ELSEVIER
www.elsevier.com/locate/worlddev

CrossMark

World Development Vol. 94, pp. 232–249, 2017
0305-750X/© 2017 The Authors. Published by Elsevier Ltd.

http://dx.doi.org/10.1016/j.worlddev.2017.01.011

Changes Over Time in Multidimensional Poverty: Methodology and Results for 34 Countries

SABINA ALKIRE [a], JOSÉ MANUEL ROCHE [b] and ANA VAZ [a,*]
[a] *University of Oxford, UK*
[b] *Save the Children, UK*

Summary. — This paper sets out a systemic account of intertemporal changes in multidimensional poverty using the Alkire–Foster Adjusted Headcount Ratio and its consistent sub-indices. It uses three techniques to assess the pro-poorness of multidimensional poverty reduction. The analysis of changes in multidimensional poverty draws on the global Multidimensional Poverty Index (MPI) and related destitution measure in 34 countries and 338 sub-national regions, covering 2.5 billion people, for which there is a recent MPI estimation and comparable Demographic and Health Survey (DHS) dataset across time. First, it assesses overall changes in poverty and its incidence and intensity, and compares this with changes in $1.90 poverty. Next, utilizing the property of subgroup decomposability, it examines changes in the MPI and its consistent sub-indices over time across urban–rural regions, sub-national regions and ethnic groups. The decomposition analysis identifies relevant national patterns, including those in which the pace of poverty reduction is higher for the poorest subgroups. Finally, the paper analyzes the dynamics of a strict subset of the poor, who are identified as "destitute" using a more extreme deprivation cutoff vector, and studies relative rates of reduction of destitution and poverty by country and region. 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. Naturally, some further research questions emerge.

Key words — multidimensional poverty, poverty analysis, poverty trends

1. INTRODUCTION

The aim of poverty measurement is to aid, incentivize, and confirm the successful reduction of disadvantages that blight people's lives. Comparing poverty levels in different countries across time reveals how and in what dimensions poverty has been reduced. These accounts illustrate what is possible and point out where progress has been slow or nonexistent. For example, the Sustainable Development Goal target 1.2 aims to halve the proportion of people experiencing poverty in all its dimensions. How can this be done?

Methodologically, this paper sets out the core components of intertemporal multidimensional poverty analysis then outlines how to analyze the pro-poorness of multidimensional poverty reduction patterns by considering changes in intensity as well as incidence of poverty, population subgroup decompositions, and changes in a destitute subset of the poor. Applying these techniques, it documents how multidimensional poverty and its incidence and intensity has changed in 34 countries representing 2.5 billion people, and further assesses the pro-poorness of those changes across 338 subnational regions, ethnic groups in three countries, and destitution in all 34 countries. In the course of this paper we rule out certain methodological options and illustrate others in some detail.

To measure multidimensional poverty, we use the global Multidimensional Poverty Index (MPI), which is an internationally comparable measure of acute poverty in over 100 developing countries. The MPI 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, Foster, & Santos, 2011; Alkire & Santos, 2014; UNDP, 2010a, 2010b). We also explore the changes over time in a destitution measure (Alkire, Conconi, & Seth, 2014a), which identifies the subset of the MPI poor who are destitute according to more severe deprivation cutoffs (e.g. severe undernutrition instead of undernutrition).

The MPI follows a direct method by assessing the extent to which people satisfy minimum international standards in social rights or valuable ends. It is identically formulated across rural and urban areas. Thus it complements indirect methods that use income or consumption levels to identify a minimum living standard (Alkire & Santos, 2014), and in particular complements global monetary measures such as the $1.90/day figures (Chen & Ravallion, 2010, 2012; Ferreira et al., 2016). The MPI builds on the counting traditions used in Latin America and Europe (Alkire etr al., 2015; Atkinson, 2003, chap. 4) and seeks to advance the work of Amartya Sen (1979, 1992, 1997, 1999, 2009), who has persuasively argued for more comprehensive conceptualizations and measures of capability poverty. Drèze and Sen (2013) among others empirically motivate such analysis, observing that the level (and change) of income per capita or of monetary poverty does not necessarily predict the levels of achieved functionings in social indicators (c.f. Bourguignon & et al., 2010).

The MPI, like any internationally comparable poverty measure, is data constrained and imperfect. Alkire and Santos (2014) articulate its limitations at length, applied robustness tests for several parameters in the MPI, and found national comparisons to be robust to a wider range of deprivation cutoffs, poverty cutoff, and dimensional weights; they also explored household composition as raised by Dotter and

* We would like to thank Mihika Chatterjee, Ivan Gonzalez de la Alba, Maria Mancilla-Garcia, Christian Oldiges and Gisela Robles for splendid research assistance, our colleagues at OPHI and particularly Suman Seth and Adriana Conconi for perceptive comments and substantive inputs, and Maarit Kivilo for timely support in its preparation. All errors remain our own. Final revision accepted: January 7, 2017.

Klasen (2014). They found comparisons using the DHS datasets to be particularly robust, hence this paper restricts analyses to DHS datasets. An important strength of the MPI is that the final measure reflects the joint distribution of deprivations and is sensitive to the intensity of deprivation among the poor. Also, because the measure is direct, comparisons do not require additional adjustments, such as for rural–urban prices, inflation, or PPPs (see Alkire and Foster, 2011b; Alkire et al., 2011). Acknowledging imperfections discussed elsewhere, we further explore MPI comparisons in this paper.

The contribution of this paper is threefold. First, it is the first paper to set forth a systematic account of changes over time in multidimensional poverty using the Alkire–Foster Adjusted Headcount Ratio and its consistent sub-indices. Such an account is essential to the Sustainable Development Goal's (SDGs) aim to halve the proportion of people who are poor in many dimensions. Second, it provides three methodological approaches to assessing the pro-poorness of poverty reduction. Such methods are required in order to assess policy success related to the "Leave No One Behind" pledge in the SDG 2030 agenda. Third, it applies these methodologies exhaustively using the global MPI and a linked destitution measure in 34 countries representing 2.5 billion people. The data are harmonized to enable definitive assessments across poverty and destitution for two or three points of time for each country contributing to evaluating progress during the era of the Millenium Development Goals (MDGs), and laying the groundwork for SDG analyses. Although precise indicator definitions across countries vary, country experiences can also be compared in informative ways, as can monetary poverty trends for certain countries.

The paper is organized as follows. Section 2 presents the measurement methodology for poverty and destitution, and the associated statistics used to analyze changes over time, subnational and ethnic decompositions and dimensional breakdown. Section 3 describes the DHS datasets used in this study and their harmonization, and delineates the levels of comparability that have been achieved over time and across countries. Section 4 presents key findings from the MPI estimates at the national level. Section 5 analyzes changes over time by regional and ethnic groups, finding diverse country patterns. Section 6 explores the changes over time in destitution among the poor. Section 7 concludes.

2. MEASUREMENT METHODOLOGY

(a) *Alkire and Foster* $\boldsymbol{M_0}$ *measure*

The global MPI follows the functional form of the Adjusted Headcount Ratio (M_0), which is the simplest measure within the family of poverty measures developed by Alkire and Foster (2011a). The methodology begins at the level of the person or household, identifies the set of indicators in which they are deprived at the same time by applying a vector of deprivation cutoffs (denoted z) and creating a deprivation matrix which provides a score each person in each dimension, denoting their entry as one if they are deprived in that indicator and zero otherwise. Using a vector of weights on each dimension, denoted w_j, that sum to one their poverty profile is summarized in a weighted deprivation score c_i. If their deprivation score exceeds the poverty cutoff (denoted k), they are identified as multidimensionally poor. After identification, the deprivations of non-poor persons are *censored* or replaced with zero values in the censored deprivation matrix. The Adjusted Headcount Ratio M_0 reflects all deprivations of persons who have been identified as poor, and is the mean of this weighted matrix, multipled by the number of indicators it contains. More intuitively, the M_0 can also be expressed as the product of two intuitive partial indices incidence and intensity $M_0 = HA$. The: headcount ratio or *incidence* is defined by $H = q/n$, where q is the number of poor persons. The average deprivation share across the poor, or *intensity*, is denoted by A and reflects the percentage of deprivations the average poor person experiences—their average deprivation score value.

Consistent Subindices: The M_0 can be broken down after identification into consistent dimensional subindices called "censored headcount ratios" that depict the percentage of the population who are poor and are deprived in dimension j. These are the mean of the respective column vector of the censored matrix and are denoted $h_j(k)$. The percentage contribution of the jth dimension is $(w_j\, h_j(k))/M_0$ (Alkire et al., 2015, chap. 5).

The global MPI is an Adjusted Headcount Ratio M_0 implemented with specific parameters. The MPI is based on ten indicators, which are organized into three equally weighted dimensions: health, education, and living standards. Its ten indicators and deprivation cutoffs reflect deprivations within a household such as undernutrition or child mortality, being educated, or lacking access to safe water and adequate sanitation, and are equally weighted within each dimension (Table 1). A person is identified as poor if they are deprived in at least one-third of the weighted indicators.

This paper also analyzes a related measure of destitution (Alkire et al., 2014a Alkire & Seth, 2016). This measure has the same indicators, weights, and poverty cutoff as the MPI. However for eight of the ten indicators, destitution deprivation cutoffs are used: for example, severe malnutrition instead of malnutrition, losing at least two children, having all primary school-aged children out of school, not having anyone with at least a year of schooling in the household, practicing open defecation, and so on. For electricity and flooring, the cutoffs do not change. A person is destitute if he or she is deprived in at least a third of the weighted destitution indicators. By definition, a destitute person is always multidimensionally poor. The destitution Adjusted Headcount Ratio (and other consistent partial indices) is constructed using the same mathematical formulations as the MPI and is denoted by a superscript 'D' as in MPI^{D}. Table 1 presents the structure of both MPI and Destitution measures.

(b) *Changes in* M_0, *H, and A across two time periods*

This section describes how to compare M_0 and its associated partial indices over time using repeated cross-sectional data. Such comparisons may also be importantly affected by migration and demographic shifts, which require separate treatment.

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. Changes (increases or decreases) in poverty across two time periods can also be reported as a relative rate. The *relative rate of change* is the difference in levels across two periods as a percentage of the initial period. The analysis of absolute and relative changes together provides an elementary sense of overall progress.

For any two periods we denote the initial period by t^1 and the final period by t^2. The achievement matrices for periods t^1 and t^2 are denoted by X_{t^1} and X_{t^2}, respectively. The same set of parameters—deprivation cutoff vector $\boldsymbol{z}$, weight vector $\boldsymbol{w}$, and poverty cutoff k—are used in each period.

The *absolute rate of change* (Δ) is simply the difference in Adjusted Headcount Ratios (M_0) between two periods and is computed as

Table 1. *Multidimensional Poverty Index (MPI) and Multidimensional Destitution (MPI^{D}): Dimensions, Indicators, and Deprivation Cutoffs*

Dimensions of poverty	Indicator	Deprived if…
Education	Years of Schooling	MPI: No household member has completed five years of schooling Dest: No household member has completed more than one year of schooling
	Child School Attendance	MPI: Any school-aged child is not attending school up to the age at which they would complete class 8 Dest: No child is attending school up to the age at which they would complete class 6
Health	Child Mortality	MPI: Any child has died in the family Dest: Two or more children have died in the family
	Nutrition	MPI: Any adult or child for whom there is nutritional information is malnourished Dest: Any adult or child for whom there is nutritional information is *severely* malnourished.
Living Standard	Electricity	MPI & Dest: The household has no electricity
	Improved Sanitation	MPI: The household's sanitation facility is not improved (according to MDG guidelines) or it is improved but shared with other households Dest: The household has no facility.
	Improved Drinking Water	MPI: The household does not have access to improved drinking water (according to MDG guidelines) or safe drinking water is more than a 30-min walk from home, roundtrip Dest: The household does not have access to safe drinking water or safe water is more than a 45-min walk (round trip).
	Flooring	MPI & Dest: The household has a dirt, sand, or dung floor
	Cooking Fuel	MPI: The household cooks with dung, wood, or charcoal Dest: The household cooks with dung or wood.
	Assets ownership	MPI: The household does not own more than one radio, TV, telephone, bike, motorbike, or refrigerator and does not own a car or truck Dest: The household has no assets listed above (radio, telephone etc.) and no car.

Source: Alkire et al. (2014a).

$$\Delta M_0 = M_0(X_{t^2}) - M_0(X_{t^1}). \tag{1}$$

Similarly, for the incidence of poverty H and for intensity A.

The *relative rate of change* (δ) is the difference in poverty as a percentage of the initial poverty level and is computed for M_0 as

$$\delta M_0 = \frac{M_0(X_{t^2}) - M_0(X_{t^1})}{M_0(X_{t^1})} \times 100. \tag{2}$$

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 Adjusted Headcount Ratios between two periods divided by the difference in the two time periods ($t^2 - t^1$) and is computed for M_0 as

$$\bar{\Delta} M_0 = \frac{M_0(X_{t^2}) - M_0(X_{t^1})}{t^2 - t^1}. \tag{3}$$

The *annualized relative rate of change* ($\bar{\delta}$) is the compound rate of reduction in M_0 per year between the initial and the final periods, and is computed for M_0 as

$$\bar{\delta} M_0 = \left[\left(\frac{M_0(X_{t^2})}{M_0(X_{t^1})}\right)^{\frac{1}{t^2-t^1}} - 1\right] \times 100. \tag{4}$$

The same formula can be used to compute and report annualized changes in the other partial indices, namely, H, A, censored headcount ratios, or percent contributions.

(i) *Dimensional changes (uncensored and censored headcount ratios)*

The reductions in M_0, H, or A can be broken down by dimensions. The analysis of dimensional changes considers both the raw or uncensored headcount ratios (h_j) and the censored headcount ratios ($h_j(k)$). These are the means of the j^{th} column of the uncensored or censored deprivation matrix, divided by w_j. By definition, the uncensored headcount ratio of an indicator is equal to or higher than the censored headcount ratio of that indicator, and the changes in censored headcount ratios depict changes in deprivations among the poor. When deprivations are reduced among the poor, or when a poor person becomes non-poor, the censored deprivations change.

(i) *Decomposition by population subgroup*

One important property that the Alkire–Foster family of measures satisfies is population subgroup decomposability. The overall M_0 can be expressed as $M_0 = \sum_{\ell=1}^{m} v^{\ell} M_0(X^{\ell})$, where $M_0(X^{\ell})$ denotes the Adjusted Headcount Ratio $v^{\ell} = n^{\ell}/n$ and the population share of subgroup ℓ. It is especially useful to analyze poverty changes by population subgroups, to see if the poorest subgroups reduced poverty faster than less poor subgroups, and to compare the dimensional composition of reduction across subgroups (Alkire & Seth, 2015). Population-shares for each time period must be analyzed alongside subgroup trends.

To supplement the above analysis it is useful to explore the contribution of population subgroups to overall poverty reduction, M_0 which not only depends on the changes in subgroups' poverty but also on changes in the population composition. This can be seen by presenting the overall change in M_0 between two periods (t^1, t^2) as

$$\Delta M_0 = \sum_{\ell=1}^{m} (v^{\ell,t^2} M_0(X^{\ell}_{t^2}) - v^{\ell,t^1} M_0(X^{\ell}_{t^1})). \tag{5}$$

Note that the overall change depends both on the changes in subgroups and the changes in population shares of the subgroups.

(ii) *Theoretical decompositions*

A valid question is whether it is possible to go beyond the cross-sectional analysis presented above and make some assessment of poverty transitions—for example to see if only the least poor persons left poverty (leaving the poorest behind), or whether it was the poorest among the poor who moved out. This section explains the motivation for doing so using panel data, and then introduces two interesting theoretical approaches for M_0 decompositions that have been proposed for use with cross-sectional data. But when we assess the assumptions they entail empirically, we find they cannot be justified in our datasets. Thus we limit analysis to previously mentioned components.

Panel data analysis. Consider a fixed set of population of size n across two periods, t^1 and t^2. The population can be categorized into four mutually exclusive and collectively exhaustive groups that we refer to as the following dynamic subgroups:

Subgroup N Contains n^N people who are *non-poor* in *both* periods t^1 and t^2,

Subgroup O Contains n^O people who are *poor* in *both* periods t^1 and t^2 (*ongoing poor*),

Subgroup E^- Contains n^{E^-} people who are poor in period t^1 but *exit poverty* in period t^2,

Subgroup E^+ Contains n^{E^+} people who are non-poor in period t^1 but *enter poverty* in period t^2 .

We denote the achievement matrices of these four subgroups in period t by X_t^N, X_t^O, $X_t^{E^-}$, and $X_t^{E^+}$ for all $t = t^1, t^2$. The proportion of the multidimensionally poor population in period t^1 is $H(X_{t^1}) = (n^O + n^{E^-})/n$ and that in period t^2 is $H(X_{t^2}) = (n^O + n^{E^+})/n$. The change in the proportion of poor people between these two periods is $\Delta H = H(X_{t^2}) - H(X_{t^1}) = (n^{E^+} - n^{E^-})/n = H(X_{t^2}^{E^+}) - H(X_{t^1}^{E^-})$. In other words, the change in the overall multidimensional headcount ratio is the difference between the proportion of poor entering and the proportion of poor exiting poverty. Note that, by construction, no person is poor in $X_{t^1}^N$, $X_{t^2}^N$, $X_{t^2}^{E^-}$, and $X_{t^1}^{E^+}$ and thus $H(X_{t^1}^N) = H(X_{t^2}^N) = H(X_{t^2}^{E^-}) = H(X_{t^1}^{E^+}) = 0$. Thus also $M_0(X_{t^1}^N) = M_0(X_{t^2}^N) = M_0(X_{t^2}^{E^-}) = M_0(X_{t^1}^{E^+}) = 0$. In contrast, all persons in $X_{t^1}^{E^-}$, $X_{t^2}^{E^+}$, $X_{t^1}^O$, and $X_{t^2}^O$ are poor and thus $H(X_{t^1}^O) = H(X_{t^2}^O) = H(X_{t^1}^{E^-}) = H(X_{t^2}^{E^+}) = 1$. Therefore the M_0 of each of these four subgroups is equal to its intensity of poverty.

In a fixed population, the overall population and the population share of each dynamic subgroup remains unchanged across two time periods. [1] The change in the overall M_0 can be decomposed by these population subgroups using Eqn. (5) as

$$\Delta M_0 = \frac{n^O}{n}(M_0(X_{t^2}^O) - M_0(X_{t^1}^O)) - \frac{n^{E^-}}{n}M_0(X_{t^1}^{E^-}) + \frac{n^{E^+}}{n}M_0(X_{t^2}^{E^+}). \tag{6}$$

Thus, the right-hand side of Eqn. (6) has three additive components. The first component $\Delta M_0^O = \frac{n^O}{n}(M_0(X_{t^2}^O) - M_0(X_{t^1}^O))$ is due to the change in the intensity of those who remain poor in both periods—the ongoing poor—weighted by the size of this dynamic subgroup. The second component $\Delta M_0^{E^-} = \frac{n^{E^-}}{n}M_0(X_{t^1}^{E^-})$ reflects the change in the intensity of those who exit poverty (weighted by the size of this subgroup) and the third component $\Delta M_0^{E^+} = \frac{n^{E^+}}{n}M_0(X_{t^2}^{E^+})$ reflects the population-weighted change in the intensity of those who enter poverty. In sum, $\Delta M_0 = \Delta M_0^O - \Delta M_0^{E^-} + \Delta M_0^{E^+}$.

These indicators can be estimated using panel data with a fixed population to monitor how the change in M_0 was produced by changes in different parts of the distribution of the poor. The analysis is pro-poor because we can ascertain whether the poorest exited poverty or only the barely poor, and see whose deprivation scores declined—those with the highest deprivation scores or not.

Approximations using cross-sectional data. Cross-sectional data cannot distinguish between these dynamic subgroups. So how do we assess these important questions? As a rough approximation, consider two observable groups, roughly defined as *movers* and *stayers.* We define movers as the ΔH people who reflect the net change in poverty levels across the two periods. Stayers are ongoing poor plus the proportion of previously poor people who were replaced by 'new poor' and totals those who are poor in period two $H(X_{t^2})$. In considering only the 'net' change in headcount, one effectively permits the larger of $E^- or E^+$ to dominate: if poverty rose nationally, the group who entered poverty dominate; otherwise, it is the group who exited poverty. The subordinate third group is allocated among the ongoing poor and the dominant group. For the remainder of this section we presume that both M_0 and H decreased and that $E^- > E^+$. So we presume $\Delta H = (H^{E^-} - H^{E^+})$ and $H(X_{t^2}) = (H^O + H^{E^+})$. Evidently, ΔH and $H(X_{t^2})$ may be estimated using cross-sectional data.

If poverty has reduced and there has not been a large influx of new poor, that is, if $H^{E^+} = n^{E^+}/n$ is negligible, this strategy could also approximate the relative intensity levels of those who moved out of poverty, $H^{E^-} = n^{E^-}/n$, and the changes in intensity among those who remained poor, $H^O = n^O/n$. If H^{E^+} is expected (from other sources of information) to be large, or if the intensity of the new poor is expected to differ greatly from the average, this assumption is not warranted. The corresponding considerations apply if poverty has increased and H^{E^-} is expected to be small.

Consider the intensity of the net population who exited poverty—under these simplifying assumptions reflected by the net change in headcount, denoted $A^{\hat{E}}$—and the intensity change of the net ongoing poor, whom we will presume to be $H(X_{t^2})$, denoted $\Delta A^{\hat{O}}$. The ΔM_0 can be decomposed according to these two groups. These decompositions can be interpreted (given the foregoing assumptions) as showing the percentage of the change in M_0 that can be attributed to those who moved out of poverty—versus the percentage of change that was mainly caused by a decrease in intensity among those who stayed poor.

$$\Delta M_0 = \underbrace{\Delta H \times A^{\hat{E}}}_{\text{Movers}} + \underbrace{H(X_{t^2}) \times \Delta A^{\hat{O}}}_{\text{Stayers}} \tag{7}$$

Cross-sectional data do not provide the intensity of those who stayed poor or of those who moved out of poverty. One empirical strategy is to estimate upper and lower bounds for these using each dataset. First, identify the $\Delta H \times n$ poor persons having the lowest deprivation scores in the dataset (sampling weights applied) and use the average of these scores for $A^{\hat{E}}$, then solve for $A^{\hat{O}}$ Subsequently, identify the $\Delta H \times n$ poor persons having the highest deprivation scores in that dataset and repeat the procedure. This generates upper and lower estimates for $A^{\hat{E}}$ and $A^{\hat{O}}$ in a given dataset, which will illuminate the degree of uncertainty that different assumptions introduce. To estimate maximum upper and lower bounds it could be assumed that all those moved out of poverty had an intensity score of the value of k (the minimum), and subsequently assume that their intensity was 100% (the maximum).

Theoretical Incidence-Intensity decompositions. Two theory-based approaches to decomposing changes in repeated cross-sectional data according to 'incidence' and 'intensity' have recently been proposed. In each approach assumptions are made regarding the intensity of those who exit or remain poor.

For simplicity of notation, we here denote the M_0, H, and A for period t^1 by $M_0^{t^1}$, H^{t^1}, and A^{t^1} that for period t^2 by $M_0^{t^2}$, H^{t^2}, and A^{t^2}. Apablaza and Yalonetzky (2013) propose an additive decomposition. Since $M_0 = H \times A$, they propose to decompose the change in M_0 by changes in its partial indices as follows:

$$\Delta M_0 = \underbrace{A^{t^1}(H^{t^2} - H^{t^1})}_{\text{Poverty effect from entry and exit}} + \underbrace{H^{t^1}(A^{t^2} - A^{t^1})}_{\text{Poverty effect}} + \underbrace{((H^{t^2} - H^{t^1})(A^{t^2} - A^{t^1}))}_{\text{Interaction effect}}. \tag{8}$$

Their approach entails two assumptions. First, the intensity among those who left poverty is assumed to be the same as the average intensity in period t^2. Second, the intensity change among the ongoing poor is assumed to equal the simple difference in intensities of the poor across the two periods. The decomposition is completed using an interaction term. Apablaza and Yalonetzky interpret this decomposition of changes in the Adjusted Headcount Ratio (M_0) (M_0). as reflecting: (1) changes in poverty incidence (H), (2) changes in intensity (A), and (3) a joint effect reflecting the interaction between incidence and intensity ($\Delta H \times \Delta A$).

Building on Apablaza and Yalonetzky (2013), Roche (2013) proposes a Shapley value decomposition following Shorrocks (1999) under a set of assumptions discussed below. It provides the marginal effect of changes in incidence and intensity as follows:

$$\Delta M_0 = \underbrace{\frac{A^{t^2} + A^{t^1}}{2}(H^{t^2} - H^{t^1})}_{\text{Incidence of Poverty effect}} + \underbrace{\frac{H^{t^2} + H^{t^1}}{2}(A^{t^2} - A^{t^1})}_{\text{Intensity of Poverty effect}} \tag{9}$$

Formula (9) assumes that the intensity of those who exited poverty is the average intensity of the two periods $\frac{A^{t^2}+A^{t^1}}{2}(H^{t^2} - H^{t^1})$ and calls this the 'incidence effect'. It also assumes the other group has the average headcount ratio between the two periods and their change in intensity is the simple difference in intensities across the periods, $\frac{H^{t^2}+H^{t^1}}{2}(A^{t^2} - A^{t^1})$, and describes this as the "intensity effect".

As Roche demonstrates, Shapley decompositions could be applied to each step of dynamic analysis using the Alkire–Foster (AF) method. For example, if the underlying assumptions are transparently stated and accepted, the theoretically derived marginal contribution of changes in incidence and marginal contribution of changes in intensity can be expressed as a percentage of the overall change in M_0 so they both add to 100%:

$$\Phi_H^0 = \frac{\left(\frac{A^{t^2}+A^{t^1}}{2}(H^{t^2} - H^{t^1})\right) \times 100}{\Delta M_0} \tag{10}$$

$$\Phi_A^0 = \frac{\left(\frac{H^{t^2}+H^{t^1}}{2}(A^{t^2} - A^{t^1})\right) \times 100}{\Delta M_0}. \tag{11}$$

To address demographic shifts, Roche follows a similar decomposition of change as that used in FGT unidimensional poverty measures (Ravallion & Huppi, 1991) and Shapely decompositions (Duclos & Araar, 2006; Shorrocks, 1999).

Shall we apply such theoretical decompositions in our investigation of the pro-poorness of multidimensional poverty reduction in order to address the important question of whether the poorest were left behind? Table 2 presents the empirical estimations for the upper and lower bounds for the "movers" (incidence) and "stayers" (intensity) effects. At the upper bound, where we assume the poorest of the poor moved out of poverty, those who moved out of poverty could have had average intensities ranging from 37% in Armenia (the least poor country in the analysis) to 100% in Ethiopia and Niger. In most countries, at the upper bound, over 100% of the poverty reduction is due to movers; the exceptions are Ethiopia, Malawi, Mozambique, and Niger. At the lower bound, where we assume the least (barely) poor people moved out of poverty, those who moved out of poverty could have intensities between 33% and 38%. At the lower bound, movers' contribution to poverty reduction would range from 16.6% in Niger to 93.6% in Armenia. [2]

The last columns of Table 2 (p. 18) provide the Shapley decompositions. In all cases the Shapley decompositions lie between the upper and lower bounds. But the empirical upper and lower bounds are wide and vary greatly across countries. Thus based on our repeated cross-sectional data, we cannot justify the assumptions required to precisely decompose changes in MPI by incidence and intensity. [3] While this can seem disappointing, for policy purposes, as Sen stresses, it may be better to be 'vaguely right than precisely wrong'. It remains informative to explore the absolute changes in each partial index across time, as our subsequent empirical analysis will demonstrate.

3. DATA

The analysis of changes in MPI over time in this paper focuses on 34 countries: Armenia, Bangladesh, Benin, Bolivia, Cambodia, Cameroon, Colombia, Dominican Republic, Egypt, Ethiopia, Gabon, Ghana, Guyana, Haiti, India, Indonesia, Jordan, Kenya, Lesotho, Madagascar, Malawi, Mozambique, Namibia, Nepal, Niger, Nigeria, Pakistan, Peru, Rwanda, Senegal, Tanzania, Uganda, Zambia, and Zimbabwe. These are the countries for which there is a recent MPI estimation and comparable Demographic and Health Survey (DHS) datasets for analysis across time. The 34 countries come from every geographic region in the developing world. They contain more than 2.5 billion people, [4] which is around 37% of the world's population as per population estimates for 2010. [5] They are Low, Lower Middle, and Upper Middle-Income Countries with a GNI per capita in 2012 from \$320 in Malawi to \$10,040 in Gabon. [6] Poverty levels range from low to high: the proportion of MPI poor [7] in the starting period ranged from 1% to 94% across these countries.

The most recent estimate in 20 out of the 37 comparisons is for 2010, 2011, or 2012; 12 countries' most recent estimates are during 2007–09; and two countries' most recent estimates are during 2005–06. The first data point ranges between 1998/9–2008. The time period ranges between 2 and 12 years depending on the frequency of data collection in each context; 30 of the periods last 4 to 7 years, for 5 countries the range is less than 4 years, for Mozambique it is 8 years, and for Gabon the comparison covers 12 years. We have two periods of comparison for Ethiopia, 2000–05 and 2005–10; for Bangladesh, 2004–07 and 2007–11; and for Peru, 2005–08 and 2008–12. Hence, we have a total of 37 comparisons. Given the diversity

Table 2. *Decomposing the change in MPI by dynamic subgroup*

	Upper Bound				Lower Bound				Shapley Decomposition	
	A Movers	ΔA Stayers	Movers Effect (%)	Stayers Effect (%)	A Movers	ΔA Stayers	Movers Effect (%)	Stayers Effect (%)	Incidence effect H (%)	Intensity effect A (%)
Armenia 2005–10	0.37	0.02	**103.3**	**−3.3**	0.33	−0.04	**93.6**	**6.4**	**99.2**	**0.8**
Bangladesh 2004–07	0.83	0.01	**114.2**	**−14.2**	0.35	−0.05	**48.2**	**51.8**	**73.2**	**26.8**
Bangladesh 2007–11	0.78	0.03	**120.6**	**−20.6**	0.35	−0.06	**54.3**	**45.7**	**78.2**	**21.8**
Benin 2001–06	0.93	0.01	**107.7**	**−7.7**	0.34	−0.05	**39.5**	**60.5**	**68.2**	**31.8**
Bolivia 2003–08	0.60	0.04	**110.7**	**−10.7**	0.38	−0.13	**69.5**	**30.5**	**84.8**	**15.2**
Cambodia 2005–10	0.74	0.02	**112.9**	**−12.9**	0.34	−0.09	**52.3**	**47.7**	**73.5**	**26.5**
Cameroon 2004–11	0.87	0.04	**135.4**	**−35.4**	0.33	−0.05	**51.9**	**48.1**	**85.0**	**15.0**
Colombia 2005–10	0.55	0.05	**118.3**	**−18.3**	0.34	−0.08	**72.5**	**27.5**	**90.8**	**9.2**
Dom. Rep. 2002–07	0.52	0.04	**109.7**	**−9.7**	0.35	−0.11	**73.3**	**26.7**	**86.7**	**13.3**
Egypt 2005–08	0.54	0.04	**125.7**	**−25.7**	0.33	−0.04	**77.3**	**22.7**	**95.1**	**4.9**
Ethiopia 2000–05	1.00	−0.04	**51.0**	**49.0**	0.34	−0.07	**17.2**	**82.8**	**35.6**	**64.4**
Ethiopia 2005–11	1.00	−0.04	**60.0**	**40.0**	0.35	−0.07	**21.1**	**78.9**	**38.7**	**61.3**
Gabon 2000–12	0.54	0.06	**112.8**	**−12.8**	0.37	−0.11	**78.2**	**21.8**	**93.2**	**6.8**
Ghana 2003–08	0.73	0.04	**115.5**	**−15.5**	0.36	−0.11	**56.7**	**43.3**	**79.3**	**20.7**
Guyana 2005–09	0.54	0.03	**134.2**	**−34.2**	0.33	−0.01	**83.2**	**16.8**	**97.7**	**2.3**
Haiti 2005/6–12	0.83	0.01	**107.3**	**−7.3**	0.35	−0.10	**45.8**	**54.2**	**68.2**	**31.8**
India 1998/9–05/6	0.82	0.04	**136.0**	**−36.0**	0.34	−0.05	**55.7**	**44.3**	**87.0**	**13.0**
Indonesia 2007–12	0.63	0.03	**115.1**	**−15.1**	0.34	−0.07	**61.5**	**38.5**	**81.4**	**18.6**
Jordan 2007–09	0.44	0.01	**108.9**	**−8.9**	0.33	−0.01	**82.4**	**17.6**	**86.5**	**13.5**
Kenya 2003–08/9	0.76	0.03	**129.9**	**−29.9**	0.33	−0.04	**56.7**	**43.3**	**82.5**	**17.5**
Lesotho 2004–09	0.68	0.02	**121.9**	**−21.9**	0.33	−0.05	**59.9**	**40.1**	**82.6**	**17.4**
Madagascar 2004–08/9	0.87	−0.02	**136.1**	**−36.1**	0.34	0.03	**53.9**	**46.1**	**87.7**	**12.3**
Malawi 2004–10	0.86	0.00	**99.7**	**0.3**	0.33	−0.04	**38.8**	**61.2**	**59.8**	**40.2**
Mozambique 2003–11	0.89	−0.01	**95.3**	**4.7**	0.37	−0.09	**40.1**	**59.9**	**62.8**	**37.2**
Namibia 2000–07	0.68	0.04	**129.8**	**−29.8**	0.33	−0.04	**63.3**	**36.7**	**88.2**	**11.8**
Nepal 2006–11	0.74	0.04	**113.4**	**−13.4**	0.38	−0.13	**58.2**	**41.8**	**79.5**	**20.5**
Niger 2006–12	1.00	−0.04	**46.7**	**53.3**	0.35	−0.07	**16.6**	**83.4**	**33.5**	**66.5**
Nigeria 2003–08	0.91	0.05	**148.4**	**−48.4**	0.34	−0.04	**55.0**	**45.0**	**93.9**	**6.1**
Pakistan 2006/7–12/13	0.90	0.02	**126.7**	**−26.7**	0.33	−0.03	**47.0**	**53.0**	**74.3**	**25.7**
Peru 2005–08	0.59	0.02	**119.5**	**−19.5**	0.33	−0.04	**67.1**	**32.9**	**86.4**	**13.6**
Peru 2008–12	0.52	0.04	**117.9**	**−17.9**	0.33	−0.06	**74.9**	**25.1**	**93.5**	**6.5**
Rwanda 2005–10	0.79	0.00	**101.1**	**−1.1**	0.36	−0.10	**46.9**	**53.1**	**67.8**	**32.2**
Senegal 2005–10/11	1.00	−0.02	**20.7**	**79.3**	0.33	−0.02	**6.9**	**93.1**	**12.6**	**87.4**
Tanzania 2008–10	0.89	0.01	**109.8**	**−9.8**	0.33	−0.04	**41.1**	**58.9**	**68.7**	**31.3**
Uganda 2006–11	0.81	0.02	**116.6**	**−16.6**	0.34	−0.06	**49.0**	**51.0**	**76.3**	**23.7**
Zambia 2001/2–07	0.87	0.00	**95.8**	**4.2**	0.33	−0.06	**36.9**	**63.1**	**58.8**	**41.2**
Zimbabwe 2006–10/11	0.66	0.02	**117.7**	**−17.7**	0.33	−0.04	**59.2**	**40.8**	**78.6**	**21.4**

in the length of period we undertake analysis based on the annualized change. Note that statistical significance refers to the full period of comparison, not to the annualized change, thus longer periods of comparison are more likely to generate significant results.

To describe this sample of countries, we present some of the population aggregates for them. If we aggregate the global MPI estimates published in 2014 using 2010 population weights, this group of countries as a whole would be roughly as poor as Haiti (the illustrative aggregate MPI would be 0.249 and 47.1% of people would be poor).

OPHI's global MPI estimations for each country, reported in Alkire, Conconi, and Seth (2014b) and in the UNDP's Human Development Reports, use the maximum information available in the survey on which the estimation is based. As a result, improvements in the questionnaire or survey design imply improvements in the MPI estimation. This methodological strategy produces the most accurate estimation for a given year, but estimates are not designed for comparison over time. In order to allow accurate assessment of trends in MPI over time, this paper rigorously standardizes the MPI indicator sets and parameters for those countries for which changes in the questionnaire design may affect comparability across time. It must be noted that in some cases the harmonized data may be less accurate because we have dropped some information to create comparability. For example, in India we do not have nutrition information for children older than 3 years in 1999, nor data from never-married women, so we must drop this information in 2006 to attain comparability. We have sought to ascertain that the rest of the survey design—sampling, fieldwork, etc - permits comparability. Comparable MPI values are denoted by MPI_T as their values may differ from published MPI values. We have information on the 10 MPI indicators for 29 countries; Guyana, Indonesia, Pakistan, and Tanzania lack information on nutrition, and Egypt lacks information on cooking fuel. Details on the MPI adjustment for comparability and differences with the published figures are provided in Annex 2.

4. NATIONAL RESULTS

(a) *Overview of poverty reduction*

Table 3 presents the level, change, and statistical significance of changes in the MPI_T (see also figures for H_T and A_T in Annex 1, Tables A1 and A2). The first insight from the

Table 3. *Level, Change, and Statistical Significance of Changes in MPI*

	Multidimensional Poverty Index (MPI_T)				Annualized change		*t*-Statistics for difference
	Year 1		Year 2		Absolute	% Relative	
Armenia 2005–10	.003	(.001)	.001	(.000)	.000	−17.7%	2.22**
Bangladesh 2004–07	.364	(.007)	.306	(.007)	−0.020	−5.7%	5.60***
Bangladesh 2007–11	.306	(.007)	.245	(.006)	−0.015	−5.4%	6.92***
Benin 2001–06	.474	(.008)	.414	(.006)	−0.012	−2.7%	5.70***
Bolivia 2003–08	.175	(.005)	.089	(.003)	−0.017	−12.6%	13.68***
Cambodia 2005–10	.299	(.006)	.212	(.006)	−0.017	−6.7%	10.11***
Cameroon 2004–11	.298	(.009)	.248	(.007)	−0.007	−2.6%	4.39***
Colombia 2005–10	.039	(.002)	.023	(.001)	−0.003	−9.8%	8.04***
Dominican Rep. 2002–07	.040	(.002)	.020	(.001)	−0.004	−13.0%	9.27***
Egypt 2005–08	.034	(.002)	.024	(.001)	−0.003	−10.7%	4.69***
Ethiopia 2000–05	.677	(.004)	.604	(.006)	−0.014	−2.2%	6.56***
Ethiopia 2005–11	.604	(.006)	.526	(.007)	−0.013	−2.3%	7.83***
Gabon 2000–12	.161	(.006)	.075	(.004)	−0.007	−6.1%	10.74***
Ghana 2003–08	.309	(.007)	.202	(.007)	−0.021	−8.1%	10.39***
Guyana 2005–09	.050	(.004)	.041	(.002)	−0.002	−4.5%	1.71*
Haiti 2005/6–12	.335	(.010)	.248	(.008)	−0.013	−4.5%	6.43***
India 1998/9–05/6	.304	(.002)	.254	(.003)	−0.007	−2.5%	12.81***
Indonesia 2007–12	.095	(.003)	.066	(.002)	−0.006	−7.0%	8.93***
Jordan 2007–09	.013	(.002)	.011	(.001)	−0.001	−8.9%	0.89
Kenya 2003–08/9	.296	(.008)	.244	(.010)	−0.009	−3.5%	4.10***
Lesotho 2004–09	.238	(.005)	.190	(.007)	−0.010	−4.4%	5.09***
Madagascar 2004–08/9	.374	(.015)	.414	(.007)	.009	2.3%	2.64***
Malawi 2004–10	.381	(.006)	.334	(.005)	−0.008	−2.2%	6.06***
Mozambique 2003–11	.505	(.007)	.393	(.007)	−0.014	−3.1%	11.86***
Namibia 2000–07	.194	(.008)	.154	(.005)	−0.006	−3.2%	3.17***
Nepal 2006–11	.350	(.013)	.217	(.012)	−0.027	−9.1%	7.61***
Niger 2006–12	.696	(.007)	.621	(.007)	−0.012	−1.9%	7.80***
Nigeria 2003–08	.368	(.011)	.313	(.006)	−0.011	−3.2%	4.04***
Pakistan 2006/7–12/13	.264	(.005)	.235	(.009)	−0.005	−2.0%	2.86***
Peru 2005–08	.085	(.007)	.066	(.003)	−0.006	−8.0%	1.83*
Peru 2008–12	.066	(.003)	.043	(.002)	−0.006	−10.3%	5.47***
Rwanda 2005–10	.461	(.005)	.330	(.006)	−0.026	−6.4%	15.65***
Senegal 2005–10/11	.440	(.019)	.423	(.010)	−0.003	−0.7%	1.03
Tanzania 2008–10	.371	(.008)	.335	(.007)	−0.018	−5.0%	3.48***
Uganda 2006–11	.420	(.007)	.343	(.009)	−0.015	−3.9%	5.83***
Zambia 2001/2–07	.397	(.008)	.332	(.007)	−0.012	−3.2%	4.59***
Zimbabwe 2006–10/11	.180	(.006)	.145	(.005)	−0.008	−4.7%	4.61***

Note: ***statistically significant at $\alpha = 0.01$, **statistically significant at $\alpha = 0.05$, *statistically significant at $\alpha = 0.10$.
Standard errors reported between brackets.

analysis is that of the 34 countries, 30—covering 98% of the poor people across all 34—had statistically significant reductions in multidimensional poverty at the $\alpha = 0.05$ significance level and 29 countries at $\alpha = 0.01$. Guyana and Peru (2005–08) had reductions that were only significant at $\alpha = 0.10$.

The pace of progress varied considerably across countries. Nepal, Rwanda, Ghana, and Tanzania had the largest absolute reductions in MPI poverty, greater than 0.018 per annum. Bangladesh, Cambodia, and Bolivia also proved to be strong performers, with reductions above 0.015 per year. In relative terms, Armenia, the Dominican Republic, and Bolivia had the fastest decrease in MPI_T, reducing their starting poverty levels by more than 12% per year. Each of the top-performing countries—Nepal, Rwanda, Ghana, Tanzania, Cambodia, and Bangladesh—decreased their original level of MPI_T by 5% to 9% per year—making them successes in both relative and absolute terms.

On the other hand, Jordan and Senegal had no significant reduction, and Madagascar had a statistically significant (at $\alpha = 0.01$) increase in multidimensional poverty.

As in other studies, we do not find a perfect relation between economic growth and poverty reduction (Donaldson, 2008; Ferreira, Leite, & Ravallion, 2010). The level of success in translating the gains of growth into poverty reduction varies across countries and also sometimes across periods (see Table A3 in Annex 1). For instance, in the periods under analysis, Bangladesh and India registered similar rates of growth in GNI per capita, but Bangladesh reduced MPI_T more than twice as fast as India. On the other hand, although India has grown six times faster than Cameroon, the latter reduced MPI_T as fast as India. Finally, although the average growth rate in Ethiopia more than doubled between the period 2000–05 and 2005–08, the annualized relative change in the MPI_T remained practically the same. Our results indicate economic growth on its own is not sufficient to deliver multidimensional poverty reduction opening a line of enquiry for future research (for more on this see: Santos, Dabu, & Delbianco, 2016).The MPI uses a poverty cutoff of 33.33%, but the findings discussed above are robust to a range of different poverty cutoffs (see Annex 3 for more details).

(b) *Comparing the evolution of headcount ratios for MPI and monetary poverty*

The previous section focused on the rate of poverty reduction in MPI_T. Now we focus on changes in the headcount ratio. The multidimensional headcount ratio (H_T) and its annualized rates of change are presented in the first columns of Table 4 (see statistical significance in Table A3 in Annex 1). The same 30 countries had significant changes in the headcount ratio, and those that were most successful in reducing the MPI—Nepal, Ghana, Bolivia, Cambodia, Rwanda, Tanzania, and Bangladesh—also strongly reduced the incidence of multidimensional poverty, both in absolute and relative terms. Nepal reduced incidence from 65% to 44% in a five year period (2006–11), a yearly decrease of 4.1 percentage points. The other top performing countries registered annualized reductions between 2.3 and 3.4 percentage points.

The multidimensional headcount ratio (H_T) can be seen as the multidimensional equivalent to the $1.90 a day poverty headcount. Thus, we proceed in comparing the evolution of

Table 4. *Comparison between Change in Annualized Incidence of MPI and $1.90/day*

Country and Period	MPI Headcount Ratio (H_T)						$1.90 Headcount Ratio					
	Level				Annualized change		Level		Annualized change		Years of income information used	
	Year 1		Year 2		Absolute	Relative	Year 1	Year 2	Absolute	Relative	Year 1	Year 2
Armenia 2005–10	.8	(.2)	.3	(.1)	−0.1	−12.4%	4.5	2.5	−0.4	−10.6%	2005	2010
Bangladesh 2004–11[(1)]	67.1	(.9)	49.6	(.9)	−2.5	−4.2%	26.4	17.3	−1.3	−5.8%	2000, 2005	2005, 2010
Bangladesh 2004–07	67.1	(.9)	59.0	(1.1)	−2.7	−4.2%	26.4	22.1	−1.4	−5.7%	2000, 2005	2005, 2010
Bangladesh 2007–11	59.0	(1.1)	49.6	(.9)	−2.4	−4.2%	22.1	17.3	−1.2	−5.9%	2005, 2010	2005, 2010
Benin 2001–06	79.1	(.9)	72.1	(.8)	−1.4	−1.8%	47.8	50.4	.5	1.1%	2003, 2011	2003, 2011
Bolivia 2003–08	36.3	(.8)	20.5	(.7)	−3.2	−10.8%	19.3	11.9	−1.5	−9.2%	2002, 2004	2008
Cambodia 2005–10	59.2	(1.1)	45.9	(1.1)	−2.7	−5.0%	18.0	4.6	−2.7	−23.9%	2004, 2007	2009
Cameroon 2004–11	53.8	(1.3)	46.0	(1.1)	−1.1	−2.2%	26.2	26.2	.0	0.0%	2001, 2007	2007, 2014
Colombia 2005–10	9.0	(.3)	5.7	(.2)	−0.7	−8.9%	10.4	8.1	−0.5	−5.0%	2005	2010
Dominican Rep. 2002–07	9.3	(.4)	5.1	(.3)	−0.8	−11.5%	5.8	4.3	−0.3	−5.8%	2002	2007
Egypt 2005–08[(2)]	8.2	(.4)	6.0	(.3)	−0.8	−10.2%	.	.	.	.	–	–
Ethiopia 2000–11[(1)]	93.6	(.4)	85.2	(.9)	−0.8	−0.8%	51.6	33.1	−1.7	−4.0%	1999, 2004	2004, 2010
Ethiopia 2000–05	93.6	(.4)	89.9	(.6)	−0.7	−0.8%	51.6	35.8	−3.1	−7.0%	1999, 2004	2004, 2010
Ethiopia 2005–11	89.9	(.6)	85.2	(.9)	−0.8	−0.9%	35.8	33.1	−0.5	−1.3%	2004, 2010	2004, 2010
Gabon 2000–12[(3)]	35.4	(1.2)	17.4	(1.0)	−1.5	−5.7%	.	.	.	.	–	–
Ghana 2003–08	58.7	(1.1)	41.9	(1.2)	−3.4	−6.5%	27.7	21.5	−1.2	−4.9%	1998, 2005	1998, 2005
Guyana 2005–09[(4)]	12.7	(1.0)	10.6	(.6)	−0.5	−4.4%	.	.	.	.	–	–
Haiti 2005/6–12	60.6	(1.5)	49.4	(1.3)	−1.7	−3.1%	54.8	53.9	−0.2	−0.3%	2001, 2012	2012
India 1998/9–2005/6	57.3	(.4)	49.0	(.4)	−1.2	−2.2%	41.7	35.4	−0.9	−2.3%	1993, 2004	2004, 2009
Indonesia 2007–12	20.8	(.5)	15.5	(.4)	−1.1	−5.7%	22.8	11.8	−2.2	−12.4%	2007	2009, 2011
Jordan 2007–09[(2)]	3.6	(.6)	3.0	(.4)	−0.3	−7.8%	.	.	.	.	–	–
Kenya 2003–08/9	60.1	(1.2)	51.2	(1.6)	−1.6	−2.9%	30.6	39.7	1.5	4.4%	1997, 2005	1997, 2005
Lesotho 2004–09	50.8	(1.0)	42.2	(1.4)	−1.7	−3.7%	60.9	59.9	−0.2	−0.3%	2002, 2010	2002, 2010
Madagascar 2004–08/9	67.0	(2.1)	73.3	(1.1)	1.4	2.0%	72.7	80.2	1.5	2.0%	2001, 2005	2005, 2010
Malawi 2004–10	72.1	(1.0)	66.7	(.8)	−0.9	−1.3%	73.6	70.9	−0.5	−0.6%	2004	2010
Mozambique 2003–11	82.3	(.7)	70.3	(1.0)	−1.5	−1.9%	78.4	62.9	−1.9	−2.7%	2002, 2008	2002, 2008
Namibia 2000–07	41.3	(1.6)	33.7	(1.0)	−1.1	−2.9%	37.9	25.6	−1.8	−5.5%	1993, 2003	2003, 2009
Nepal 2006–11	64.7	(2.0)	44.2	(2.0)	−4.1	−7.4%	32.8	10.5	−4.4	−20.3%	2003, 2010	2003, 2010
Niger 2006–12	93.5	(.5)	90	(.6)	−0.6	−0.6%	73.5	48.8	−4.1	−6.6%	2005, 2007	2011, 2014
Nigeria 2003–08	63.5	(1.6)	54.7	(.9)	−1.8	−3.0%	53.5	53.5	.0	0.0%	2003	2003, 2009
Pakistan 2006/7–12/13	49.4	(.8)	45.2	(1.3)	−0.7	−1.5%	13.1	6.1	−1.2	−12.1%	2007	2013
Peru 2005–12[(1)]	19.5	(1.4)	10.5	(.4)	−1.3	−8.5%	14.2	4.1	−1.4	−16.1%	2005	2012
Peru 2005–08	19.5	(1.4)	15.7	(.7)	−1.3	−6.9%	14.2	7.9	−2.1	−17.6%	2005	2008
Peru 2008–12	15.7	(.7)	10.5	(.4)	−1.3	−9.6%	7.9	4.1	−1.0	−15.1%	2008	2012
Rwanda 2005–10	82.9	(.8)	66.1	(1.0)	−3.4	−4.4%	68.0	60.3	−1.6	−2.4%	2005	2010
Senegal 2005–10/11	71.2	(2.4)	70.8	(1.5)	−0.1	−0.1%	38.4	38.0	−0.1	−0.2%	2005	2011
Tanzania 2008–10	65.6	(1.2)	61.1	(1.1)	−2.3	−3.5%	51.2	48.1	−1.5	−3.0%	2007, 2011	2007, 2011
Uganda 2006–11	77.9	(1.1)	66.8	(1.5)	−2.2	−3.0%	50.3	36.9	−2.7	−6.0%	2005, 2009	2009, 2012
Zambia 2001/2–07	72.0	(1.3)	64.8	(1.2)	−1.3	−1.9%	49.4	61.5	2.4	4.4%	2002	2006, 2010
Zimbabwe 2006–10/11[(5)]	39.7	(1.1)	33.5	(1.1)	−1.4	−3.7%	.	.	.	.	–	–

Source: Data on MPI authors' estimation. Data on $1.90/day incidence downloaded in October 2016 from World Development Indicators (World Bank, 2016).

(1) Bangladesh, Ethiopia, and Peru have an additional a row showing the overall change between the first and third periods.

(2) There are no $1.90/day estimates for Egypt and Jordan.

(3) In Gabon, since 1990, there is only monetary poverty data for 2005. Thus, it is not possible to accurately compute the poverty reduction rate 2000–12.

(4) The most recent monetary poverty measure available for Guyana is for 1998 making it impossible to know the rate of reduction 2005–09.

(5) In Zimbabwe, since 1990, there is only income poverty data for 2011. Thus, it is not possible to accurately compute the poverty reduction rate 2006–10/11.

these two poverty measures. The \$1.90 a day monetary poverty headcount ratios and their annualized rate of change are presented in the last columns of Table 4.

This comparison is not straightforward so some caveats are necessary. The key limitation in comparing these two measures is the lack of frequently updated poverty data. For example, matching year monetary poverty comparisons in both the first and last MPI period are only available for eight of the countries under analysis: Armenia, Colombia, Dominican Republic, Malawi, Pakistan, Peru, Rwanda, and Senegal. In another eight countries, the \$1.90 data are older than the comparable MPI (Bangladesh, Cambodia, Ethiopia, Ghana, Indonesia, Kenya, Mozambique, and Nepal); while in five countries there is not enough monetary poverty data to compute a comparable rate of monetary poverty reduction (Egypt, Gabon, Guyana, Jordan, and Zimbabwe). Hence, we have matched data when possible. When monetary poverty data were not available from the same year of a survey, we used a linear interpolation or extrapolation between the two closest data points to estimate the level of monetary poverty at the year of the survey. The final comparison covers 29 countries for which very roughly comparable monetary poverty data are available from World Development Indicators (World Bank, 2016, accessed in October 2016), but the conclusions may be affected by the lack of matching data points.

Multidimensional poverty incidence was larger than monetary poverty at the beginning of the comparison period in 23 of the 29 countries. The gap between the two figures varied from 1.4 percentage points for Colombia in 2005 (with an MPI headcount of 9.0% and monetary poverty of 10.4%) to 42 percentage points for Ethiopia 2000 (with an MPI and income incidence of 93.6% and 51.6%, respectively).

Figure 1 depicts the annualized absolute rates of change in MPI and \$1.90/day incidence for the 27 countries that reduced the multidimensional headcount significantly and for which we have monetary data. There is no uniform pattern. In some countries, such as Niger, Indonesia, Ethiopia and Namibia, monetary poverty reductions appear to have exceeded H_T reductions. In other countries, apparently the reverse happened. Dominican Republic, Ghana, Rwanda, Bolivia, and Malawi seem to have cut MPI incidence two to three times faster than monetary poverty in absolute terms, and closed the gap to eradication faster in relative terms, too. In Haiti and Lesotho the MPI incidence seems to have reduced more than 8 times faster than monetary poverty in absolute terms. In Kenya, Benin, and Zambia, the two kinds of poverty changed in different directions: MPI incidence reduced, but monetary poverty increased. Note that as we cannot estimate the standard errors for the changes in income poverty, we cannot infer if the differences between MPI and \$1.90/day incidences are statistically significant or not.

If progress was only measured by reducing monetary poverty, Nepal, Niger, Cambodia, Uganda, and Indonesia would be considered the leaders in poverty reduction, in that order. The tremendous gains of Rwanda, Ghana, and Bolivia would have been invisible.

If monetary and multidimensional poverty measures moved together, and if they both identified the same people as poor, there would be no need for two separate measures. While the issue of identification of who is poor 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 shows that MPI trends may diverge from \$1.90 trends, and thus merit separate analysis. The right policy measures need to be then oriented to reduce all forms of poverty and having separate poverty analysis would provide the right information for policy makers. If decision makers are informed by partial analysis they are likely to also take incomplete actions to overcome poverty in all its dimensions.

In order to eradicate multidimensional poverty, the rate of reduction in the multidimensional headcount ratio (H) must exceed the rate of population growth (see Table A4 in Annex 1). Of the 30 countries that reduced H_T significantly, when population growth (using the 'medium' hypothesis) is taken

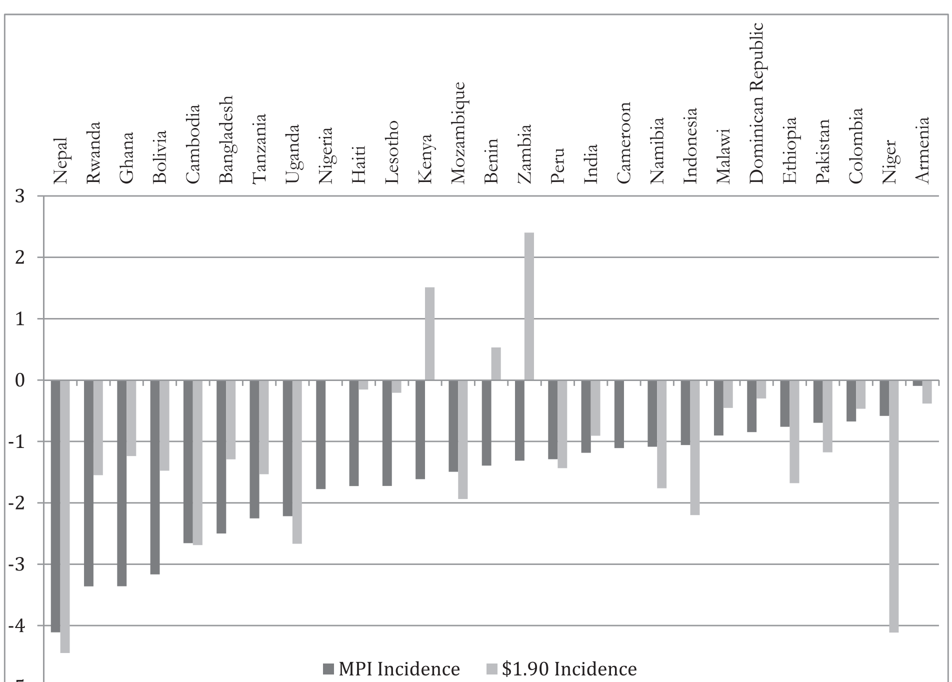

Figure 1. *Absolute Reduction of MPI and \$1.90/day Headcount Ratios (annualized).*

into account, only 20 countries reduced the absolute number of poor people. In ten countries—Benin, Cameroon, Ethiopia, Kenya, Malawi, Mozambique, Niger, Pakistan, Uganda, and Zambia—the number of poor people increased.

5. DECOMPOSITION OF CHANGES OVER TIME: DIFFERENT PATHS TO POVERTY REDUCTION

(a) *Incidence and intensity*

A reduction in MPI occurs because a country has succeeded in reducing H_T, the incidence of poverty, or in reducing A_T, the intensity of poverty among poor people, or doing both in some proportion. In policy terms, reducing incidence is familiar: reporting intensity changes provides an incentive to policy makers to reduce deprivations among the poor also, which is vital to leaving no-one behind.

Figure 2 depicts the annualized absolute change in incidence and intensity (in percentage points) in each of the 34 countries. An overview of these figures suggests they have followed a wide range of reduction pathways. Nearly all countries reduced incidence (H_T) more than intensity, which is to be anticipated as we describe below. The exceptions were Ethiopia, where incidence fell by around 0.8 percentage points per year while intensity fell by 1.0, and Niger, where incidence dropped 0.6 percentage points and intensity dropped 0.9.[8] Interestingly, the 'top performing' countries reduced both the incidence (H_T) and the intensity (A_T) of MPI poverty. Absolute reductions in intensity (A_T) were strongest in Rwanda, Nepal, Ethiopia, Bolivia, Niger, Tanzania, Cambodia, and Ghana, showing the important progress made in the poorest countries to reduce the share of hardships experienced by those who are poor.

It is expected that the absolute reduction of incidence will be greater than that of intensity for three reasons. First, and importantly, the 'natural' tendency of intensity might be to rise if incidence decreases. Why? Consider a simple case in which average intensity is 50%, which is the mean of three persons' deprivations which are [40%, 45% 50%, 55%, 60%]. Now imagine the person who leaves poverty had a deprivation score of 40%. If so, then if no other deprivations are changed, intensity will rise to 52.5% in that population. Simply to maintain the intensity without increase it is necessary either a) that those who left poverty were not the 'barely' poor, but rather their average deprivation score was the same as the average intensity among the poor or b) that in addition to moving out of poverty, some of the deprivations of poor persons were reduced. The second reason is that every reduction in intensity means an actual deprivation was reduced. It is very clear; a reduction in headcount ratio shows a great gain, but persons leaving poverty may still experience some (censored) deprivations. The third reason that the absolute rate of change of incidence will be greater in a non-union identification environment, is that the range of intensity will be lower. For example, in this case it is from 33% to 100%, whereas that of incidence is the full 100%. So a 1 percentage point change in both scales reflects a relatively large change in intensity. To "leave no one behind" it is important to reduce both incidence and intensity, but it is important to interpret these accurately.

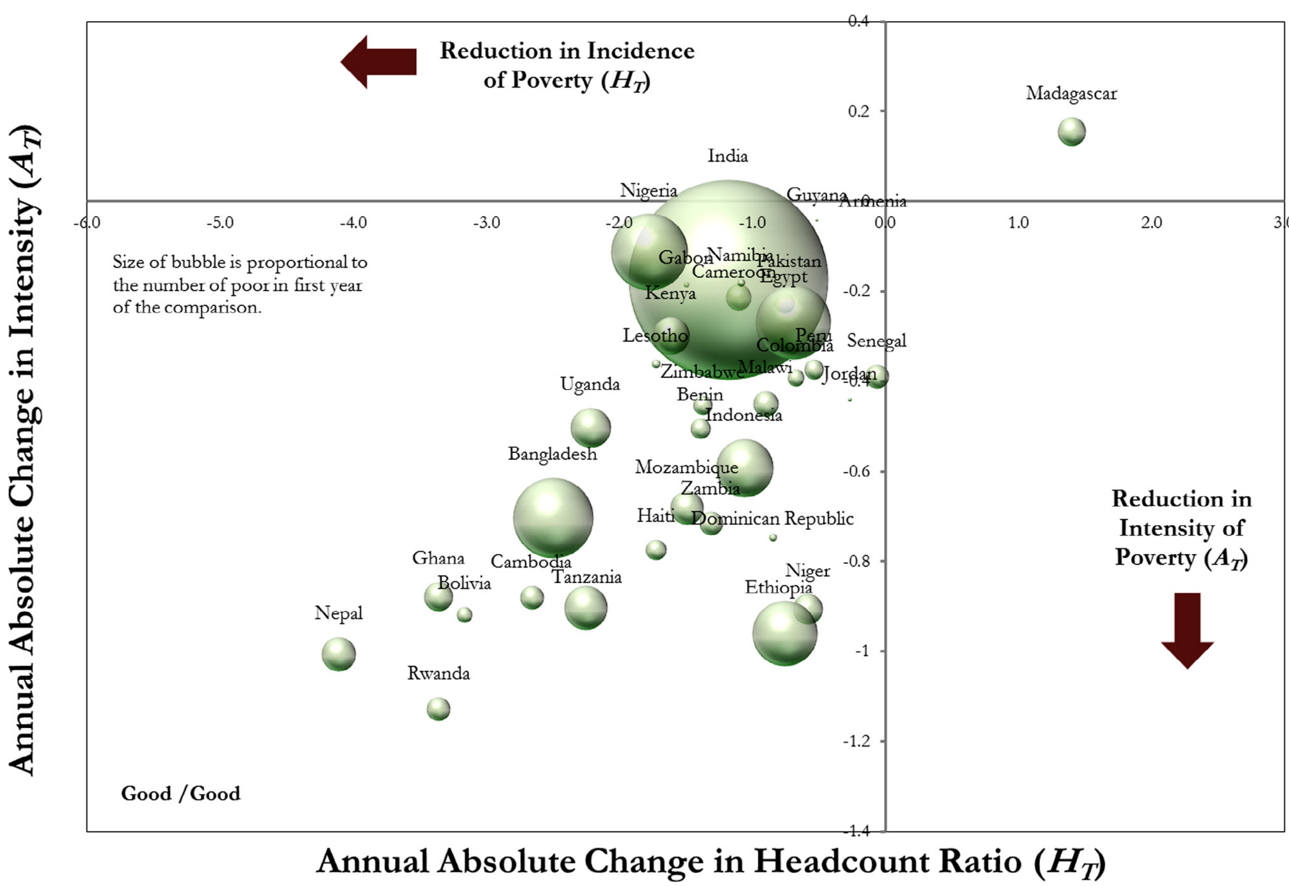

Figure 2. *Annual Absolute Change in Incidence and Intensity.*

Some countries reduced intensity more than incidence—countries like Ethiopia and Niger, which are among the poorest countries. In the poorest countries, each poor person has such a high deprivation score it is very challenging to reduce incidence; rather, intensity reductions drive MPI reduction. This, again, draws out the importance of looking at intensity also, not only incidence. Otherwise Ethiopia and Niger would not have 'credit' for their accomplishments which, as explained above, are very solid.

We can complement this analysis using Table 2 presented earlier. According to those upper and lower bounds we confirm that in 22 of the 34 countries, the reduction in poverty was achieved more through moving people out of poverty (in these countries the lowest estimate of the movers' effect is above 50%). This is the case, for example, of Armenia where movers contributed between 93.6% and 103.3% to poverty reduction, and Cambodia where this contribution was between 52.3% and 112.9%. In Niger, in contrast, poverty reduction was mostly due to decreases in the deprivation scores of the ongoing poor: the stayers' effect explained between 53.3% and 83.4% of the poverty reduction. In 11 countries the results are ambiguous: Bangladesh (2004–07), Benin, Ethiopia, Haiti, Malawi, Mozambique, Pakistan, Rwanda, Tanzania, Uganda, and Zambia.

(b) *How MPI changes: reductions in each indicator*

A key question for policy is which deprivations were successfully reduced. The MPI provides part of the information needed to assess which ministries and policies were successful in the previous period. To analyze dimensional changes, we first review population-wide changes, and subsequently those among the poor. Table A5 presents the annualized absolute change of the uncensored headcount ratios of all indicators. The progress in each dimension varies greatly across countries. Bolivia, India, Indonesia, and Nepal statistically reduced deprivations in all indicators.[9] Nepal made remarkable improvements in assets and electricity coverage, the respective raw headcount ratios reduced 6.2 and 5.3 percentage points per year. Bolivia registered its highest advance in school attendance and sanitation, with reductions of 5.2 and 3.9 percentage points per year, respectively. The reductions in India and Indonesia were overall more modest. In India the biggest improvements were in sanitation and flooring (1.6 percentage points).

To focus on the poor, we examine changes in the censored headcount ratios. Note that any real reduction in any deprivation among the poor always directly reduces poverty, by either reducing the intensity of an ongoing poor person or enabling their exit from multidimensional poverty. The censored headcount of an indicator may also decline if poor people who were deprived in this indicator became non-poor due to decreases only in *other* indicators (but *retain* this deprivation in their non-poor status). Table A6 displays the annualized absolute change of the censored headcount ratios of all indicators. When focusing exclusively on the poor, we find that all the countries listed above plus Cambodia, Colombia, the Dominican Republic, Gabon, Mozambique, and Rwanda significantly reduce the censored headcount ratios in all indicators. Rwanda made exceptional progress in sanitation and drinking water. The percentage of people who were poor and deprived in sanitation reduced on average 7.6 percentage points per year, between 2005 and 2010; with respect to drinking water, the reduction was 5.6 percentage points. Gabon made the highest advancements in sanitation and cooking fuel (1.4 percentage points); Colombia had the biggest improvements in cooking fuel and assets (0.5 percentage points); and the Dominican Republic made the highest reductions in school attendance and years of school.

A change in MPI is accelerated more by improvements in indicators that bear higher weights, such as education and health (one-sixth rather than one-eighteenth).[10] Considering the rate of change and indicator weights together, we see that Bolivia's changes were strongly driven by improvements in child school attendance and child mortality; India's were slightly more influenced by nutrition and child mortality; Indonesia's gains in child school attendance and child mortality were more visible; and Nepal's progress was strongly supported by improvements in all four health and education indicators plus electricity (Table A7).

It is interesting to see and track the changes in all the relevant indicators and notice that not one of the ten MPI indicators remained unchanged in these analyses over time. This puts to rest concerns that some MPI indicators are "stock indicators" unlikely to change in short period of time.

Table 5 presents the average annualized rates of absolute change in raw and censored headcount ratios by world region.[11] Overall, the deprivation which registered the highest reduction on average was access to sanitation. It is the indicator whose raw and censored headcounts have the highest average rate of annualized absolute change across all countries. In Sub-Saharan Africa, Latin America, and the Caribbean, nutrition was among the indicators that improved more slowly; while in South Asia the education indicators changed more slowly on average.

(c) *Subnational MPI changes*

When assessing poverty reduction patterns, it is important to ensure that no population sub-group is left behind. This is indeed one of the commitments agreed by head of states in the 2030 SDG declaration when they promised to ensure that progress will be shared and goals achieved by all segments of society. A useful trait of the MPI measure is its ability to go beyond the national level and be applied to population subgroups. This feature allows us to compare the progress of different groups and potentially identify those at risk of falling behind. This section examines whether progress was evenly achieved across subnational regions and different ethnic groups.

(i) *Rural–urban disaggregation*

Table A8 presents the levels and changes in MPI_T, H_T, and A_T by rural and urban areas for each of the 34 countries studied. Poverty was higher in rural than urban areas in all of the countries in both of the periods. Twenty-six countries had significant reductions in urban poverty and 30 in rural areas.

Rural areas as a whole reduced multidimensional poverty faster than urban areas. On average, rural areas reduced the headcount ratio by 1.3 percentage points per year as compared to 1 percentage point per year for urban areas. The annualized average rural MPI_T reduction was 0.009, whereas the urban MPI_T reduction was 0.005.[12] Naturally starting levels of poverty and rural–urban migration will also have affected these rates. Rural areas had faster rates of reduction in most indicators which suggests a tendency towards convergence.

(ii) *Disaggregation by subnational regions*

In this section we compare the MPI_T reduction across subnational regions. Data representative at the regional level are available for 31 countries (omitting Armenia, Guyana, and Peru), covering 338 regions. Table A9 presents the percentage

Table 5. *Average annual absolute change in raw and censored headcount ratios by world region*

Indicators		All countries			Sub-Saharan African countries			Latin America and Caribbean countries			South Asia countries		
		Raw	Censored	No. countries	Raw	Censored	No. countries	Raw	Censored	No. countries	Raw	Censored	No. countries
Years of schooling	Initial headcount (%)	22.3	21.4	34	34.1	33.9	19	10.1	7.5	6	22.4	21.7	4
	Annual change (p.p.)	−0.6	−0.6		−0.9	−0.9		−0.4	−0.4		−0.6	−0.6	
Child school attendance	Initial headcount (%)	22.7	20.8	34	34.8	33.9	19	9.4	6.6	6	22.3	20.5	4
	Annual change (p.p.)	−0.6	−0.6		−1.1	−1.1		−1.1	−0.8		−0.4	−0.4	
Child mortality	Initial headcount (%)	28.8	26.0	34	41.5	39.1	19	14.2	9.1	6	28.1	25.5	4
	Annual change (p.p.)	−0.7	−0.8		−1.0	−1.2		−0.5	−0.5		−0.6	−0.7	
Nutrition	Initial headcount (%)	36.0	32.0	30	32.5	30.7	18	9.8	5.2	5	41.4	36.5	3
	Annual change (p.p.)	−0.6	−0.7		−0.5	−0.5		−0.4	−0.3		−0.7	−0.9	
Electricity	Initial headcount (%)	40.8	33.8	34	72.9	61.5	19	18.4	12.6	6	37.8	31.7	4
	Annual change (p.p.)	−0.9	−1.0		−0.5	−1.1		−1.0	−0.8		−1.1	−1.1	
Improved sanitation	Initial headcount (%)	72.1	49.0	34	91.1	68.9	19	37.3	16.4	6	76.3	52.5	4
	Annual change (p.p.)	−2.1	−1.8		−2.6	−2.8		−1.4	−1.1		−2.0	−1.7	
Drinking water	Initial headcount (%)	29.7	22.3	34	62.8	53.8	19	17.1	10.0	6	19.5	14.8	4
	Annual change (p.p.)	−1.2	−1.0		−2.0	−2.1		−0.2	−0.5		−0.8	−0.7	
Flooring	Initial headcount (%)	51.9	40.0	34	58.0	52.0	19	21.8	12.3	6	61.1	45.9	4
	Annual change (p.p.)	−1.1	−1.1		−0.3	−0.8		−0.4	−0.7		−1.5	−1.4	
Cooking fuel	Initial headcount (%)	75.3	51.8	33	88.3	69.4	19	34.2	16.9	6	77.1	54.1	4
	Annual change (p.p.)	−0.6	−1.2		0.1	−1.3		−0.6	−1.0		−0.4	−1.2	
Asset ownership	Initial headcount (%)	49.8	38.2	34	59.2	51.0	19	25.0	13.8	6	54.6	42.1	4
	Annual change (p.p.)	−1.2	−1.2		−1.4	−1.5		−1.6	−1.1		−0.9	−1.2	

Note: The averages were computed considering all countries (including those in which the change in the headcount was not significant), and using as weights the countries' population in the second period of the comparison.

of regions in each country that have reduced poverty significantly at a significance level of at least $\alpha = 0.05$, as well as the percentage of poor people who lived in those regions at the initial year of the comparison period.

Eight cases—Bangladesh, between 2007 and 2011; Bolivia; Gabon; Ghana; Malawi; Mozambique; Niger; and Rwanda—showed statistically significant reductions in each of their subnational regions. In Bangladesh (2004–07) and Benin only one of the regions did not reduce poverty. In total, 208 regions containing 78% of the poor population in our sample showed statistically significant reductions in MPI_T.

In nine countries, Bangladesh (2007–11), Bolivia, Colombia, Egypt, Kenya, Malawi, Mozambique, Namibia, and Niger, the fastest MPI_T reduction occurred in the poorest subnational area, which is a positive finding (Annex 4).[13]

Subnational decompositions are vital in order to display regional disparities. The country with the largest range of subnational MPI_T values at the initial year was Kenya. In 2003, Nairobi, the capital, had an MPI_T of 0.048, while the North Eastern region, which borders Somalia, had an MPI_T of 0.681. In Zimbabwe the ratio between regions was largest. In 2006, the province Matabeleland North had an MPI_T of 0.301, almost 30 times higher than the MPI_T of the least poor province Bulawayo. Other regions have greater equity. For instance, at the initial year, the three regions of Jordan had an MPI_T between 0.01 and 0.018. In 2005, the gap in Egypt was 0.071 and it actually decreased to 0.054 in 2008. In Bangladesh, Malawi, Rwanda, Tanzania, and Jordan, the MPI_T of the poorest region was less than twice the MPI_T of the richest region in the initial year.[14] Any study of subnational poverty requires simultaneous consideration of the number and population share of the regions over time.

Most countries are moving towards convergence; hence, the gap between the poorest and richest subnational regions is closing in absolute terms.[15] But the subnational disparities increased in Ethiopia (2000–05), Indonesia, Jordan, Mozambique, Niger, Nigeria, Pakistan, Tanzania, and Zambia.

It can also be useful to identify whether national MPI reduction is driven by progress in just a few regions. In Uganda only two of the nine regions reduced poverty more than the national average: Western and East Central, at 0.029 and 0.020 points per year, respectively, versus the average of 0.015 points. In Nigeria only one of the six regions, South South (which had 17.1% of Nigeria's population in the initial period of comparison, 2003) significantly reduced poverty.

Most of the top performers in reducing poverty, also decreased disparities across regions relatively well. Ghana, Cambodia, and Bolivia have reduced the differences between regions in absolute terms. Rwanda has reduced the dispersion of the distribution and the gap between the bottom and top regions. In Tanzania only the gap between the MPI_T of the bottom and the national average was reduced. These findings suggest that is important to analyze MPI_T reduction by subnational regions, as they may have very different paths.

A useful graphic for this purpose plots the annualized absolute change in MPI on the vertical axis against the initial MPI for all regions. Figure 3 depicts all regions of Mozambique (light) and Nepal (dark). The size of the bubbles is proportional to the number of poor people living in the region in the initial year. In Nepal, we see a strong negative trend

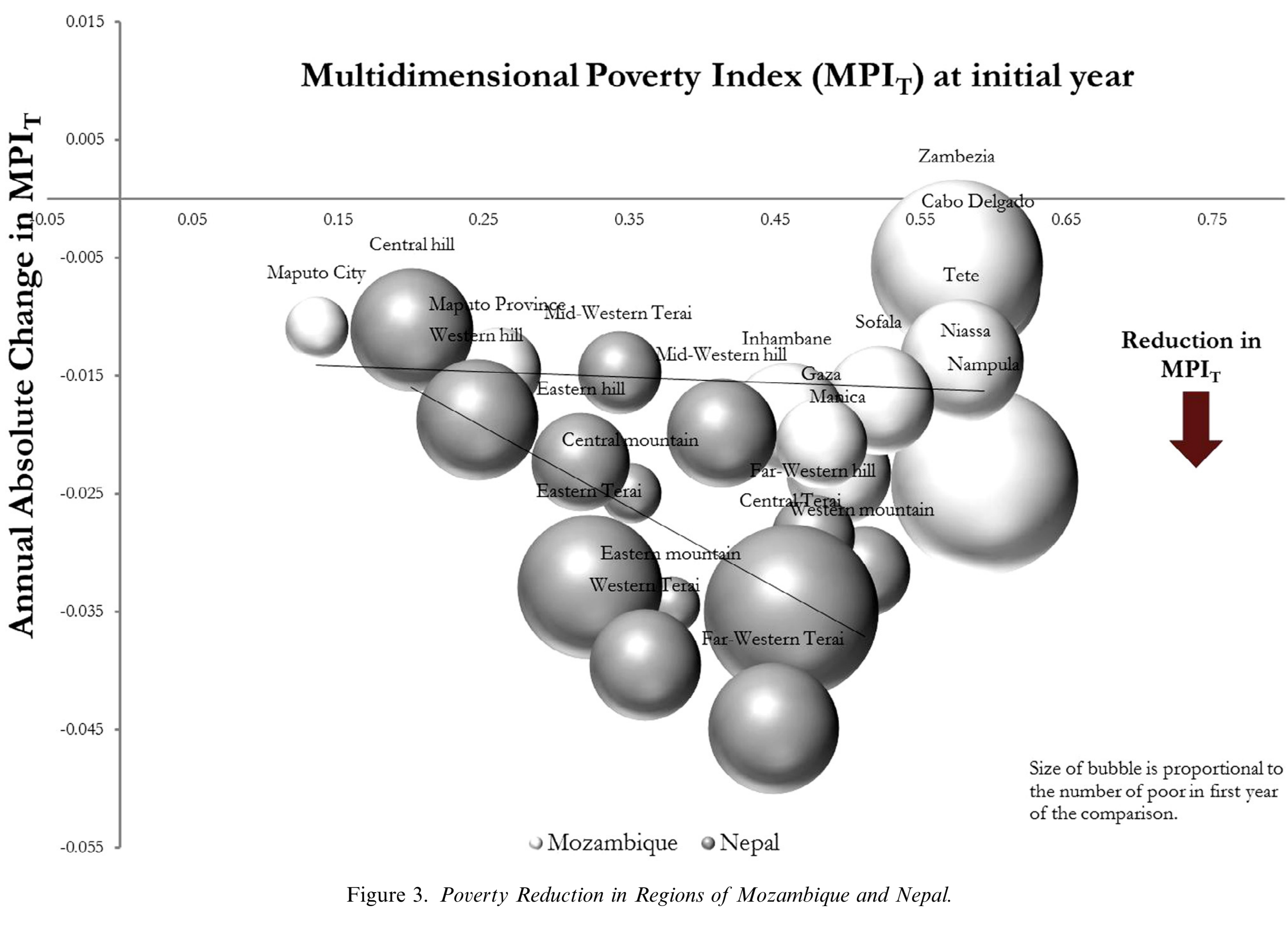

Figure 3. *Poverty Reduction in Regions of Mozambique and Nepal.*

between the initial level of the MPI and the annualized absolute change in the MPI. This means that in Nepal poorer regions have tended to reduce poverty faster than less poor regions, hence they are converging in absolute terms. In Mozambique the trend line is almost flat. Although the poorest region, Nampula, has the highest reduction (0.021 points),

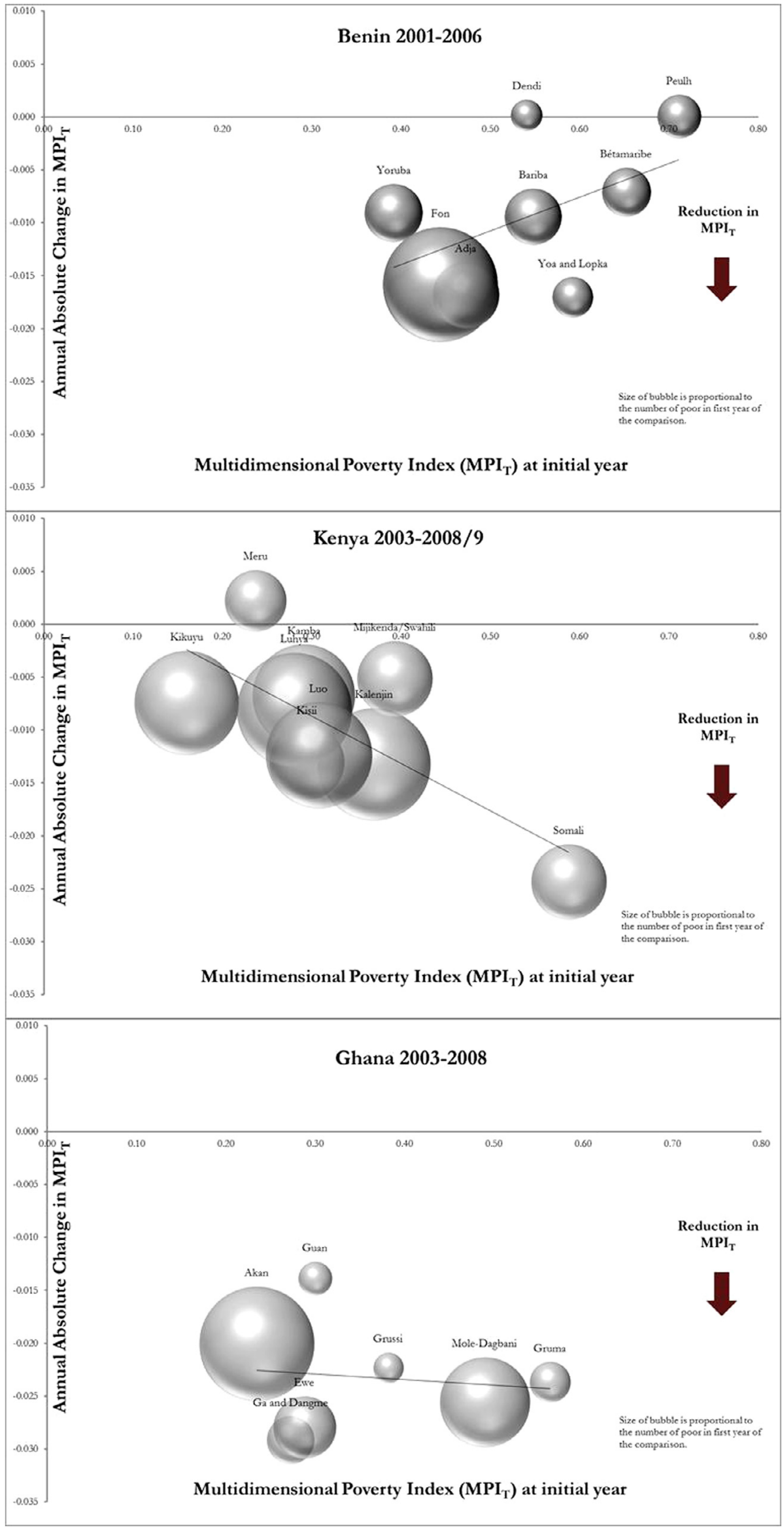

Figure 4. *Poverty Reduction among Ethnic Groups in Benin, Kenya, and Ghana.*

Zambezia and Cabo Delgado, the other two poorest regions, have slower progress. Overall, this graph shows that Nepal's poverty reduction was more equitable, favoring the poorest regions; while Mozambique's did not and will arguably leave the most deprived regions behind if progress continues with the same trend.

(iii) *Disaggregation by ethnic groups*

It is also interesting to assess poverty reduction trends across ethnic groups. In Benin, Ghana, and Kenya, we decomposed the population by the main ethnic groups; a group "o ther"—small ethnic groups (each generally representing less than 3% of the population); and "missing", which includes all individuals missing information on ethnicity. The population-weighted average MPI_T of these groups corresponds to the national MPI_T.

The MPI_T levels and change by ethnic group for Benin, Ghana, and Kenya are presented in Table A10 in Annex 1. All three countries had statistically significant reductions in MPI_T. But these gains were distributed very differently across ethnic groups. Figure 4 replicates Figure 3 for the disaggregation by ethnic groups for the three countries.

Benin reduced MPI_T significantly for only two out of the eight main ethnic groups, representing 52% of the population at the initial year. Poverty reduction was insignificant among the poorest ethnic group, the Peulh. The figure for Benin shows a clear upward trend. The poorer ethnic groups tend to reduce poverty less. This increase in disparity across ethnic groups reflects an increase in horizontal inequality among the poor (Stewart, 2010). In policy terms, Benin is therefore an example of unequal progress where the most deprived ethnic groups are being left further behind.

Ghana cut poverty among all ethnic groups at similar rate, although the reduction was not statistically significant among the Guan.

Kenya shows a clear pro-poorest reduction across ethnic groups which indicates poverty reduction has been more inclusive. Poverty was significantly reduced at $\alpha = 0.05$ for only three groups: Somali, Kikuyu, and Luo. The poorest group, the Somali, had the biggest (absolute) reduction in poverty, reducing poverty at an annualized rate of 4.6%, well above the national rate of 3.5%. The result is a reduction of horizontal inequality, where poorer and more disadvantaged groups were able to "catch up" with more advantaged groups.

6. CHANGES IN DESTITUTION

Lastly, this section analyzes trends in destitution, using a second vector of deprivation cutoffs (Section 2(a)) for the same countries and periods, in order to explore the changes over time in the destitute subset of the poor in comparison with those who are poor but not destitute.

Table A11 presents the levels and changes in destitution and in the headcount ratio of the destitute. Considering a significance level of $\alpha = 0.05$, 28 of the 34 countries reduced destitution and 29 reduced its incidence. The largest absolute reduction in destitution (MPI_T^D) was seen in Ethiopia, followed

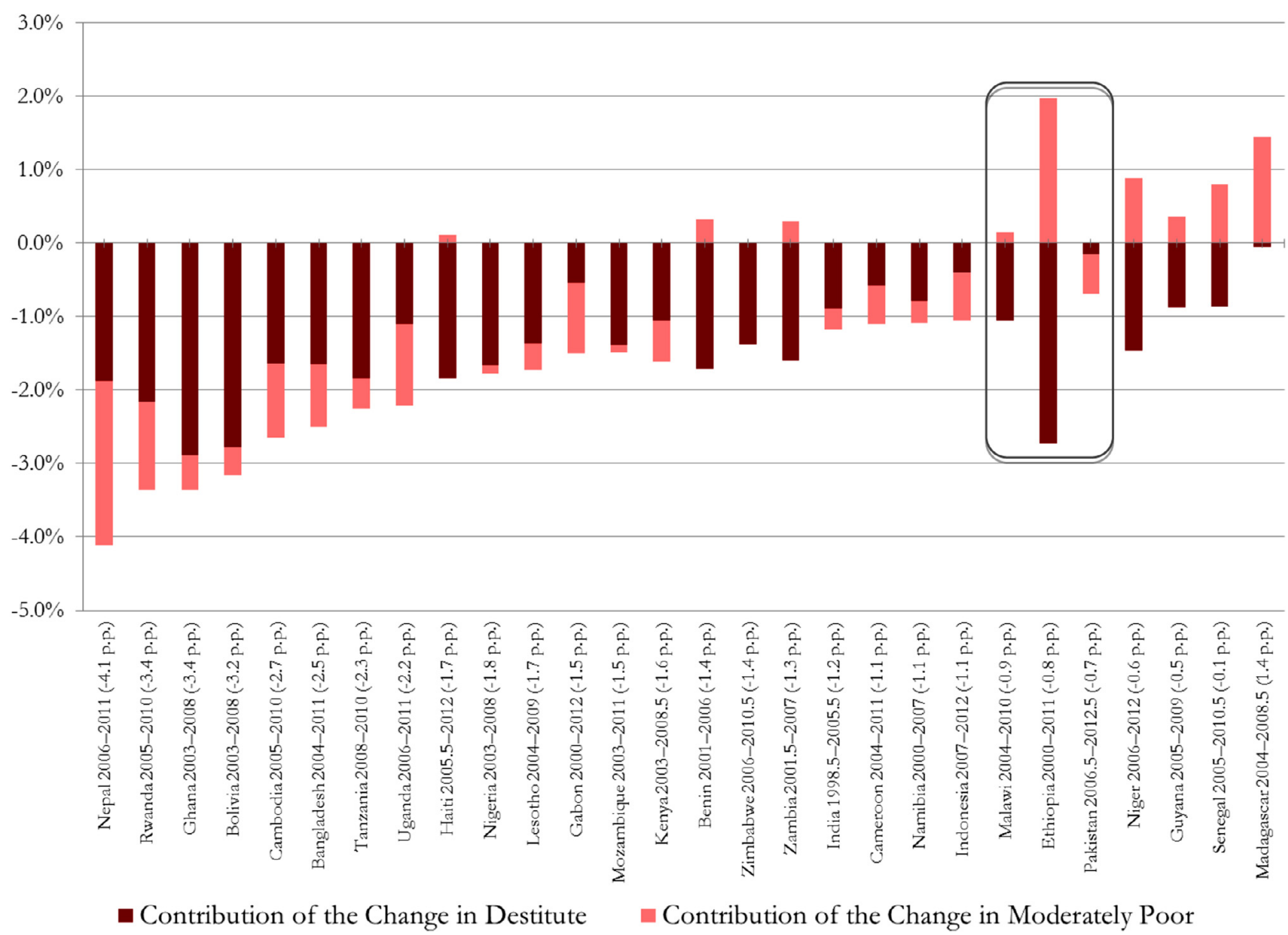

Figure 5. *Breaking Down the Absolute Change in Multidimensional Headcount Ratio into Change in Moderate Poverty and Change in Destitute.*

by Niger, Ghana, Bolivia, Rwanda, Tanzania, Nepal, Haiti, Bangladesh (2004–07), and Zambia—all of them Low Income or Least Developed Countries except Ghana and Bolivia. Armenia, Egypt, Jordan, Madagascar, and Pakistan had no change in destitution.

In nearly all these countries, destitution is being reduced in relative annualized terms faster than multidimensional poverty. In Ethiopia, Guyana, Niger, and Tanzania that is also true in absolute terms. When this happens, the destitute are being reached, and poverty reduction is clearly pro-poorest. In other words, the destitute have seen greater improvements.

During 2000–11, Ethiopia reduced the percentage of the population who were destitute by fully 30 percentage points and reduced intensity among the destitute by 10 percentage points. It achieved significant reductions in all indicators and the strongest gains in water, sanitation, and educational variables.

Comparing the annualized absolute changes in the MPI poverty headcount ratio (Table 3) and in the MPI_T^D destitute headcount (Table A11), performance is not uniform across both the poor and the subset who are destitute. Of course this also depends upon initial levels of destitution. Figure 5 illustrates the decomposition of the change in the multidimensional headcount ratio into change according to two groups: those who are destitute and the non-destitute poor, whom we call 'moderately poor', following the methodology developed by Alkire and Seth (2015).[16]

For instance Ethiopia, Pakistan, and Malawi reduced the incidence of MPI at similar absolute rates, between 0.7 and 0.9 percentage points per year. But underlying patterns vary: in Malawi, the most pro-poor, destitute people mostly moved out of poverty altogether. Ethiopia mostly graduated destitute people to moderate poverty. Pakistan, the least pro-poor, reduced moderate poverty, leaving destitution nearly untouched. These comparisons need to be made carefully, however.

The incidence of destitution at the starting year was much higher in Ethiopia, 82.1% in 2000, than in Pakistan, 23.2% in 2007. In Ethiopia the destitute represented 87.7% of the MPI poor, while in Pakistan this proportion was only 47.0%. Therefore, the scope for absolute reduction of destitution incidence was higher in Ethiopia than in Pakistan. But on the other hand, less poor countries should be able to eradicate destitution.

Similarly, Gabon and Mozambique both cut poverty incidence at the same rate, but Gabon predominantly reduced moderate poverty, whereas in Mozambique, more destitute people exited poverty. Again, in Mozambique the incidence of destitution was 48.5% and the destitute represented 58.9% of the MPI poor; while in Gabon the incidence of destitution was only 10.0% and the destitute represented 28.1% of the MPI poor. This measure makes visible 'pockets' of destitution, and shows which countries are managing to control or eradicate it.

The rural absolute reductions in destitution were statistically significant in 27 countries, which have higher rates of destitution; urban reductions were significant in 20 countries (Table A12 in Annex 1). In terms of destitution indicators, Cambodia, the Dominican Republic, Ethiopia (2000–05), Haiti, India, Indonesia, Mozambique, Niger, and Rwanda have registered reductions significant at least at the 5% level in all censored headcount ratios.

7. CONCLUDING REMARKS

This paper set out a systemic account of changes over time in multidimensional poverty using the Alkire–Foster Adjusted Headcount Ratio and its consistent sub-indices. It also scrutinized various approaches to assessing the pro-poorness of multidimensional poverty reduction. These techniques were applied to the analysis of changes in multidimensional poverty based on the global MPI and related destitution measure. The analysis focused on 34 countries, covering 2.5 billion people, for which there is a recent MPI estimation and comparable DHS dataset for analysis across time. A rigorous standardization of the MPI indicator sets and parameters were undertaken for those countries for which changes in the survey questionnaire may affect comparability.

Fully 31 out of the 34 countries considered in this paper significantly reduced multidimensional poverty over two or three periods, and 28 of these reduced destitution. Nepal, Rwanda, Ghana, and Tanzania were the best performers in reducing MPI in absolute terms. Armenia, the Dominican Republic, and Bolivia achieved the fastest reductions in relative terms. The relationships between the pace of multidimensional poverty reduction and reduction in \$1.90/day poverty were variable, which suggests each measure merits separate analysis to inform the appropriate policy design and decision making.

The paper also assessed different paths to poverty reduction. Methodologically, we considered various approaches to measuring the incidence or intensity effect in reducing the Adjusted Headcount Ratio of multidimensional poverty. Despite being an attractive technique, we concluded that Shapley decompositions require assumptions that could not be justified empirically in cross-sectional datasets. So we analyze the absolute rates of change in headcount (H) and intensity (A) by countries and region and find an informative range of relative rates of reduction of these two partial indices. Most countries reduced poverty relatively more through a reduction in the incidence of poverty, although in Ethiopia and Niger the MPI was mainly reduced by a decrease in the intensity of deprivation among the poor. This finding demonstrated empirically the value-added of using the adjusted headcount measure MPI, rather than merely a headcount ratio. In terms of dimensional changes, we found significant changes in all ten MPI indicators. The dimensional reduction profile varied across country. Deprivation in nutrition reduced the most in Sub-Saharan Africa and Latin America and the Caribbean, while education indicators did in South Asia. Naturally, panel data would permit a more precise analysis of dimensional pathways to multidimensional poverty reduction.

Next, the paper assessed the extent to which poverty reduction has been pro-poor by decomposing MPI by rural–urban areas, by subnational regions, and by ethnic groups. We found convergence between urban and rural areas in all countries but significant reduction in urban areas only in six countries, as opposed to 30 countries with respect to rural areas. A total of 208 subnational regions, representing 78% of our sample, showed a statistically significant reduction in MPI. In terms of pro-poor subnational analysis, in 9 out of the 31 countries having regional decompositions, the poorest region experienced the fastest reduction. Countries like Uganda or Nigeria are negative cases where poverty reduction was driven by only a few regions. Finally, three country examples were presented to illustrate decomposition by ethnicity. In Benin, the poorest ethnic groups reduced poverty more slowly, leading to an increase in horizontal inequality; in Ghana ethnic groups reduced poverty at a similar rate, while Kenya's MPI reduction greatly decreased disparities between ethnic groups. This study could be expanded by harmonizing existing data from the Multiple Indicator Cluster Surveys (MICS) with other MICS and DHS surveys, as well as by including other national household surveys. In addition, 64 new datasets covering 52 countries are expected to be released within three years. Therefore, there is potential to expand this time series analysis for multidimensional poverty monitoring significantly.

This study constitutes a first attempt to analyze the changes over time in multidimensional poverty using the Global MPI, and to set out the kinds of observations that make such analyses poverty relevant. It also raises further research questions. One topic is to calculate and study different multidimensional measures, including a gendered MPI or a global child poverty measure to note different patterns. A second is to use longitudinal data to study the determinants of the movements in and out of multidimensional poverty dynamically, investigate the different poverty trajectories, examine the average characteristics of people in each trajectory, and compare the most common deprivation across poverty trajectories.

A third topic is to study the effectiveness of particular policies or intermediary factors to reduce multidimensional poverty. A fourth is to probe further how to design MPIs that accurately reflect poverty across different household sizes, structures, and compositions. While there are many other potential topics, the last one mentioned here is to expand this study to include additional countries, all decomposed by region, ethnicity, age cohort and so on, in order to monitor the SDG commitment of halving the proportion of men, women and children experiencing poverty in all its dimensions, as well as the "Leave No One Behind" commitment.

NOTES

1. Suitable adjustments can be made for demographic shifts when the population is not fixed across two periods.

2. The upper bound estimate of the movers' effect in Senegal is 20.7%, also below 100%. The lowest lower bound estimate for the movers' effect is of 6.9% in Senegal. We do not refer to Senegal because it did not register a significant poverty reduction.

3. A necessary topic for future research is to replicate this analysis using panel datasets, to compare actual information on poverty transitions with the upper and lower bounds and with the theoretical and Shapley point estimates; if, across a large set of panel datasets reflecting a large population of countries and subnational regions, a clear pattern emerges, this could justify the assumptions required for theoretical decompositions.

4. In this case, that is true using either population data from the 'closing' year of the survey or from 2010 for all countries.

5. India alone corresponds to 1.2 billion people or 17.4% the world population. Other large countries in the analysis are Indonesia –3.5%, Pakistan—2.5%, Bangladesh—2.2%, Nigeria—2.3%, and Ethiopia—1.3%.

6. The income categories correspond to World Bank (2016). *World Development Indicators*. Washington DC: World Bank, accessed October 2016.

7. The term "MPI poor" refers to people who are in acute poverty because they are deprived in at least one-third (33%) of the weighted indicators (Alkire & Santos, 2014).

8. The estimate of the reduction in intensity was larger than the estimate of the reduction in incidence also in Senegal and Jordan. We did not list these countries because they did not register a significant poverty reduction.

9. All these reductions were significant at $\alpha = 0.01$ or $\alpha = 0.05$, with the exception of the reduction in deprivation in drinking water in Nepal that was significant only at $\alpha = 0.1$.

10. This means that, for instance, a one percentage point reduction in the censored headcount ratio of malnutrition has a three times greater impact on changes in MPI than a one percentage point reduction in the censored headcount ratio of the use of cooking fuel, everything else remaining unchanged. The weights rebalance policy incentives, so that each dimension has roughly equivalent prominence.

11. These findings are based on the average uncensored and censored headcount ratios across countries (including those in which the change in the headcount ratio was not significant) and use as weights the countries' population in the second period of the comparison. Note that low starting levels of deprivation usually have lower absolute rates of change.

12. These figures are weighted using the population in period 2.

13. Annex 4 includes graphics with the annualized absolute change in MPI_T against the initial MPI_T for all regions for a select group of countries. The levels and changes in MPI_T for all subnational regions in or sample can be found at http://www.ophi.org.uk/multidimensional-poverty-index/mpi-2014-2015/mpi-data/.

14. Bangladesh, Malawi, Rwanda, and Tanzania have relatively high levels of poverty. Therefore, some may argue that is the reason why the relative differences between regions are smaller. However, there are countries with similar poverty levels where that was not the case.

15. The same does not hold for relative rates, as might be anticipated; the only countries where poverty reduction in relative terms was faster in the poorest than the richest region were Egypt, Haiti, Malawi, Namibia, Nepal, Senegal, and Zimbabwe.

16. We are grateful to Suman Seth for this graphic.

REFERENCES

Alkire, S., & Foster, J. (2011a). Counting and multidimensional poverty measurement. *Journal of Public Economics, 95*, 476–487.

Alkire, S., & Foster, J. (2011b). Understandings and misunderstandings of multidimensional poverty measurement. *Journal of Economic Inequality, 9*, 289–314.

Alkire, S., Foster, J., Seth, S., Santos, M. E., Roche, J. M., & Ballon, P. (2015). *Multidimensional poverty measurement and analysis*. Oxford: Oxford University Press.

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

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

Alkire, S., Conconi, A., & Seth, S. (2014a). *Multidimensional destitution: An ordinal counting methodology for constructing linked subsets of the* *poor*. Oxford Poverty and Human Development Initiative (OPHI) Research in Progress 41a.

Alkire, S., Conconi, A., & Seth, S. (2014b). *Multidimensional Poverty Index 2013: Brief methodological note and results*. Oxford Poverty and Human Development Initiative (OPHI).

Alkire, S., Foster, J., & Santos, M. E. (2011). Where did identification go?. *Journal of Economic Inequality, 9*, 501–505.

Alkire, S., & Seth, S. (2016). *Identifying destitution through linked subsets of multidimensionally poor: An ordinal approach*, OPHI Working Paper 99. University of Oxford.

Apablaza, M., & Yalonetzky, G. (2013). Decomposing multidimensional poverty dynamics, Young Lives Working Paper 101.

Atkinson, A. B. (2003). Multidimensional deprivation: Contrasting social welfare and counting approaches. *Journal of Economic Inequality, 1*, 51–65.

Bourguignon *et al.* (2010). Millennium development goals: An assessment. In R. Kanbur, & M. Spencer (Eds.), *Equity and growth in a globalizing world*. Washington, DC: World Bank.

Chen, S., & Ravallion, M. (2012). *An update to the World Bank's estimates of consumption poverty in the developing world*. Washington, DC: World Bank.

Chen, S., & Ravallion, M. (2010). The developing world is poorer than we thought, but no less successful in the fight against poverty. *Quarterly Journal of Economics, 125*, 1577–1625.

Donaldson, J. A. (2008). Growth is good for whom, when, how? Economic growth and poverty reduction in exceptional cases. *World Development, 36*(11), 2127–2143.

Dotter, C., & Klasen, S. (2014). *The multidimensional poverty index: Achievements,conceptual and empirical issues*, Occasional paper. UNDP Human Development Report Office.

Drèze, J., & Sen, A. (2013). *Uncertain glory: India and its contradictions*. London: Allen Lane.

Duclos, J.-Y., & Araar, A. (2006). *Poverty and equity: Measurement, policy and estimation with DAD*. New York: Springer.

Ferreira, F. H. G., Leite, P. G., & Ravallion, M. (2010). Poverty reduction without economic growth? Explaining Brazil's poverty dynamics, 1985–2004. *Journal of Development Economics, 93*(1), 20–36.

Ferreira, F. H. G., Chen, S., Dabalen, A. L., Dikhanov, Y. M., Hamadeh, N., Jolliffe, D. M., ... Yoshida, N. (2016). A global count of the extreme poor in 2012: Data issues, methodology and initial results. *Journal of Economic Inequality, 14*, 141–172.

Ravallion, M., & Huppi, M. (1991). Measuring changes in poverty: A methodological case study of Indonesia during an adjustment period. *World Bank Economic Review, 5*(1), 57–82.

Roche, J. M. (2013). Monitoring progress in child poverty reduction: Methodological insights and illustration to the case study of Bangladesh. *Social Indicators Research, 112*(2), 363–390.

Santos, M. E., Dabu, C., & Delbianco, F. (2016). *Growth and Poverty Revisited from a Multidimensional Perspective*, Working Paper No. 105. Oxford Poverty and Human Development Initiative (OPHI).

Sen, A. K. (1979). Equality of what?. In S. McMurrin (Ed.), *Tanner lectures on human values*. Cambridge: Cambridge University Press.

Sen, A. K. (1992). *Inequality re-examined*. Oxford: Oxford University Press.

Sen, A. K. (1997). *On economic inequality*, Expanded edition with a substantial annex by James Foster and Amartya Sen. Oxford: Oxford University Press.

Sen, A. K. (1999). *Development as freedom*. Oxford: Oxford University Press.

Sen, A. K. (2009). *The idea of justice*. London: Penguin.

Shorrocks, A. (1999). Decomposition procedures for distributional analysis: A unified framework based on the Shapley Value. *Journal of Economic Inequality*, 1–28.

Stewart, F. (2010). *Horizontal inequalities and conflict*. Basingstoke: Palgrave Macmillan.

UNDP (2010a). *What will it take to achieve the Millennium Development Goals? An international assessment*. New York: UNDP.

UNDP (2010b). *The real wealth of nations: Pathways to human development*, Human Development Report 2010. New York: UNDP.

World Bank (2016). *Monitoring global poverty: Report of the commission on global poverty*. Washington, DC: World Bank.

FURTHER READING

Alkire, S. (2002). *Valuing freedoms*. Oxford: Oxford University Press.

APPENDIX A. SUPPLEMENTARY DATA

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.worlddev.2017.01.011.

Available online at www.sciencedirect.com

ScienceDirect