.25	-13.91	-0.28	-2.45	-0.03
Lao PDR 2011/12 - 2017	East Asia and the Pacific	68.60	42.89	-25.71	-0.37	-17.73	-0.22	7.98	0.16
Lesotho 2009 - 2014	Sub-Saharan Africa	6.80	8.80	2.00	0.29	-5.60	-0.73	-7.60	-1.03
Liberia 2007 - 2013	Sub-Saharan Africa	70.76	76.55	5.79	0.08	0.86	0.01	-4.92	-0.07
Madagascar 2008/09 - 2018	Sub-Saharan Africa	71.70	70.42	-1.28	-0.02	-13.89	-0.20	-12.61	-0.19

Malawi 2010 - 2015/16	Sub-Saharan Africa	7.30	0.00	-7.30	-1.00	-1.44	-0.68	5.86	0.32
Mali 2006 - 2015	Sub-Saharan Africa	51.20	46.70	-4.50	-0.09	-10.72	-0.13	-6.22	-0.04
Mauritania 2011 - 2015	Sub-Saharan Africa	8.40	5.20	-3.20	-0.38	-12.50	-0.20	-9.30	0.18
Mexico 2012 - 2016	Latin America and Caribbean	13.90	0.30	-13.60	-0.98	-0.64	-0.43	12.96	0.55
Moldova 2005 - 2012	Europe and Central Asia	0.80	0.30	-0.50	-0.63	-6.70	-0.33	-6.20	0.29
Mongolia 2010 - 2013	Europe and Central Asia	5.45	3.20	-2.25	-0.41	-0.57	-0.16	1.68	0.25
Montenegro 2005/06 - 2013	Europe and Central Asia	77.53	65.80	-11.73	-0.15	-13.17	-0.16	-1.43	0.00
Mozambique 2003 - 2011	Sub-Saharan Africa	26.31	16.47	-9.84	-0.37	-7.55	-0.18	2.29	0.20
Namibia 2006/07 - 2013	Sub-Saharan Africa	10.01	0.00	-10.01	-1.00	-13.41	-0.31	-3.40	0.69
Nepal 2011 - 2016	South Asia	16.50	5.25	-11.25	-0.68	-25.28	-0.61	-14.03	0.08
Nicaragua 2001 - 2011/12	Latin America and Caribbean	73.45	48.37	-25.08	-0.34	-3.04	-0.03	22.04	0.31
Niger 2006 - 2012	Sub-Saharan Africa	53.50	53.50	0.00	0.00	1.93	0.04	1.93	0.04
Nigeria 2013 - 2018	Sub-Saharan Africa	6.55	1.15	-5.40	-0.82	-6.78	-0.15	-1.38	0.67
North Macedonia 2005/06 - 2011	Europe and Central Asia	15.30	4.70	-10.60	-0.69	-7.54	-0.37	3.06	0.32
Pakistan 2012/13 - 2017/18	South Asia	9.03	3.17	-5.87	-0.65	-1.56	-0.22	4.31	0.43
Palestine, State of 2010 - 2014	Sub-Saharan Africa	0.20	0.68	0.48	2.40	-0.34	-0.26	-0.82	-2.66

Peru 2012 – 2018	Arab States	53.40	27.43	-25.97	-0.49	-29.04	-0.54	-3.07	-0.05
Philippines 2013 - 2017	Latin America and Caribbean	62.30	56.15	-6.15	-0.10	-15.83	-0.23	-9.68	-0.13
Rwanda 2010 - 2014/15	East Asia and the Pacific	31.93	33.56	1.63	0.05	-18.67	-0.46	-20.30	-0.51
Sao Tome and Principe 2008/09 - 2014	Sub-Saharan Africa	37.40	38.60	1.20	0.03	-11.74	-0.18	-12.94	-0.21
Senegal 2005 - 2017	Sub-Saharan Africa	4.40	7.10	2.70	0.61	0.17	0.89	-2.53	0.28
Serbia 2010 - 2014	Sub-Saharan Africa	48.74	41.83	-6.91	-0.14	-15.79	-0.21	-8.87	-0.07
Sierra Leone 2013 - 2017	Europe and Central Asia	16.90	20.10	3.20	0.19	-3.27	-0.36	-6.47	-0.55
Sudan 2010 - 2014	Arab States	15.50	12.70	-2.80	-0.18	-4.63	-0.08	-1.83	0.10
Suriname 2006 - 2010	Latin America and Caribbean			0.00	0.00	-4.41	-0.34		
Tajikistan 2012 - 2017	Europe and Central Asia	4.75	4.83	0.08	0.02	-4.79	-0.39	-4.87	-0.41
Tanzania 2010 - 2015/16	Sub-Saharan Africa	51.80	49.10	-2.70	-0.05	-10.63	-0.16	-7.93	-0.10
Thailand 2012 – 2015/16	East Asia and the Pacific	0.10	0.00	-0.10	-1.00	-0.54	-0.39	-0.44	0.61
Timor-Leste 2009/10 - 2016	East Asia and the Pacific	41.18	26.04	-15.14	-0.37	-22.72	-0.33	-7.59	0.04
Togo 2010 - 2013/14	Sub-Saharan Africa	54.48	51.45	-3.03	-0.06	-2.17	-0.04	0.86	0.02
Trinidad and Tobago 2006 - 2011	Latin America and Caribbean	12.85	16.23	3.38	0.26	-0.75	-0.13	-4.12	-0.39
Turkmenistan 2006 - 2015/16	Europe and Central Asia			0.00	0.00	-2.31	-0.69		

Uganda 2011 - 2016	Sub-Saharan Africa	38.80	41.70	2.90	0.07	-10.54	-0.16	-13.44	-0.23
Ukraine 2007 - 2012	Europe and Central Asia	0.10	0.00	-0.10	-1.00	-0.12	-0.34	-0.02	0.66
Vietnam 2010/11 - 2014	East Asia and the Pacific	3.85	2.70	-1.15	-0.30	-0.51	-0.05	0.64	0.24
Yemen 2006 - 2013	Arab States	10.80	17.80	7.00	0.65	-8.76	-0.23	-15.76	-0.88
Zambia 2007 - 2013/14	Sub-Saharan Africa	61.48	59.57	-1.91	-0.03	-11.24	-0.17	-9.34	-0.14
Zimbabwe 2010/11 - 2015	Sub-Saharan Africa	20.36	29.73	9.38	0.46	-6.15	-0.15	-15.53	-0.61

Appendix D

For eight subnational regions, we observed high relative differences (≥40%) in the population shares between the two periods, most of which could be attributed to population growth or internal migration patterns. This appendix details the cases where these ≥40% relative differences were due to sample drop as a result of applying the specifications of the MPIT.

Androy, in Madagascar, has a weighted retained population share of 0.0283 in 2008/09 and 0.0424 in 2018. In 2008/09, Androy has a weighted retained sample of 94.4%, and in 2018, 91.8%, so we investigated whether the high relative difference was the result of the sample drop. The sample drop for Androy in 2018 occurs in three indicators: child mortality (6.38% of the 4,167 observations in Androy), nutrition (5.51% of the 4,167 observations in Androy), and education. Overall, 8.16% of the Androy sample is dropped. The child mortality and nutrition indicator drop in Madagascar MICS 2018 are fairly high in any case (4.34% and 3.48%, respectively). Considering the MICS 2018 report has not yet been released, we cannot read data quality tables or any explanation of nutrition measurement or child mortality data collection that might explain why we have high missings in these indicators. We do not have a report to verify the missing data, but we can see that the missings are genuine.

Granada, in Nicaragua, has a weighted retained population share of 0.0201 in 2001 and 0.0344 in 2011/12. In 2001, Granada has a weighted retained sample of 92.4%, and in 2011/12, 92.9%, so the jump between the two years may be the result of the retained sample drop. The sample drop for Granada in 2001 occurs in seven indicators: child mortality, nutrition (6.38% of the 3,072 observations in Granada), education, toilet, electricity, housing, and cooking fuel. Overall, 7.65% of the Granada sample is dropped. The sample drop for Granada in 2011/12 occurs in three indicators: child mortality, nutrition (6.97% of the 3,903 observations in Granada), and school attendance. Overall, 7.15% of the Granada sample is dropped. The nutrition drop in Nicaragua DHS 2001 is fairly high in any case: "The high missing values (4.65%) for the nutrition indicator are likely due to the 8.9% missing information on children under 5 years' height and weight (Table C.7, p.361) or the missing information for women aged 15 to 49 years on their height (3.3%), weight (2.8%), or body mass index (3.3%) (Table C.8 of the 2001 report, p.362)." The jump in the population shares in Granada is a reflection of the sample drop in both years, as well as due to the fact that Granda has a small population share regardless (0.02/0.03), so that the sample drop is a comparably bigger proportion of the region. While the report does not discuss anything about non-response bias in the anthropometric estimates, we can see that the missing nutrition observations are genuine.

Islamabad (ICT), in Pakistan, has a weighted retained population share of 0.0046 in 2012/13 and 0.0086 in 2017/18. In 2012/13, Islamabad has a weighted retained sample of 80.5%, and in 2017/18, 83.3%, so the jump between the two years may be the result of the retained sample drop. Islamabad (ICT) had the lowest response rates of any province in 2012/13, for both women and men respondents. The overall women response rate was 77.6% (Table B.3 of the 2012/13 report, p.247), and the overall men response rate was 70.5% (Table B.4, p.248). Islamabad (ICT) also had the lowest response rates of any province in 2017/18, for both women and men respondents. The overall women response rate was 82.8% (Table A.4 of the 2017/18 report, p.350), and the overall men response rate was 63.7% (Table A.5, p.351). We confirm this low response rate in our raw data as well. The sample drop for Islamabad in 2012/13 occurs in six indicators: child mortality, nutrition (18.91% of the 2,490 observations in Islamabad), school attendance, electricity, toilet, and cooking fuel. Overall, 19.51% of the Islamabad sample is dropped. The sample drop for Islamabad in 2017/18 occurs in three indicators: child mortality, nutrition (16.30% of the 2,637 observations in Islamabad), and housing. Overall, 16.72% of the Islamabad sample is dropped. The nutrition drop in Pakistan DHS 2012/13 is fairly high in any case (7.94%), and the high missing value observed in the nutrition indicator is likely due to the 10.33% missing information on children's height or weight (Table D.3 of the 2012/13 report, p.265) or the 8.2% missing information on the height or weight of women aged 15 to 49 years. The nutrition drop in Pakistan DHS 2017/18 is fairly high in any case (6.11%), and the high missing value observed in the nutrition indicator closely corresponds with the report (p.211) which indicate that valid height data was available for 87% and weight data for 91% of eligible children under 5. In addition, valid measurements were only available for some 94% of the ever-married women 15-49 years (p.218). The jump in the population shares in Islamabad (ICT) is due to three primary reasons: a) it is a reflection of the provincial sample drop in both years, b) Islamabad saw the lowest overall response rates of any province in both survey years, and c) the fact that Islamabad has a small population share regardless (0.00/0.01 means that the sample drop is a comparably bigger proportion of the region. Further, while the report does not discuss anything about non-response bias in the anthropometric estimates (beyond a short description of the data collection in the 2017/18 report, accompanied by [p.211] "the anthropometry data should be interpreted with caution"), we can see that the missing nutrition observations are genuine and are the primary drivers for the sample drop in both years.

Kono, in Sierra Leone, has a weighted retained population share of 0.0556 in 2013 and 0.0676 in 2017. In 2013, Kono has a weighted retained sample of 80.5%, and in 2017 99.2%, so we can trust that the jump between the two years is indeed the result the retained sample drop. The sample

drop for Kono in 2013 occurs in two indicators: child mortality and nutrition (19.46% of the 2,636 observations in Kono). Overall, 19.46% of the Kono sample is dropped. The nutrition drop in Sierra Leone DHS 2013 is fairly high in any case (5.92%), and the missing values in the nutrition indicator are likely due to the 5.66% missing values on children's height and weight (Table C.3 of the 2013 report, p.349). The report also notes (p.145): "Valid height and weight measurements were obtained for 81 percent of the children under age 5 in the sampled households. Another 13 percent of children were considered to have implausibly high or low values for the height or weight and measurements, and 6 percent were missing the child's age in months. The analysis focuses on the children for whom complete and credible anthropometric and valid age data were collected." Since Kono does not have an overall low response rate for women (96.6%, Table A.4, p.315), we may assume that the dropped nutrition observations are due to the implausible anthropometric values for children under 5 years. We have confirmed this by looking into the raw data, which verify that the majority of the implausible observations are in Kono: 123/594 (20.71%). The jump in the population shares in Kono is a reflection of the sample drop in the first year. While the report does not discuss anything about non-response bias in the anthropometric estimates, it does acknowledge that the missing nutrition observations are genuine. Further, Kono may be double hit by the nutrition data quality problem with implausible anthropometric estimates for children that are transferred to missing values.

Menabe, in Madagascar, has a weighted retained population share of 0.0250 in 2008/09 and 0.0352 in 2018. In 2008/09, Menabe has a weighted retained sample of 91.5%, and in 2018, 96.4%, so we investigated whether the high relative difference was the result of the sample drop. The sample drop for Menabe in 2008/09 occurs in all ten indicators: with the highest proportion in nutrition (5.70% of the 1,598 observations in Menabe). Overall, 8.54% of the Menabe sample is dropped. The nutrition drop in Madagascar DHS 2008/09 is fairly high in any case (4.20%). These missing values may be from the 5.43% of women missing anemia information (Table C.3 of the 2008/09 report, p.311), but also, "during the survey, all children under five year of age present in the surveyed households had to be measured. 5,436 out of 6,289 children responding to these criteria have accurate data on age and size, which represents 86% of the children under 5 (p. 202). For logistical reasons, the 4th DHS survey for Madagascar (EDSMD-IV) could not use electronic scales with digital display for weight measurement. They used mechanical scales with needle. These scales did not produce sufficiently accurate weights for children under 5 and, after verification of the collected data, the data on the weight of the children has not been validated and therefore it is not presented in this report. Only the size-based indicator for children has been analyzed" (p.9 of

the 2008/09 report). While the report does not discuss anything about non-response bias in the anthropometric estimates, we can see that the missing nutrition observations are genuine.

Neno, in Malawi, has a weighted retained population share of 0.0056 in 2010 and 0.0100 in 2015/16. In 2010, Neno has a weighted retained sample of 88.6%, and in 2015/16, 94.3%, so the jump between the two years may be the result of the retained sample drop. The sample drop for Neno in 2010 occurs in four indicators: child mortality, nutrition (10.33% of the 1,352 observations in Neno), education, and toilet. Overall, 11.39% of the Neno sample is dropped. The nutrition drop in Malawi DHS 2010 is fairly high in any case. The high missing values (3.69%) in the nutrition indicator are likely due to the genuinely missing anthropometric information of children aged 0-5 years (0.67%), according to Table D.3 on p.433 of the 2010 report. Further, it is possible this missing information derives from women aged 15-49 who refused or did not complete anemia measurements (10.41%) and thus did not complete anthropometry testing. Of the 395 (6.95%) missing from the under-5 underweight indicator, 375 observations are due to genuinely missing data (and the other 20 were recoded based on the improbability of their scores). Of the 594 (10.45%) missing from the under-5 stunting indicator, 428 observations are due to genuinely missing data (and the other 166 were recoded based on the improbability of their scores). Of the 461 (23.64%) missing from the low-BMI-for-age indicator for girls aged 15-19 years, 192 observations are due to genuinely missing data (and the other 269 were recoded based on the improbability of their scores). Of the 616 (7.44%) missing from the women's 15-49 low-BMI indicator, 581 observations are due to genuinely missing data (and the other 35 were recoded based on the improbability of their scores). The jump in the population shares in Neno is a reflection of the sample drop in the first year, as well as due to the fact that Neno has a small population share regardless (0.01), so that the sample drop is a comparably bigger proportion of the region. While the report does not discuss anything about non-response bias in the anthropometric estimates, we can see that the missing nutrition observations are genuine.

Pointe Norte, in Congo, has a weighted retained population share of 0.1528 in 2005 and 0.2431 in 2014/15. In 2005, Pointe Norte has a weighted retained sample of 92.9%, and in 2014/15, 98.1%, so we can trust that the jump between the two years is indeed the result of the survey samples and the retained sample drop. The sample drop for Pointe Norte in 2005 occurs in six indicators: child mortality, nutrition (3.73% of the 6,560 observations in Pointe Norte), school attendance, education, electricity, and cooking fuel. Overall, 7.00% of the Pointe Norte sample is dropped. The jump in the population shares in Pointe Norte is mostly a reflection of the sample drop in the first year. While the report does not discuss anything about non-response bias in the anthropometric estimates, we can see that the missing nutrition observations are genuine.

Somali, in Ethiopia, has a weighted retained population share of 0.0223 in 2011 and 0.0334 in 2016. In 2011, Somali has a weighted retained sample of 92.8%, and in 2016, 93.3%, so we investigated whether the relative difference in the population shares was the result of sample drop. The sample drop for Somali in 2011 occurs in five indicators: child mortality, nutrition (5.08% of the 5,150 observations in Somali), education, school attendance, and water. Overall, 7.16% of the Somali sample is dropped. The sample drop for Somali in 2016 occurs in three indicators: child mortality, nutrition (6.07% of the 8,102 observations in Somali), and education. Overall, 6.68% of the Somali sample is dropped. Missings in the nutrition indicator overall are under 3% in Year 1, but in Year 2, there are 4.93% missing values. According to Table C.3 on page 357 of the 2016 report, 5.0% of children under 5 years, 7.09% of women aged 15-49 years, and 14.63% of men aged 15-49 years are missing height or weight information. Page 189 of the 2016 report further elaborates: "For some eligible children, however, complete or valid data were not obtained due to misclassifications or errors. In this report, height-for-age data are analysed based on 88% of eligible children with complete and credible measurement, weight-for-height on 89% of eligible children, and weight-for-age data on 90% of eligible children." The jump in the population shares in Somali is a reflection of the sample drop in both years. While the report does not discuss anything about non-response bias in the anthropometric estimates, it does acknowledge that the missing nutrition observations are genuine.

Appendix E

See online Appendix E, available here.