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Assessing trends in multidimensional poverty during the MDGs

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Abstract

While we have extensive information on the trends in income poverty, little is known about the trends in multidimensional poverty. This paper tries to fill this gap by assessing the changes in multidimensional poverty in 55 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% of the countries assessed have reduced multidimensional poverty. However, progress has been very limited in Sub-Saharan Africa. Different decomposition analyses indicate that poverty alleviation has mainly been triggered by a reduction in health deprivations and by improvements in rural areas. A comparison with changes in income poverty suggests that the correlation is not strong, and that multidimensional poverty has decreased significantly less than income poverty.

Keywords

Poverty trends, multidimensional poverty, poverty measurement, development economics, comparative analysis

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 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 organisations over the past three decades (Sen, 1985, 1987, 1999; UNDP, 1997, 2010; Narayan-Parker & Patel, 2000). The most notable critiques of the view of poverty as a lack of sufficient income have been made by Amartya Sen. The Nobel prize-winning economist argued that income is only one of the possible instruments by which to avoid or escape poverty; 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 the one hand, and these poverty dimensions on the other hand, is not straightforward, but mediated by several factors at the individual (eg age, gender, health, metabolism), social (eg formal and informal rules, power relations) and environmental (climate) levels (Sen, 1985; Robeyns, 2005).[1] Moreover, this way we can account for non-market attributes, namely characteristics such as education or social participation, which people may value but for which markets are either non-existent or

[1] For example, Robeyns (2005) argues that the *utility* derived from owning a good, such as a bicycle, depends on the possibility of making use of its main characteristics, that is, the possibility to move around freely. She states: "if there are no paved roads or if a government or the dominant societal culture imposes a social or legal norm that women are not allowed to cycle without being accompanied by a male family member, then it becomes much more difficult or even impossible to use the good to enable the functioning" (p 99).

imperfect (Thorbecke, 2007).[2] For all these reasons, the broader understanding of poverty as recognised in SDG 1 is highly appreciated.

Given the aforementioned goals to eradicate poverty, what do we know about the evolution of poverty in the past few decades? A considerable bulk of work has analysed 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% in 1990 to 10% 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% to 2.3%. On the other hand, Sub-Saharan Africa (SSA) had a much slower pace of poverty reduction and currently has by far the largest incidence of extreme poverty (54.3% in 1990 and 41.1% in 2015).

Alongside income poverty, we have evidence of trends in other dimensions of poverty, based on specific indicators (see, for example, UNDP, 2013; Horner & Hulme, 2019). For example, Horner and Hulme (2019) found some convergence between the Global South and the Global North in indicators such as morality rates and literacy. Specifically, for the educational dimension, the illiteracy rate among people aged 15 and above in the world fell from 25.6% to 14.4%, especially thanks to the remarkable performance of two regions: South Asia and the Middle East and North Africa. There have also been remarkable reductions in health deprivations, as measured by child mortality. In the 1990–2015 period, the 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, 2009) Despite these tremendous

[2] Other critiques of the monetary approach to poverty pertain to the difficulty of measuring income or consumption, especially in the rural contexts of developing countries. Some scholars have raised serious doubts about the international poverty lines identified by the World Bank (Reddy, 2011; Reddy & Pogge, 2010), thereby contesting the quality of the data on poverty incidence and depth.

improvements, the situation still looks worrisome, however, especially in SSA.[3] Less information 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 equally deprived in education (Stiglitz et al, 2009). Moreover, a dashboard approach leaves unanswered questions, such as the priority and weights of the different indicators, and trade-offs among them (OPHI, 2016). Finally, the use of a dashboard approach does not provide 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 these kinds of composite index is scarce. Most studies have focused on specific countries, such as Vietnam (Mahadevan & Hoang, 2016; Tran et al, 2015), Indonesia (Hanandita & Tampubolon, 2016), South Africa (Fransman & Yu, 2019) and Ecuador (Mideros, 2012), or a specific region (Santos & Villatoro, 2018, for Latin America). Only one study, by Alkire et al (2017) has provided an in-depth analysis of the evolution of multidimensional poverty, using the global Multidimensional Poverty Index (MPI) (Alkire & Santos, 2010). This index combines three equally weighted dimensions: education, health and standard of living, comprising a total of ten indicators. The three dimensions are aggregated through the Alkire–Foster Method (Alkire & Foster, 2011) and account for both poverty incidence and poverty intensity. Based on this index, Alkire et al (2017) examined poverty trends since around 2000 in 34 countries. The authors found that multidimensional poverty had significantly declined (at least at the 10% significance level) in 31 countries, while in two countries (Jordan and Senegal) the reduction was not statistically significant.

[3] Based on data from UNICEF in 2018, for example, the under-five mortality rate in SSA was still about 78 per thousand, almost double that of the second worst performing region, South Asia (41%). Data from the UNESCO Institute of Statistics show that SSA has a youth illiteracy rate of almost 25%, which represents more than double the rate experienced by the second region with the lowest performance, South Asia (11.7%).

The only exception was Madagascar, which registered a statistically significant increase in poverty between 2004 and 2008–09.

While positive developments have emerged, the existing empirical literature on multidimensional poverty trends falls short in providing a broad picture, especially given the relatively low coverage in cross-country studies or the lack of a high number of truly comparable country studies. In addition, the work of Alkire et al (2017), while original and informative, has some drawbacks. Some of these limitations are related to the global MPI, the index used to assess poverty changes. First, the three dimensions used are not adequately justified by a clear and sound theoretical approach (Wisor et al, 2016).[4] Second, the MPI is insensitive to inequality among the poor, which is an important property that every poverty index should have (Dotter & Klasen, 2014; Jenkins & Lambert, 1997; Rippin, 2014, 2017). 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 multi-dimensionally poor. Third, a specific weakness of the MPI when used for trend analysis is that its variation over time is, because of the dual cut-off method, almost entirely triggered by changes in the headcount ratio and only minimally by changes in poverty intensity (Dotter & Klasen, 2014; Tran et al, 2015). It is difficult to justify the calculation of a more complex index if, because of its construction, it provides little information besides the headcount ratio. Another important limitation of Alkire et al's work is that some indicators are not available for some countries; thus, not all 34 countries are

[4] In the initial paper proposing the global MPI, Alkire and Santos (2010) generally argued that they had identified the three dimensions – education, health and standard of living – by looking at the results of large participatory exercises and at the contents of international agreements, such as the MDGs. However, in the MDGs, for example, there is no focus on asset ownership or access to electricity, while the attention paid to access to sanitation and drinking water is rather limited compared to other dimensions. For this reason, Wisor et al (2016) and Burchi et al (2018b) concluded that the selection of dimensions in the global MPI was strongly data-driven.

evaluated on the basis of exactly the same number and typology of indicators.[5] Finally, the assessment of poverty changes is based on years and time-frames, which are sometimes very different; in a few cases, there is no overlap of the time periods across countries. For example, the authors analysed trends in Jordan and Tanzania over a period of only two years, while in Gabon over a period of 12 years. The fact that the authors examined the annualised 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 1998–99 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, the Alkire et al's (2017) findings should be treated with caution.[6]

The present paper tries to fill this research gap, assessing the evolution of multidimensional poverty in a considerably larger sample of low- and middle-income countries (55). To investigate these trends, we rely on a new index of multidimensional poverty: the Global Correlation Sensitive Poverty Index (G-CSPI) (Burchi et al, 2018b). This index combines deprivations in three dimensions (work, education and health), derived using the new Constitutional Approach (Burchi et al, 2020). Unlike the global MPI, the G-CSPI is an individual-based poverty index, as it focuses on people in the 15–65 age group. Finally, compared with the MPI, the final index requires only the dimensional cut-offs and accounts not just for poverty incidence and poverty intensity, but also for inequality among the poor. Given that the M_0 measure – used to calculate the global MPI – is widely known and can be directly and fully decomposed to capture dimensional contributions, we complement the analysis based on the G-CSPI with that using M_0 as poverty measure (called G-M_0). We computed both the indices for more than 550 nationally representative surveys.

[5] The same problem is present in Santos and Villatoro's (2018) study, which examines multidimensional poverty trends in 17 countries in Latin America using a revised and expanded version of the global MPI.

[6] In the 2018 *Poverty and Shared Prosperity* report, the World Bank proposed a new measure of multidimensional poverty and calculated it for 119 countries for the years around 2013 (World Bank, 2018). For each country the indicator was calculated only for one point in time, therefore no analysis of poverty trends was carried out.

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 six years later. This way we have a more uniform interval of time to compare poverty trends across countries (55) that meet the above requirements. We thereby assess whether, and to what degree, multidimensional poverty has declined 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), in rural and urban areas, and among the three dimensions. Finally, we compare trends in multidimensional poverty with the traditional measures of income poverty. One of the advantages of our data, compared with the MPI, is that we can make an accurate comparison of the two, as we have data from the same years.

In a nutshell the empirical analysis reveals that multidimensional poverty has significantly declined in more than 80% of the countries examined. However, progress has been slow in SSA, where a considerable number of countries seems to be in a poverty trap. Poverty reduction has mainly been driven by a reduction in health deprivations and improvements in rural areas. Finally, a comparative analysis between multidimensional and monetary poverty reveals that, in aggregate terms, the former declined at a much slower rate. More generally, the temporal changes in income and multidimensional poverty are not strongly correlated, pointing to the conclusion that income poverty indicators are not able to adequately capture 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 employed. Section 4 provides an analysis of historical trends in the multidimensional poverty indices at country level, while Section 5 presents different sub-group analyses. Section 6, includes a comparison between changes in multidimensional poverty and those in income poverty. Finally, we present our concluding remarks, including the policy implications 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, as well as the steps followed for their computation.[7] We start from the household data used to calculate the indices, as this has influenced the final choices regarding dimensions and indicators.

2.1 Household data

In order to construct the G-CSPI and the G-M_0 for several countries and different points in time, we relied on the International Income Distribution Database (I2D2). The I2D2 is the result of a tremendous initiative of the World Bank to standardise several demographic, socioeconomic and income/consumption variables across countries, drawing on nationally representative household surveys, including household budget surveys, household income and consumption surveys, labour force surveys and multi-topic surveys (for example, the Living Standards Measurement Study surveys).

2.2 Poverty dimensions and their weights

To identify the most relevant dimensions of poverty and compare different countries, we used a new approach, called the Constitutional Approach (Burchi et al, 2014, 2018a). It relies on Rawls' method of political constructivism and uses the country constitutions together with all the relevant documents to interpret this as an ethically suitable informational basis for identifying shared poverty dimensions. In line with this approach and based on a large list of constitutions from all world regions, three dimensions were found to be most important: education, (decent) work and health (Burchi et al, 2020). Cross checking this ideal list with the information available in the I2D2 database, the dimensions we finally selected were: education, decent work, and access to potable water and adequate sanitation (also used as a proxy for health).

Direct information on health status was not available. However, substantial empirical evidence supports the idea that a lack of access to safe drinkable water and basic sanitation impedes a good health status (Checkley et al, 2004; Fink et al, 2011; Fogden, 2009). Under this assumption, we have data on the dimensions that emerged as the most important based on the Constitutional Approach. Since they emerged as

[7] All the details are discussed in Burchi et al (2018b).

being of similar relevance, we used an equal weighting scheme: each dimension was assigned a weight of one-third.[8]

2.3 Indicators of dimensional deprivations and thresholds

Given the choice of dimension, the choice of indicator also depends also on data availability. 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 fewer than four years of schooling were classified as poor in education.[9] In cases where there were no data on years of schooling for two-thirds of the sample population, we used the variable 'educational level'. An individual who has not completed primary education is, in this case, considered poor in the education dimension.

Decent work was measured by combining two variables from the I2D2 dataset, one indicating labour status and one employment status. The first variable indicates whether a person is employed, unemployed or not in the labour force. The second variable contains five categories: paid employee, non-paid employee, employer, self-employed and other type of worker.[10] 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.

To construct the health indicator, we merged 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

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[8] This choice is, thus, based on theoretical considerations, rather than on the basis of data-driven approaches (see Klasen, 2000).

[9] 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.

[10] The measurement of decent work does not cover all the aspects of the comprehensive concept developed by the International Labour Organization (ILO). As discussed in Burchi et al (2018b), the I2D2 dataset has further information, for example on working hours, wage and duration of unemployment; however, because of the absence of certain values for several countries, it was not possible to use this information for the computation of an index used to compare several countries.

were treated as poor in the health dimension, while those with access to at least one were considered non-poor.

2.4 The poverty measures: CSPI and M_0

We employed two different poverty measures. The first is the Correlation Sensitive Poverty Index (CSPI), developed by Rippin (2014, 2017) and applied in several studies (Rippin, 2016; Tosi, 2015; Milan et al., 2016; Bérenger, 2017). The CSPI is based on a 'fuzzy' identification function, meaning that people are not simply differentiated on the basis of whether they are multi-dimensionally poor or not, but rather on the basis of 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 individual achievements [$\mathbf{x}_{i.} = (x_{i1}, \dots, x_{id})$], the vectors of dimensional cut-offs (z) and the weights [$\mathbf{w} = (w_1, \dots, w_d)$],[11] can be generally expressed in the following way:

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

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

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

$$\text{CSPI} = \frac{1}{n}\sum_{i=1}^{n}[c_i(x_i; z; w)]^2 \qquad (2)$$

Thus, the CSPI is the squared sum of weighted deprivations suffered by the multi-dimensionally poor 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 multi-dimensionally poor from those who are non-poor. In all the applications of the MPI, at the global as well as national level (Alkire & 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 with an intermediate cut-off – among other

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

reasons, to have a lower headcount ratio, as compared to using a union approach – and this is the way it has usually been endorsed by policy-makers, we also utilised an intermediate cut-off. Since the only intermediate cut-off in our setting is 2: any individual deprived in at least two dimensions is considered poor. However, we also carry out the analyses with k=1 and report the results in Table A1 in the Appendix.[12] The M_0 poverty measure is simply the sum of weighted deprivations suffered by the multi-dimensionally poor divided by the maximum possible number of deprivations:

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

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

The two final indices, employing the two different measures, are the G-CSPI and the G-M_0. In comparison to the G-M_0, the G-CSPI has a number of advantages. The first is that it is distribution-sensitive (Rippin, 2014; 2017) and can 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 Generalised Entropy measure of inequality),[13] while the G-M_0 can only be decomposed into the product of poverty incidence and poverty intensity.[14]

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

[13] For a comparison of the CSPI with other distribution-sensitive measures of multidimensional poverty, such as those developed by Bossert et al (2013), and Chakravarty and D'Ambrosio (2006), see Rippin (2017) and Burchi et al (2018b).

[14] In general, the CSPI can be decomposed in the following way:

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

where *q* is the number of the poor, H is the headcount, A is the average deprivation share among the poor and GE is a Generalised Entropy measure of inequality (Rippin, 2014). M_0, instead, can be decomposed in the following way:

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

This is a very important feature: as Sen (1976) argued, any reasonable poverty index should be decomposable according to what Jenkins and Lambert (1997) called the "three 'I's of poverty": incidence, intensity and inequality. The possibility of incorporating 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*). More generally, the CSPI allows for more informed and detailed policy making.

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.[15] 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 analysing trends, which is the objective of this paper. Dotter and Klasen (2014) have demonstrated that, in the case of the MPI, this truncation implies that any variation of M_0, between countries, as well as over time, is almost exclusively driven by the headcount.

On the other hand, the M_0 accompanied by an intermediate cut-off is a well-known measure of poverty and one that is relatively easier to calculate. Moreover, it can be directly and fully decomposed in order to detect the relative contribution of each

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where H is the poverty headcount and A the average deprivation share among the poor. In the case of an intermediate cut-off, as for our G-CSPI and 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.

[15] See Burchi et al (2018b) for an analysis of robustness of the G-CSPI to alternative weights, as well as to alternative indicators of the three dimensions.

dimension to overall poverty.[16] For these reasons, in order to investigate the trends in multidimensional poverty, in addition to the G-CSPI we also use the G-M_0 index.

2.5 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 is an individual-level index. Therefore, we do not need to make assumptions about intra-household distribution of resources or capabilities, and we can identify whether two individuals living in the same household have a different poverty status.[17] Specifically, the G-CSPI and the G-M_0 are calculated for individuals between 15 and 65 years of age. This is because poverty among children and the elderly should be assessed using different dimensions and indicators (Biggeri et al, 2006; Domínguez-Serrano et al, 2019; Gopinath, 2018; Lloyd-Sherlock, 2002). The population in this age group represents around 60% of the total population in the sample of countries used in our empirical analysis (see Section 3).

3 Data and methodology

Using the I2D2 database, we were able to compute the G-CSPI and the G-$M_{0,}$ and all their components, for about 580 surveys and 108 countries. As the derived dataset at our disposal was an unbalanced panel, to look at aggregate trends we had to take a few decisions to ensure data comparability.

Our first decision concerned the timeframe: we decided to focus on the period starting around 2000 until the most recent survey years, as this represents the period of the MDGs. Although the reference period for MDG 1 started 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:

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[16] If the two steps, identification and aggregation, are viewed as separate, which allows the additivity of the CSPI in the aggregation step, the CSPI is decomposable, too (Bérenger, 2017; Dotter & Klasen, 2014; Jolliffe, 2014; Rippin, 2014, 2017).

[17] It is important to make a clarification. Information on the dimension of access to drinkable water and sanitation (our proxy for health) is collected at the household level and not at the individual level. However, it is difficult to imagine that some household members could be excluded from the use of these facilities. Therefore, it is reasonable to assign the same value (0 or 1) to all household members and treat the information as if it were collected at the individual level.

choosing this timeframe allowed us to utilise nearly all the data at our disposal, as information on previous periods was scarce.

Given that surveys were carried out in different years in different countries, our second choice consisted of identifying the first and 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.[18] The ‘endline’ was the latest available year as long as the survey was conducted more than five years after the baseline survey. This ensured an overlap in the years across countries and a better identification of the overall trends. In order to test the hypothesis of linearity of the trends, in a following step we also considered the surveys available for the period between baseline and endline.

Another important decision concerned the indicator of education. In order to ensure within-country comparability across time, 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 removal of the country from our study.[19]

The final dataset includes estimates of multidimensional poverty trends for 55 countries: 35 of them were not included in Alkire et al’s (2017) poverty analysis. Regarding the geographical distribution of the countries, 19 (34.6%) are in SSA, 17 (31%) in Latin America and the Caribbean (LAC), ten (18.2%) in Europe and Central Asia (ECA), and nine (16.4%) in South Asia, East Asia and the Pacific. The latter sample is particularly under-represented, given also the absence of big countries, such as China and India, for which we have data from just one point in time. Of the remaining population of low- and middle-income countries, the sample represents around 54% of the total. With regard to the time-frame used for the different countries, on average the number of years between

[18] In case of two surveys with the same ‘distance’ from 2000 (eg 1999 and 2001), we used the oldest survey, as this allowed us to focus on longer-term trends.

[19] Some other surveys were excluded because the sample of individuals for whom full information was available on our variables covered less than 66.6% of the overall sampled population (in the age group 15–65).

the endline and the baseline years was 10.7.[20] The list of survey years used for each period for every country is provided in Table 1.

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

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

$$Absolute\ annualised\ change = \frac{x_{t+n} - x_{t+n}}{n} \qquad (4)$$

The *relative* proportional annualised changes were calculated, following the literature (McArthur & Rasmussen, 2018), in the following way:[21]

$$Relative\ annualised\ change = \left(\frac{x_{t+n}}{x_t}\right)^{\frac{1}{n}} - 1 \qquad (5)$$

where x_t is the initial value, n is the number of years, and $x_t + n$ is the final year.

We were also able to determine whether the changes were statistically significant, given that we had information on the standard errors and the confidence intervals of the G-CSPI and G-M_0 estimates for each country and data point.[22]

4 Trends in multidimensional poverty

In this section, we analyse country-level poverty trajectories in the studied period. This way we can verify whether poverty really has fallen everywhere, and to what extent,

[20] With a minimum of six and a maximum of 18 years.

[21] The same occurs in the dominant literature on income poverty, where average differences in the logarithms of poverty estimates are used to assess the relative annualised changes (Ravallion, 2012).

[22] 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%, following the bootstrap estimate of the standard errors and the bootstrap percentile method, with 1000 stratified bootstrap replications. With this information, we can analyse how much each point estimate varies around its true value.

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 analyse separately the specific contribution of the three 'I's: incidence, intensity and inequality of poverty.

4.1 Country-level trends in multidimensional poverty

Table 1 shows the changes in multidimensional poverty for our sample of 55 countries. Based on the G-CSPI, 46 of the 55 countries have seen their poverty decrease. All these changes are statistically significant at the 1% significance level, except for Mozambique, where the change is significant only at the 5% level (see column 11).

Bhutan and Chad witnessed the highest decreases in absolute terms (more than two percentage points on average per year), immediately followed by Bangladesh, Timor-Leste and South Africa (more than one percentage point per year). For four of these five countries, the results are not available in the study by Alkire et al (2017): the only exception is Bangladesh, where these authors too found one of the largest absolute reductions in multidimensional poverty. For Bhutan and Chad, a comparison with trends in income poverty reveals that the latter has also substantially declined in these two countries. Looking at the (compound) proportional change, the largest declines in the G-CSPI were registered in Serbia, South Africa and Belarus – more than 10% per year.[23] Bhutan, Bulgaria, Kosovo, Albania, Vietnam and Ukraine, too, had an outstanding performance, with an average yearly decrease of more than 5%. It is important to note that large proportional decreases within ECA countries (especially eastern European countries) result particularly from their small initial G-CSPI value.[24]

The nine countries that witnessed an increase in the G-CSPI are the Dominican Republic, Ethiopia, Ghana, Kenya, Lithuania, Nigeria, Paraguay, São Tomé and

[23] In this case too it is impossible to compare our findings with those of Alkire et al (2017), as these countries are not included in their sample.

[24] It is also important to emphasise 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).

Principe, and Zimbabwe.[25] However, in the case of the Dominican Republic, the change is not statistically significant at the 10% level. Of the eight remaining countries, six are in SSA. This means a remarkable over-representation of countries from this region in this group (75%, against 34.6% in the total sample). More importantly, this means that nearly 32% 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% (as a result of low initial values),[26] while in Ethiopia, Ghana, Kenya and São Tomé and Principe this increase was more moderate, but still not negligible (+ 1% in relative terms per year).

[25] The results for Ethiopia and Ghana may look puzzling, as these countries are often labelled developmental states. For Ethiopia, the global MPI in the same period registers a decline, though one of the slowest in the sample used by Alkire et al (2011). Our findings for Ghana are quite different from those for the MPI and income poverty: further investigation is needed to understand what lies behind this.

[26] Measurement error, previously mentioned, could be a potential problem for a country like Lithuania.

Table 1: Values and changes over time of G-CSPI and G-M_0

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	
	Start year	Final year	G-CSPI start	G-CSPI final	G-M_0 start	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+++	
											G-CSPI	G-M_0
Albania	2002	2012	0.096	0.050	0.078	0.022	-0.005	-0.07	-0.006	-0.127	***	***
Argentina	2000	2014	0.029	0.020	0.005	0.001	-0.001	-0.03	-0.000	-0.111	***	***
Armenia	2001	2011	0.067	0.049	0.037	0.015	-0.002	-0.03	-0.002	-0.089	***	***
Bangladesh	2003	2015	0.431	0.259	0.503	0.282	-0.014	-0.04	-0.018	-0.048	***	***
Belarus	2001	2010	0.045	0.015	0.035	0.003	-0.003	-0.13	-0.004	-0.271	***	***
Bhutan	2003	2012	0.424	0.206	0.476	0.221	-0.024	-0.08	-0.028	-0.085	***	***
Bolivia	2000	2014	0.141	0.099	0.132	0.083	-0.003	-0.03	-0.004	-0.033	***	***
Brazil	1999	2014	0.093	0.048	0.078	0.027	-0.003	-0.04	-0.003	-0.070	***	***
Bulgaria	2001	2007	0.037	0.024	0.008	0.009	-0.002	-0.07	0.000	0.036	***	***
Cape Verde	2000	2007	0.224	0.160	0.240	0.158	-0.009	-0.05	-0.012	-0.060	***	***
Cambodia	1997	2009	0.457	0.390	0.541	0.459	-0.006	-0.01	-0.007	-0.014	***	***
Cameroon	2001	2014	0.408	0.313	0.452	0.346	-0.007	-0.02	-0.008	-0.021	***	***
Chad	2003	2011	0.539	0.376	0.619	0.438	-0.020	-0.04	-0.023	-0.043	***	***
Chile	2000	2013	0.039	0.029	0.019	0.010	-0.001	-0.02	-0.001	-0.046	***	***
Colombia	1999	2014	0.078	0.066	0.054	0.034	-0.001	-0.01	-0.001	-0.030	***	***
Costa Rica	2000	2012	0.032	0.026	0.012	0.006	-0.001	-0.02	-0.000	-0.055	***	***
Côte d'Ivoire	2002	2015	0.461	0.342	0.501	0.392	-0.009	-0.02	-0.008	-0.019	***	***
Dominican Republic	2000	2013	0.104	0.104	0.089	0.090	0.000	0.00	0.000	0.001		**
Ecuador	1998	2014	0.114	0.060	0.101	0.035	-0.003	-0.04	-0.004	-0.066	***	***
El Salvador	2000	2014	0.148	0.088	0.143	0.070	-0.004	-0.04	-0.005	-0.051	***	***
Ethiopia	2000	2011	0.478	0.565	0.570	0.628	0.008	0.02	0.005	0.009	***	***
Ghana	1998	2012	0.360	0.447	0.389	0.487	0.006	0.02	0.007	0.016	***	***
Guatemala	2000	2011	0.167	0.124	0.171	0.118	-0.004	-0.03	-0.005	-0.034	***	***
Guinea	2002	2012	0.633	0.586	0.679	0.623	-0.005	-0.01	-0.006	-0.009	***	***
Honduras	1999	2011	0.104	0.086	0.089	0.068	-0.001	-0.02	-0.002	-0.022	***	***
Kenya	1997	2005	0.279	0.304	0.305	0.338	0.003	0.01	0.004	0.013	***	***
Kosovo	2002	2011	0.096	0.050	0.075	0.013	-0.005	-0.07	-0.007	-0.193	***	***
Laos	2002	2012	0.447	0.286	0.545	0.297	-0.016	-0.04	-0.025	-0.061	***	***
Lithuania	2000	2008	0.045	0.058	0.030	0.025	0.002	0.03	-0.001	-0.023	***	***
Madagascar	1999	2012	0.578	0.474	0.655	0.556	-0.008	-0.02	-0.008	-0.013	***	***
Mexico	2000	2012	0.054	0.043	0.038	0.027	-0.001	-0.02	-0.001	-0.027	***	***
Mongolia	2002	2009	0.184	0.175	0.207	0.189	-0.001	-0.01	-0.003	-0.013	***	***
Mozambique	2002	2008	0.613	0.612	0.657	0.670	-0.000	-0.00	0.002	0.003	**	**
Namibia	2003	2009	0.227	0.177	0.253	0.176	-0.008	-0.04	-0.013	-0.060	***	***
Nicaragua	1998	2009	0.179	0.156	0.181	0.153	-0.002	-0.01	-0.003	-0.015	***	***
Nigeria	2003	2009	0.289	0.303	0.312	0.341	0.002	0.01	0.005	0.015	***	***
Pakistan	2001	2011	0.369	0.275	0.423	0.306	-0.009	-0.03	-0.012	-0.032	***	***
Paraguay	1999	2012	0.081	0.082	0.059	0.060	0.000	0.00	0.000	0.001	***	
Peru	2000	2014	0.151	0.091	0.147	0.070	-0.004	-0.04	-0.005	-0.053	***	***
Philippines	1997	2015	0.154	0.059	0.150	0.039	-0.005	-0.05	-0.006	-0.074	***	***
Romania	2001	2013	0.142	0.098	0.166	0.101	-0.004	-0.03	-0.005	-0.041	***	***
Rwanda	2000	2010	0.558	0.534	0.630	0.612	-0.002	-0.00	-0.002	-0.003	***	***
Serbia	2003	2010	0.087	0.034	0.034	0.002	-0.007	-0.13	-0.005	-0.427	***	***
South Africa	2002	2008	0.125	0.059	0.119	0.031	-0.011	-0.13	-0.015	-0.223	***	***
Swaziland	2000	2009	0.220	0.160	0.230	0.151	-0.007	-0.04	-0.009	-0.047	***	***
São Tomé and Principe	2000	2010	0.202	0.256	0.204	0.276	0.005	0.02	0.007	0.030	***	***
Tanzania	2000	2014	0.443	0.381	0.525	0.458	-0.004	-0.01	-0.005	-0.010	***	***
Timor-Leste	2001	2007	0.418	0.349	0.459	0.383	-0.011	-0.03	-0.013	-0.030	***	***
Turkey	2003	2012	0.054	0.039	0.032	0.017	-0.002	-0.04	-0.002	-0.071	***	***
Ukraine	2002	2013	0.084	0.047	0.068	0.029	-0.003	-0.05	-0.004	-0.078	***	***
Uruguay	2000	2014	0.032	0.025	0.005	0.003	-0.000	-0.02	-0.000	-0.038	***	***
Venezuela, RB	2000	2006	0.061	0.053	0.033	0.026	-0.001	-0.02	-0.001	-0.039	***	***
Vietnam	1998	2008	0.356	0.211	0.467	0.239	-0.014	-0.05	-0.023	-0.067	***	***
Zambia	1998	2015	0.360	0.293	0.414	0.337	-0.004	-0.01	-0.005	-0.012	***	***
Zimbabwe	2001	2007	0.267	0.275	0.313	0.337	0.001	0.00	0.004	0.012	***	***
Aggregate (pop. weight. average)							-0.004	-0.03	-0.006	-0.049		

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

To analyse the aggregate trends, we also calculated the population-weighted mean changes (both proportional and absolute) for the two periods (last line of Table 1).[27] In aggregate terms, multidimensional poverty declined in absolute terms by nearly 0.4 percentage points annually, and in relative terms by 2%.

The 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 the case of Lithuania. In the case of Paraguay, however, both indices show an increase in poverty, but this is not statistically significant in the case of the G-M_0. If we look at the overall change, the decrease in the G-M_0 is higher than the overall decrease in the G-CSPI.[28]

In summary, multidimensional poverty has decreased in about 84% of the low- and middle-income countries examined. The situation looks worrisome in SSA, however, where about one-third of the countries experienced a rise in poverty.

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 – 45 out of the initial sample of 55 – we also have some estimates of our indices for (one or several) intermediate periods. In particular, for countries in LAC we have, on average, 12 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.[29] Figures A1-A4 in the Appendix show the values by period and country, for both the G-CSPI and the G-M_0.[30]

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[27] Weights were assigned to each country for each period based on the country's share of the population in the 15–65-year-old age group.

[28] A further comparison in country-level trends based on the G-CSPI and the G-M_0 computed with k=1 reveals that the sign of the change differs for only one country, Mozambique.

[29] The countries with just two data points are Cape Verde, Chad, Mozambique, Namibia, Nigeria, Swaziland, São Tomé and Principe, Timor-Leste and Zimbabwe.

[30] Apart from the use of all the available data points, the importance of looking at all data points arises from the length of the periods considered. As explained in Section 3, on average the number of years between the endline and baseline years is 10.7 (from a minimum of six years to a maximum of 18 years).

As a first exercise, we checked 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 11 countries (out of 45) there was no change of direction compared to the general trend, while in 34 countries there was at least one change. Similarly, when considering the G-M_0, in 10 countries there was a change of direction in at least one sub-period.[31] In particular, we are interested in verifying whether the identified changes in direction compared to the overall trend were large, defined as being at least 2% proportionally or one percentage point.[32] Based on the G-CSPI, only eight countries (18%) experienced this deviation from the general trends, while the number slightly increases when we employ the G-M_0 (10).

For those countries that either always had a decrease or always an increase in poverty in all the sub-periods, we checked whether there were periods of clear acceleration or deceleration. For any country where there was at least a sub-period with a relative annualised change at least twice as large as the overall relative annualised change we concluded that the trend was not linear. Following this approach, based on both the G-CSPI and the G-M_0, 32 countries did not experience linear trends. In conclusion, only for the 12 remaining countries (out of the 45 with more than two data points) does the hypothesis of linear trend hold.[33]

5. Decomposition analysis

5.1 Trends by poverty component

Using the G-CSPI we analysed the (absolute and relative) changes in the three poverty components – incidence, intensity and inequality – between 2000 and the latest available year.[34] As shown in Figure 1, in none of the 55 countries was there an

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[31] Chile between 2011 and 2013 represents the only exception, as it experienced an increase in the G-M_0 and a decline in the G-CSPI.

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

[33] When considering the G-SPI. These countries are: Albania, Bangladesh, Bhutan, Ghana, Guatemala, Kosovo, Laos, Nicaragua, Pakistan, Philippines, Turkey, Vietnam.

[34] As emphasised in Section 3, by construction the different components contribute to the final value of the two indices, G-CSPI and G-M_0, in different ways. See, in particular, footnote 12.

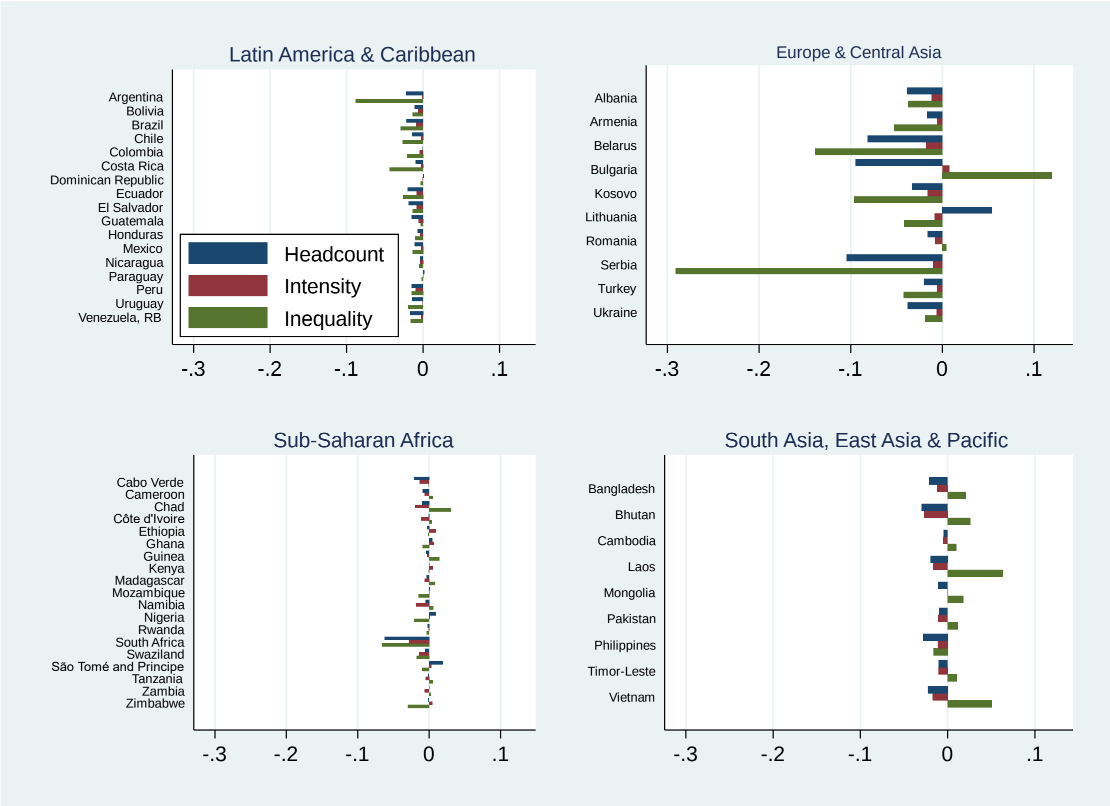
increase in deprivations in all three components. On the other hand, for 23 countries deprivations in all three components decreased. This was especially the case in LAC and ECA. More specifically, in our sample of 55 countries, there was a statistically significant decline in the headcount in 45, in the intensity in 45, too and, finally, in the inequality component in 37.[35] This reveals that the inequality component, captured with our G-CSPI, is the one that was reduced in the lowest number of countries.

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%), followed by Bulgaria, Belarus and South Africa (all between 5% and 10%). The largest increase was witnessed by Lithuania (over 5%). While the intensity decreased the most in South Africa and Bhutan (over 2%), Kenya, Ghana, Bulgaria and Ethiopia witnessed the highest increase (over 0.5%). Finally, the largest relative change in the intensity (-29%) was registered in Serbia, followed by Belarus and Kosovo (10% and 14%, respectively). The sharpest increase occurred in Vietnam, Laos and Bulgaria (over 5%).

Moving our attention to the regional level, we noticed that the increase in the inequality component was highly concentrated in SSA and, even more so, in the aggregated East Asia–Pacific and South Asia region. Indeed, in 42% of the countries in SSA (8/19) there was a rise in inequality among the poor. This value goes up to 88% (8/9) in Asian countries (other than central Asia), the only exception here being the Philippines.

[35] In all the other cases, there was a statistically significant increase in the components at the 1% significance level. The only exceptions are the headcount for Cambodia and the intensity for Mozambique, where no statistically significant change was detected even at the 10% significance level.

Figure 1: Relative changes over time of G-CSPI components, by country and region



Source: Authors' own elaboration

Finally, we repeated the analysis for the G-M_0 (see Figure A5). As clarified in Section 2.4, this index includes only two components: headcount and intensity. We detected a statistically significant decline in the headcount in 45 countries, and in the intensity in 41. For 35 countries, both components decreased. In line with the findings of Dotter and Klasen (2014) for the MPI, the size of the relative change was much higher for the headcount as compared to the intensity, indicating that the temporal changes in the G-M_0 were almost entirely driven by changes in the headcount.

In conclusion, there was a substantial reduction in all the components of poverty. However, a lower number of countries managed to alleviate multidimensional poverty by acting on the inequality component. This important information for policy makers would be disregarded without the use of a distribution-sensitive index of poverty, such as the G-CSPI.

5.2 Trends by poverty dimension

This sub-section deals with the decomposition of the trends by poverty dimension. As explained in Section 2.4, for this purpose we used 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.

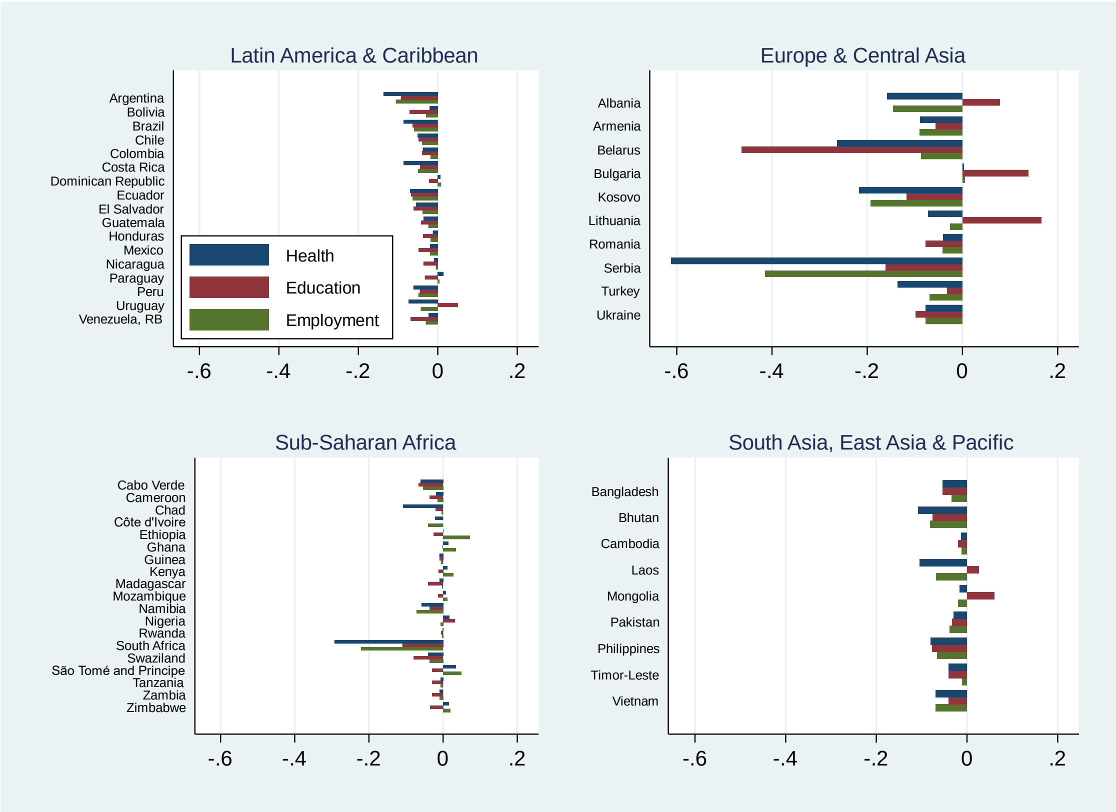
The majority of countries witnessed decreases in all dimensions. Out of 55 countries in our sample, 45, 48 and 46 had a reduction in health, education and employment deprivations, respectively. In summary, 40 countries had fewer deprivations in all three dimensions, while only one country, Bulgaria, had more 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 decreases in health deprivations were in Serbia (61%), South Africa, Belarus and Kosovo (all above 20%). Conversely, Kenya, Ghana, Paraguay, Zimbabwe, Nigeria and São Tomé and Principe faced an increase in health deprivations of over 1%. For education, Belarus had the greatest decrease (46%), while Bulgaria and Lithuania had increases of more than 10%. Finally, Serbia witnessed by far the largest relative change in employment (-41%), followed by South Africa (-22%). The largest increase happened in Mozambique, Zimbabwe, Kenya, Ghana, São Tomé and Principe, and Ethiopia (all over 1%).

Again, SSA presents the most heterogeneous picture: in seven of the 19 countries in the region, there was a rise in the G-M_0 for at least one dimension: seven increases in health; one (Nigeria) in education; and six in employment. In LAC, 14 countries out of 17 showed a decrease in all dimensions; Uruguay increased deprivation in education, while Dominican Republic and Paraguay increased deprivations in both health and employment. However, the size of the changes in LAC was very small. Similarly, ECA had just three countries (Bulgaria, Albania, Lithuania) with a slight decrease in education, and Asia had two (Laos and Mongolia).

Looking at the aggregate average figures, health deprivations decreased by 5.9% in relative terms and by 0.3 percentage points in absolute terms; education by 4.5% and by 0.1 percentage points; finally, employment by 4.3% and 0.2 percentage points (see Figure 2).

Figure 2: Relative changes over time of G-M_0 dimensions, by country and region

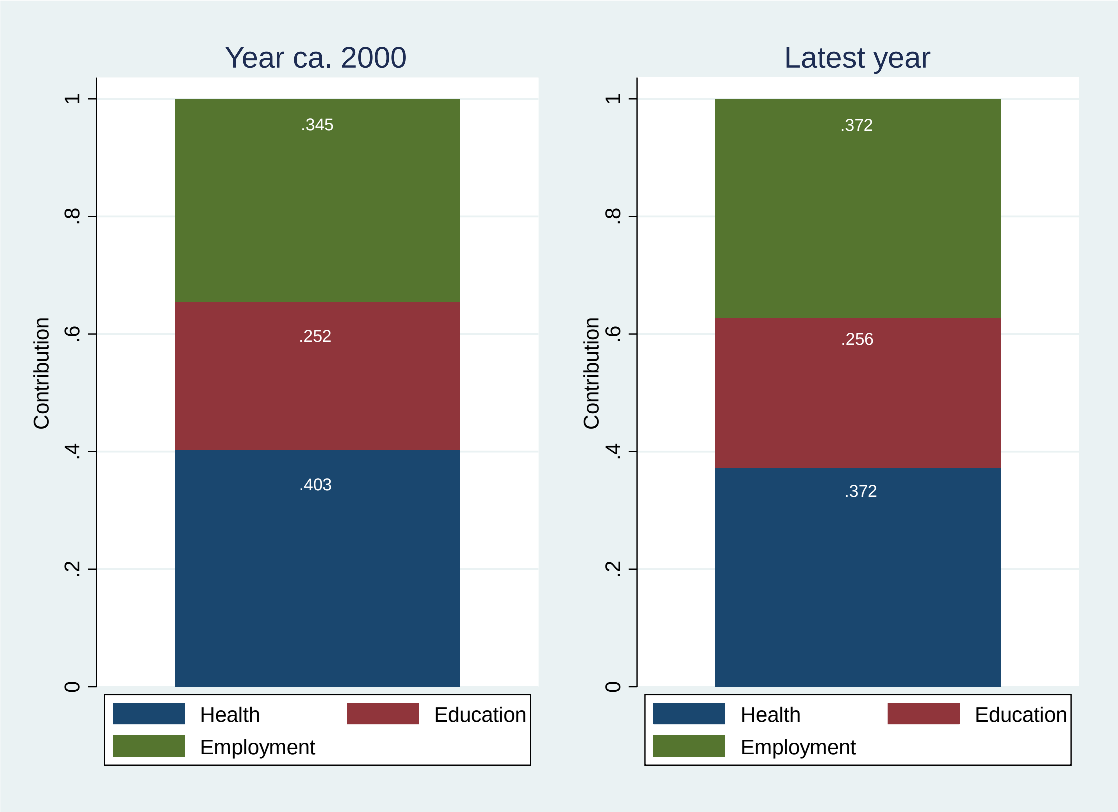


Source: Authors' own elaboration

As a consequence, the relative contributions of the three dimensions to the overall G-M_0 also changed, as shown in Figure 3. It is therefore 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 sanitation – also a proxy for health deprivations – accounted for 40.3% of overall multidimensional poverty, while employment and education deprivations accounted for 34.5% and 25.2%, respectively. In the latest available year, the contribution of employment appears higher (37.2%) and identical to that of health, while the contribution of education remains about the same (25.6%). These results point again to the relatively slower progress in alleviating employment deprivations.[36]

[36] The shares presented in Figure 3 should be viewed with caution as figures from different years were aggregated (and are therefore not fully comparable). This has been done for illustrative reasons.

Figure 3: Percentage contribution of each dimension to the overall G-M_0 c. 2000, and latest survey (population-weighted average)



Source: Authors' own elaboration

5.3 Trends in rural and urban poverty

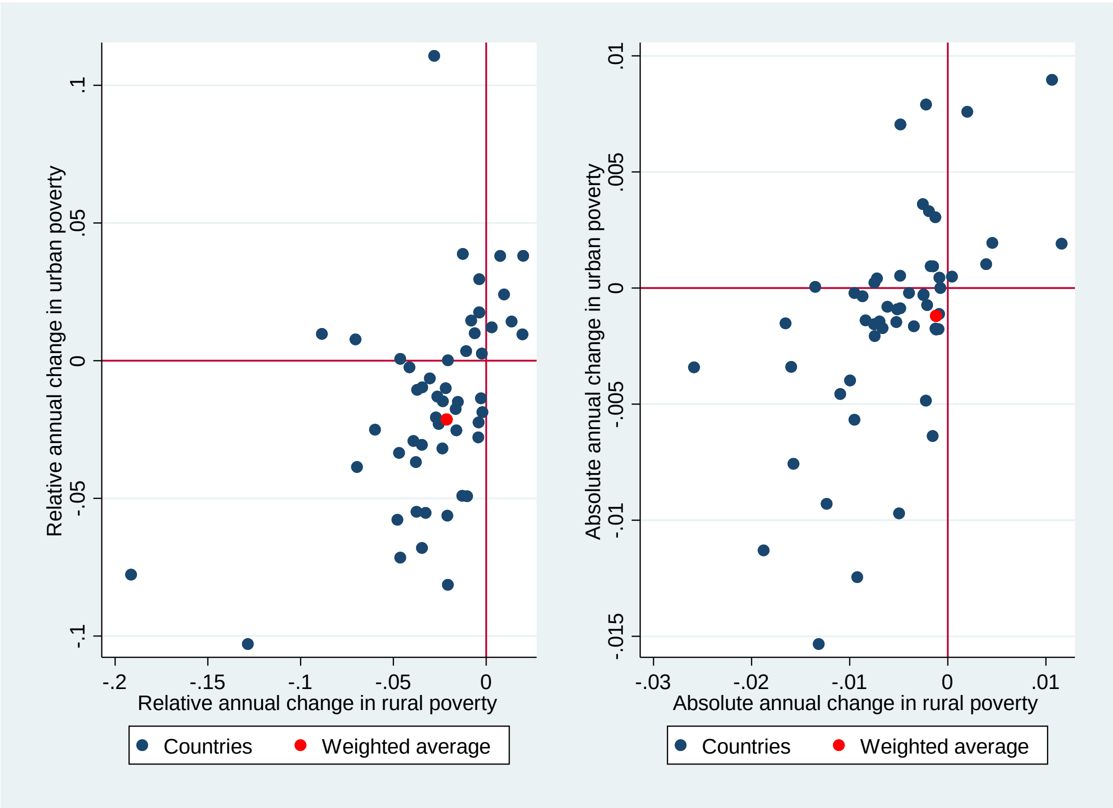
To understand better the country-level poverty trajectories, we analysed the trends in urban and rural areas separately. Figure 4 depicts the long-run annual trends for urban and rural areas for the single countries and the (population-weighted) average (red dot). In order to do this, four countries – South Africa, Philippines, Laos and Venezuela – were removed from the analysis because at least one of the samples, rural and urban, had too many missing values. For two countries – Argentina and Uruguay – there was no observation for rural areas as the household surveys cover only urban areas, given their geographic conformation. Therefore, Argentina and Uruguay are included in the computation of the estimates of the aggregated urban poverty change but do not appear in the figure.

Figure 4 shows that the majority of countries – 31, equivalent to 63.3% of the sample – managed to reduce both urban and rural poverty. For 12 countries, urban poverty increased while rural poverty decreased; in no country did the opposite occur. Finally, six countries experienced an increase in both urban and rural poverty.

In 33 countries, rural areas had faster rates of poverty reduction (or slower rates of poverty increase), while in 16 these rates were faster in urban areas. As a consequence, the average relative annualized change is higher for rural areas (2.6%) compared to urban ones (2.2%). Therefore, there is some indication of convergence between rural and urban areas. Compared to the results of Alkire et al (2017), however, the convergence identified in our study is substantially lower. The difference in the results could be related to the differences in the poverty indices employed, in the sample of countries, or in the time interval examined.

The picture looks very similar with the G-M_0. In this case too, 31 countries managed to reduce both urban and rural poverty and in none of the countries was there a simultaneous increase in both urban and rural poverty.

Figure 4: Relative changes in urban and rural G-CSPI



Source: Authors' own elaboration

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, since in most of the cases the survey that was used to calculate the G-CSPI and the G-M_0 was the same as that used to measure income poverty. Only in a few cases was this not so, but it was still conducted in the same year. In contrast, the comparison between the trends in multidimensional and income poverty presented in Alkire et al (2017, p 239) is problematic. This is because the global MPI is calculated predominantly on the Demographic and Health Surveys, which have a very different sample size and sampling strategy from the surveys used for the calculation of monetary poverty. Even more relevant is the fact that the two types of surveys are conducted in different years. Therefore, it is hard to say if diverging country trends in monetary and multidimensional poverty are genuinely to the result of 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.[37]

Merging our dataset with data from PovcalNet on income poverty led us to drop 13 countries where the observations (country/year) lacked information on monetary poverty.[38] Of the original sample of 55 countries, the analysis in this section includes 42 countries with complete data for the baseline and endline periods. The analysis uses the extreme international poverty line of US$1.90 a day, adjusted for purchasing power parity, which is the poverty line used to track progress in SDG 1.

[37] In order to achieve this, we keep the country-year observations with both multidimensional and income poverty.

[38] The countries that were dropped are Argentina, Bangladesh, Cape Verde, Cambodia, Ethiopia, Guatemala, Kosovo, Mongolia, South Africa, Uruguay, Venezuela, Zimbabwe. As I2D2 and PovcalNet do not follow the same method to identify the survey year, when a survey was run in two consecutive years, we adjusted the PovcalNet survey year to match that of I2D2.

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 measures 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 include this analysis since it is the best known and most used measure of poverty in the monetary space.

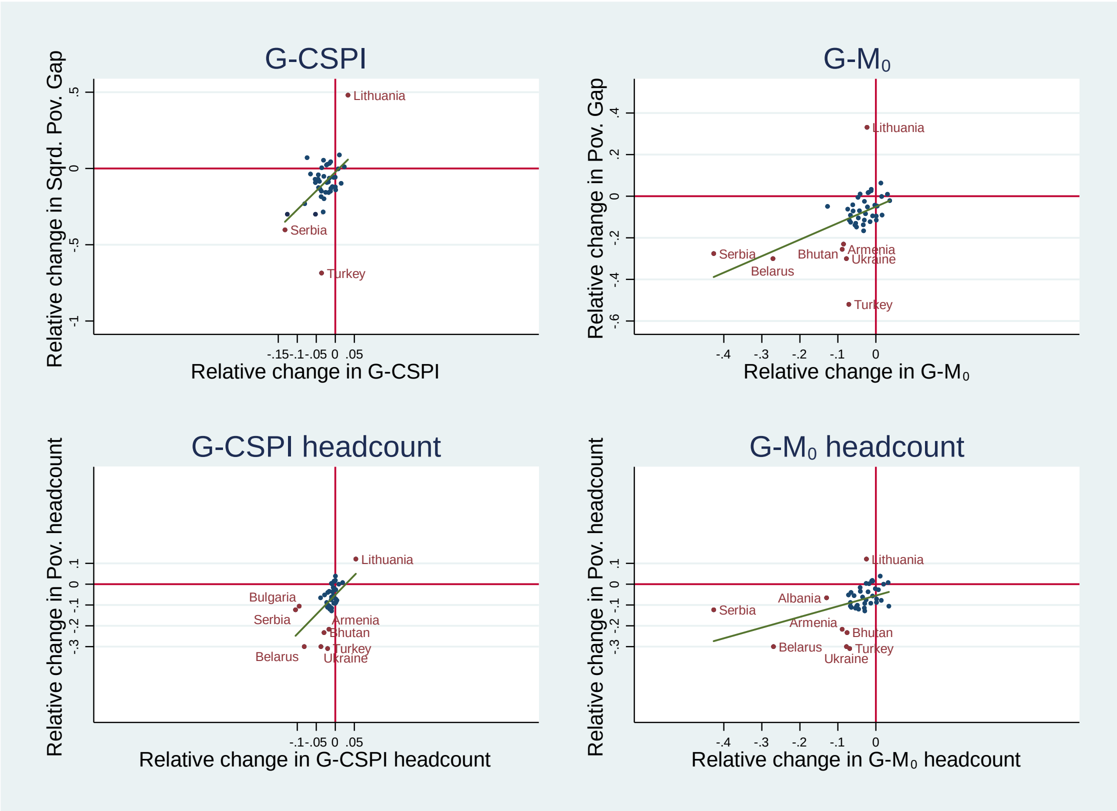
The upper-left quadrant of Figure 5 shows the relationship between the relative changes of the G-CSPI and those of the squared poverty gap.[39] As expected, there is a positive correlation. However, the intensity of this relationship is not strong, as confirmed by the Pearson's coefficient (0.45) and, even more, by the Spearman's coefficient (0.28). The relationship between income and multidimensional poverty is even weaker when we use the G-M_0 instead of the G-CSPI (upper-right quadrant of Figure 5) and the income poverty gap instead of the squared poverty gap, with the Pearson's coefficient only being equal to 0.42. Moreover, in none of the two cases, especially for the G-M_0, does the relationship seem linear. There are several outliers. Most of them, however, are countries with relatively low scores of multidimensional poverty around 2000.[40] The only clear exception is Bhutan, which managed to reduce both forms of poverty, but relatively more the income poverty gap as compared to the G-M_0.

The lower quadrants of Figure 5 show the correlation between changes in the income poverty headcount and, respectively, the G-CSPI and the G-M_0 headcounts. For the case of the G-CSPI headcount, the Pearson's coefficient (0.47) is similar to the case of the G-CSPI. On the other hand, the correlation between the income poverty headcount and the G-M_0 headcount is even lower (0.33).

[39] Ukraine and Belarus are excluded from the figure and the computation of the correlation coefficients as all indicators of monetary poverty are zero for the latest year.

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

Figure 5: Relative changes in multidimensional and income poverty



Source: Authors' own elaboration

Based on the G-CSPI, for 31 countries, equivalent to about 74% of the sample, at least the direction of the changes was the same for the two indices (see Table 2). Specifically, 28 countries managed to reduce both income and multidimensional poverty, while both types of poverty increased in three countries: Kenya, Lithuania and São Tomé and Principe. In 11 cases, the direction of change was different,[41] 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 over-representation of countries from SSA in this group of 'outliers': they represent 63.6% (7/11) of the sample, while they form 'only' 33.3% (14/42) of it for this empirical analysis. This means that particularly in this region – the region with the highest poverty scores in

[41] For some of them the direction of the trend is not so clear, as the change is very close to zero. Given that Povcalnet does not compute the standard errors for the income poverty figures, we cannot make causal inferences and discover whether the changes in the two types of poverty are statistically significant.

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. In particular, the number of countries succeeding in alleviating both income and multidimensional poverty is substantially stable (28 or 29).

Finally, we analysed the aggregated trends, using the population-weighted means of 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 four times lower than the decline in monetary poverty.

Table 2: Direction of change for multidimensional and income poverty, by indicator

	G-CSPI (G-CSPI headcount)					G-M_0 (G-M_0 headcount)		
Income poverty, US$1.90 a day – PPP Squared poverty gap (headcount ratio)		Increase	Decrease	Countries	Income poverty, US$1.90 a day – PPP poverty gap (headcount ratio)	Increase	Decrease	Countries
	Increase	3 (5)	7 (4)	10 (9)		2 (3)	6 (6)	8 (9)
	Decrease	4 (4)	28 (29)	32 (33)		6 (5)	28 (28)	34 (33)
	Countries	7 (9)	35 (33)	42 (42)		8 (8)	34 (34))	42 (42)

Source: Authors' own elaboration

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 has been to analyse the trends in multidimensional poverty in low- and middle-income countries during the period of the MDGs. While several studies have shown a massive reduction in income poverty, little was actually known about deprivations in other dimensions, especially when examined by means of composite indices.

This paper relies on two new indices of multidimensional poverty, the Global Correlation Sensitive Poverty Index (G-CSPI) and the G-M_0, calculated for more than 550 household surveys (Burchi et al, 2018b). These indices have various advantages compared with existing ones, including the well known MPI. First, they are individual-based indices of poverty, while the MPI is constructed at the household level. Therefore, we can directly explore intra-household differences (eg by gender) without having to make risky assumptions about intra-household 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. Our two indices differ in the poverty measure used. The G-CSPI uses the CSPI, which endorses a fuzzy identification function, and permits the capture of inequality among the poor. The G-M_0, rather, uses the M_0 measure and identifies as poor all individuals with deprivations in two or three dimensions. It has the main advantage of being easily and fully decomposable by dimension. This way, we were also able to test the robustness of poverty trends to alternative indices.

The main objective of the paper was to analyse the changes in multidimensional poverty for the first time in a large sample (55) of low- and middle-income countries. This is the biggest sample so far in the literature; in particular, for 35 countries we provided information on multidimensional poverty trends that has not been available in a comparative way. The analysis shows that, since 2000, there has been a statistically significant decline in poverty in 82% or 84% of the countries, based on the G-CSPI and the G-M_0, respectively. Substantial differences exist across regions, however. In particular, the progress in poverty eradication registered in SSA has been slow: almost one-third of the countries in this region in fact experienced an increase in multidimensional poverty. This confirms findings from studies on monetary poverty and points to the existence of poverty traps.

The paper then tried to shed some light on the drivers of poverty trends through different decomposition analyses. First, it appears clear that most of the countries reduced poverty by acting on the headcount. In contrast, it was the inequality component that was reduced in the lowest number of countries, especially in Asia and SSA. This valuable information for policy makers can be obtained only by employing a poverty index sensitive to the inequality among the poor, such as the G-CSPI. This is particularly relevant in light of the overarching principle of the 2030 Agenda, "leaving no one behind".

Some additional analyses have revealed 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 which – together with health – contributes the most to overall poverty:

therefore, major attention should be given by policy makers to the functioning of labour markets. Furthermore, a separate analysis shows that rural poverty had a higher rate of decrease compared to poverty in urban areas in the majority of countries. In aggregate terms, this indicates a limited process of convergence in poverty between rural and urban areas.

Finally, the paper compared 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 other hand, compared with the few 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 conclusion are derived. First, the correlation between the changes in income and multidimensional poverty is not strong, and there are even a few countries 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 indicators of multidimensional poverty, the reduction in multidimensional poverty has been two to four times lower than that in income poverty. These findings highlight the fact that – once we take other, non-monetary dimensions into account – the progress in poverty eradication has not been as remarkable as believed, and calls for stronger efforts in tackling the different forms of poverty.

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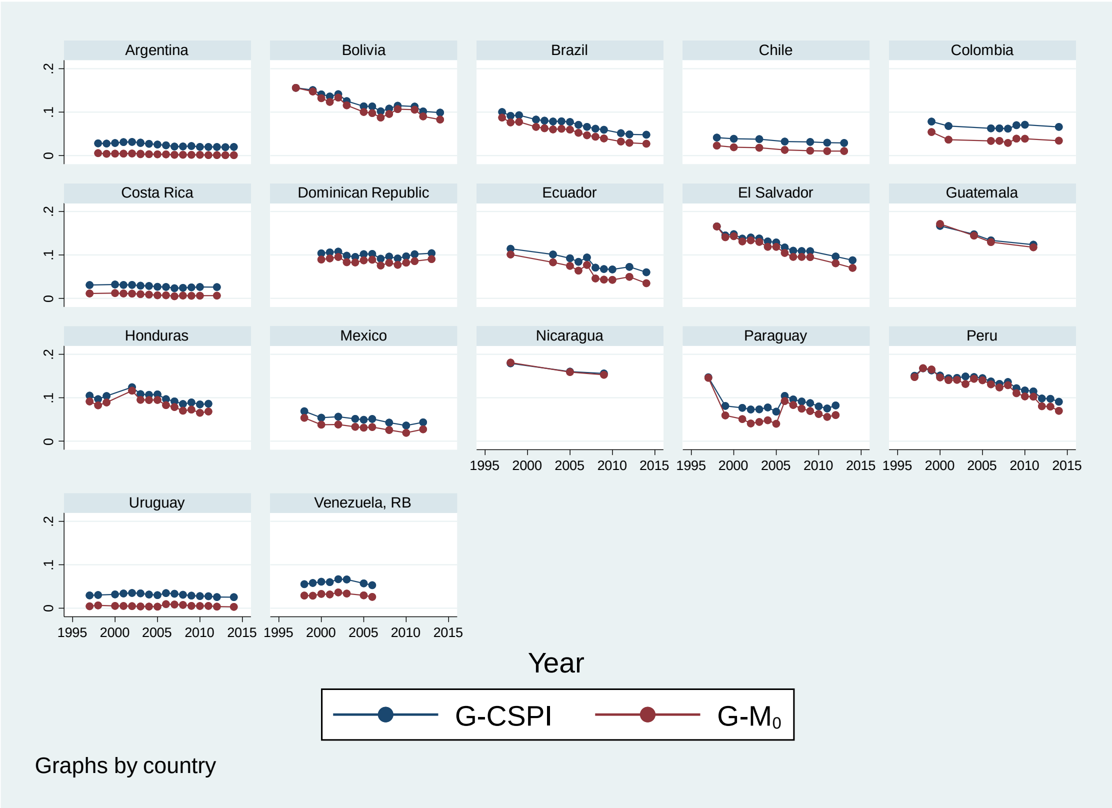
Appendix 1: Additional empirical analyses

Table A1: Values and changes over time of G-M_0 with k=1

	Start year	Final year	G-M_0 K1 start	G-M_0 K1 start (s.e.)	G-M_0 K1 final	G-M_0 K1 final (s.e.)	Abs. ann. change G-M_0 K1	Rel. ann. change G-M_0 K1	Significance of difference+++
Albania	2002	2012	0.209	0.002	0.126	0.001	-0.008	-0.05	***
Argentina	2000	2014	0.082	0.000	0.059	0.000	-0.002	-0.02	***
Armenia	2001	2011	0.166	0.001	0.132	0.001	-0.003	-0.02	***
Bangladesh	2003	2015	0.605	0.001	0.406	0.001	-0.017	-0.03	***
Belarus	2001	2010	0.100	0.001	0.041	0.000	-0.007	-0.10	***
Bhutan	2003	2012	0.554	0.004	0.332	0.002	-0.025	-0.06	***
Bolivia	2000	2014	0.255	0.002	0.201	0.002	-0.004	-0.02	***
Brazil	1999	2014	0.177	0.000	0.111	0.000	-0.004	-0.03	***
Bulgaria	2001	2007	0.103	0.001	0.061	0.001	-0.007	-0.09	***
Cape Verde	2000	2007	0.366	0.001	0.287	0.003	-0.011	-0.03	***
Cambodia	1997	2009	0.620	0.003	0.554	0.002	-0.006	-0.01	***
Cameroon	2001	2014	0.554	0.003	0.455	0.003	-0.008	-0.02	***
Chad	2003	2011	0.685	0.003	0.542	0.004	-0.018	-0.03	***
Chile	2000	2013	0.095	0.000	0.076	0.000	-0.001	-0.02	***
Colombia	1999	2014	0.171	0.001	0.159	0.001	-0.001	-0.00	***
Costa Rica	2000	2012	0.083	0.000	0.071	0.001	-0.001	-0.01	***
Côte d'Ivoire	2002	2015	0.579	0.003	0.493	0.002	-0.007	-0.01	***
Dominican Republic	2000	2013	0.202	0.002	0.205	0.002	0.000	0.00	***
Ecuador	1998	2014	0.225	0.002	0.143	0.001	-0.005	-0.03	***
El Salvador	2000	2014	0.268	0.001	0.183	0.001	-0.006	-0.03	***
Ethiopia	2000	2011	0.641	0.002	0.686	0.002	0.004	0.01	***
Ghana	1998	2012	0.504	0.003	0.584	0.002	0.006	0.01	***
Guatemala	2000	2011	0.290	0.002	0.231	0.002	-0.005	-0.02	***
Guinea	2002	2012	0.735	0.002	0.689	0.003	-0.005	-0.01	***
Honduras	1999	2011	0.204	0.002	0.179	0.001	-0.002	-0.01	***
Kenya	1997	2005	0.456	0.002	0.477	0.002	0.003	0.01	***
Kosovo	2002	2011	0.211	0.003	0.136	0.001	-0.008	-0.05	***
Laos	2002	2012	0.619	0.002	0.430	.	-0.019	-0.04	***
Lithuania	2000	2008	0.103	0.001	0.148	0.001	0.006	0.05	***
Madagascar	1999	2012	0.714	0.003	0.629	0.002	-0.006	-0.01	***
Mexico	2000	2012	0.117	0.001	0.099	0.001	-0.001	-0.01	***
Mongolia	2002	2009	0.322	0.003	0.299	0.001	-0.003	-0.01	***
Mozambique	2002	2008	0.718	0.004	0.724	0.003	0.001	0.00	***
Namibia	2003	2009	0.373	0.002	0.323	0.002	-0.008	-0.02	***
Nicaragua	1998	2009	0.305	0.002	0.279	0.002	-0.002	-0.01	***
Nigeria	2003	2009	0.439	0.001	0.466	0.001	0.005	0.01	***
Pakistan	2001	2011	0.521	0.002	0.424	0.001	-0.010	-0.02	***
Paraguay	1999	2012	0.176	0.002	0.179	0.002	0.000	0.00	***
Peru	2000	2014	0.270	0.002	0.191	0.001	-0.006	-0.02	***
Philippines	1997	2015	0.262	0.001	0.129	.	-0.007	-0.04	***
Romania	2001	2013	0.253	0.001	0.191	0.001	-0.005	-0.02	***
Rwanda	2000	2010	0.697	0.003	0.675	0.002	-0.002	-0.00	***
Serbia	2003	2010	0.226	0.001	0.102	0.001	-0.018	-0.11	***
South Africa	2002	2008	0.244	0.001	0.141	0.000	-0.017	-0.09	***
Swaziland	2000	2009	0.367	0.003	0.309	0.003	-0.007	-0.02	***
São Tomé and Principe	2000	2010	0.364	0.003	0.455	0.003	0.009	0.02	***
Tanzania	2000	2014	0.596	0.003	0.547	0.003	-0.004	-0.01	***
Timor-Leste	2001	2007	0.562	0.006	0.495	0.004	-0.011	-0.02	***
Turkey	2003	2012	0.123	0.000	0.097	0.001	-0.003	-0.03	***
Ukraine	2002	2013	0.183	0.001	0.113	0.001	-0.006	-0.04	***
Uruguay	2000	2014	0.090	0.000	0.073	0.000	-0.001	-0.01	***
Venezuela, RB	2000	2006	0.145	0.001	0.129	0.000	-0.003	-0.02	***
Vietnam	1998	2008	0.545	0.002	0.365	0.001	-0.018	-0.04	***
Zambia	1998	2015	0.510	0.002	0.460	0.002	-0.003	-0.01	***
Zimbabwe	2001	2007	0.412	0.002	0.420	0.002	0.001	0.00	***

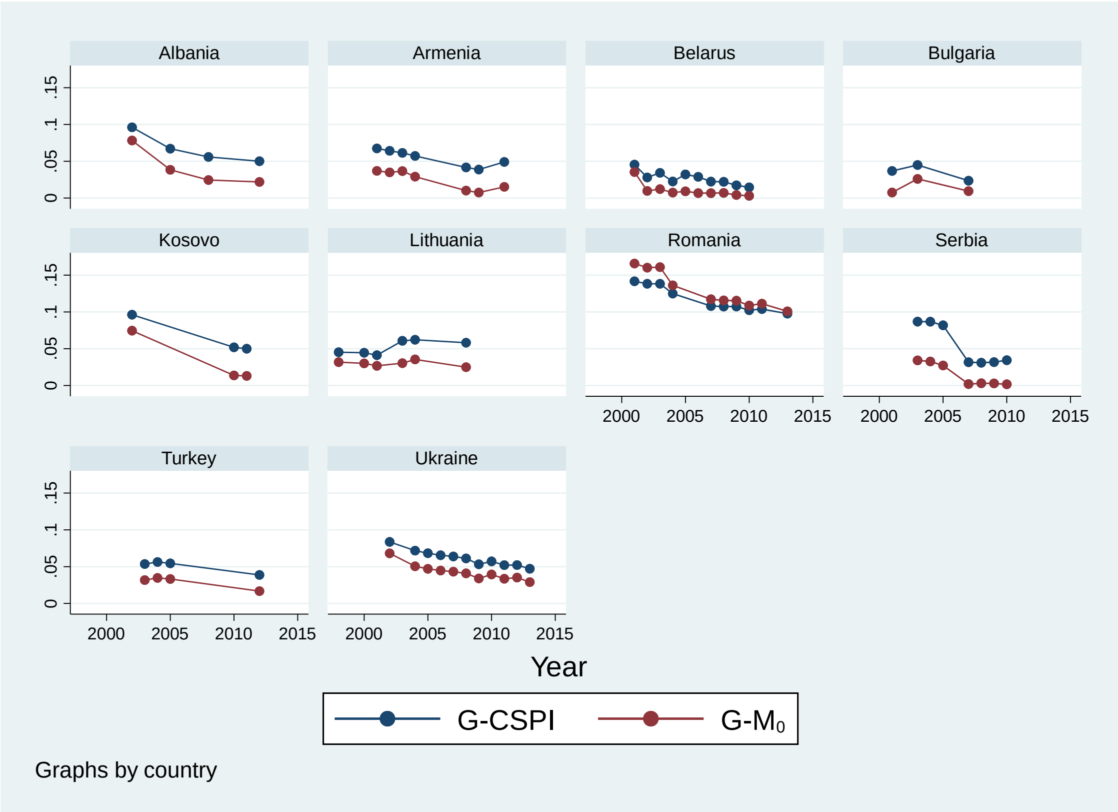
Note: +++Significance: *** = 1%; ** = 5%; * = 10%.
Source: Authors' own elaboration.

Figure A1: Values over time of G-CSPI and G-M_0, by country in LAC



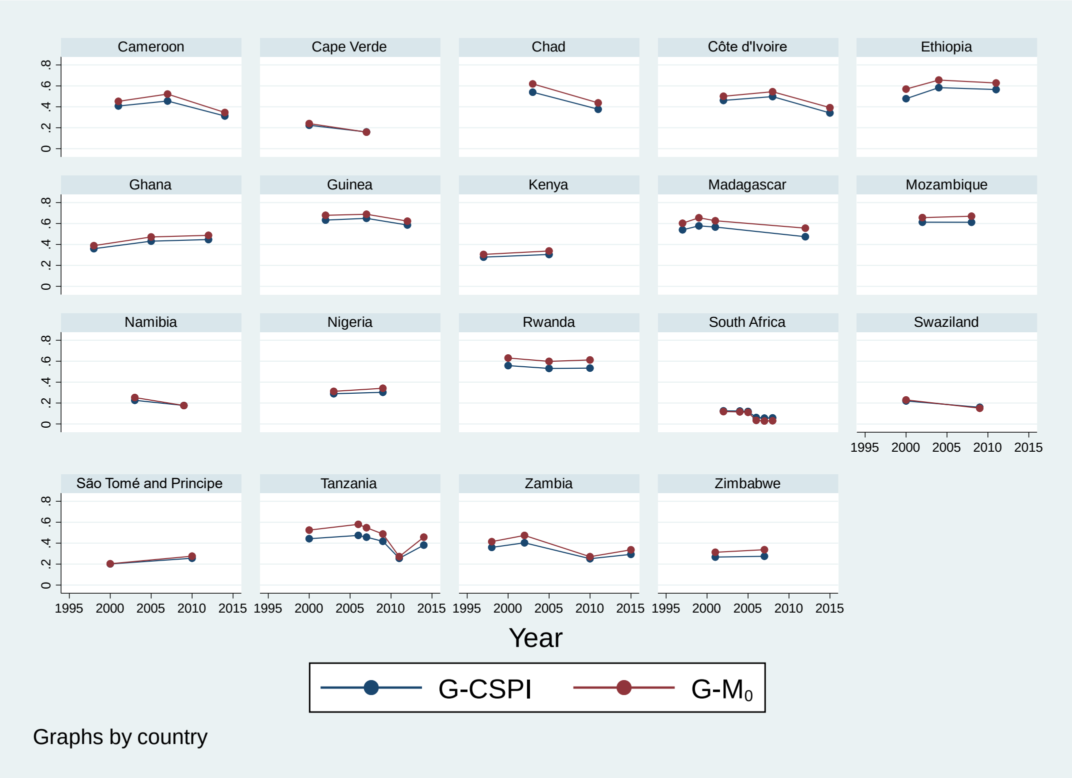
Source: Authors' own elaboration.

Figure A2: Values over time of G-CSPI and G-M_0, by country in ECA



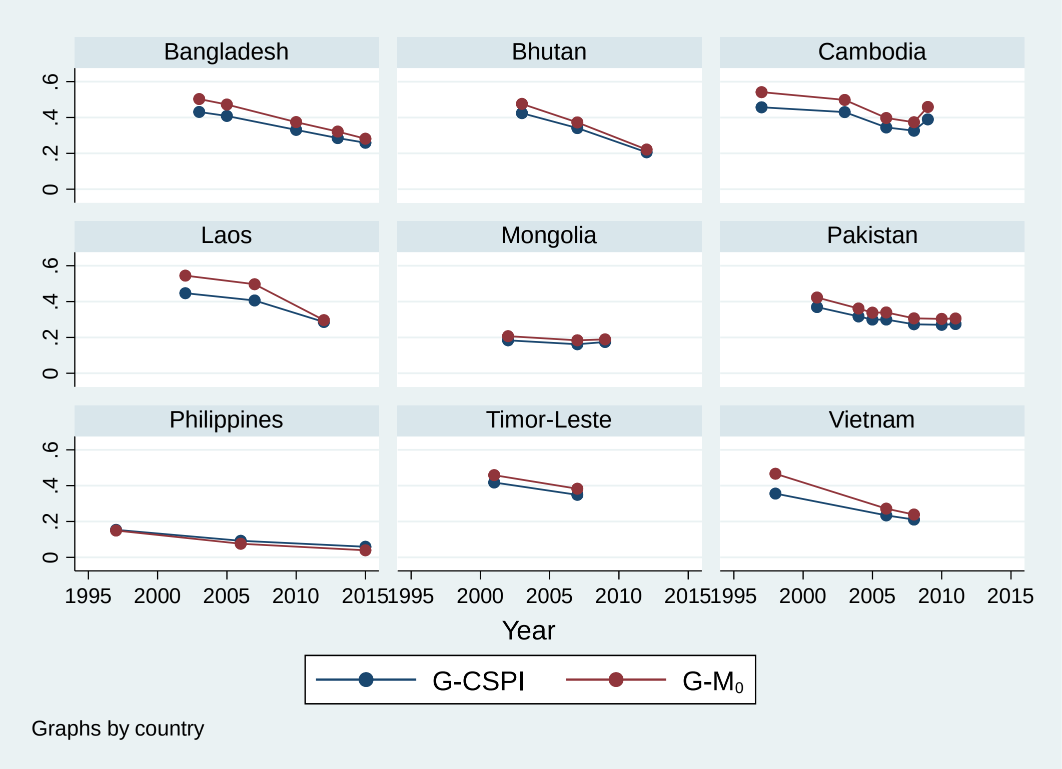
Source: Authors' own elaboration.

Figure A3: Values over time of G-CSPI and G-M_0, by country in SSA



Source: Authors' own elaboration.

A4: Values over time of G-CSPI and G-M_0, by country in EAP & SA



Source: Authors' own elaboration.

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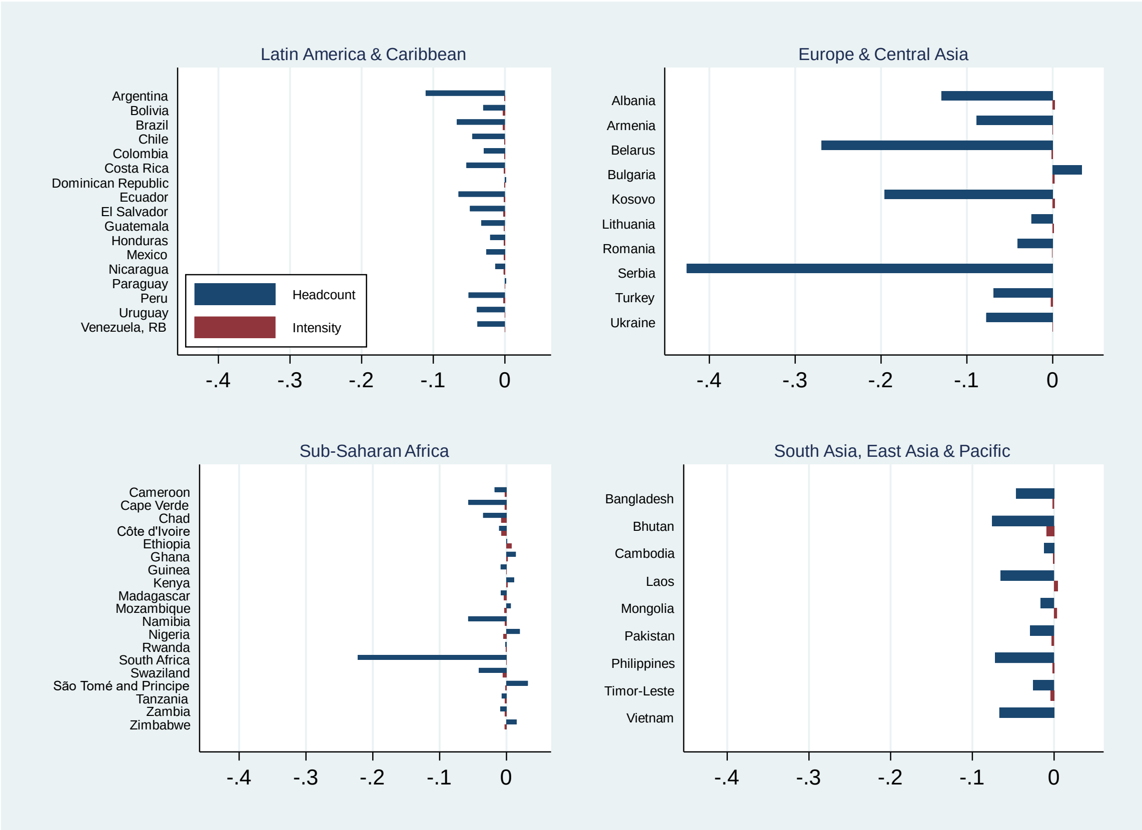
Figure A5: Relative changes over time of G-M_0 components, by country and region



Source: Authors' own elaboration.