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ASSESSING TRENDS IN MULTIDIMENSIONAL POVERTY DURING THE MDGS

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While we have extensive information on the trends in income poverty, little is known about the trends in multidimensional poverty. The paper tries to fill this gap by assessing the changes in multidimensional poverty in 54 countries since 2000. The analysis relies on two individual-based indices, the G-CSPI and the G-M_0, which combine three dimensions: education, health, and employment, derived through the constitutional approach. The G-CSPI is a distribution-sensitive index, while the G-M_0 allows decomposition by dimension. The results reveal that more than 80 percent of the countries have reduced multidimensional poverty. However, progress was very limited in sub-Saharan Africa. Different decomposition analyses indicate that poverty alleviation was mainly driven by a reduction in the incidence of poverty and a decline in health deprivations. A comparison with changes in income poverty suggests that the correlation is not strong and that multidimensional poverty has decreased significantly less.

JEL Codes: I32, I3, D6

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1. INTRODUCTION

Poverty reduction has long been one of the most important policy goals for the international development community. The first target of the first Millennium Development Goal (MDG) called for halving the proportion of people with an income below the international extreme poverty line in the period 1990–2015. The centrality of poverty is confirmed in the 2030 Agenda, specifically in the Sustainable Development Goal (SDG) 1. While Target 1.1 concentrates on the eradication of

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income poverty, now measured as the proportion of people living on less than US$1.90 a day, Target 1.2 goes beyond the income dimension and calls for a reduction of "poverty in all its dimensions according to national definitions." The latter target is a direct consequence of the debate that has taken place both in academia and in some international organizations over the past three decades (Sen, 1985, 1987, 1999; UNDP, 1997, 2010; Narayan-Parker and Patel, 2000). The most notable critiques of the view of poverty as lack of sufficient income have been raised by Amartya Sen. Sen argued that income is only one of the possible instruments to avoid or escape poverty, and that the focus should rather be on deprivations in key domains, such as education, health, nutrition, employment, and participation in political life. This is because the relationship between income (or commodities) on one hand and these poverty dimensions on the other hand is not straightforward, but mediated by several factors at the individual (e.g., age, gender, health, and metabolism), social (e.g., formal and informal rules and power relations), and environmental (climate) levels (Sen, 1985; Robeyns, 2005). Moreover, this way we can account for non-market attributes, namely characteristics such as education or social participation that people may value but for which markets are either non-existent or imperfect (Thorbecke, 2007). Other limitations of the monetary approach to poverty pertain to the difficulty in measuring income or consumption, especially in rural contexts of developing countries. Some scholars have raised serious doubts about the international poverty lines identified by the World Bank (Reddy and Pogge, 2010; Reddy, 2011), thereby contesting the quality of the data on poverty incidence and depth. For all these reasons, the broader understanding of poverty as recognized in SDG1 is highly appreciated.

Given the aforementioned goals to eradicate poverty, what do we know about the evolution of poverty in the past decades? Considerable bulk of work has analyzed income poverty trends. Based on the international estimates carried out by the World Bank, the incidence of extreme poverty in the world fell from 35.9 percent in 1990 to 10.0 percent in 2015. In the same period, a reduction in poverty was registered in all world regions, with East Asia and the Pacific being the best-performing region with a decrease from 61.6 percent to 2.3 percent. On the contrary, SSA had a much slower pace of poverty reduction and currently has by far the largest incidence of extreme poverty (54.3 percent in 1990 and 41.1 percent in 2015).

Alongside income poverty, we do have evidence of trends in other dimensions of poverty, based on specific indicators. For example, for the educational dimension, the illiteracy rate among people aged 15 and above in the world fell from 25.6 percent to 14.4 percent, thanks especially to the remarkable performance of two regions: South Asia and Middle East and North Africa (MENA). There have been also remarkable reductions in health deprivations, as measured by child mortality. In the 1990–2015 period, under-five mortality rate declined from 93 per thousand to 42 per thousand, while in the same period neonatal mortality declined from 37 per thousand to 18 per thousand (UNICEF *et al.*, 2019) Despite these tremendous improvements, the situation still looks worrisome, especially in SSA. Less information, instead, is available for other indicators in the health and education dimensions, as well as for other dimensions.

While informative, a focus on several, separate indicators of dimensional deprivations (dashboard approach) has drawbacks. In particular, this approach is insensitive to the joint distribution of deprivations. Instead, it is extremely important for policy-makers to know, for example, whether individuals (or households) deprived in health are those who are also deprived in education (Stiglitz *et al*., 2009). Moreover, a dashboard approach leaves unanswered questions, such as priority and weights of the different indicators, and trade-off among them (OPHI, 2016). Finally, using a dashboard approach it is impossible to have a summary, aggregate picture of multidimensional poverty trends. This is possible only with composite indices, which capture the joint distribution of deprivations.

The evidence of poverty trends based on this kind of composite indices is scarce. Most studies have focused on specific countries, such as Vietnam (Tran *et al*., 2015; Mahadevan and Hoang, 2016), India (Alkire and Seth, 2015), Indonesia (Hanandita and Tampubolon, 2016), South Africa (Fransman and Yu, 2019), and Ecuador (Mideros, 2012), or a specific region (Santos and Villatoro, 2018 for Latin America; Alkire *et al*., 2017a in sub-Saharan Africa). Only one study, by Alkire *et al*. (2017b), has provided an in-depth analysis of the evolution of multidimensional poverty across several countries from different world regions. The study uses the global Multidimensional Poverty Index (MPI) (Alkire and Santos, 2010), which combines three equally weighted dimensions: education, health, and standard of living, comprising ten indicators in total. The three dimensions are aggregated through the Alkire–Foster method (Alkire and Foster, 2011) and account for both poverty incidence and poverty intensity. Based on this index, Alkire et al. (2017b) examine poverty trends in the 21st century in 34 countries. The authors find that multidimensional poverty has significantly declined (at least at the 10 percent significance level) in 31 countries, while in two countries (Jordan and Senegal) the reduction is not statistically significant. The only exception is Madagascar, which registered a statistically significant increase in poverty between 2004 and 2008/2009.

The work of Alkire *et al*. (2017b), while original and informative, has some limitations. Some of them are related to the global MPI, the index used to assess poverty changes. First, the three dimensions used are not adequately justified on theoretical grounds (Wisor *et al*., 2016).[1] Second, the MPI is insensitive to inequality among the poor, which is an important property that every poverty index should have (Jenkins and Lambert, 1997; Dotter and Klasen, 2014; Rippin, 2014, 2017; Datt, 2019). This means that the MPI implicitly overestimates the poverty-eradication efforts of countries trying to lift those individuals out of poverty who are closest to the cut-off point used to identify the multidimensionally poor. Third, several applications of the MPI (e.g., Dotter and Klasen, 2014; Tran *et al*., 2015; Hanandita and Tampubolon, 2016; Alkire *et al*., 2017b) for trend analysis

[1]In the initial paper proposing the global MPI, Alkire and Santos (2010) generally argue that they identified the three dimensions—education, health, and standard of living—looking at the results of large participatory exercises and at the contents of international agreements, such as the MDGs. However, for example, in the MDGs there is no focus on asset ownership or access to electricity, while the attention toward access to sanitation and drinking water is rather limited compared to other dimensions. Due to this, Wisor *et al*. (2016) and Burchi *et al*. (2018b) concluded that the selection of dimensions in the global MPI was strongly data-driven. To address these criticisms, in 2018 some of the indicators of the MPI have been revised to align them more to the SDGs (Alkire *et al*., 2020b).

highlight that its variation over time is, due to the dual cut-off method, triggered substantially more by changes in the headcount ratio than changes in the poverty intensity.[2] It is difficult to justify the calculation of a more complex index if it does not provide substantial additional information to that given by the headcount ratio. Another important limitation of the work of Alkire *et al*. (2017b) is that some indicators are not available for some countries; thus, not all 34 countries are evaluated based on exactly the same number and typology of indicators. Finally, the assessment of poverty changes is based on years and time frames, which are sometimes very different; and, in few cases, there is no overlap of the time periods across countries. For example, the authors analyze trends in Jordan and Tanzania in a period of only 2 years, while in Gabon in a period of 12 years. The fact that the authors examine the annualized changes to compare the speed of poverty changes across countries only partly solves this problem. Moreover, there is high variability in the first year used: this ranges from 1998–1999 in India to 2008 in Tanzania. This makes it complicated to obtain an overall picture of changes in multidimensional poverty. For all the above reasons, there is a need to complement the findings of Alkire *et al*. (2017b) with further empirical studies.

The present paper tries to fill this research gap, assessing the evolution of multidimensional poverty in a very large sample of low- and middle-income countries (54) and with a robust methodology. To investigate these trends, we rely on two new indices of multidimensional poverty: the Global Correlation Sensitive Poverty Index (G-CSPI) (Burchi *et al*., 2021) and the Global M_0 (called G-M_0). These indices combine deprivations in three dimensions (work, education, and health) derived using the Constitutional Approach (Burchi *et al*., 2020). Unlike the global MPI, which is computed at the household level, the G-CSPI and the G-M_0 are individual-based poverty index, as they focus on people in the 15–65 age group. In line with the global MPI, the G-M_0 uses the M_0 (or adjusted headcount) measure, as this is widely known and can be directly and fully decomposed to capture dimensional contributions. Given that the G-M_0 (and the MPI) account only for poverty incidence and intensity, we also adopt the G-CSPI, which is sensitive to the inequality among the poor, too.

This paper examines the long-term and mid-term trends in multidimensional poverty during the period of the MDGs: specifically, we focus on the time frame beginning around 2000 and ending at least 6 years later. This way we have a more uniform interval of time to compare poverty trends across countries (54) that meet the above requirements. We thereby assess whether, and to what degree, multidimensional poverty has declined across countries and avoid most of the pitfalls of previous studies. The paper also presents a detailed explanation of the changes in multidimensional poverty through decomposition analysis: in particular, we compare the trends across poverty components (headcount, intensity, and inequality) and among the three dimensions. Finally, we compare

[2]For example, in the study of Alkire *et al*. (2017b), on average, changes in the headcount ratio explain about 76 percent of overall changes in the MPI. Only in 3 of 34 countries examined, changes in the MPI are predominantly triggered by changes in the headcount ratio. As one of the two indices used in the present paper uses the M_0 measure with a dual cut-off like that in the MPI, we will also investigate to what extent are the changes in this index driven by changes in the headcount ratio and in the poverty intensity.

trends in multidimensional poverty with the traditional measures of income poverty. One of the advantages of our data is that we can do an accurate comparison of the two as we have data from the same years (and in most of the cases from the same surveys).

In brief, the empirical analysis reveals that multidimensional poverty has significantly declined in more than 80 percent of the countries examined. However, progress has been slow in SSA, where a considerable number of countries seem to be in a poverty trap. Poverty reduction has been mainly driven by reduction in health deprivations and a decline in the incidence component. Finally, a comparative analysis between multidimensional and monetary poverty reveals that, in aggregate terms, the former declined at a much slower rate and that the temporal changes in income and multidimensional poverty are not strongly correlated. This finding points to the conclusion that income poverty indicators are not able to capture adequately trends in multidimensional poverty.

The remainder of this paper is structured as follows. Section 2 introduces our indices of multidimensional poverty. Section 3 describes our sample of countries, the period of analysis, and the methodology used. Section 4 provides an analysis of historical trends in the multidimensional poverty indices at country level, while Section 5 presents different sub-group analysis. Section 6, instead, includes a comparison between changes in multidimensional poverty and those in income poverty. Finally, our concluding remarks, including the policy implications, are presented in Section 7.

2. The Global Correlation Sensitive Poverty Index (G-CSPI) and Global M_0 (G-M_0)

In this section, we illustrate in brief the most important features of the two multidimensional poverty indices used in the analysis. All the details are, instead, discussed in Burchi *et al*. (2021).

2.1. *Poverty Dimensions and Their Weights*

The two indices used in this paper incorporate the following three dimensions of poverty: education, decent work, and health. These were obtained by applying the constitutional approach (Burchi *et al*., 2014, 2018a), originally proposed to identify ethically sound dimensions of poverty and well-being within a society from their constitution and all its relevant interpretative documents. Burchi *et al*. (2018b, 2020) expanded this approach beyond the level of the single country and examined a large list of constitutions from all world regions to search for shared poverty dimensions. Cross-checking this ideal list with the information available in the International Income Distribution Database (I2D2)—the database of household surveys used for the computation of the two multidimensional poverty indices (see Section 3)—leads to the selection of the three dimensions highlighted above.

While the indices do not contain direct information on health, they do have information on access to safe drinkable water and basic sanitation. Substantial empirical evidence supports the idea that a lack of access to safe drinkable water and adequate sanitation impedes a good health status (Checkley *et al*., 2004;

Fogden, 2009; Fink *et al*., 2011). Under this assumption, the two indices of multidimensional poverty incorporate the dimensions that emerged as the most important based on the constitutional approach. As they have similar relevance, each dimension carries a weight of one-third. The choice of the weighting scheme is, thus, based on theoretical/normative grounds, rather than derived through data-driven approaches (Klasen, 2000).

2.2. *Indicators of Dimensional Deprivations and Thresholds*

The main variable used to measure education is literacy. If a person is not literate, they are poor in the education dimension. In cases where a survey did not have data on literacy for at least two-thirds of the sample population, education was measured as the number of years of schooling: all individuals with less than 4 years of schooling were classified as poor in education. This threshold was obtained by comparing the number of years of schooling with the literacy rate in a sample of countries with information on both variables. In cases where there were no data on years of schooling for two-thirds of the sample population, the variable "educational level" was used. In this case, an individual who has not completed primary education is considered poor in the education dimension.

Decent work is measured by combining two variables from the I2D2 data set, one indicating the labor status and one the employment status. The first variable indicates whether a person is employed, unemployed, or not in the labor force. The second variable contains five categories: paid employee, non-paid employee, employer, self-employed, and other type of worker. By construction, the categories "non-paid employees" and "self-employed" indicate a lower pay and lower job quality. "Unemployed" individuals and individuals who are "self-employed" or "non-paid employees" are classified as poor in the work dimension; all others are non-poor.

The health indicator combines information on access to drinkable water and adequate sanitation. Given the objective of measuring extreme poverty and based on empirical evidence (Fuller *et al*., 2015), individuals without access to either facility are treated as poor in the health dimension, while those with access to at least one are considered non-poor.

2.3. *The Poverty Measures: CSPI and M_0*

We use two different poverty measures. The first one is the Correlation Sensitive Poverty Index (CSPI), which is a specific measure of the broader family of correlation-sensitive multidimensional poverty indices proposed by Rippin (2012, 2014, 2017) in the context of ordinal variables. This family of indices builds on previous pioneering work of Chakravarty and D'Ambrosio (2006), who suggested introducing considerations of distributive justice into the measurement of social exclusion, by looking at the number of dimensions in which individuals are deprived. The axiom that they developed—called equality promoting change—was later on formally introduced by Javaraj and Subramanian (2010) for the measurement of multidimensional poverty.

The CSPI is based on a "fuzzy" identification function, meaning that people are not simply differentiated based on whether they are multidimensionally poor or not, but rather based on their degree of poverty severity. Given i = 1,…,n individuals and j = 1,…,d dimensions of poverty, the fuzzy identification function of the CSPI (φ_f), which depends on the vector of individual achievements [$\mathbf{x}_i = (x_{i1}, \cdots, x_{id})$], the vector of dimensional cut-offs [$\mathbf{z} = (z_1, \cdots, z_d)$] and that of the weights [$\mathbf{w} = (w_1, \cdots, w_d)$],[3] can be generally expressed in the following way:

$$\varphi_f(\mathbf{x_i}; \mathbf{z}; \mathbf{w}) = \sum_{j=1}^{d} g_{ij}^0 = c_i, \tag{1}$$

where g_{ij}^0 is the weighted deprivation of individual i in dimension j and thus $\sum_{j=1}^{d} g_{ij}^0$ is the sum of weighted deprivations suffered by individual i, also called *individual weighted deprivation count* and indicated with $c_i$in equation (1).

As a second step for the computation of the CSPI, it is necessary to square the individual weighted deprivation count to capture the breadth of poverty. In the aggregation phase, the final index is obtained by averaging the squared individual weighted deprivation counts.

$$\text{CSPI} = \frac{1}{n} \sum_{i=1}^{n} \left[c_i(\mathbf{x_i}; \mathbf{z}; \mathbf{w})\right]^2. \tag{2}$$

Thus, the CSPI is the squared sum of weighted deprivations suffered by the population divided by the maximum possible number of weighted deprivations.

The second poverty measure is the $M_{0,}$ or "adjusted headcount ratio," proposed by Alkire and Foster (2011). This measure uses a dual cut-off method: in addition to the dimensional cut-off (z) there is a second cut-off (k), which distinguishes the individuals who are multidimensionally poor from those who are non-poor. In all the applications of the MPI, at the global as well as national level (Alkire and Santos, 2014), the MPI uses an "intermediate" cut-off. Given that the advocates of the MPI strongly support an application of the M_0 measure together an intermediate cut-off—among other reasons, to have a lower headcount ratio, as compared to using a union approach—and this is the way it has been usually endorsed by policy-makers, we used an intermediate cut-off, too. As the only intermediate cut-off in our setting is 2, any individual who is deprived in at least two dimensions is considered poor. As a robustness check we also carry out the analyses with $k = 1$ and report the results in Table A1 in the Appendix.[4] The M_0 poverty measure is simply the sum of weighted deprivations suffered by the multidimensionally poor divided by the maximum possible number of deprivations:

$$M_0 = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{d} g_{ij}^0(k) = \frac{1}{n} \sum_{i=1}^{n} c_i(k), \tag{3}$$

[3]In our case, the three dimensions have the same weight (1/3), and $\sum_{j=1}^{d} w_j = 1$.

[4]Alkire and Foster (2011) argue that the intermediate cut-off is particularly necessary in case of many dimensions. As we have only three dimensions here, we decided to add the analysis with $k = 1$ in the Appendix.

where $\sum_{j=1}^{d} g_{ij}^{0}(k) = c_i(k)$ is the sum of weighted deprivations suffered by individual *i* in case individual *i* is multidimensionally poor.

The two final indices, using the two different measures, are the G-CSPI and the G-M_0.[5] In comparison to the G-M_0, the G-CSPI has a number of advantages. The first one is that it is distribution-sensitive (Rippin, 2014, 2017) as it accounts for the inequality among the poor. This is a very important feature. As Sen (1976) argued, any reasonable poverty index should be sensitive to what Jenkins and Lambert (1997) called the "three 'I's of poverty": incidence, intensity, and inequality. The possibility to incorporate inequality among the poor in the multidimensional poverty measure has crucial implications for policy-makers. When there is a transfer from a poorer to a less poor individual, the CSPI increases (as one would expect), whereas M_0 remains unchanged (when both individuals remain poor even after the transfer) or even decreases (when the less poor individual manages to have a number of deprivations below the cut-off level k).[6] Therefore, the CSPI allows for more informed and detailed policy making.[7]

The G-CSPI is not only sensitive to inequality, but can also be decomposed into the product of poverty incidence (the headcount), poverty intensity (the average deprivation share among the poor), and poverty inequality (a component including a Generalized Entropy measure of inequality). In general, the CSPI can be decomposed in the following way:

$$(4)\ \mathrm{CSPI} = \frac{q}{n}\left[\frac{\sum_{i=1}^{n} c_i}{q}\right]^2 \left\{1 + 2\left[\frac{1}{2}\left(\frac{1}{q}\frac{\sum_{i=1}^{n} c_i^2}{\left(\frac{\sum_{i=1}^{n} c_i}{q}\right)^2} - 1\right)\right]\right\} = \mathrm{HA}^2(1 + 2\mathrm{GE}),$$

[5]This way, we apply a similar strategy to that of the World Bank (2018) in the Poverty and Shared Prosperity Report. The report tests two alternative ways to combine information on a different set of dimensions and indicators of poverty: the first, like in our case, is the M_0 measure, while the second one is the distribution-sensitive measure developed by Datt (2019). As already stressed, no analysis of multidimensional poverty trends is presented in this report. It is also important to highlight that throughout the 2018 report the analysis concentrates almost exclusively on the multidimensional headcount ratio, and in the 2020 report the figures obtained applying the Alkire–Foster method and the Datt measure are neither commented nor reported (World Bank, 2020).

[6]Note that this discussion refers to measures applied to ordinal variables. In fact, in the setting presented in Sections 2.1 and 2.2, the individual deprivation for each indicator can be expressed only in terms of 0 or 1 (Pattanaik and Xu, 2018). Under these conditions, the claim of Datt (2019) that the CSPI does not satisfy the "strong transfer" axiom is invalid. This point is also stressed by Alkire and Foster (2019). Referring to this argument raised by Datt (2019), they argue: "The axiom, and indeed the entire paper, seems oriented to measures requiring cardinal data" (Alkire and Foster, 2019, p. 12). Indeed, for cardinal variables Rippin (2012, 2014) proposed another family of indices, called inequality sensitive poverty indices, which account *also* for within-dimension inequality.

[7]Seth and Alkire (2014) have developed a separate measure of inequality across the poor that since 2014 accompanies the MPI. This measure is computed as the variance of the deprivation scores of the multidimensionally poor, normalized between 0 and 1. While this measure provides useful additional information, the fact that is not a natural part of the index is a limitation. Policy-makers who want to assess the poverty impacts of their policies would be confronted with two different types of information, which may also go in opposite directions. Only by having an inequality component incorporated in the poverty index distributive aspects would be automatically considered in the evaluation of policies.

where q is the number of the poor (individuals deprived in at least one dimension), H is the headcount, A is the average deprivation share among the poor, and GE is a Generalized Entropy measure of inequality among the poor. The full proof of the decomposition—which relies on the work of Aristondo *et al*. (2010)—can be found in Rippin (2014, 2017) and Bérenger (2017).

In contrast, M_0 can only be decomposed into the product of poverty incidence and poverty intensity:

$$M_0 = \frac{q}{n} \frac{\sum_{1=1}^{n} c_i(k)}{q} = HA, \tag{5}$$

where H is the poverty headcount and A the average deprivation share among the poor. In the case of an intermediate cut-off, like for our main G-M_0 and the MPI, these two components are censored because they are calculated only for those individuals with a sum of weighted deprivations ≥k.

While there are other important measures of multidimensional poverty accounting for inequality among the poor in a context of ordinal variables (e.g., Chakravarty and D'Ambrosio, 2006; Bossert *et al*., 2013; Datt, 2019), none of them can be decomposed by the three poverty components (Dotter and Klasen, 2014; Espinoza-Delgado and Klasen, 2018). As we find this feature particularly appealing for the study of multidimensional poverty trends, we selected the CSPI. The CSPI—as well as Rippin's broader family of correlation sensitive poverty indices—has already been extensively used in empirical studies on multidimensional poverty (Tosi, 2015; Bérenger, 2016, 2017; Rippin, 2016; Espinoza-Delgado and Klasen, 2018; Espinoza-Delgado and Silber, 2018; Espinoza-Delgado, 2020).

Another relative strength of the G-CSPI is that it is more robust to the selection of weights, a choice that is sometimes not easily justifiable on a theoretical basis (Burchi *et al*., 2021). Finally, unlike the G-M_0, the average poverty intensity of the G-CSPI is not truncated from below, allowing for more variation and, consequently, more information, in particular when it comes to analyzing trends, which is the objective of this paper. Dotter and Klasen (2014) show that in the case of the MPI, this truncation implies that any variation of M_0, between countries and over time, is predominantly driven by the headcount.

On the contrary, the M_0 accompanied by an intermediate cut-off is a well-known and relatively easy-to-calculate measure of poverty. Moreover, it can be directly and fully decomposed to detect the relative contribution of each dimension to overall poverty.[8] For these reasons, to investigate the trends in multidimensional poverty, we use both the G-CSPI and the G-M_0 indices. With the relative strengths

[8]None of the distribution-sensitive multidimensional poverty measures can be fully decomposed by dimension (Alkire and Foster, 2016, 2019). Only if the two steps, identification and aggregation, are viewed as separate, which allows the additivity of the CSPI in the aggregation step, the CSPI can be considered decomposable (Dotter and Klasen, 2014; Jolliffe, 2014; Rippin, 2014; 2017). Datt (2019) suggests overcoming this limitation of the distribution-sensitive measures by using the Shapley decomposition methods proposed by Shorrocks (2013).

and weaknesses of both, our analysis aims to give a more comprehensive picture of poverty trends.

2.4. *Unit of Analysis*

While the World Bank measures of poverty (both the monetary and the recently introduced multidimensional measures) and the MPI are computed at the household level, the G-CSPI and G-M_0 are individual-level indices. Therefore, we need not make assumptions about intrahousehold distribution of resources/capabilities.[9] Specifically, the G-CSPI and the G-M_0 are calculated for individuals between 15 and 65 years of age: this is because poverty for children and the elderly should be assessed on the basis of different dimensions and indicators (Lloyd-Sherlock, 2002; Biggeri *et al.*, 2006; Gopinath, 2018; Domínguez-Serrano *et al.*, 2019). The population in this age group represents around 60 percent of the total population in the sample of countries used in our empirical analysis (see Section 3).

3. Data and Methodology

To carry out the cross-country analysis of poverty trends, we used country-level estimations of the G-CSPI and the G-M_0 computed on household surveys from the I2D2 database. The I2D2 is the result of a tremendous initiative of the World Bank to standardize several demographic, socioeconomic, and income/consumption variables across countries, drawing on nationally representative household surveys.

To ensure data comparability we had to make a few decisions. The first decision concerned the time frame: we decided to focus on the period starting around 2000 until the most recent survey year as this represents the period of the MDGs. Although the reference period for MDG 1 starts in 1990, the MDG agenda was agreed on only in 2001. It is important to examine the trends in poverty after this major event in the international arena. Moreover, this choice is related to data availability: choosing this time frame allows us to utilize nearly all the data at our disposal, as information on previous periods is scarce.

Given that surveys were carried out in different years in different countries, our second choice consisted of identifying the first and the last year. We considered "baseline" to be around 2000: thus, where available, we used the 2000 survey, while in the other cases we considered the survey closer in time to 2000 as long as it was conducted between 1997 and 2003. In case of two surveys with the same "distance" from 2000 (e.g., 1999 and 2001), we used the oldest survey as this allows to focus on longer-term trends. The "endline" was the latest available year as long as the survey was conducted more than 5 years after the baseline survey. This assures overlap in the years across countries and a better

[9]It is important to make a clarification. Information on the dimension of access to drinkable water and sanitation is collected at the household level and not at the individual level. However, in line with other works (Vijaya *et al.*, 2014; Espinoza-Delgado and Klasen, 2018; Klasen and Lahoti, 2021), we consider them as public goods (non-rival and non-excludable) and assume that they are accessible to the same extent by all household members. Therefore, we treat these variables as if they were collected at the individual level.

identification of the overall trends. To test the hypothesis of linearity of the trends, in the following step we also considered the surveys available for the period between baseline and endline.

Another important decision concerned the indicator of education. To ensure full within-country comparability across time (called *harmonization* in Alkire *et al*., 2020a), we considered only the surveys that used the same indicator for both baseline and endline. For the same purpose, some data points have been removed because the surveys were not comparable with the other surveys conducted in the same country. In some cases, this has led to the exclusion of the country.[10]

The final data set includes estimates of multidimensional poverty trends for 54 countries: 18 (33.3 percent) from SSA, 17 (31.5 percent) from Latin America and the Caribbean (LAC), 10 (18.5 percent) from Europe and Central Asia (ECA), and 9 (16.7 percent) from South Asia, East Asia, and the Pacific. The latter sample is particularly underrepresented, given also the absence of big countries, such as China and India, for which we have data for just one point in time. Of the remaining population of low- and middle-income countries, the sample represents around 54 percent of the total. With regard to the time frame used for the different countries, on average the number of years between the endline and the baseline year is 10.6. The list of 108 survey years used for the 54 countries in Sections 4.1, 5.1, and 5.2 is reported in Table 1. In Section 4.2, where we explore nonlinearity, we use all intermediate survey-years and not just the baseline and endline surveys. In this case, we focus on the 44 countries with more than two surveys, for a total of 296 surveys (see Table A2). Finally, in Section 6 we merge the previous data set of 54 countries and 108 surveys with income poverty data from the World Bank. We keep the survey-years with both observations (for the same year), ending up with 43 countries (and 86 surveys). The estimates of multidimensional poverty were obtained using an educational indicator literacy for 85 percent of the countries, years of schooling for 13 percent of the countries, and, finally, the educational level for 2 percent of the countries (see Table 1).

To assess the intensity of the change in multidimensional poverty (see Section 4.1), we examine both the *absolute* differences in the values of the poverty indices between the endline and the baseline, and the changes *relative* to the value at the baseline. The latter is particularly important given that the MDG 1 was formulated taking into consideration the initial levels of poverty.

As length of periods between observations differs among countries, we use annualized rates to make figures comparable. Therefore, the absolute annualized change is computed in the following way:

$$\text{Absolute annualized change} = \frac{x_{t+y} - x_t}{y}. \tag{6}$$

The relative proportional annualized changes are calculated, following the literature (McArthur and Rasmussen, 2018), in the following way:

[10]Some surveys were also excluded because the sample of individuals with full information on our variables covered less than 66.6 percent of the overall sampled population (in the age group 15–65).

TABLE 1
VALUES AND CHANGES OVER TIME OF G-CSPI AND G-M_0 ($\kappa = 2$)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Initial year	Final year	G-CSPI initial	G-CSPI final	G-M_0 initial	G-M_0 final	Abs. ann. change G-CSPI	Rel. ann. change G-CSPI	Abs. ann. change G- M_0	Rel. ann. change G-M_0	Statistical significance of difference+++		Educ. indicator
											G-CSPI	G-M_0	
Albania	2002	2012	0.096	0.050	0.078	0.022	−0.005	−0.06	−0.006	−0.119	***	***	liter.
Argentina	2000	2014	0.029	0.020	0.005	0.001	−0.001	−0.03	−0.000	−0.105	***	***	liter.
Armenia	2001	2011	0.067	0.049	0.037	0.015	−0.002	−0.03	−0.002	−0.085	***	***	liter.
Bangladesh	2003	2015	0.431	0.259	0.503	0.282	−0.014	−0.04	−0.018	−0.047	***	***	liter.
Belarus	2001	2010	0.045	0.015	0.035	0.003	−0.003	−0.12	−0.004	−0.237	***	***	liter.
Bhutan	2003	2012	0.424	0.206	0.476	0.221	−0.024	−0.08	−0.028	−0.082	***	***	liter.
Bolivia	2000	2014	0.141	0.099	0.132	0.083	−0.003	−0.02	−0.004	−0.033	***	***	liter.
Brazil	1999	2014	0.093	0.048	0.078	0.027	−0.003	−0.04	−0.003	−0.067	***	***	liter.
Bulgaria	2001	2007	0.037	0.024	0.008	0.009	−0.002	−0.07	0.000	0.037	***	***	liter.
Cambodia	1997	2009	0.457	0.390	0.541	0.459	−0.006	−0.01	−0.007	−0.014	***	***	liter.
Cameroon	2001	2014	0.408	0.313	0.452	0.346	−0.007	−0.02	−0.008	−0.020	***	***	liter.
Chad	2003	2011	0.539	0.376	0.619	0.438	−0.020	−0.04	−0.023	−0.042	***	***	liter.
Chile	2000	2013	0.039	0.029	0.019	0.010	−0.001	−0.02	−0.001	−0.045	***	***	liter.
Colombia	2001	2014	0.068	0.066	0.037	0.034	−0.000	−0.00	−0.000	−0.005	***	***	liter.
Costa Rica	2000	2012	0.032	0.026	0.012	0.006	−0.001	−0.02	−0.000	−0.054	***	***	liter.
Côte d'Ivoire	2002	2015	0.461	0.342	0.501	0.392	−0.009	−0.02	−0.008	−0.019	***	***	liter.
Dom. Republic	2000	2013	0.104	0.104	0.089	0.090	0.000	0.00	0.000	0.001		**	liter.
Ecuador	2003	2014	0.101	0.060	0.083	0.035	−0.004	−0.05	−0.004	−0.076	***	***	liter.
El Salvador	2000	2014	0.148	0.088	0.143	0.070	−0.004	−0.04	−0.005	−0.050	***	***	liter.
Eswatini	2000	2009	0.220	0.160	0.230	0.151	−0.007	−0.04	−0.009	−0.046	***	***	liter.
Ethiopia	2000	2011	0.478	0.565	0.570	0.628	0.008	0.02	0.005	0.009	***	***	liter.
Ghana	1998	2012	0.360	0.447	0.389	0.487	0.006	0.02	0.007	0.016	***	***	liter.
Guatemala	2000	2011	0.167	0.124	0.171	0.118	−0.004	−0.03	−0.005	−0.034	***	***	liter.
Guinea	2002	2012	0.633	0.586	0.679	0.623	−0.005	−0.01	−0.006	−0.009	***	***	liter.
Honduras	1999	2011	0.104	0.086	0.089	0.068	−0.001	−0.02	−0.002	−0.022	***	***	liter.

(Continues)

TABLE 1 (CONTINUED)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Initial year	Final year	G-CSPI initial	G-CSPI final	G-M_0 initial	G-M_0 final	Abs. ann. change G-CSPI	Rel. ann. change G-CSPI	Abs. ann. change G- M_0	Rel. ann. change G-M_0	Statistical significance of difference+++		Educ. indicator
											G-CSPI	G-M_0	
Kenya	1997	2005	0.279	0.304	0.305	0.338	0.003	0.01	0.004	0.013	***	***	liter.
Kosovo	2002	2011	0.096	0.050	0.075	0.013	−0.005	−0.07	−0.007	−0.176	***	***	years
Laos	2002	2012	0.447	0.286	0.545	0.297	−0.016	−0.04	−0.025	−0.059	***	***	liter.
Lithuania	2000	2008	0.045	0.058	0.030	0.025	0.002	0.03	−0.001	−0.023	***	***	level
Madagascar	1997	2012	0.540	0.474	0.603	0.556	−0.004	−0.01	−0.003	−0.005	***	***	liter.
Mexico	2000	2012	0.054	0.043	0.038	0.027	−0.001	−0.02	−0.001	−0.027	***	***	liter.
Mongolia	2002	2009	0.184	0.175	0.207	0.189	−0.001	−0.01	−0.003	−0.013	***	***	liter.
Mozambique	2002	2008	0.613	0.612	0.657	0.670	−0.000	−0.00	0.002	0.003	**	**	liter.
Namibia	2003	2009	0.227	0.177	0.253	0.176	−0.008	−0.04	−0.013	−0.058	***	***	liter.
Nicaragua	1998	2009	0.179	0.156	0.181	0.153	−0.002	−0.01	−0.003	−0.015	***	***	liter.
Nigeria	2003	2009	0.289	0.303	0.312	0.341	0.002	0.01	0.005	0.015	***	***	liter.
Pakistan	2001	2010	0.369	0.270	0.423	0.303	−0.011	−0.03	−0.013	−0.036	***	***	liter.
Paraguay	1999	2012	0.081	0.082	0.059	0.060	0.000	0.00	0.000	0.001	***		liter.
Peru	2000	2014	0.151	0.091	0.147	0.070	−0.004	−0.04	−0.005	−0.052	***	***	liter.
Philippines	1997	2015	0.154	0.059	0.150	0.039	−0.005	−0.05	−0.006	−0.071	***	***	liter.
Romania	2001	2013	0.142	0.098	0.166	0.101	−0.004	−0.03	−0.005	−0.041	***	***	years
Rwanda	2000	2010	0.558	0.534	0.630	0.612	−0.002	−0.00	−0.002	−0.003	***	***	years
Serbia	2003	2010	0.087	0.034	0.034	0.002	−0.007	−0.12	−0.005	−0.347	***	***	years
South Africa	2002	2008	0.125	0.059	0.119	0.031	−0.011	−0.12	−0.015	−0.200	***	***	liter.
Sao Tome & Principe	2000	2010	0.202	0.256	0.204	0.276	0.005	0.02	0.007	0.031	***	***	liter.
Tanzania	2000	2011	0.443	0.255	0.525	0.271	−0.017	−0.05	−0.023	−0.058	***	***	liter.
Timor-Leste	2001	2007	0.418	0.349	0.459	0.383	−0.011	−0.03	−0.013	−0.030	***	***	liter.
Turkey	2003	2012	0.054	0.039	0.032	0.017	−0.002	−0.04	−0.002	−0.069	***	***	liter.
Ukraine	2002	2013	0.084	0.047	0.068	0.029	−0.003	−0.05	−0.004	−0.075	***	***	years

(Continues)

TABLE 1 (CONTINUED)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Initial year	Final year	G-CSPI initial	G-CSPI final	G-M_0 initial	G-M_0 final	Abs. ann. change G-CSPI	Rel. ann. change G-CSPI	Abs. ann. change G- M_0	Rel. ann. change G-M_0	Statistical significance of difference+++		Educ. indicator
											G-CSPI	G-M_0	
Uruguay	2000	2014	0.032	0.025	0.005	0.003	−0.000	−0.02	−0.000	−0.038	***	***	liter.
Venezuela, RB	2000	2006	0.061	0.053	0.033	0.026	−0.001	−0.02	−0.001	−0.038	***	***	liter.
Vietnam	1998	2008	0.356	0.211	0.467	0.239	−0.014	−0.05	−0.023	−0.065	***	***	liter.
Zambia	1998	2015	0.360	0.293	0.414	0.337	−0.004	−0.01	−0.005	−0.012	***	***	years
Zimbabwe	2001	2007	0.267	0.275	0.313	0.337	0.001	0.00	0.004	0.013	***	***	years
Aggregate (pop. weighted average)							−0.005	−0.032	−0.006	−0.048			

+++Significance: *** = 1%; ** = 5%; * = 10%.
Source: own elaboration.

$$\text{(7)} \qquad \text{Relative annualized change} = \left(\frac{x_{t+y}}{x_t}\right)^{\frac{1}{y}} - 1,$$

where x_t is the initial value, $y$is the number of years, and $x_t + y$ is the final one.

We are also able to determine whether the changes are statistically significant, given that we have information on the standard errors of the G-CSPI and G-M_0 estimates for each country and data point.[11]

4. Trends in Multidimensional Poverty

In this section, we analyze country-level poverty trajectories in the studied period. This way we can verify whether poverty has really fallen everywhere and to what extent, since the introduction of the MDGs. The trends in multidimensional poverty are assessed through the overall G-CSPI index and the G-M_0 index. In Section 5.1, we then analyze separately the specific contribution of the three 'I's: poverty incidence, intensity, and inequality.

4.1. *Country-Level Trends in Multidimensional Poverty*

Table 1 shows the changes in multidimensional poverty for our sample of 54 countries. Based on the G-CSPI, 45 of the 54 countries have seen their poverty decreasing. All these changes are statistically significant at the 1 percent significance level, except for Mozambique, where the change is significant only at the 5 percent level (see column 11).

Bhutan and Chad witnessed the highest decreases in absolute terms (more than 2 percentage points on average per year), immediately followed by Tanzania and Laos (more than 1.5 percentage point per year). Looking at the (compound) proportional change, the largest declines in the G-CSPI were registered in Serbia, South Africa, and Belarus—more than 10 percent per year. Bhutan, Bulgaria, Kosovo, Albania, Philippines, Vietnam, and Ukraine, too, had an outstanding performance, with an average yearly decrease by more than 5 percent. It is important to note that large proportional decreases of ECA countries (especially, eastern European countries) are especially due to their small initial G-CSPI value.[12]

The nine countries that witnessed an increase in the G-CSPI are the Dominican Republic, Ethiopia, Ghana, Kenya, Lithuania, Nigeria, Paraguay, São Tomé and Principe, and Zimbabwe. However, in the case of Dominican Republic, the change is not statistically significant at the 10 percent level. Of the eight remaining

[11]In line with the procedure suggested by Efron (1981), for each survey we calculated the bootstrapped standard errors and the corresponding confidence intervals at 95 percent, following the bootstrap estimate of the standard errors and the bootstrap percentile method, with 1,000 stratified bootstrap replications. With this information, we can analyze how much each point estimate varies around its true value. Using information on the poverty estimates and its standard errors in two different points in time, we can then assess whether a change in poverty is statistically significant and at which significance level.

[12]It is also important to highlight that in cases of very low values of the G-CSPI, such as those often encountered in European countries, there are also more risks of measurement errors (Adams, 2004).

countries, six are in SSA. Thus, there is a remarkable overrepresentation of countries from this region in this group (75 percent against 33.3 percent in the total sample). More important, this means that one-third of the countries in SSA have experienced an increase in multidimensional poverty.

In absolute terms, the increases in the G-CSPI are low, never exceeding one percentage point. Looking at the relative changes, in Lithuania multidimensional poverty increased by more than 3 percent (due to low initial values), while in Ethiopia, Ghana, Kenya, and São Tomé and Principe this increase was more moderate, but still not negligible (>1 percent in relative terms, per year).

Results largely hold when we use the G-M_0. The sign of the temporal change differs only for three countries: the G-M_0 increases significantly in Bulgaria and Mozambique while the G-CSPI declines, and the opposite occurs in Lithuania. In the case of Paraguay, instead, both indices show an increase in poverty, but this is not statistically significant in the case of the G-M_0. In summary, multidimensional poverty has decreased in 83 percent and 81 percent of the low- and middle-income countries examined, based on the G-CSPI and the G-M_0, respectively. The situation, however, looks worrisome in SSA, where about one-third of the countries experienced an increase in poverty.

Finally, we analyzed the aggregate trends by calculating also the population-weighted average annual changes (both proportional and absolute) for the two periods (last line of Table 1). In aggregate terms, multidimensional poverty declined annually in absolute terms by 0.5–0.6 percentage points and in relative terms by 3–5 percent, based on the G-CSPI and G-M_0, respectively.

4.2. *Beyond the Hypothesis of "Linear" Trends*

In Section 4.1, we implicitly assumed that there was a linear trend in poverty between the baseline and the endline period. However, for the majority of countries—44 out of the initial sample of 54—we also have some estimates of our indices for (one or several) intermediate periods. In particular, for countries in LAC we have, on average, 10 observations. Therefore, we decided to use all the available data points to paint a more detailed picture of poverty trajectories and test whether the poverty trends really followed a linear path. Figures A1–A4 in the Appendix show the values by survey year and country, for both the G-CSPI and the G-M_0. The presence of a line connecting poverty levels in two consequent periods indicates that the change is statistically significant at least at the 5 percent level. To the opposite, the line is not displayed in cases of changes in poverty that are not statistically significant at least at the 5 percent level.

As a first exercise, we check whether some countries that experienced a decline (increase) in multidimensional poverty between the first and last year available actually witnessed an increase (decline) in multidimensional poverty in some sub-periods between the baseline and endline years. Based on the G-CSPI, in 12 countries (out of 44) there was no change of direction compared to the general trend, while in 32 countries there was at least one change. Similarly, when considering the G-M_0, in 33 countries there was a change of direction in at least one sub-period. In particular, we are interested in verifying whether the identified changes in the direction compared to the overall trend were large, defined as being at least 2 percent proportionally or 1 percentage point.[13] Based on the G-CSPI, only three countries (9 percent) experience this deviation from the general trends, while the number increases when we use the G-M_0 (6).

For those countries that either always decreased or always increased poverty in all the sub-periods, we checked whether there were periods of clear acceleration or deceleration. For any country where there was a minimum of a sub-period with a relative annualized change at least twice as large as the overall relative annualized change, we concluded that the trend was not linear. Following this approach, based on both the G-CSPI and G-M_0, 30 countries did not experience linear trends. In conclusion, only for the 14 remaining countries the hypothesis of linear trend holds for each index.

5. Decomposition Analysis

5.1. *Trends by Poverty Component*

Using the G-CSPI, we analyzed the (absolute and relative) changes in the three poverty components—incidence, intensity, and inequality—between 2000 and the latest available year. As in Section 4.1, this analysis as well as that of the next subsection relies only on baseline and endline estimates of poverty for the 54 countries (thus, for 108 surveys). As shown in Figure 1, in none of the 54 countries, there was an increase in deprivations in all three components. On the contrary, for 27 countries deprivations in all three components decreased. This was especially the case in LAC and ECA. More specifically, in our sample of 54 countries, there was a statistically significant (at 1 percent level) decline in the headcount in 45, in the intensity in 45, too and, finally, in the inequality component in 37.[14] This reveals that the inequality component, captured with our G-CSPI, is the one that was reduced in the lowest number of countries.[15]

A focus on the magnitude of the relative changes reveals that the headcount and intensity components experienced a larger range of change in absolute terms, while the inequality component witnessed a larger range regarding the relative changes. The largest relative decrease in headcount was in Serbia (−10 percent), followed by Bulgaria, Belarus, and South Africa (all between 5 and 10 percent). The largest increase was witnessed by Lithuania (over 5 percent). While the intensity decreased the most in South Africa, Bhutan, and Tanzania (over 2 percent), Kenya, Ghana, Bulgaria, and Ethiopia witnessed the highest increase (over 0.5

[13] This choice is discretionary as there was no existing benchmark in the literature; but results are robust to changes in the thresholds.

[14] In all the other cases, there was a statistically significant increase in the components at the 1 percent significance level. The only exception is the intensity for Mozambique, where no statistically significant change was detected even at the 10 percent significance level.

[15] As stressed in Section 3, the G-CSPI is not additive: by construction, the three components contribute to the final value of the index in different ways. Consequently, the changes over time in the components do not provide a straightforward explanation of the changes in the overall G-CSPI. To confirm the importance of each component, it is interesting to highlight that there are even four countries—all in SSA—where the G-CSPI headcount goes in the opposite direction of the overall G-CSPI. The G-CSPI increases while its headcount decreases in Ethiopia and Zimbabwe while the opposite occurs in Mozambique and Zambia.

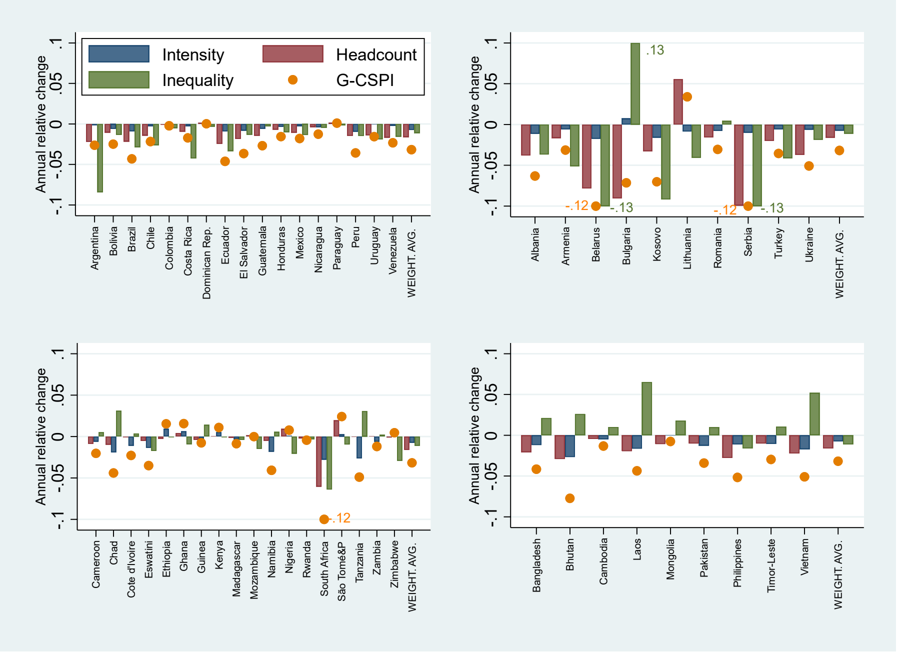

Figure 1. Relative Changes Over Time of G-CSPI Components, by Country and Region (54 Countries and 108 Surveys)

Notes: The outliers (annual relative changes above 0.1 or below −0.1) are the following: for Belarus and Serbia, changes in the G-CSPI is −0.12, and in the inequality component −0.13; for Bulgaria increase in the inequality component is +0.13; for South Africa change in the G-CSPI was −0.12.

WEIGHT. AVG. represents the population weighted average annual relative change among all countries in the sample.

Source: Own elaboration. [Colour figure can be viewed at wileyonlinelibrary.com]

percent). Finally, the largest relative change in the inequality (−25 percent) was registered in Serbia, followed by Belarus (13 percent). The sharpest increase occurred in Vietnam, Laos, and Bulgaria (over 5 percent).

Moving the attention to the regional level, we notice that the increase in the inequality component is highly concentrated in SSA and, even more, in the aggregated East Asia-Pacific and South Asia regions. Indeed, in 39 percent of the countries in SSA (7/18) there was an increase in inequality among the poor. This value goes up to 88 percent (8/9) in Asian countries (other than central Asia): the only exception here is the Philippines.

Then, we repeated the analysis for the G-M_0. As clarified in Section 2.3, this index includes only two components: headcount and intensity. We detect a statistically significant decline in the headcount in 44 countries, and in the intensity in 40. For 34 countries, deprivations in both components decreased. Figure 2 shows that the size of the relative change is much higher for the headcount than for the intensity component. In all the cases (16 countries) in which the headcount and poverty intensity move in opposite directions, the G-M_0 moves in the same direction of the former. Following the procedure adopted by Alkire *et al*. (2017b), we also used the

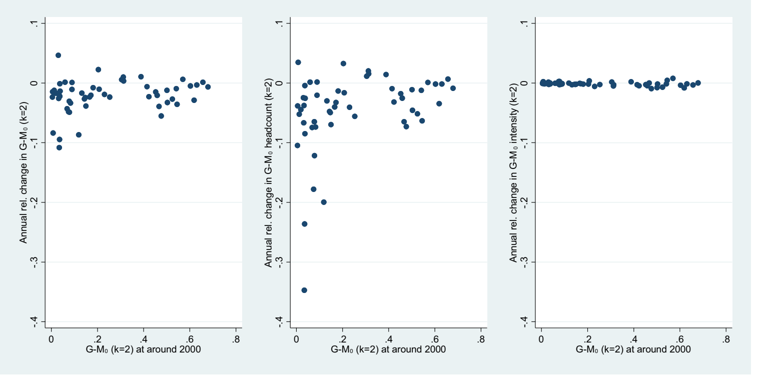

Figure 2. Relative Changes Over Time of G-M$_0$ (k = 2) Components, by Country and Starting Value of G-M$_0$ (54 Countries and 108 Surveys)
Source: Own elaboration. [Colour figure can be viewed at wileyonlinelibrary.com]

Shapley decomposition to detect the marginal effect of changes in incidence and intensity. The results, reported in Table A3 and Figure A5 in the Appendix, indicate that, on average, 88 percent of the changes in the G-M$_0$ are due to changes in the headcount and 12 percent due to changes in the intensity. For only 2 of the 54 countries—Ethiopia and Madagascar—the marginal effect of poverty intensity is higher than that of incidence. This shows clearly that the temporal changes in the G-M$_0$ are driven far more by changes in the headcount, supporting the findings of previous studies on the MPI or, more generally, on the M$_0$ measure used with an intermediate cut-off (Dotter and Klasen, 2014; Tran *et al.*, 2015; Hanandita and Tampubolon, 2016; Alkire *et al.*, 2017b; Bérenger, 2017). Our findings also corroborate previous results showing that the relative contribution of the changes in the intensity measure is significantly higher for higher levels of G-M$_0$. Indeed, using the results of the Shapley decomposition, the correlation between the marginal relative contribution of the changes in the intensity component and the baseline value of the G-M$_0$ is 0.537.

In conclusion, there was a substantial decline in all the components of poverty. The inequality component was the one that was reduced in the lowest number of countries.

5.2. *Trends by Poverty Dimension*

This subsection deals with the decomposition of the trends by poverty dimension. As explained in Section 2.4, for this purpose we use the G-M$_0$. As the index combines three dimensions—employment, health, and education—it is important, especially from a policy perspective, to understand which of these dimensions drives the trends in multidimensional poverty illustrated in Section 4.1.

The majority of countries witnessed decreases in deprivations in all dimensions, as shown in Figure 3 (Table A4 gives the dimensional G-M$_0$ values for both the initial and final years by country). Out of 54 countries in our sample, 42, 46, and 43 decreased significantly (at 1 percent level) health, education, and

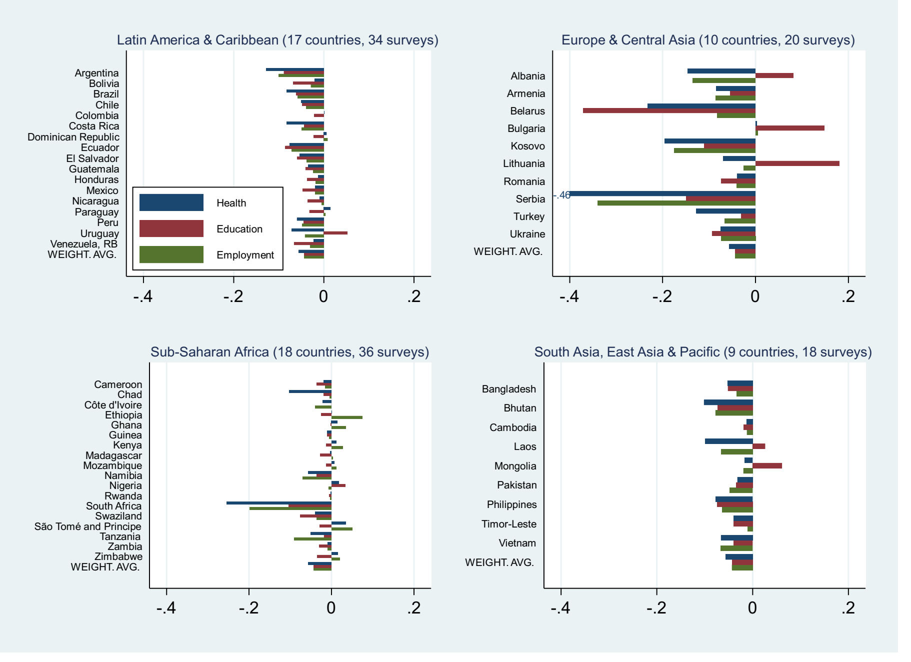

Figure 3. Relative Changes Over Time of G-M_0 (k = 2) Dimensions, by Country and Region (54 Countries and 108 Surveys)

Note: The only outlier (annual relative changes above 0.2 or below −0.4) is the reduction of the health dimension for Serbia, which is equal to −0.46.

WEIGHT. AVG. represents the population weighted average annual relative change among all 54 countries in the sample.

Source: Own elaboration. [Colour figure can be viewed at wileyonlinelibrary.com]

employment deprivations, respectively.[16] In summary, 37 countries decreased deprivations in all three dimensions, while only one country, Bulgaria, increased deprivations in all dimensions.

If we look at the magnitude of the relative changes, the three dimensions experienced similar ranges of change. The largest relative decrease in health deprivations was in Serbia (46 percent), South Africa, and Belarus (above 20 percent). Conversely, Kenya, Ghana, Paraguay, Zimbabwe, Nigeria, and São Tomé and Principe increased health deprivations by more than 1 percent. For education, Belarus decreased the most (37 percent), while Bulgaria and Lithuania increased by more than 10 percent. Finally, Serbia witnessed by far the largest relative change in the employment (−34 percent), followed by South Africa (−20 percent). The largest increase happened in Mozambique, Zimbabwe, Kenya, Ghana, São Tomé and Principe, and Ethiopia (all over 1 percent).

[16]In the other cases deprivations increased significantly. The only exceptions are Bulgaria, which experienced a nonsignificant increase in the health dimension, the Ivory Coast, which experienced a nonsignificant reduction in education deprivations, and Colombia, which experienced a nonsignificant increase in employment deprivations.

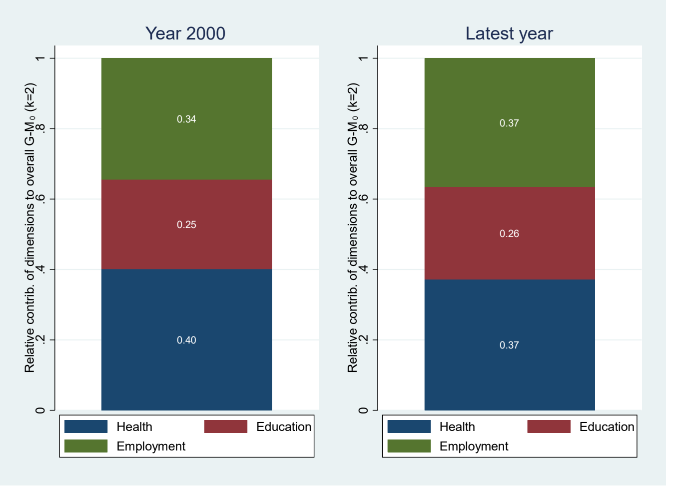

Figure 4. Relative Contribution of Each Dimension to the Overall G-M_0: ca. 2000 and Latest Survey (Population-Weighted Average; 54 Countries and 108 Surveys)
Source: Own elaboration. [Colour figure can be viewed at wileyonlinelibrary.com]

Again, SSA shows the most heterogeneous picture: in 8 of the 18 countries in the region, there was a statistically significant increase in the G-M_0 for at least one dimension: seven increase in health; one (Nigeria) in education; and seven in employment. In LAC, 13 out of 17 countries show decreases in all dimensions; Uruguay increased deprivations in education, Colombia in health, and Dominican Republic and Paraguay in both health and employment. However, the size of the changes in LAC is very small. Similarly, ECA has just three countries (Bulgaria, Albania, and Lithuania) with slight decrease in education. Bulgaria also increased its value of health (not statistically significant) and employment deprivations (5 percent significance). Finally, Asia has two countries (Laos and Mongolia) increasing both the heath and employment dimensions.

Looking at the weighted average changes, health deprivations decreased by 5.6 percent in relative terms and by 0.3 percentage points in absolute terms, while education and employment by 4.3 percent and by 0.2 percentage points.

Consequently, the relative contributions of the three dimensions to the overall G-M_0 also changed, as shown in Figure 4. It is then useful to investigate the changes in the relative contribution of each dimension to the overall G-M_0. Around 2000, deprivations in access to drinkable water and adequate sanitations—proxy for health deprivations—accounted for 40.1 percent of overall multidimensional poverty, while employment and education deprivations accounted for 34.5 percent and 25.4 percent, respectively. In the latest available year, the contribution of employment appears higher (36.6 percent), slightly lower than that of health, while the contribution of education remains about the same (26.2 percent). These results point again to the relatively slower progress in alleviating employment deprivations.

6. Comparing Trends in Multidimensional and Income Poverty

This section compares the trends in multidimensional poverty with those in income poverty. Our data ensure high comparability with those on income poverty provided by PovcalNet because in most of the cases the survey that was used to calculate the G-CSPI and the G-M_0 is the same as that used to measure income poverty. Only in few cases it is not, but is still conducted in the same year. In contrast, to compare the trends in multidimensional and income poverty, Alkire *et al.* (2017b)—and, more recently, Alkire *et al.* (2020a)—rely on two different types of surveys for the computation of the estimates of the two forms of poverty, which were conducted in the vast majority of the cases in different years. Therefore, it is hard to say if diverging country trends in monetary and multidimensional poverty are genuinely due to the form of poverty examined.

We are aware that the comparison is not straightforward as our multidimensional poverty indices refer to individuals in a specific life stage, while income poverty measures are constructed at the household level and are supposed to be representative of the entire universe of households. However, this exercise is particularly important given that both types of poverty are explicitly addressed by SDG 1, and it is, therefore, useful to explore how they develop relative to each other.

Merging our data set with data from PovcalNet on income poverty led to dropping 11 countries due to observations (country/year) that lacked information on monetary poverty. The analysis in this section includes 43 countries with complete data for the baseline and endline periods (thus, 86 surveys in total). The analysis uses the extreme international poverty line of US$1.90 per day, adjusted for purchasing power parity, which is the poverty line used to track progress in SDG1.

In the empirical analysis, we compare first the changes in the comprehensive indices of multidimensional poverty with the changes in the equivalent indices in the income space. Therefore, we compare the G-CSPI index with the squared poverty gap as both are distribution-sensitive measures of poverty, and the G-M_0 with the poverty gap as both measure incorporate poverty intensity. Second, we compare the headcount ratios of the G-CSPI and that of the G-M_0 with the headcount ratio of income poverty. While we are aware of the limitations in focusing only on the headcount, we decided to also include this analysis as this is the most known and used measure of poverty in the monetary space.

The upper-left part of Figure 5 shows the relationship between the relative changes of the G-CSPI and those of the squared poverty gap. As expected, there is a positive correlation. However, the intensity of this relationship is not very strong, as confirmed by the Pearson's coefficient (0.47) and, even more, the Spearman's coefficient (0.31).[17] These correlations were computed excluding Ukraine and Belarus, as they are clear outlier because all indicators of monetary poverty are zero for the latest year. The relationship between income and multidimensional poverty is even weaker when we use the G-M_0 instead of the G-CSPI (upper-right part of Figure 5) and the income poverty gap instead of the squared poverty gap, with the Pearson's coefficient being only equal to 0.41. Moreover, in none of the

[17]If Ukraine and Belarus are included, the Pearson's coefficient becomes 0.56 (and 0.50 in the case of the G-M_0 that we present below).

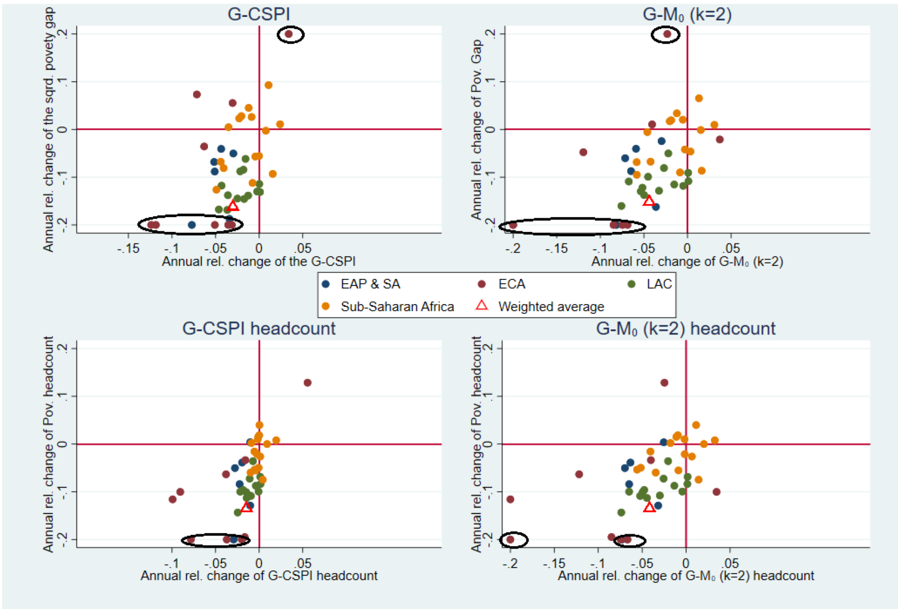

Figure 5. Relative Changes in Multidimensional and Income Poverty (43 Countries and 86 Surveys)

Notes: The circled outliers (annual relative changes above 0.1 or below −0.1) are the following: for the changes in the poverty gap squared are Serbia: −0.33, Belarus: −1; Bhutan: −0.21, Ukraine: −1, Turkey: −0.50; Armenia: −0.25; Lithuania: 0.62.

For the poverty gap, the outliers are Serbia: −0.24; Belarus: −1; Bhutan: −0.21; Ukraine: −1; Turkey: −0.41; Armenia: −0.23; Lithuania: 0.39. For the income poverty headcount, the outliers are Belarus: −1; Bhutan: −0.21; Ukraine: −1; Turkey: −0.27.

For G-M_0, the outliers are Serbia: −0.35; Belarus: −0.24.

For the G-M_0 headcount, the outliers are Serbia: −0.35; Belarus: −0.24.

The weighted average represents the population weighted average annual relative change among all countries in the restricted sample used for this section.

Source: Own elaboration. [Colour figure can be viewed at wileyonlinelibrary.com]

two cases, does the relationship seem linear. There are several outliers. Most of them, however, are countries with relatively low scores of multidimensional poverty around 2000.[18] The only clear exception is Bhutan, which managed to reduce both forms of poverty, but relatively more the income poverty gap than the G-M_0.

The bottom panels in Figure 5 show the relationship between the changes in the income poverty headcount and those in the multidimensional poverty headcounts. The correlation is stronger when multidimensional poverty is measured through the G-CSPI headcount (left panel) rather than the G-M_0 headcount (right panel). Indeed, in the first case the Pearson's coefficient is 0.51, while it is 0.36 in the second case.

Based on the G-CSPI, for 31 countries, equivalent to about 72 percent of the sample, at least the direction of the changes is the same for the two indices (see Table 2). Specifically, 29 countries managed to reduce both income (the squared poverty gap)

[18]This result may be expected as a small absolute change for this group of countries translates into large relative changes.

TABLE 2
Direction of Change for Multidimensional and Income Poverty, by Indicator

		G-CSPI (G-CSPI Headcount)				$G\text{-}M_0$ ($\boldsymbol{k}$ = 2) ($G\text{-}M_0$ Headcount)		
		Increase	Decrease	Countries		Increase	Decrease	Countries
Income poverty, US$1.90 a day—PPP Squared poverty gap (headcount ratio)	Increase	3 (5)	7 (4)	10 (9)	Income poverty, US$1.90 a day—PPP Poverty gap (headcount ratio)	2 (3)	6 (6)	8 (9)
	Decrease	4 (4)	29 (30)	33 (34)		6 (5)	29 (29)	35 (34)
	Countries	7 (9)	36 (34)	43 (43)		8 (8)	35 (35)	43 (43)

Source: Own elaboration.

and multidimensional poverty (the G-CSPI), while both types of poverty increased in three countries: Kenya, Lithuania, and São Tomé and Principe. In 11 cases, the direction of change is different, pointing to the conclusion that income poverty is not an accurate proxy measure of multidimensional poverty, especially if the objective is to assess changes over time. Interestingly, there is an overrepresentation of countries from SSA in this group of “outliers”: they are 63.6 percent (7/11), while they form “only” 34.9 percent (15/43) of the sample for this empirical analysis. Specifically, five countries in this region experienced an increase in income poverty accompanied by a reduction in multidimensional poverty, while the opposite is true for two countries (Nigeria and Ghana). These results are in line with those of Alkire *et al.* (2017), which show that where multidimensional and income poverty go in opposite direction, poverty alleviation is usually achieved in the multidimensional space. Overall, these findings indicate that particularly in this region—the region with the highest poverty scores in both income and multidimensional spaces—monetary measures do not adequately capture deprivations in other dimensions.

The results are very similar when we compare changes in the G-M_0 with changes in the poverty gap, as well as when we compare the changes in multidimensional poverty headcounts with those in the income poverty headcounts (see Table 2). In particular, the number of countries succeeding in alleviating both income and multidimensional poverty is substantially stable (29 or 30).

Finally, we analyzed the population-weighted changes in the indices. The results are striking. Depending on which of the four indicators of multidimensional poverty we use, the decline in multidimensional poverty is between two and six times lower than the decline in monetary poverty. More specifically, the population-weighted average annual decrease of the squared poverty gap and the poverty headcount are four and six times larger than that of the G-CSPI index and its headcount, respectively. Considering the G-M_0 and its headcount, the decrease in the income poverty indices (poverty gap and poverty headcount) are 2.5 and 2.1 times larger. The numbers become even more striking if Belarus and Ukraine are included. For example, the decrease in the income poverty headcount is almost nine times higher than the decrease in the G-CSPI headcount.

7. Conclusions

Poverty alleviation has historically been one of the main policy goals of development cooperation. With the 2030 Agenda, poverty is no longer defined strictly as a lack of sufficient income, but rather as deprivation in several dimensions of life. Against this background, the general aim of this paper was to analyze the trends in multidimensional poverty in low- and middle-income countries during the period of the MDGs. While several studies show a massive reduction in income poverty, little was actually known about deprivations in other dimensions, especially examined by means of composite indices.

This paper relies on two new indices of multidimensional poverty, the G-CSPI and the G-M_0. These indices have various strengths. First, they are individual-based indices of poverty, while existing international indices of income and multidimensional poverty are constructed at the household level. This makes it possible to explore intrahousehold differences (e.g., by gender) without having to make risky assumptions about intrahousehold allocation of resources. Second, they encompass three dimensions—education, employment, and health—that are deemed the most relevant when looking at the constitutions of several countries in the world. In particular, the employment dimension is not present in the global MPI. Our two indices differ in the poverty measure used. The G-CSPI uses the CSPI, which permits to capture inequality among the poor. The G-M_0, instead, uses the M_0 measure, which has the main advantage of being easier to calculate and fully decomposable by dimension. This way, we could also test the robustness of poverty trends to alternative measures.

The main objective of the paper was to analyze the changes in multidimensional poverty in a large sample of low- and middle-income countries (54) since the turn of the millennium. The analysis shows that since 2000, there has been a statistically significant decline in poverty in about 82 percent of the countries examined. In aggregate terms, multidimensional poverty declined annually by 0.5–0.6 percentage points in absolute terms and by 3–5 percent in relative terms, based on the G-CSPI and G-M_0, respectively. Substantial differences, however, exist across regions. In particular, the progress in poverty eradication registered in SSA has been slow: one-third of the countries in this region even experienced an increase in multidimensional poverty. This confirms findings from studies on monetary poverty and points to the existence of poverty traps.

An additional investigation reveals that the poverty trends experienced between the baseline year and the endline year were often nonlinear. Of the 44 countries for which we had data for more than two data points, 30 experienced a substantial change in the direction of poverty in at least one sub-period. Thus, the hypothesis of linearity holds only for 14 countries.

The paper then tried to shed some light on the drivers of poverty trends through different decomposition analyses. First, the poverty component that decreased in the largest number of countries is the headcount. To the opposite, the inequality component is the one that was reduced in the lowest number of countries, especially in Asia and SSA. This information is particularly relevant in light of the overarching principle of the 2030 Agenda, "leaving no one behind."

Some additional analyses reveal further important policy information. While deprivations in all three dimensions of poverty have declined, the employment dimension has registered the smallest improvements. Moreover, the latter is the dimension that—together with health—contributes the most to overall poverty: therefore, policy makers should pay major attention to the functioning of labor markets.

Finally, the paper compares the trends in multidimensional and income poverty. This analysis has the limitation that the multidimensional poverty indices refer to individuals in the 15–65 age group, while the income poverty indices are representative of the entire (household) population. On the contrary, compared to the rare studies conducted so far, it has a major advantage: the survey that was used to calculate the G-CSPI and the G-M_0 is the same as that used to measure income poverty. Two main conclusions are derived. First, the correlation between the changes in income and multidimensional poverty is not strong, and there are even 11 countries—mostly located in SSA—witnessing diverging trends between the two. Therefore, interventions succeeding in alleviating income poverty are not necessarily effective in reducing multidimensional poverty (and vice versa).

Second, the analysis reveals that income poverty has declined significantly more than multidimensional poverty. Depending on the indicator of multidimensional poverty used, the reduction in multidimensional poverty has been two to six times lower compared to that in income poverty. These findings highlight that—once we consider other, non-monetary dimensions—the progress in poverty eradication has not been as remarkable as believed and calls for stronger efforts in tackling the different forms of poverty.

In conclusion, the findings of this paper provide new valuable information on the trends in multidimensional poverty. Further research is needed to understand better group disparities—by gender, by age, by location—in poverty and their evolution over time, as well as the role of economic growth and social policies in tacking the different forms of poverty.

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Supporting Information

Additional supporting information may be found in the online version of this article at the publisher's web site:

Table A1. Values and Changes over Time of G-M_0 with k = 1

Table A2. Survey-Years by Country

Table A3. Shapley Decomposition of Marginal Effects of Changes in G-M_0 (k = 2) Incidence and Intensity

Table A4. G-M_0 (k = 2) Values, by Dimension and Year

Figure A1. Values Over Time of G-CSPI and G-M_0 (k = 2), by Country in LAC

Figure A2. Values Over Time of G-CSPI and G-M_0 (k = 2), by Country in ECA

Figure A3. Values Over Time of G-CSPI and G-M_0 (k = 2), by Country in SSA

Figure A4. Values Over Time of G-CSPI and G-M_0, by Country in EAP and SA

Figure A5. Shapley Decomposition of G-M_0 (k = 2) Changes into Incidence and Intensity Effects, by Country INITIAL G-M_0 Value