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Monetary and Multidimensional Poverty: Correlation, Mismatches, and a Combined Approach

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ABSTRACT *We consider the relationships between multidimensional and monetary poverty indices in international and national poverty profiles, and empirically explore the consequences of identifying poor people relying on a combination of both approaches. Taking first a cross-country perspective, focusing on 90 countries in the developing world, we corroborate that the incidence of poverty by money metrics and the global Multidimensional Poverty Index, a non-monetary measure of poverty, are correlated. Digging deeper, we use microdata from six countries—Bolivia, Brazil, Ecuador, Ethiopia, Ghana, and Uganda—to study the joint densities of monetary and multidimensional welfare and the poverty identification mismatches for a comprehensive array of poverty line pairs. Mismatches are important, particularly in the poorer countries. Although mismatches could be avoided by combining both approaches in a dual cutoff-based poverty measure, the choice of the monetary poverty line remains a considerable issue as it changes the nonmonetary composition of poverty.*

KEYWORDS: Poverty measurement; developing world; poverty identification mismatch; distributional analysis; poverty lines; multidimensional poverty

JEL CODES: I31; I32; D31

1. Introduction

Eliminating poverty is a pressing issue in development policy and recent developments in multidimensional poverty analysis have improved our understanding of complexity and the ability of poverty measures to capture it. The ways in which human lives can be impoverished are inherently plural (Alkire & Santos, 2014; Laderchi et al., 2003; Sen, 1976; 1980; 1988), yet the dominance of monetary approaches remains in many development analyses (see e.g., Gamboa et al., 2020; Sumner, 2007). There has, however, been a rapid and wide acceptance of a need to adopt a wider multidimensional notion of poverty to effectively identify people who suffer welfare

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deprivations (Atkinson, 2019). We focus our analysis and arguments on recent initiatives that have created multidimensional poverty indices that combine both monetary and non-monetary measurement (e.g., Santos & Villatoro, 2018; World Bank, 2018).

Understanding how and why different approaches to poverty capture different types of deprivations is a fundamental matter for effective policy against poverty. Policy can vary greatly depending on who is identified as poor and how much poverty is found in a society. There is little consensus on the extent to which monetary shortfalls can be considered as good proxies for many human welfare deprivations (Atkinson et al., 2002; Nolan & Whelan, 1996; 2011). When analyzing the case of Bhutan, Santos (2013) made a strong case for identification mismatches when income is included within a set of deprivation indicators alongside non-monetary ones. People can be included or excluded from the poverty set depending on the chosen multidimensional poverty line insofar as income is an imperfect (i.e., partially correlated) indicator of non-monetary hardships. In fact, a large number of empirical studies found monetary and multidimensional poverty to be 'mismatched' (see e.g., Iceland & Bauman, 2007; Roelen, 2017; Santos, 2013; Suppa, 2016; Tran et al., 2015). For instance, in 2016, the government of Honduras noticed that although multidimensional and monetary poverty rates were similar (around 70%), the proportion of people that were poor by both measures was only around 50% (see OPHI-UNDP, 2019). Some studies make the case that each approach sheds a different and distinct light on understanding poverty and acting against it (Bag & Seth, 2018; Bradshaw & Finch, 2003; Laderchi, 1997). This may be the main reason why monetary and multidimensional poverty measures are normally considered as separate indicators for policy actions against human deprivations. Until recently, only a handful of multidimensional measures have considered income deprivations as in indicator of multidimensional poverty (such as the Latin American and the Caribbean MPI posited by Santos and Villatoro (2018), CONEVAL's multidimensional poverty measure for Mexico[1], and the Ecuador MPI[2]). Yet, the debate around the appropriateness of including a money metric in a multidimensional measure is far from being over. For instance, since 2020, the World Bank publishes the Multidimensional Poverty Measure, which is akin to the UNDP-OPHI global MPI in that it aims at being an internationally comparable measure of multifaceted poverty, but crucially replaces the health dimension with an income dimension (Diaz-Bonilla & Sabatino, 2022).

From a methodological perspective, the consensus for multidimensional poverty measurement in developing countries has been to use 'counting indices.' This form of measurement was directly recommended by Atkinson (2017) and subsequently adopted by the World Bank (2018). In this strand, the adoption of the Alkire-Foster method to compute the global Multidimensional Poverty Index (global MPI, Alkire and Santos (2014); OPHI (2018)) produced annually by the UNDP and the Oxford Poverty & Human Development Initiative (OPHI) since 2010 remains a highly influential measure of non-monetary aspects of poverty in the developing world (Atkinson, 2019). This index is also a key methodological constant for the many countries that have adopted national multidimensional poverty indices. This means that 'MPI indices' coexist with separate monetary valuations of poverty and there continues to be the real differences in terms of conceptualization, data, and method (Alkire et al., 2015; Ravallion, 2011).

In this paper we consider some empirical issues that arise from combining monetary and non-monetary poverty measures into a single counting index. What is gained and lost by such an approach, and how could it potentially influence the interpretation of poverty profiles across a range of countries? We first take a global perspective to analyse the cross-country relationship between these two measures, leading up to selected country case-studies to empirically assess the extent to which a poverty measure that combines the monetary and non-monetary approaches may reconcile mismatch and divergence. This is particularly relevant and timely as multidimensional poverty is now formally entrenched in the Sustainable Development Goals (SDGs) and targets for poverty reduction[3] following international development agencies such as UNDP, UNICEF and ECLAC had already adopted multidimensional poverty measurement prior to 2015 (UNDP., 2010; De Neubourg et al., 2013; Feres & Mancero, 2001) and the World Bank has adopted it since 2018. Both World Bank and ECLAC use combined indices that incorporate monetary poverty as a dimension of multidimensional poverty.

This paper empirically revisits the relationship between monetary and multidimensional poverty to set solid ground for a discussion about a measure that combines both. Our approach follows the conventions of poverty measurement that consists of first, identifying the poor population and then aggregating the poverty characteristics of different people into one overall measure. We take two complementary perspectives to gauge the extent to which differences in both approaches coincide in these two basic steps of poverty measurement. We first assess their relationship at the aggregate level in terms of correlation and the stability of orderings among 90 countries for which there is comparable information. That analysis allows us to choose a set of illustrative case-study countries that reflect stable and unstable comparisons of monetary and multi-dimensional headcounts. We then focus on data at the individual level coming from six case study countries (Bolivia, Brazil, Ecuador, Ethiopia, Ghana, and Uganda) to assess the similarity of poverty sets defined by both approaches using a joint distribution analysis. Finally, we compute an index for these six countries combining the structure of the global MPI with monetary welfare as an additional dimension of multidimensional poverty in order to empirically explore the main characteristics of such an index.

Through this, our paper seeks to contribute to the literature in three ways. First, focusing on the developing world, our approach allows for a comprehensive view of the issues surrounding relationships between monetary and multidimensional poverty, at both the aggregate and individual level. Second, our joint distribution analysis allows us to not only identify the mismatches and overlaps between the measures, but also the sensitivity of poverty classifications by both approaches. Third, by computing a combined index we are able to address the role of the monetary poverty line and its effect on the non-monetary characteristics of the poverty set, in a context where mismatches are avoided.

Our paper proceeds as follows. In Section 2 we present a brief discussion of the development of both approaches, highlighting why they are regularly considered as different but complementary to each other rather than overlapping. In Section 3 we present the methods that we use for our empirical analysis. In Section 4 we present the empirical relationship between both approaches at the aggregate country level. This allows us to justify the selection of our country case-studies. In Section 5 we use our data at the individual level to assess the poverty identification mismatches by both approaches. In Section 6 we explore the inclusion of monetary poverty in revised forms of multidimensional indices and the sensitivity of resulting indices to the monetary poverty threshold chosen. We discuss the findings in a concluding section that lays out further issues to be explored in future research.

2. The relationship between monetary and non-monetary poverty measures

Monetary and non-monetary approaches are unlikely to produce perfectly correlated welfare distributions. Differences between them can be expected from a range of factors. Non-monetary aspects of poverty, such as those dimensions within the global MPI (health, education and living standards, OPHI (2018); Alkire and Santos (2014)), can be determined by factors other than people's purchasing power. Many observable indicators of these dimensions, such as access to school, access to drinking water or adequate sanitation are often subjected to public provision or heavily subsidized. Even where indicators may be related to purchasing power, they reflect different assumptions about time. Monetary welfare is measured as a flow variable; it is observed at one point in time and likely to be volatile (Jolliffe & Ziliak, 2008). In contrast, many non-monetary indicators are inelastic stock variables, which are less likely to vary over short time spans, such as the education levels of adults or stunting in children.

Measurement error may also underlie differences. Measuring consumption and income is inherently more likely to include errors of response affecting the level of the final welfare aggregate, than relying on more verifiable indicators on the presence of goods in the household or of recorded participation. The methodologies for computing monetary welfare aggregates also vary hugely at the national level, not only between income and consumption but in the treatment of elements of income and consumption and the inclusion of values given to imputed elements such as rent and use-rents of durable goods, and the valuation of production for home use.

However, these differences do not themselves form a good reason to doubt that monetary welfare and multiple deprivation are correlated. It can be expected that high levels of monetary advantage are associated with lower disadvantage in non-monetary terms. It is reasonable to assume that a gradient will be seen in many cases. Setting poverty thresholds across different distributions amounts to restricting the analysis to a single point in the gradients. This means that the different thresholds and their comparison are major elements in poverty identification when they relate to underlying different measurement approaches. For example, the monetary poverty status can be responsive to small marginal changes in the monetary welfare variable due to its continuous nature, while changes in the non-monetary multidimensional poverty status occur only for discrete, qualitative changes in indicator-wise deprivation status. Thus, the likelihood of change in poverty status varies greatly either by small increments of currency units or by 'lumpy' differently sized increments, which also may have larger marginal value to the poverty threshold than a single cent. This gives rise to empirical considerations of sensitivity around the poverty thresholds. Indeed, differences between poverty levels and poverty sets may not be as different as the labels 'poor' and 'non-poor' suggest. Mismatches may be the result of the intersection of small marginal differences in monetary welfare and the 'lumpy' steps of multidimensional deprivation.

Importantly, and as stated previously, the use of a poverty (or welfare) threshold reduces monetary and non-monetary welfare distributions into a binary comparison: poor and non-poor in both approaches. This dichotomization is the unequivocal first step of any poverty analysis, which consists of identifying those who are poor (Sen, 1976). Thus, any comparison across both distributions using a common data set that can be used to operationalize both approaches produces a four-cell matrix based on these binary states. We show this four-cell matrix in the left graph of Figure 1, where the 'overlap' population are those who are identified as poor or non-poor in both monetary and multi-dimensional terms, and the two areas of 'mismatch' depict populations that are poor using one measure but not poor using the other.

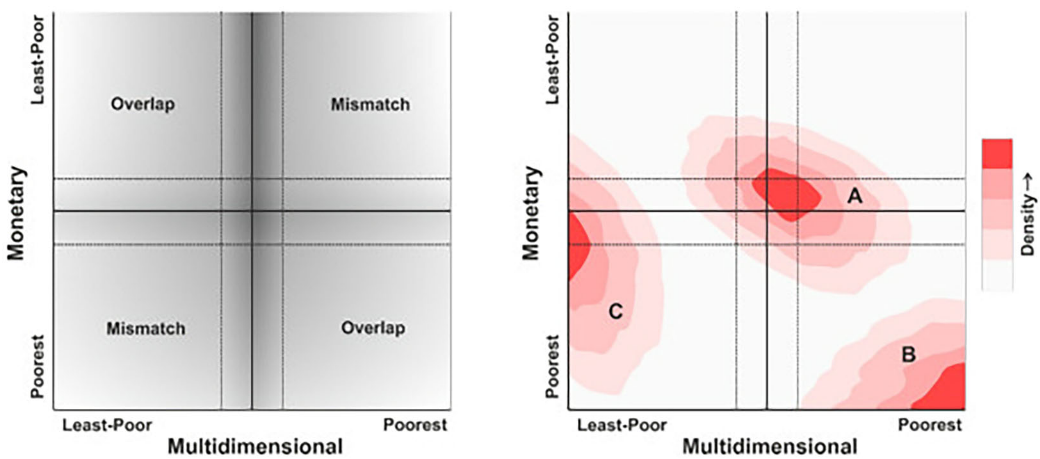

Figure 1. Overlap, mismatch and density.
Source: Own elaboration.

As we set out in previous discussion, the boundaries between these groups are intrinsically uncertain due to measurement characteristics, measurement error and sensitivity around the thresholds. We show these issues diagrammatically through the dark 'grey area' surrounding the boundaries of each cell. The whiter the colour, the more certainty can be ascribed to an individual belonging to a particular quadrant. Although poverty identification requires sorting of the population based on a single characteristic, namely poverty status, the underlying characteristics of populations in each quadrant may not be so clearly different as such status suggests. Indeed, it is often the case that identifying the monetary poor by their non-monetary characteristics – through a proxy means test or a similar approach - produces considerable uncertainty as near-poor populations have many similar characteristics (Brown et al., 2016; Fortin et al., 2016).

When sorting the population into the four quadrants two important elements are at play. First, the *pair* of monetary and multidimensional poverty lines which are chosen. Second, the density of the joint distribution of underlying welfare variables surrounding those poverty lines. The right graph of Figure 1 illustrates this point. Three stylised joint distributions are shown, where the more intense the red, the higher the density of the population at a particular level of monetary and multidimensional welfare. As before, the horizontal and vertical lines show potential poverty lines. It is the interaction of the poverty lines and the joint density which determines the proportion of the population in each quadrant. The entire population of B is classed as poor by both measures regardless of the poverty lines chosen among the ones that we depict in that figure. For C, while no one is ever classed as multidimensionally poor, the sorting into monetary poor or non-poor depends on the monetary poverty line chosen. For A, as the population is very dense at the intersection of the poverty lines, small movements in either line would result in large changes to the respective classifications. It is, then, the proportion of the population which lies around the respective poverty lines which determines how stable the sorting into these four quadrants.

3. Methods

Poverty measurement is the combination of two ordered steps (Alkire et al., 2015; Atkinson, 2019; Foster et al., 2010; Sen, 1976). The first is the identification step, which consists of sorting out the poor people from the non-poor by adopting a poverty line, and second is poverty aggregation, which consists of estimating summary measures of overall poverty in a society.

Let us now briefly present how these steps are performed in the two approaches to poverty that we empirically scrutinize, namely (one-dimensional) monetary and multidimensional. Note that, when we analyze secondary data, these methods correspond to the ones that are effectively performed by academic institutions and international organizations to compute their flagship poverty measures (the World Bank for monetary measures, and OPHI-UNDP for the global MPI), while they also correspond to the ones that we carry out on our own for the analysis of data at the individual level.

3.1. Monetary poverty

Household aggregate income and/or consumption is used to assess monetary poverty. We argue that it would be preferable to rely solely on consumption data (Deaton, 2006), but internationally comparable microdata deficiencies prevent us from taking this ideal route. For practical purposes, we restrict ourselves to use the World Bank's international monetary poverty lines to identify the poor, aiming at aligning our study with one of the most prominent approaches to assess monetary poverty globally (see Jolliffe & Prydz, 2016). These daily thresholds per person, in 2011 USD PPP, are \$1.90, \$3.20, and \$5.50 for low income, lower-middle income and upper-middle income countries, respectively. To compute an aggregate monetary poverty measure, the usual FGT_0 headcount ratio is used (Foster et al., 2010).

3.2. Multidimensional poverty

The notion of multidimensional poverty is operationalized here using the dual-counting approach pioneered by Alkire and Foster (2011) (AF henceforth). This method is not the only way to measure multidimensional poverty (see e.g., Bourguignon & Chakravarty, 2003), but it is the one underlying the influential OPHI-UNDP's global MPI (OPHI, 2018). This index is undoubtedly the most well-known application of the AF method, but the approach is flexible enough to allow for a thorough analysis of alternative operationalisations of the multidimensional notion of poverty, particularly one including monetary deprivation as one 'dimension' of poverty, among others. Let us mention the essential aspects of the AF method that are useful for our subsequent empirical analysis. Further details can be found in Alkire and Foster (2011) and Alkire et al. (2015).

Consider matrix y sized $n \times d$ describing achievements in d relevant indicators for a poverty analysis across a population of n individuals. These indicators can be monetary (e.g., consumption) or non-monetary (e.g., years of schooling). Individual i is deemed as deprived in indicator j if they fall short of a minimum threshold denoted as z_j. Thus, the binary deprivation indicator denoted as g_{ij}^0 takes a unity value if $y_{ij} < z_j$, and it is zero-valued if $y_{ij} > z_j$. The relative importance of each indicator can be represented by a $d \times 1$ vector of weights w such that $\sum_{j=1}^{d} w_j = 1$. The number of weighted deprivations experienced by individual i, c_i can thus be computed as $c_i = \sum_{j=1}^{d} w_j g_{ij}^0$, which can be termed their *deprivation score*. A second threshold, k, applied to vector $c = \{c_1, \ldots, c_n\}$ allows to identify people suffering a number of simultaneous deprivations that define them as being multidimensionally poor. Hence, the multidimensional poverty identifier ρ_{ij} takes a unity value if $c_i \geq k$ and it is zero-valued if $c_i < k$. Thus, k effectively corresponds to a multidimensional poverty line.

The structure of the UNDP-OPHI global MPI is depicted in Figure 2. This index is formed by ten indicators pertaining to three dimensions (two indicators of health, two of education and six of living standards), where each dimension is given the same weight (one-third) and each indicator is given the same weight within dimensions. A detailed description of the deprivation thresholds and indicator definitions can be found in Alkire and Jahan (2018) as well as Appendix B. In the spirit of the global MPI, a person is multidimensionally poor if they face deprivations in one-third or more of the considered indicators (i.e., they are deprived in the equivalent of one dimension or more), which amounts to setting $k = 1/3$ as the multidimensional poverty line. In this study we draw inspiration from Alkire and Santos (2014); Alkire et al. (2022a) to explore a parsimonious set of k-values that we posit may be approximate analytical counterparts of the World Bank's set of international poverty lines: $k = \{1/5, 1/3, 1/2\}$. The $k-$value of 1/5 was first used in the UNDP, 2010 HDR (UNDP, 2010) to define people being 'at risk of being poor' or 'vulnerable to poverty' if their deprivation score is between 1/5 and 1/3. In turn, people living in 'severe poverty' were first identified in the UNDP, 2011 HDR (UNDP, 2011) as those whose deprivation score is greater or equal than 1/2. Notice that, by construction, *higher* k-values denote *more severe* forms of multidimensional poverty.

After identification, a number of aggregate multidimensional poverty measures can be estimated (see Alkire & Foster, 2011). In particular, the multidimensional poverty headcount ratio depicting the proportion of the $n-$sized population living in multidimensional poverty according to a certain k-value can be computed as $H = \frac{1}{n}\sum_{i=1}^{n} \rho_{ik}$. This ratio can be meaningfully compared to the usual FGT_0 headcount ratio of monetary poverty, as they both correspond to proportions of poor people.

As depicted in Figure 2, it is possible to envision a structure of an alternative MPI – different from OPHI-UNDP's global MPI – that includes income/consumption as an additional relevant

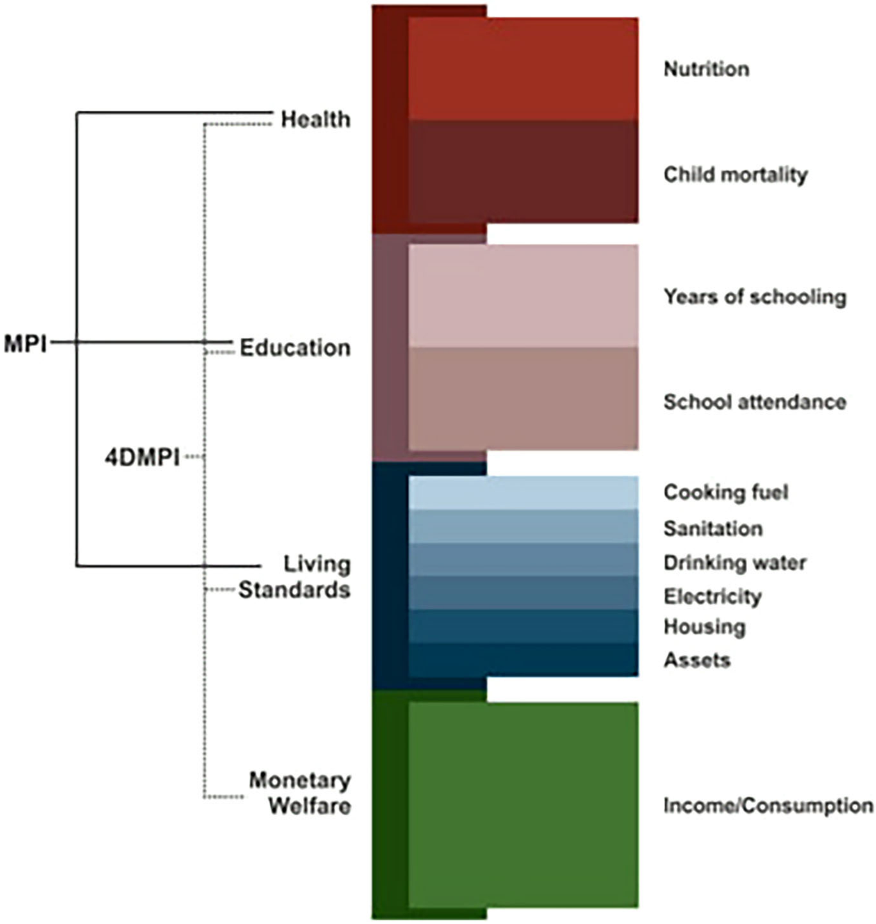

Figure 2. MPI and 4DMPI.
Source: Own elaboration.

indicator pertaining to a fourth dimension of poverty, say *monetary welfare*. We explore this and form examples in Section 6. Let us call this the 4DMPI structure. In this alternative operationalization of multidimensional poverty, one must think about any monetary poverty line (such as the international poverty lines, for instance) as a deprivation threshold that needs to be combined with a multidimensional poverty line (i.e. a k-value) to identify people suffering from a very particular, wider notion of poverty that combines monetary and non-monetary indicators to define the poverty status. A similar approach has been recently scrutinized by the World Bank (World Bank, 2018), albeit using a different indicator and dimension structure to that shown in Figure 2.

It is important to highlight that our 4DMPI structure holds one important technical feature: the mismatch between the monetary and the multidimensional approach to identifying the poor, can be completely avoided by (i) defining equal weights for each dimension (i.e. one-fourth), as well as equal weights for each indicator within dimensions, and (ii) setting $k = 1/4$ as the multidimensional poverty line. This identifies the '4DMPI poor' as those that suffer a number of deprivations equivalent to one dimension or more. Doing this means that all monetary poor individuals are also 4DMPI-poor, and similarly, that all individuals that are poor by the global MPI are also 4DMPI-poor. In other words, the 4DMPI poverty set is formed by the individuals who are poor by monetary terms or by the global MPI or both and any mismatch from separate measures is no longer present. Effectively, this corresponds to a the so-called 'union' approach to poverty identification (see Atkinson, 2019; see also Santos, 2013 for a similar discussion).

4. Aggregate level analysis

Our analysis begins at the aggregate level, by examining the relationship between monetary and multidimensional poverty headcounts across 90 countries. We rank countries based on their relative prevalence of poverty across a range of poverty thresholds - $1.90, $3.20, and $5.50 for monetary poverty, and k-values of 1/5, 1/3 and 1/2 for multidimensional poverty. We analyse the extent to which these ranks are correlated between measures, for each threshold. We then classify countries according to their *average rank* across all measures and thresholds, and the *instability* of each country's rank. This provides an understanding of the aggregate trends and forms a basis for the selection of case-study countries to use in our individual level analysis.

4.1. Data

Our data is drawn from a sample of 90 countries. Each of these countries has both monetary and multidimensional poverty headcount data, available from the World Bank PovCalNet database[4] and the global MPI data set,[5] respectively. For the monetary poverty data, the survey year ranges from 2004-2017, while the multidimensional survey year range from 2007-2018; in both cases at least 90% of the surveys are after 2010.[6] This gives a final sample consisting of 27 Low Income Countries, 39 Lower Middle-Income Countries, 24 Upper-Middle-Income Countries as classified by the World Bank.

4.2. Aggregate correlations

Table 1 shows the overall correlation between monetary and multidimensional poverty headcount rankings, using the six different thresholds, across the 90 countries. Kendall Rank Correlation Coefficients show the extent and significance of these correlations. We observe high and significant coefficients, with all of them above 0.64 and significant at the 1% level.[7] This shows that, when compared internationally, the incidence of monetary poverty is strongly correlated to that of multidimensional poverty.

4.3. Average ranks and instability

When measuring the incidence of poverty, a choice of poverty measure and a threshold must be made. This choice will determine the incidence of poverty of a particular country and the respective ranking of that country when compared to others. This poses difficulties when trying to classify countries, as each country's rank depends on the measure and threshold chosen.

Table 1. Monetary and MPI poverty headcounts: Kendall correlation coefficients

k value (%)	$1.90	$3.20	$5.50
50	0.641***	0.661***	0.642***
33	0.664***	0.700***	0.683***
20	0.675***	0.719***	0.699***

Note: ***: Significant at 1%. Based on the 90 country sample—see Appendix A.
Source: Own Elaboration.

To address this, we use the three poverty lines within each of the monetary and multidimensional poverty indices to generate an *average rank* of poverty.[8] The 90 countries are ranked the least to the poorest, for all thresholds within each measure. Then, the mean of those ranks is taken for each country, denoted as x, to give the *average rank*. In addition, we consider the potential *instability* of these country poverty orderings. As, for some countries, their rank may remain largely unchanged across these measures and thresholds whilst, for others, the choice may dramatically change their rank. If mismatches between monetary and multidimensional poverty exist within a country, this may emerge at the aggregate level through rank instability.

More formally, the average rank is the mean of the six ranks ($Average\ Rank = \bar{r}_x = \frac{1}{6}\sum_{m=1}^{6} r_{mx}$ with m being one generic pair of poverty lines), while instability is the Euclidean distance between the ranks and the average rank ($Instability = \sigma_x = \sqrt{\sum_{m=1}^{6}(r_{mx} - \bar{r}_x)^2}$). These measures can be used to provide further information on the relationship between monetary and multidimensional poverty. However, our primary reason is to provide a basis to select countries for our individual level country analysis.

The left panel of Figure 3 plots the average rank against rank instability and the six case studies. The choice of these countries, shown in more detail in Appendix A, aims to ensure an even spread across these two dimensions while considering the availability of data at the individual level that allows to compute both a monetary measure and a measure of multidimensional poverty with a structure mirroring, as close as possible, the global MPI. Thus, we choose Brazil and Ecuador, which are within the least poor tercile, Bolivia and Ghana in the middle, and Uganda and Ethiopia in the poorest. Ecuador, Ghana, and Uganda are countries with stable rankings, while Brazil, Bolivia, and Ethiopia have a high degree of rank instability. The right panel shows the plot of the average multidimensional rank against the average monetary rank. This highlights that for more stable countries there is a close adherence to the 45-degree

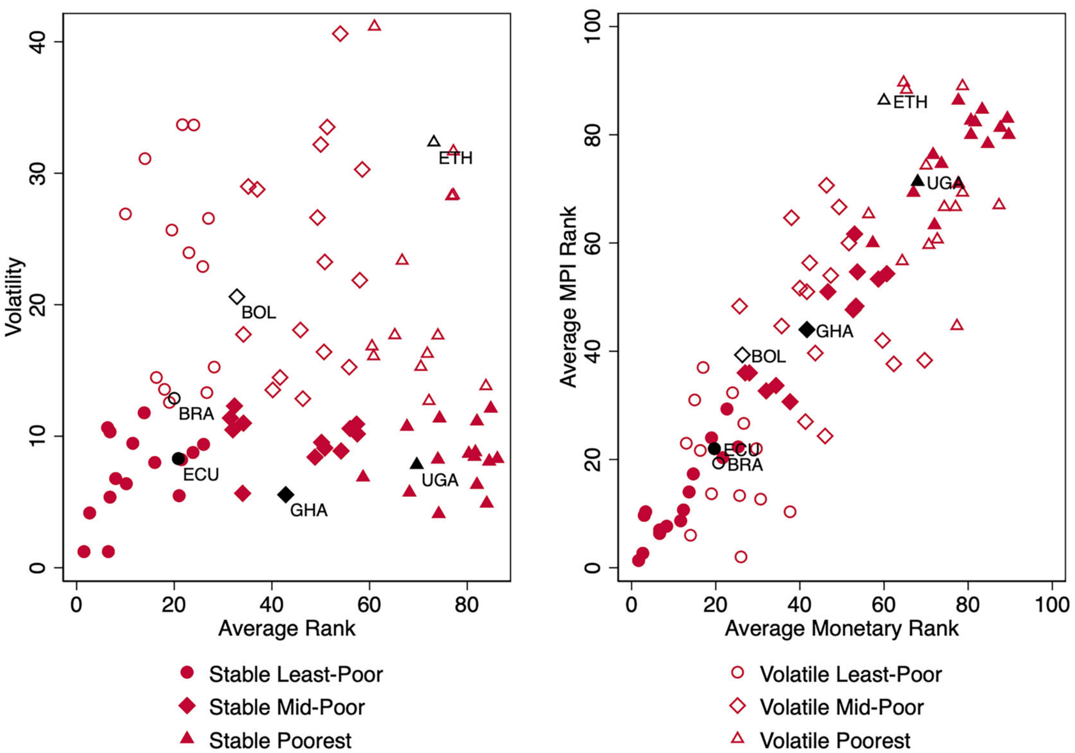

Figure 3. Average ranks and instability.
Source: Own elaboration.

line, and that this is particularly true for the least-poor countries. [9] There is a much greater spread away from the 45-degree line for the unstable countries.

Overall, our aggregate results support a 'first order' finding that MPI and monetary poverty are correlated. However, when making international comparisons, the correlation is weakest amongst the countries with highest poverty headcounts. This means that understanding the underlying relationship between monetary and multidimensional poverty needs to clearly identify how the underlying distributions are correlated and when match and mismatch matter. To do so, we need to delve into analysis of individual-level data.

5. Individual level

5.1. Data

Table 2 provides a summary of the microdata surveys we use for Brazil, Bolivia, Ethiopia, Ecuador, Ghana, and Uganda. These household surveys are undertaken between 2012 and 2016 and are all representative at the national level. Our analysis is conducted at the individual-level, with a total of 608,639 individuals across the six datasets.

A full, comparable analysis of monetary and multidimensional poverty (mis)matches is, however, limited by data deficiencies in microsurvey data (Alkire & Santos, 2014; World Bank, 2018). One key issue is the availability of nonmonetary indicators in surveys that contain data on consumption or income. Our earlier selection of six countries' survey data carefully considered indicator coverage, making sure, where necessary, that it was possible to still compute the global MPI in the face of one missing non-monetary indicator by adopting the exact same policies used for the global MPI by UNDP-OPHI (OPHI, 2018).[10] We have the full set of global MPI indicators for Ecuador and Uganda, whereas one Health indicator is missing in Brazil, Bolivia and Ghana (nutrition), as well as Ethiopia (child mortality). The structure of the global MPI, including the precise definition of deprivation cutoffs are presented in Table B1 in Appendix B. Note that the global MPI is estimated using the household as the unit of poverty identification, meaning that all members of a household have the same poverty status (see Alkire et al., 2022a).

An additional issue is that monetary variables are often only available as either income or consumption. Based on data availability we, therefore, use income as our monetary welfare variable in Brazil, Bolivia, and Ecuador, and consumption in Ethiopia, Ghana, and Uganda—both measures are converted to $2011 PPP per capita per day. Our results should be interpreted keeping these data characteristics into account.

5.2. *Welfare analysis: taking the entire distributions into account*

Returning to our earlier discussion in Section 2, we begin our analysis by assessing if there is correlation, and a clear, but imperfect negative relationship between the monetary welfare

Table 2. Data description: Individual-level analysis

Country	Survey	Year	N	$ Variable	Missing indicator
Brazil	PNAD	2015	348,258	Income	Nutrition
Bolivia	EH	2015	36,876	Income	Nutrition
Ethiopia	ESS	2015/16	26,670	Consumption	Child Mortality
Ecuador	ECV	2013/14	108,093	Income	
Ghana	GLSS	2012/13	71,277	Consumption	Nutrition
Uganda	UNPS	2015/16	17,465	Consumption	

Source: Own elaboration.

variables and the deprivation scores in each of the selected countries, irrespective of their ranking and instability characteristics discussed earlier in Section 4.

In Figure 4 we can see that, on average, people with low levels of monetary welfare tend to suffer a greater number of non-monetary deprivations. The decreasing nature of the red line in Figure 4 clearly depicts a concentration of non-monetary deprivations (right side of the horizontal axis) among the monetary poor population (lower part of the vertical axis).

As expected, higher levels of monetary welfare (higher on the vertical axes) are more frequent among the population suffering the least amount of non-monetary deprivations (left on the horizontal axes). The converse is also true but note that the dispersion around this monetary welfare concentration varies greatly between *and within* countries. Figure 4 clearly shows that there is a large variation in terms of monetary welfare between people facing simultaneous non-monetary deprivations to an identical extent. In Brazil and Ecuador, for instance, people who do not face any non-monetary hardship, i.e., they enjoy a zero-valued deprivation score (horizontal axis), can have levels of monetary welfare ranging *from the lowest to the highest level* in their respective national distributions. We find that this dispersion reduces gradually for countries with higher levels of overall poverty, such as Ethiopia and Uganda.

Our visual analysis is corroborated and extended in Tables 3 and 4. The concentration of non-monetary hardships among the monetary poor population is more marked in the least poor countries. By contrast, in the poorer countries, non-monetary hardships are more evenly distributed across the entire monetary welfare distribution. In Table 3, we can see that the mean deprivation score among people in the 1st quartile of the monetary welfare schedule (the poorest) is 0.16 in Ecuador and 0.57 in Ethiopia (Table 3). For people in the 4th quartile of this distribution (the richest), this mean score goes down to 0.04 in Ecuador (a 75% reduction) and 'only' to 0.33 (around a 42% reduction) in Ethiopia. The relative concentration of non-monetary hardships among the monetary poor population is clearly greater in the least poor countries. Also, notice that in Brazil, the standard deviation of the deprivation score among people in the 1st monetary welfare quartile (0.13) more than doubles that among people in the 4th quartile (0.06). By contrast, in Ethiopia, this standard deviation is invariant across the all the monetary welfare quartiles (0.20).

Table 4 shows that the distribution of non-monetary deprivations across monetary welfare levels does not follow the exact same pattern as shown in Table 3. The relative concentration of low levels of monetary welfare among people with high deprivation scores is similar across the six considered countries. For instance, the mean income among the most deprived population non-monetarily (4th quartile in Table 4) is \$13.57/day in Ecuador and \$2.02/day in Uganda. Among the least deprived population (1st quartile in Table 4), the mean income tends to triple in both countries (\$36.78/day in Ecuador and \$6.31/day in Uganda).

5.3. From welfare to poverty

Our analysis so far supports the assertion that monetary welfare and deprivation score distributions are undoubtedly related, but they inform fundamentally distinct foundations for a poverty analysis. Furthermore, their distinctive patterns vary considerably across the six countries, and this is crucial as we turn to consider poverty; the reason is that the poverty analysis focuses on the people sitting on selected *parts* of these distributions. This requires a sorting between the poor and non-poor population.

Figure 5 shows the relation between the distribution of welfare and the poverty headcounts at various thresholds. The density of individuals at particular levels of income/consumption is shown in panel a, and deprivation, in panel b, alongside the three respective thresholds (dotted vertical lines).[11] The incidence of poverty, for a given threshold, corresponds to the area under the curve to the left of that threshold for income, and to the right for MPI. The higher the curve, the larger that area will be. The least-poor countries have high densities to the right of the income threshold,

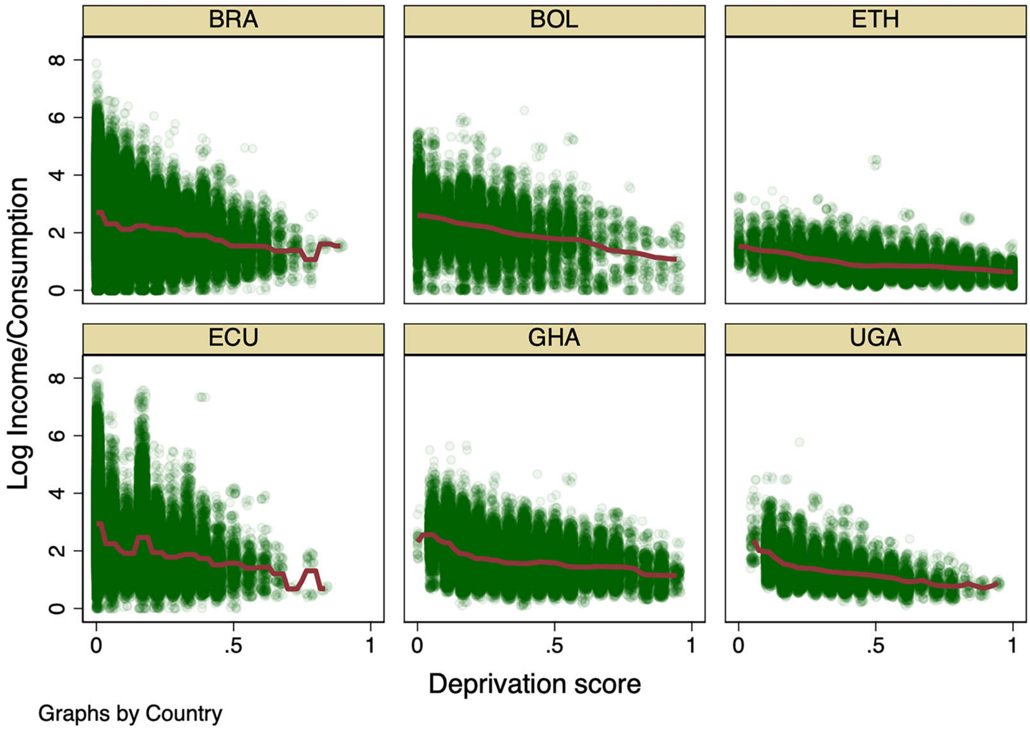

Figure 4. Level of monetary welfare vs. deprivation counting scores.
Source: Own elaboration.

Table 3. Mean deprivation score and its standard deviation by income/consumption quartiles

	BRA		BOL		ETH		ECU		GHA		UGA	
$ Quartile	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1: Poorest	0.11	0.13	0.26	0.20	0.57	0.20	0.16	0.15	0.40	0.21	0.43	0.19
2	0.06	0.10	0.17	0.16	0.50	0.20	0.10	0.11	0.33	0.18	0.36	0.15
3	0.06	0.09	0.13	0.14	0.45	0.20	0.06	0.09	0.28	0.17	0.31	0.13
4: Richest	0.03	0.06	0.09	0.12	0.33	0.20	0.04	0.08	0.20	0.14	0.22	0.12
Total	0.07	0.10	0.16	0.17	0.46	0.22	0.09	0.12	0.30	0.19	0.33	0.17
Sample Size	348258		36876		26670		108093		71277		17465	

Source: Own elaboration.

Table 4. Mean per capita income/consumption by deprivation score quartiles

	BRA		BOL		ETH		ECU		GHA		UGA	
$ Quartile	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1: Least poor	21.96	31.48	17.77	16.96	2.81	2.20	36.78	90.82	10.30	9.86	6.31	6.99
2	21.80	32.65	14.30	15.39	1.79	1.34	34.98	78.43	6.52	6.13	3.84	6.01
3	13.58	19.87	11.95	14.44	1.54	2.51	15.89	42.30	5.11	4.86	2.91	2.58
4: Poorest	10.04	11.79	8.19	11.38	1.33	1.02	13.57	51.34	4.24	3.85	2.02	1.26
Total	16.83	25.94	13.05	15.09	1.88	1.96	25.31	69.42	6.54	6.98	3.77	5.08
Sample Size	348258		36876		26670		108093		71277		17465	

Source: Own elaboration.

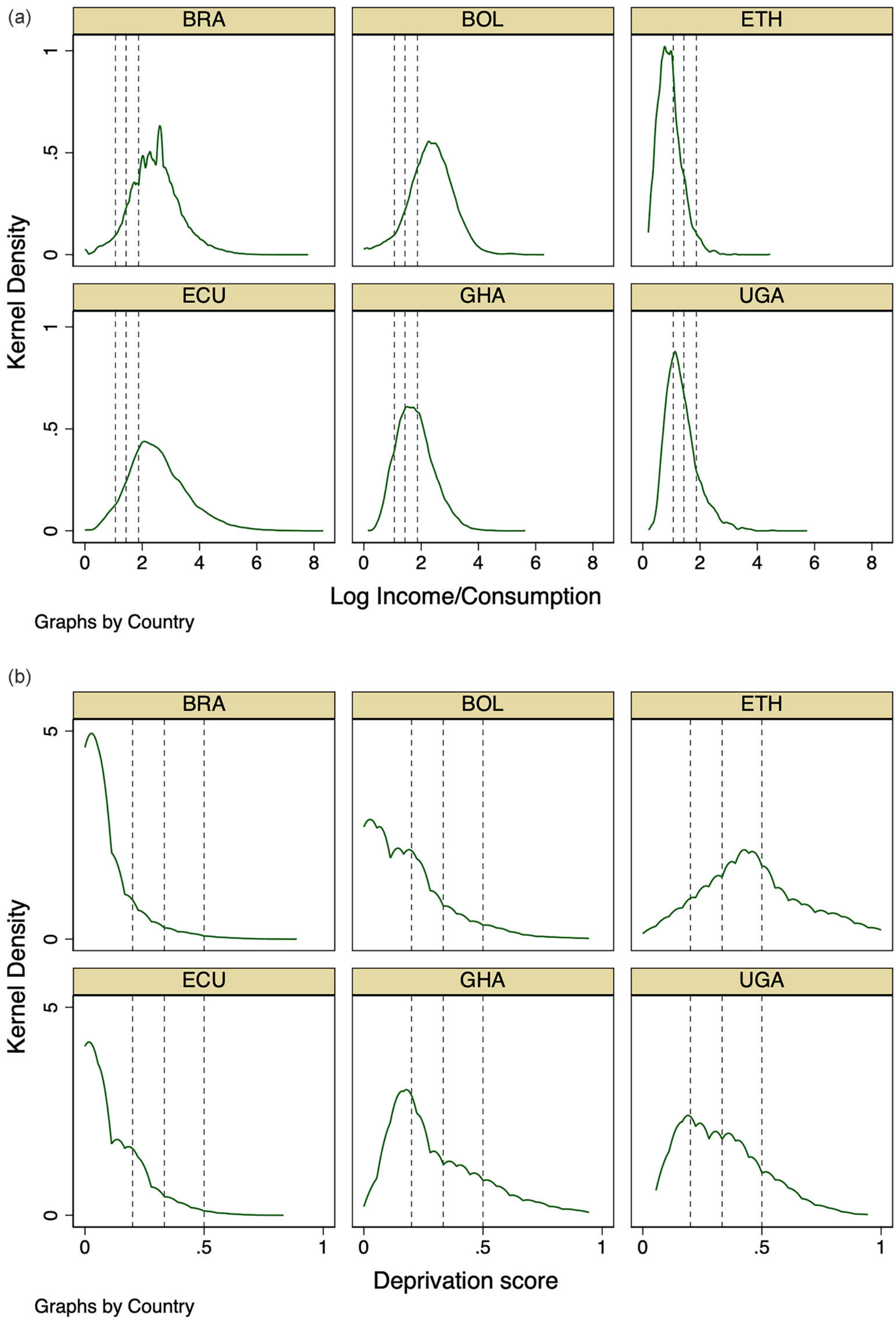

Figure 5. Kernel density functions: Monetary welfare (panel a) and deprivation scores (panel b). *Source:* Own elaboration.

and to the left of the MPI threshold. The headcounts for monetary poverty, at the \$1.90 threshold are 5%, 6%, 66%, 5%, 13% and 33%, for Brazil, Bolivia, Ethiopia, Ecuador, Ghana, and Uganda, respectively, with MPI headcounts at the $k = 1/3$ threshold of 4%, 17%, 76%, 7%, 40% and 51%.

Crucially, these graphs allow us to understand why, when different poverty lines are adopted, the change in the number of those classed as poor will vary between countries. As the threshold moves incrementally, the change in the headcount ratio depends on the density at that point. The higher the density close to the threshold, the larger the change will be, as it is the area under the curve between two thresholds which gives the difference. For example, for Uganda moving from the \$1.90 to the \$3.20 increases the headcount ratio by 30ppt, while for Brazil the increase is only 5ppt.

While useful, these univariate density functions reveal little of the change in matches and mismatch across the two measures. Instead, we must turn to the bivariate distribution of these variables to understand the potential magnitude of poverty identification mismatches. In Figure 6 we plot the bivariate or 'joint' density of these variables for each country. Each point in this space represents the proportion of the population enjoying a specific level of monetary welfare (y-coordinate) and facing a specific deprivation score (x-coordinate). Thus, darker shades represent higher proportions of the population having a specific combination of values in the underlying welfare values. In this figure, the overall low prevalence of poverty in Brazil and Ecuador is visually reflected in the high concentration of their population in the lower values of the deprivation score distribution (from 0 to around 0.15) and in mid-levels of monetary welfare. Very few people in these countries sit in the higher end of the deprivation score distribution (above 0.65). In poorer countries, however, such as Ethiopia and Uganda, we do not see such a marked concentration of the population. There is a considerable amount of the population having deprivation scores within a much wider range (0.15-0.6) while enjoying similar levels of monetary welfare.

To summarise the previous figures, and provide a clear link back to Figure 1, Table 5 provides measures of poverty set volatility for each country. The first two rows draw out what we observe in Figure 5; the proportion of the population who lie between the \$1.90 and \$5.50 monetary poverty lines and the $k = 0.2$ and $k = 0.5$ multidimensional poverty lines. The final row shows those who lie between either set of lines, akin to the cross demonstrated in Figure 1 and

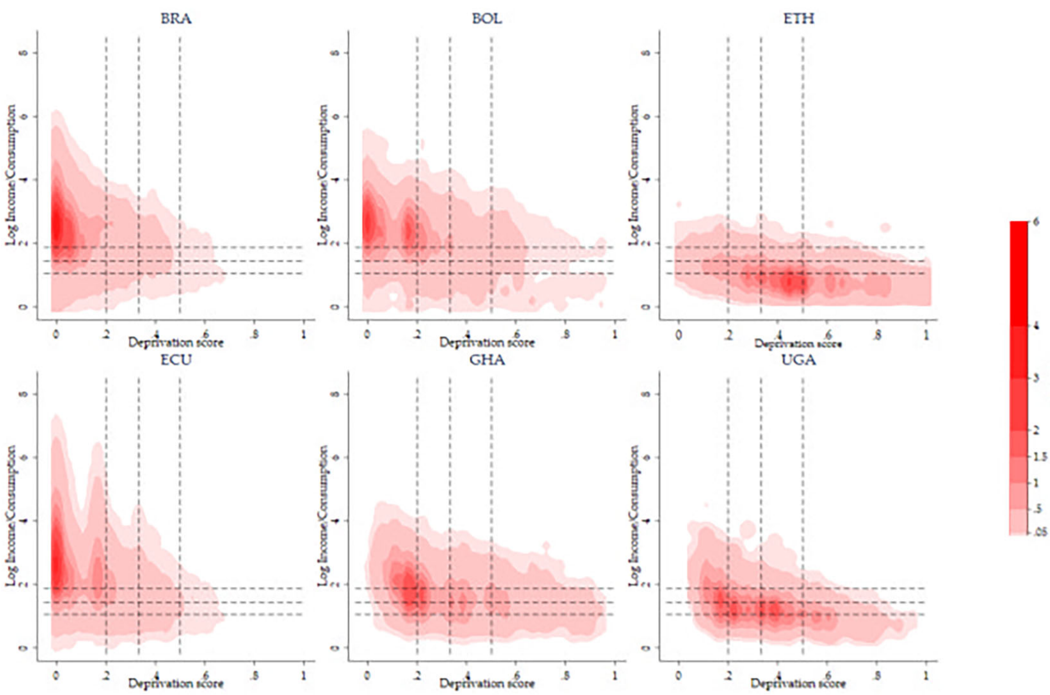

Figure 6. Bivariate density.
Source: Own elaboration.

Table 5. Volatility: % of population between poverty lines

	BRA	BOL	ETH	ECU	GHA	UGA
$ ($1.90 - $5.50)	19.3	19.5	30.4	20.8	45.6	51.2
MPI (0.2 - 0.5)	9.9	28.9	48.3	15.5	45.9	56.9
Either	26.2	39.9	62.8	30.1	67.4	75.7

Source: Own elaboration.

highlighting the joint cumulative densities within Figure 6. Results show that for those countries whose highest densities are further away from the poverty lines the volatility, or reclassification, is very low. For some, such as Ethiopia, there is relatively more volatility for one measure rather than the other. Most stark, is the large differences in the final row. For Brazil, the movement of poverty lines would lead to 26.2% being reclassified within different quadrants, while for Uganda this number is 75.7%.

Under these circumstances, setting a pair of poverty lines (one monetary and one multidimensional) to operationalise the identification steps of a simultaneous poverty measurement analysis is a critical matter. It is evident that identification mismatches will take place to varying extents depending on the pair of chosen poverty lines, and with varying degrees in each country. This empirically demonstrates the hypothetical position shown originally in Figure 1. Different people will be effectively identified as poor depending on the chosen lines, which can have considerable consequences for policymaking against poverty.

To assess the extent of the mismatches, it is important to make the difference between i) the proportion of people who are poor by the global MPI but not monetarily poor, and ii) those who are poor by a money metric without being classed as MPI poor. These proportions are respectively depicted in Figures 7 and 8, for different combinations of monetary (vertical axis) and multidimensional poverty lines (horizontal axis). We cover the whole range of potential multidimensional poverty lines, i.e. [0,1] in all the possible 18 deprivation score values defined by the structure of the global MPI. In the vertical axis we cover the $0.00, $4.00 in steps of $0.10. These proportions can be thought of as the size of the top-right and bottom-left squares within Figure 1, for Figures 7 and 8, respectively.

Figure 7 shows that the proportion of people who are poor by the MPI but not by monetary terms is less than 10% for a wide array of poverty line pairs in Brazil and Ecuador, our least poor countries. These low mismatch levels are the reflection of the overall low prevalence of deprivations in these countries irrespective of the multidimensional poverty line that is chosen. For instance, the proportion of people who would be classed MPI poor while not being monetary poor by any monetary poverty line $\leq$ $3.00 is less that 10%, *irrespective* of the multidimensional poverty line. Thus, one can say that the set of MPI poor people in these countries tends to be more stable with respect to changes in the multidimensional poverty line overall, and the monetary poverty line within a sensible, practical rage.

If we now focus on the poorer countries, Ethiopia and Uganda, comparably low levels of mismatches ($\leq$ 10%) are only found when one adopts either a very low multidimensional poverty line and/or a very low monetary poverty line. For a multidimensional poverty line below (0.10 or 1/10) the vast majority of the population in these countries would be classed as MPI poor, naturally encompassing the vast majority of people who are poor by monetary terms, *irrespective* of the monetary poverty line. Interestingly, the vast majority of the MPI poor people in Uganda would also be identified as being monetarily poor for *any* monetary poverty line $\leq$ $1.00. There is, however, a wide range of poverty line pairs for which the proportion of the population who is MPI poor while not being monetary poor is over 50%. This happens for relatively high multidimensional poverty lines ($\geq$ 1/2, i.e., 50%) combined with high monetary poverty lines ($\geq$ $2.50 in Uganda and $1.50 in Ethiopia). In fact, in Ethiopia, the proportion of people suffering from very severe forms of multidimensional poverty, which can be identified,

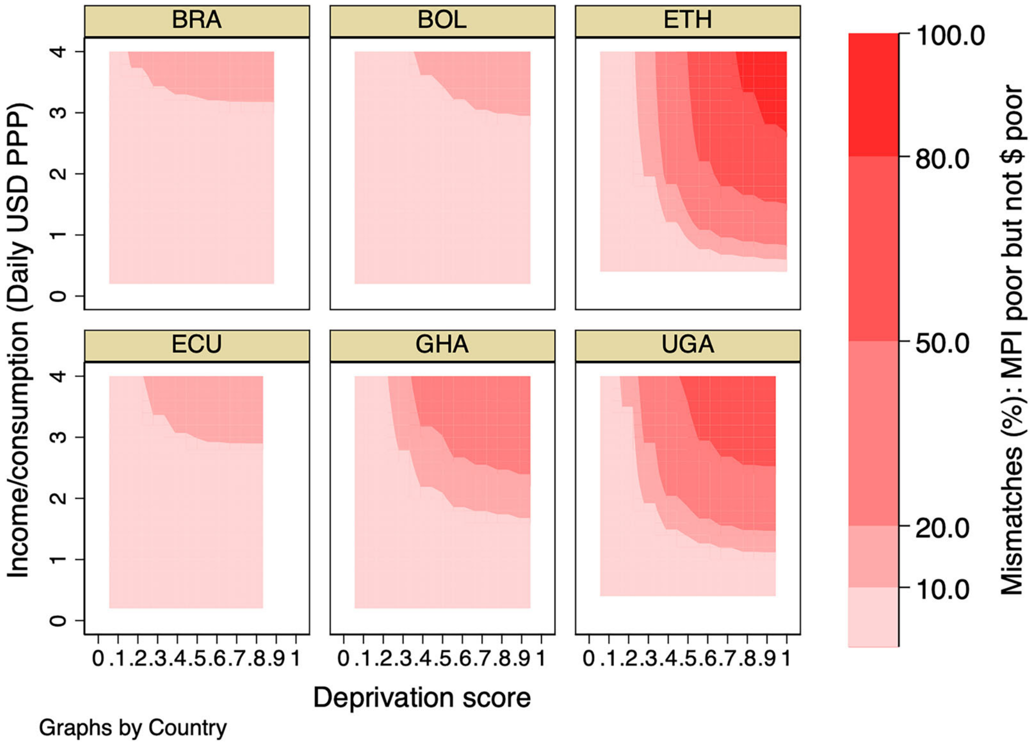

Figure 7. Frequency of mismatches: MPI poor but not $ poor.
Source: Own elaboration.

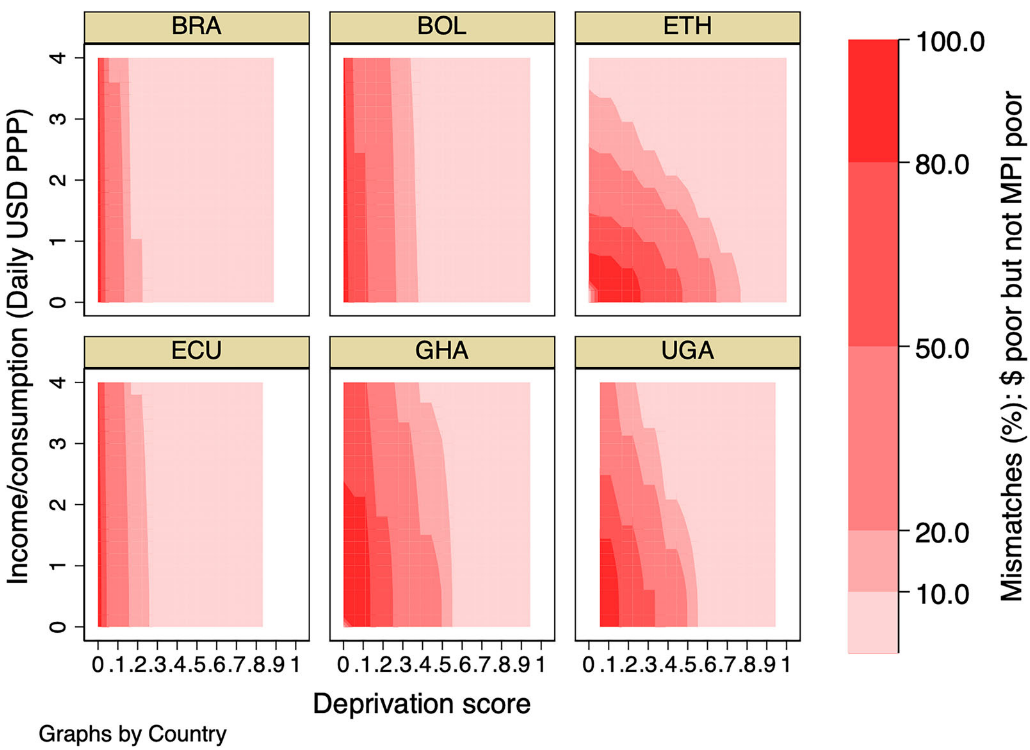

Figure 8. Frequency of mismatches: $ poor but not MPI poor.
Source: Own elaboration.

for instance, by adopting a multidimensional poverty line $\geq$ 7/10, i.e., 70%, while not being detected as poor by a monetary poverty line of at leas \$3.00 can be over 80%.

Turning now to the mismatch related to people who are monetary poor but not poor by the MPI, the cross-country qualitative pattern is similar: mismatches tend to be more frequent in the poorer countries. For instance, in Brazil and Ecuador, the proportion of the population that is monetarily poor by *any* monetary poverty line $\leq$ \$4.00 while not being multidimensionally poor by *any* poverty line $\geq$ 1/3 is less than 10%. To have such a high coincidence in terms of poverty identification in Ethiopia and Uganda, one would have to adopt multidimensional poverty lines over 2/3 (i.e., 60%) in Uganda and over 3/4 (i.e., 70%) in Ethiopia. That is, the absence of mismatches in these countries tends to be greater only for people facing very severe forms of poverty.

Let us close this section by discussing the empirical results for the regularly applied poverty lines in practice and academia, namely \$1.90, \$3.20, and \$5.50 for monetary welfare and 1/2, 1/3 and 1/5 for the multidimensional deprivation score. They define a set of poverty line pairs containing nine elements ({\$1.90;1/2}, {\$1.90;1/3}, {\$5.50;1/3}, {\$5.50;1/5}).

The bold figures in Table 6 represent the average proportions of the population that is classed in each one of the quarters that we presented back in Figure 1: poor by both measures, only monetary poor, only MPI poor, and non-poor by both measures[12]. It can be seen that average identification overlaps (either poor or non-poor by both measures) are highest for the least poor countries (85.1% in Brazil and 83.7% in Ecuador), and that this largely due to a vast majority of the population being classed as nonpoor by both approaches to poverty. As expected, the average identification overlaps in the poorer countries is primarily due to a prevalence of people being classed as poor by both approaches.

In Table 6 we also show, in parenthesis, the bounds of these average proportions (i.e., their lowest and highest values defined by each element in the nine poverty lines pairs set). We corroborate that, even for this restricted set of potential, practical poverty lines, these ranges are much wider for the poorer countries. In Ethiopia, for instance, the proportion of people identified only as being monetary poor can go from 2.7% to 54.2%, whereas this range goes from 3.3% to 23.3% in Brazil. Similarly, the proportion of people identified only as being MPI poor can go from 0.4% to 25.5% in Ethiopia but is goes from 0.3% to 9.2% in Brazil. These ranges are closely aligned with the volatility measures of Table 5. This evidence supports our initial concerns about the sensitivity to the monetary poverty threshold of any poverty identification 'mismatch,' and our antipathy to ascribing significant 'difference' in purely binary terms of 'poor' and 'non-poor' status if the marginal distance between the boundaries for these groups are small in absolute terms.

Table 6. Summary of matches and mismatches (%)

	BRA Mean (Range)	BOL Mean (Range)	ETH Mean (Range)	ECU Mean (Range)	GHA Mean (Range)	UGA Mean (Range)
Both	**1.6**	**5.8**	**61.3**	**3.0**	**18.7**	**34.5**
	(0.2 - 4.5)	(1.7 - 14.5)	(33.8 - 87.5)	(0.3 - 9.1)	(4.8 - 42.9)	(12.0 - 67.0)
Only \$	**11.3**	**8.4**	**22.2**	**11.2**	**15.7**	**25.5**
	(3.3 - 23.2)	(1.3 - 21.8)	(2.7 - 54.2)	(2.5 - 24.9)	(2.0 - 42.7)	(3.9 - 64.8)
Only MPI	**3.6**	**13.2**	**8.1**	**5.1**	**21.3**	**13.3**
	(0.3 - 9.2)	(2.8 - 28.8)	(0.4 - 25.5)	(0.2 - 13.7)	(4.0 - 49.1)	(0.2 - 43.8)
Neither	**83.5**	**72.6**	**8.4**	**80.7**	**44.3**	**26.6**
	(70.1 - 94.7)	(55.8 - 89.4)	(1.5 - 24.3)	(67.0 - 94.2)	(24.4 - 72.1)	(9.8 - 59.3)
Overlap	**85.1**	**78.3**	**69.7**	**83.7**	**63.0**	**61.2**
	(74.6 - 95.0)	(69.9 - 91.0)	(45.4 - 89.0)	(74.9 - 94.5)	(49.0 - 76.9)	(34.9 - 76.8)

Source: Own elaboration.

6. Insights from a joint index of monetary and nonmonetary deprivations

So far, our analyses have given clear hints of the related, yet fundamentally different empirical nature of the underlying welfare variables in the monetary and nonmonetary approaches to poverty. We have also stressed the large influence densities around poverty thresholds will have on matching or mismatching poor populations. This is so particularly in the poorer countries. As we mentioned earlier, a combined index, the 4DMPI (i.e. an index combining the dimensions and indicators of global MPI with a fourth dimension, namely monetary welfare) has the potential to avoid these mismatches when very specific parametric decisions are adopted within the AF dual cutoff counting approach framework (see also Santos, 2013 for a discussion on this matter):

1. consumption/income is the sole indicator in the monetary welfare dimension,
2. each dimension is equally weighted (one-fourth), and the indicators are also equally weighted within dimensions,
3. the multidimensional poverty line is set to $k = 1/4$ (which corresponds to the union approach of poverty identification in this case, see Santos, 2013).

Under this parametrization, the 4DMPI has the attractive feature of identifying the subset of the population that includes all people who suffer poverty, irrespective of the approach taken to this concept. Effectively, the 4DMPI poverty set is formed of individuals who are either monetary poor, or poor by the global MPI, or both. Hence, if the purpose of the poverty measurement analysis is to arrive at a description that avoids identification mismatches, then important parametric decisions can be taken on the grounds of transparent technical arguments. This endows the 4DMPI with an important feature amidst the vivid academic debate around normative choices in (multidimensional) poverty measurement (Alkire & Foster, 2011; Atkinson, 2019; Ravallion, 2011). Notice, however, that the identification mismatch is effectively avoided by adopting the above 4DMPI structure, irrespective of the monetary poverty line. Thus, this parameter remains as a pivotal element in the quest to establish the 'amount' of poverty in the society, as well as to determine the composition of poverty. Indeed, as a key component of the 4DMPI, the monetary poverty line interacts with the other included indicators at the poverty identification stage, thus influencing the prevalence of non-monetary deprivations among the poor. We will now go on to present an empirical discussion on these issues.

6.1. Poverty incidence and the monetary poverty line

Let us start by establishing an analytical benchmark. Notice that for the trivial monetary poverty line of \$0.00 (by which monetary poverty is nonexistent), the multidimensional poverty incidence by the 4DMPI and the global MPI are identical. A higher poverty line can increase the number of weighted deprivations experienced by every individual, which is the reason the 4DMPI headcount ratio is a nondecreasing function of the monetary poverty line. This is depicted in Figure 9, which plots the monetary poverty headcount ratio (green line), the 4DMPI headcount ratio (orange line) and the global MPI headcount ratio (horizontal blue line) against an array of plausible monetary poverty lines between \$0.00 and \$4.00.

In Figure 9 we can see the magnitude of the identification mismatches that can be avoided by the appropriately defined 4DMPI, as far as the incidence of poverty is concerned, across an array of monetary poverty lines. Let us first focus on the difference between the 4DMPI and monetary poverty headcount ratios (i.e., the vertical distance between the orange and the green lines), which represents the proportion of the population that is multidimensionally poor solely due to non-monetary hardships. As expected, this first type of potential mismatch (in absolute terms) fades out for higher monetary poverty lines, which is particularly true for both the poorer (Ethiopia and Uganda) and the least poor countries (Brazil and Ecuador). Interestingly,

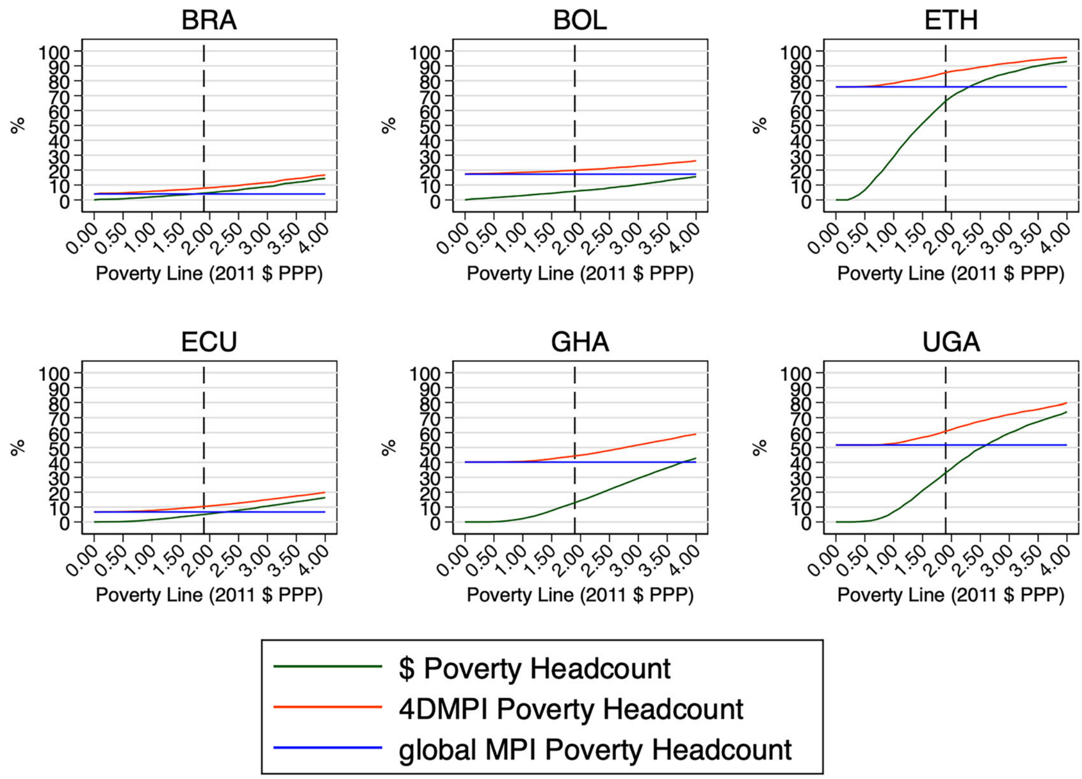

Figure 9. Poverty headcounts by monetary poverty line.
Source: Own elaboration.

even for a monetary poverty line as high as $4.00, this mismatch remains over 10% in the mid-poor countries (Bolivia and Ghana).

Turning now to the difference between the 4DMPI and the global MPI incidence (i.e., the vertical distance between the orange and the horizontal blue line), we can see the proportion of the population who is poor due solely to monetary shortfalls. Naturally, this potential mismatch is practically nonexistent for very low monetary poverty lines, but this is true to very different extents depending on the overall poverty level. In the richer countries (Ecuador and Brazil), the difference (as a mean point estimate) is over 5% ‘only’ after $2.30. In the poorer countries, however, we observe this difference for much poverty line lower values - $1.40 in Ethiopia and $1.60 in Uganda. This goes on to show that the poverty incidence differentials in the latter countries would have a greater practical relevance given the preferred extreme poverty line of $1.90.

Clearly, the choice of the monetary poverty line plays a crucial determining role for the ‘amount’ of poverty in all six countries, as measured by the 4DMPI poverty headcount ratio. In addition, there is also considerable sensitivity as the responsiveness of this ratio to changes in the monetary poverty line is determined by the proportion of the population sitting around the initial level of the latter. If we take $1.90 as the initial poverty line, shifts in the headcount ratio are expected to be greater in the poorer countries. For instance, in Ethiopia, 30.22% of the population has a level of monetary welfare between $1.40 and $2.40/day; a shift of the poverty line between these bounds yields a change in the 4DMPI headcount ratio from 81% to 89%. In Ecuador, due to overall lower levels of poverty, the proportion of population within the same range of monetary welfare is 4.40%, and a similar shift of the poverty line changes the 4DMPI from 8.7% to 12.5%.

This compelling evidence suggests a peculiar role played by the monetary poverty line as a defining factor of the 'amount' of *multidimensional* poverty as measured by the 4DMPI, that is a combination of both monetary and non-monetary deprivations. Let us recall that, since the 4DMPI structure guarantees absence of identification mismatches, the non-negligible poverty headcounts differentials that we make a case for here can be entirely attributed to shifts in the monetary poverty line, and that small shifts can have potentially much larger effects on the non-monetary characteristics of those who are at the margins of monetary poverty.

6.2. The composition of poverty and the monetary poverty line

Not only do changes in the monetary poverty line induce variations in the 'amount' of multidimensional poverty in the 4DMPI, but they also reshuffle its composition, as well as the entire poverty set. In effect, the mismatches that we made a case for in previous sections allow to posit that people who are sorted in or out of the poverty set *solely* due to a change in the monetary poverty line have distinctive non-monetary deprivation profiles. We can see this in two ways; the first is a dimensional contribution analysis and the second is an assessment of censored non-monetary deprivations (see Alkire et al., 2015).

Following the AF method, the dimensional breakdown is an axiomatic property of the *adjusted* 4DMPI headcount ratio, which is the product of the (simple) headcount ratio that is the focus of this paper and the average intensity of multidimensional poverty. This intensity measure is computed after identification as the simple empirical mean of the weighted deprivations experienced by the poor population. More technical details can be found in Alkire and Foster (2011).

In Figure 10, we plot the part of the 4DMPI adjusted headcount ratio that can be attributed to each dimension across an array of monetary poverty lines from \$0.00 to \$4.00. Naturally, we

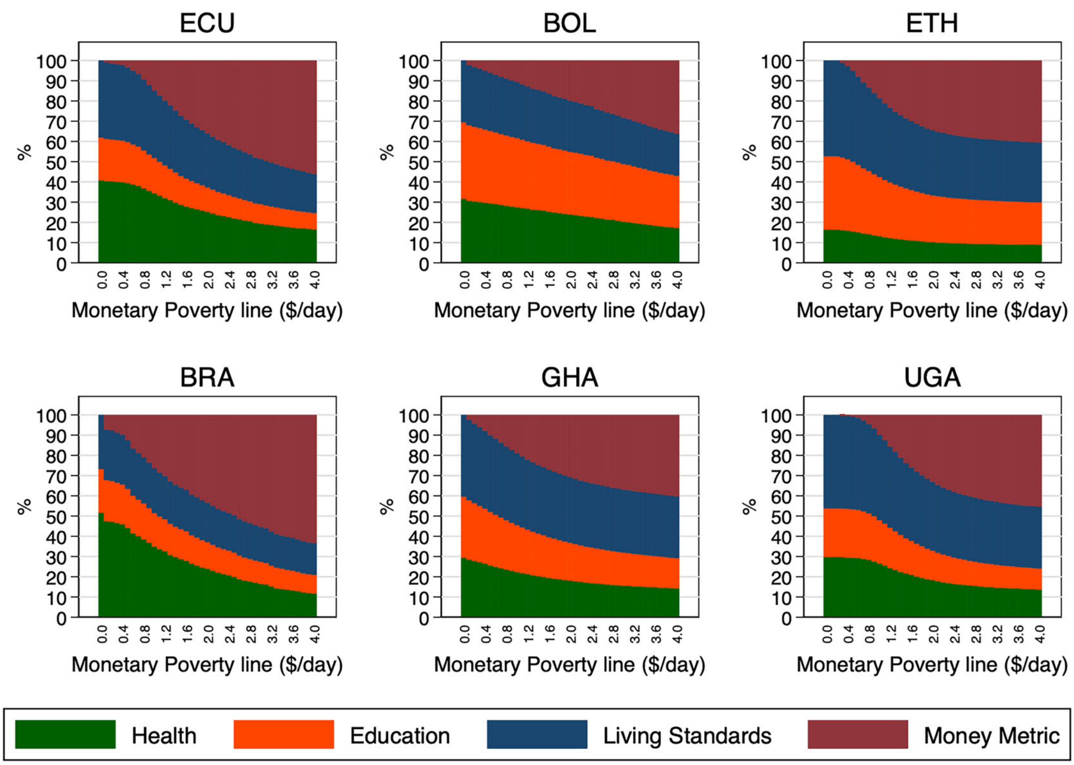

Figure 10. Dimensional relative contribution in the 4DMPI.
Source: Own elaboration.

can see that multidimensional poverty is entirely due to the non-monetary dimensions when the monetary poverty line is set to \$0.00. From that point onward, the contribution of monetary shortfalls to multidimensional poverty is a nondecreasing function of the monetary poverty line. In the case of less poor countries, the contribution of monetary shortfalls to poverty tend to increase faster compared to poorer countries. For a \$4.00 poverty line, monetary deprivations can account for more than 50% of poverty by the 4DMPI in Brazil and Ecuador, whereas it is around 40% in the other four countries.

This is one important yet unsurprising way in which the understanding of multidimensional poverty is reconfigured through the lens of the 4DMPI. Perhaps it is more informative to highlight that the contributions of the *non-monetary* dimensions *relative to each other* in the new, wider notion of poverty are also responsive to changes in the monetary poverty line. In Brazil, for instance, the contribution of deprivations in the health dimension accounts for 50% of poverty in the 4DMPI with a \$0.00 poverty line, but if one was to adopt the monetary poverty line of \$4.00, then the contribution of Health, relative to the non-monetary dimensions would approach 33%. For Bolivia, however, deprivations in Health account for roughly 30% of poverty at both the \$0.00 and \$4.00 poverty lines. The different changes of the relative contributions of non-monetary dimensions could, then, change prioritisation of non-monetary poverty relief purely due to a change in the monetary poverty line.

7. Concluding remarks

Monetary and non-monetary viewpoints differ in methods, data, and conceptual approach to poverty. Our motivation for this paper was fueled by two concerns. First, we were interested in the extent to which a combined index may actually offer a clearer view of poverty across 'mismatch' and correlation issues. Second, we wished to explore the differences or correlations between household welfare distributions produced by monetary and multidimensional welfare approaches as opposed to solely considering the differences produced from poverty thresholds set within them.

To address these concerns, we split analysis into three parts. First, we conduct an international comparison of aggregated poverty incidence for both monetary and multidimensional poverty headcounts. Second, we use microdata from a set of six countries to investigate individual-level relationships between welfare and poverty in monetary and multidimensional terms. Third, we consider a joint index of monetary and non-monetary deprivations across those six countries.

At the aggregate level we find an overall correlation across a range of poverty headcounts using differing MPI and \$PPP thresholds for the whole sample of 90 countries. However, subgroup analysis reveals that these correlations are weaker and not significant amongst the poorest countries.

By delving deeper into individual-level data we observe a clear positive relationship between monetary and multidimensional welfare across six case study countries chosen to reflect differing levels of poverty and differing instability of poverty rankings. We find that dispersion around the relationship between monetary and non-monetary poverty varies greatly both between and within countries. Non-monetary deprivations are found to be concentrated amongst those who are the poorest in monetary terms and we find this to be true to a greater extent in the poorest countries. When moving to assess poverty, meaning that poverty lines need to be chosen, we show that the change in poverty incidence is dependent upon the density of the underlying variables close to the lines chosen. Furthermore, the proportion of mismatches and overlap (between the two poverty measures) depends on the joint distribution surrounding the intersection of both poverty lines. We find that it is the poorest countries who have the least overlap and the most volatile responses the changes in the poverty lines, precisely because the typical poverty lines intersect the underlying welfare variables at their highest density.

Our final analysis considered the extent to which the issues surrounding mismatch were resolved in a combined index, which contained monetary poverty as one of four dimensions. A combined index has some desirable features, but also faces some limitations. On the one hand, a combined index prevents overlooking poor people (if the appropriate poverty cutoff is applied), regardless of which approach to poverty is adopted. This is undeniably a useful property if the purpose of the poverty measurement exercise is to determine the overall *aggregate* level of poverty in a society. However, policy against poverty often requires more than that. The combined index identifies poor people based upon a mixture of monetary and non-monetary deprivations in such a way that the deprivation profile of the individuals in the poverty set is *fundamentally* different. The intensity in which they suffer poverty (as defined by this mixture of deprivations) is different than the one that is obtained if the two approaches are kept separate. This may imply some drawbacks if *who* is identified as poor and *how* poor they are is given analytical priority compared to *how much poverty there is in a society*. Public policies such as targeting or budgeting are primarily concerned with poverty identification and the composition of poverty. Thus, a thorough analysis of the characteristics of those that are most likely to be mismatched needs is required for effective policymaking. This is context- dependent, as determining the relevant characteristics for this analysis depends on the policy priorities for each country; for instance, priority can be given to tackling the urban-rural divide, or to closing gender gaps, or to fostering child protection programmes. Public actions against deprivation in public services such as electricity or adequate sanitation, for instance, are different compared to those required to sustainably improve opportunities for income acquisition. Yet both are essential to improve people's lives and to end poverty, which is why they are prominently featured in SDGs and in virtually every global Agenda for development. Thus, a measure that identifies an individual as being poor *regardless* of whether it is because lack income *or* non-monetary welfare *or* both, may be less attractive.

Our analysis of a combined index has also raised important areas for research to take future research in this area forward. We suggest that more work is required on issues, such as disaggregation and decomposition of the dual-cutoff counting approach (Alkire & Foster, 2011), to explore possible ways to mitigate the drawbacks that we mention for combined indices. But this would not solve another issue, namely the influence of the monetary poverty line over the non-monetary characteristics of people who are identified as being poor by the combined index. In the last part of our paper, we have made a clear empirical case for this point. Future research may be able to demonstrate how to establish bounds around monetary poverty lines in combined indices that can more clearly help identify upper and lower poverty lines that can help policy makers navigate the policy and targeting difficulties faced when reducing poverty across both monetary and non-monetary approaches.

Notes

1. This measure combines monetary deprivation with lack of access to social rights. It defines a person as being multidimensionally poor if they lack access to at least one constitutional right *and* are poor by monetary terms. More information about this measure can be found here: https://www.coneval.org.mx/InformesPublicaciones/FolletosInstitucionales/Documents/Medicion-multidimensional-de-la-pobreza-en-Mexico.pdf
2. Please see: https://www.ecuadorencifras.gob.ec/documentos/web-inec/Sitios/PobrezaMultidimensional/assets/ipm−*metodologia − oficial.pdf*
3. See *Transforming Our World Report*: https://sustainabledevelopment.un.org/content/ documents/21252030%20Agenda%20for%20Sustainable%20Development%20web.pdf
4. http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx.
5. https://ophi.org.uk/multidimensional-poverty-index.
6. On average, the multidimensional poverty surveys are conducted 1.46 years later than their monetary counterparts. To increase comparability, we exclude countries where the absolute gap in years between surveys used to calculate monetary and multidimensional poverty is greater than 9.
7. Pearson's correlation coefficients show similar levels of significance, with coefficients ranging from 0.716 to 0.894.

8. We will focus on the same poverty lines/cutoffs as in the previous section.
9. To confirm this, we run a simple OLS regression of average multidimensional rank on average monetary rank, instability, and their interaction. We find that average multidimensional rank is highly correlated with average monetary rank (coef. = 1.049***), but that this correlation significantly reduces when instability increases (int. coef. = -0.013**).
10. In particular, whenever an indicator is missing, this policy assigns the weight of that missing indicator to other non-missing indicator(s) in the same dimension. For instance, where the nutrition indicator is missing, the child mortality indicator is given a weight of 1/3 instead 1/6 in the health dimension.
11. Epanechnikov kernels and 'optimal' bandwidths are used to estimate the density plots.
12. Recall that the headcounts for monetary poverty, at the $1.90 threshold are 5%, 6%, 66%, 5%, 13% and 33%, for Brazil, Bolivia, Ethiopia, Ecuador, Ghana, and Uganda, respectively, with MPI headcounts at the k = 1/3 threshold of 4%, 17%, 76%, 7%, 40% and 51%.

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