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Monetary and Multidimensional Poverty: Correlations, Mismatches and Joint Distributions

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Abstract

We consider the relationships between multidimensional and monetary poverty indices in international and national poverty profiles, and evaluate the empirical consequences of identifying poor people relying on a combination of both approaches. Taking first a cross-country perspective, focusing on the developing world, we find that the incidence of poverty according to money metrics and the global MPI, a non-monetary measure of poverty, are correlated. This correlation breaks down in poorer countries. We use micro-data from six countries 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, again, in the poorer countries. Although mismatches could be solved by combining both approaches in a dual cutoff poverty measure, the choice of the monetary poverty line remains a considerable issue as it changes the non-monetary composition of poverty.

Keywords: Poverty Measurement, Developing World, Mismatch, Distributional Analysis, Poverty Lines

JEL Classification: I31, I32, D31

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The Oxford Poverty and Human Development Initiative (OPHI) is a research centre within the Oxford Department of International Development, Queen Elizabeth House, at the University of Oxford. Led by Sabina Alkire, OPHI aspires to build and advance a more systematic methodological and economic framework for reducing multidimensional poverty, grounded in people's experiences and values.

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1 Introduction

Eliminating poverty is a pressing issue in development policy, but long-standing conceptual and measurement issues in the academic and policy-making spheres hinder progress. Poverty is complex and is increasingly recognized as such. The ways in which human lives can be impoverished are inherently plural (Sen, 1976, 1980, 1988; Laderchi et al., 2003; Alkire and Santos, 2014). The use of a monetary-only approach to poverty is still prominent in development analyses (see e.g. Sumner (2007); Gamboa et al. (2020)), but there is a rapid and wide acceptance of a need to adopt a wider, *multidimensional* notion of poverty to effectively identify people who suffer welfare deprivations (Atkinson, 2019). There remains less agreement on the extent to which monetary shortfalls can be considered as good proxies for many human welfare deprivations (Nolan et al., 1996; Atkinson et al., 2002; Nolan et al., 2011; Thorbecke, 2013).

Understanding how and why different approaches to poverty capture different types 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. A large number of empirical studies have found monetary and multidimensional poverty to be mismatched (see e.g. Iceland and Bauman (2007); Tran et al. (2015); Suppa (2016); Roelen (2017)). Some make the case that each approach sheds a different and distinct light on understanding poverty and acting against it (Laderchi, 1997; Bradshaw and Finch, 2003; Bag and Seth, 2018). Fewer studies assess a 'combined' approach: a multidimensional index that includes monetary poverty as one of its component indicators. Santos and Villatoro (2018) and Bradshaw and Finch (2003) do so to consider poverty measurement in Latin America and Great Britain, respectively.

In this paper we take a global perspective to analyse these issues, 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 mismatches and divergences. This is particularly relevant and timely as multidimensional poverty is now formally entrenched in the Sustainable Development Goals (SDGs)[1] following its adoption by international development agencies such as UNDP, UNICEF, and ECLAC (UNDP., 2010; De Neubourg et al., 2012; Feres, 2001). More recently, the World Bank has begun to actively engage with this agenda (World Bank, 2018; Atkinson, 2017).

[1]See *Transforming Our World Report*: https://sustainabledevelopment.un.org/content/documents/21252030%20Agenda%20for%20Sustainable%20Development%20web.pdf

This recent consensus sits across differences and debates that continue. The SDGs still contain distinct monetary poverty targets alongside multidimensional ones. There remains a debate around how best to measure multidimensional poverty (Alkire et al., 2011; Ravallion, 2011). 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), and many countries have adopted different versions of indices using the Alkire-Foster methodology for their own national indices. This means that MPI indices coexist with separate monetary valuations of poverty and there continues to be real differences in terms of conceptualization, data, and method (Alkire et al., 2015; Ravallion, 2011)). This paper empirically addresses the consequences of some of these differences alongside the issue of correlation between resulting welfare distributions and how these affect a measure that includes 'monetary welfare' as one relevant dimension in a cross-cutting multidimensional poverty measure.

In terms of conceptualisation, the monetary approach seeks to estimate the level of household consumption or income that meets a 'minimum needs standard' enabling them to satisfy their basic needs (Haughton and Khandker, 2009), while the non-monetary approach regularly focuses on an array of well-being 'dimensions', which have intrinsic importance for people's lives and represent people's ability to lead the life they have reason to value (Alkire and Santos, 2014). These different conceptualisations spring, in part, from different data sources. The monetary approach relies on data coming from specific surveys of household expenditure and incomes. The non-monetary approach regularly uses very different, unrelated surveys that lack data on consumption or income, such as Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS) surveys (Alkire and Santos, 2014). There are also differences in the underlying welfare variable in each approach. The poverty measures based on the Alkire-Foster method consist of recording binary deprivations to build up individual deprivation scores, which do not match the continuous nature of income or consumption used in the monetary approach. Note that the underlying welfare variable in the monetary approach is a measure of continuous rising welfare *advantage*, whereas the non-monetary welfare measure reflects a *disadvantage from multiple deprivations*. There are resulting differences between monetary and multidimensional poverty that can arise from normative and empirical sources.

Taking these potential differences into account, we empirically revisit the relationship between monetary and multidimensional poverty to set solid ground for a discussion about a measure that combines both. All poverty measurement analysis consists of 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. We then focus on data at the individual level from six 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 by adding a monetary welfare dimension to the structure of the global MPI in order to empirically assess the 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 extent of the volatility between poverty classifications. 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 in 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 welfare distributions that are perfectly correlated. 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), can be determined by factors other than people's purchasing power (OPHI, 2018; Alkire and Santos, 2014). Many observable indicators of these dimensions, such as access to school, access to drinking water, or adequate sanitation are often provided as free public services or are heavily subsidised. Even where indicators may be related to purchasing power, they reflect different assumptions about time. Monetary welfare is measured as a flow variable: observed at one point in time and likely to be volatile (Jolliffe and 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.

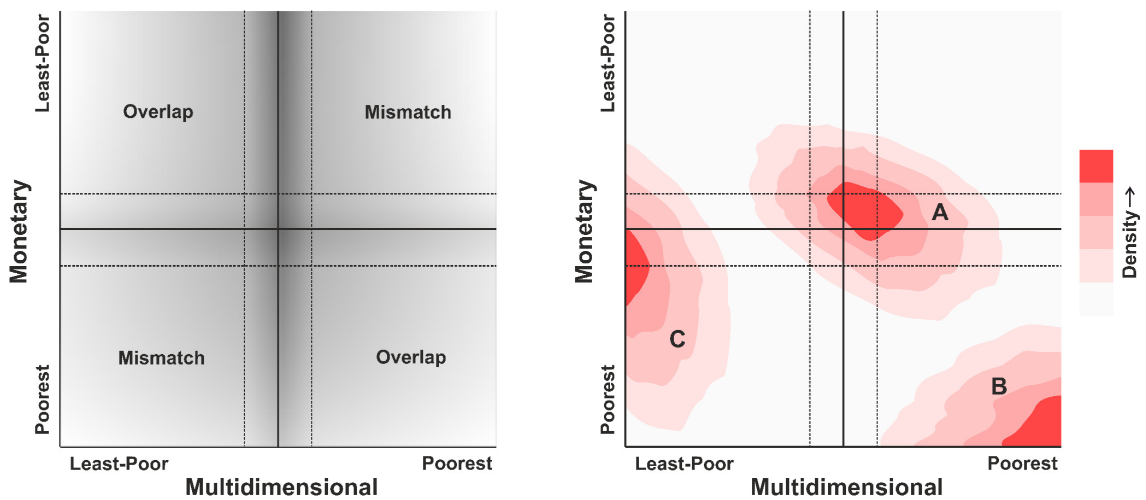
Measurement error may also underlie differences. Measuring consumption and income is inherently more likely to include errors of response, which affect the level of the final welfare aggregate, than relying on more verifiable indicators of the presence of goods in the household or of recorded participation. 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 deprivations are correlated or to believe that increases in monetary advantage are not associated with greater disadvantage in non-monetary terms. It is reasonable to assume that a gradient will be seen in many cases.

We also consider another area of difference that arises from the setting of poverty thresholds across different distributions and how these thresholds compare when different approaches are used. Monetary poverty status can be responsive to small marginal changes in the monetary welfare variable due to its continuous nature, while changes in non-monetary multidimensional poverty status occur only for discrete, qualitative changes in indicator-wise deprivation status. Thus, the likelihood of a 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 and mismatches may be the result of the intersection of small marginal differences in monetary welfare and the 'lumpy' steps of multidimensional deprivation.

Importantly, the use of a poverty line (or welfare thresholds) 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 multidimensional 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



As we stated earlier, 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 similar approach – produces considerable uncertainty, as near-poor populations have many similar characteristics (Brown et al., 2016; Fortin et al., 2015).

When sorting the population into the four quadrants, two important elements are at play: the *pair* of monetary and multidimensional poverty lines that are chosen and 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 that 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. 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 results in large changes to the respective classifications. It is, then, the proportion of the population that lies within the respective poverty lines that determines how volatile the sorting into these four quadrants is.

It is the interaction of joint densities and poverty lines, which lead to overlaps and mismatches, that this paper will investigate; followed by the construction and evaluation of a combined monetary and multidimensional index that seeks to avoid these issues of mismatch.

3 Methods

Poverty measurement is the combination of two ordered steps (Sen, 1976; Foster et al., 2010; Atkinson, 2019; Alkire et al., 2015). The first is the identification step, which consists of sorting out the poor people from the non-poor by adopting a poverty line, and the second is poverty aggregation, which consists of estimating a summary measure 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 scrutinise, namely (one-dimensional) monetary and multidimensional. Note that, when we analyse secondary data, these methods correspond to the ones that are effectively performed by academic institutions and international organisations 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 deficiencies in internationally comparable micro-data prevent us from taking this ideal route. For practical purposes, we restrict ourselves to the World Bank's international monetary poverty lines to identify the poor, aiming to align our study with one of the most prominent, albeit perfectible, approaches to assess monetary poverty globally (Ferreira et al., 2015; Jolliffe and 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 operationalised here using the dual counting approach pioneered by Alkire and Foster (2011) (AF henceforth), which underlies 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^0_{ij} takes a unity value if $y_{ij} < z_j$, and it is zero-valued if $y_{ij} \geq z_j$. 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 $c = \{c_1, ..., c_n\}$, identifies people suffering a number of simultaneous deprivations that define them as being multidimensionally poor. Hence, the multidimensional poverty identifier $\rho_{i,k}$ 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.

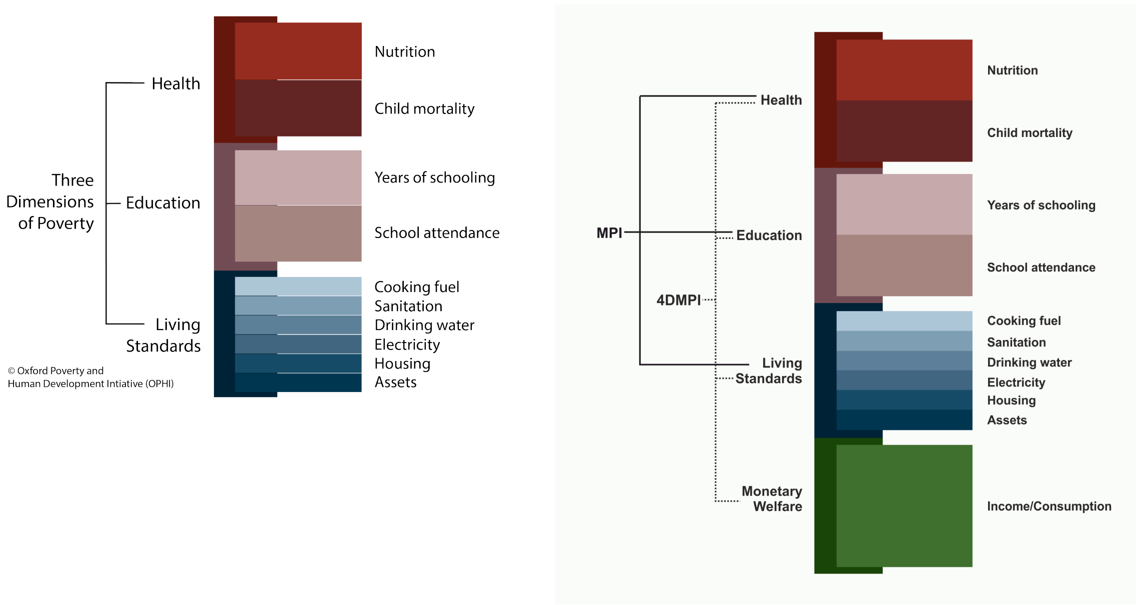
The structure of the UNDP-OPHI global MPI is depicted in Figure 2. This index is formed by ten indicators pertaining to three dimensions (two indicators for health, two for education, and six for living standards), where each dimension is given the same weight (one-third) and each indicator is given the same weight within dimensions. A detailed description of the deprivation thresholds and indicator definitions can be found in (Alkire and Jahan, 2018). 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) and OPHI (2018) 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: $k = \{1/5, 1/3, 1/2\}$. 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 and 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 $H = \frac{1}{n} \sum_{i=1}^{n} \rho_{i,k}$. 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 that includes income/consumption as an additional relevant indicator pertaining to a fourth dimension of poverty, say *monetary welfare*. We explore this and form examples in Section 6 below. Let us call this the 4DMPI structure. In this alternative operationalisation 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 poverty status. A similar approach has been recently scrutinised by the World Bank (World Bank, 2018), which uses a different indicator and dimension structure to that shown in Figure

Figure 2: Structures of the Multidimensional Poverty Indices

(a) Original structure of the MPI **(b) Structure of the 4DMPI**



Source: For the original structure of the MPI see Alkire, Kanagaratnam and Suppa (2018) and OPHI (2018) pp. 5–6

2.

It is important to highlight that our 4DMPI structure has 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 who 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 who 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 in monetary terms or according to the global MPI or both, and any mismatch from separate measures is no longer present.

4 Aggregate Level

Our analysis begins at the aggregate level. We perform international comparisons of monetary and multidimensional poverty, across the range of poverty thresholds that we mentioned earlier ($1.90, $3.20, and $5.50 per capita per day for monetary poverty, and deprivation score thresholds of 1/5, 1/3, and 1/2 for multidimensional poverty). In each instance, we rank countries based on the relative prevalence of poverty, then analyse the extent to which these ranks are correlated between measures, across each threshold. To identify potential heterogeneity in these correlations, we divide the sample into subgroups based upon the average rank and volatility of poverty levels. These subgroups form the basis for the selection of country case studies in the 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's PovCalNet database[2] and the 2018 global MPI data set,[3] respectively. To increase comparability, we exclude countries where the absolute gap in years between surveys used to calculate monetary and multidimensional poverty is greater than or equal to 10. This gives a final sample consisting of 27 low income countries, 39 lower middle income countries, and 24 upper middle income countries as defined by World Bank 2018 income group classification (World Bank 2019).

4.2 Analysis

Table 1 shows the overall correlation between monetary and multidimensional poverty headcount rankings, using the six different thresholds for all 90 countries in the sample. The Kendall Rank Correlation Coefficients show the extent and significance of these correlations. We observe high and significant coefficients, with all coefficients above 0.64 and significant at the 0.000 level. This shows that, when compared internationally, the incidence of monetary poverty is strongly correlated to that of multidimensional poverty.

4.2.1 Subgroup Analysis

While the above correlations hold at the sample level, heterogeneity in these correlations could exist within particular subgroups. However, when selecting subgroups an important

[2] http://iresearch.worldbank.org/PovcalNet/povOnDemand.aspx

[3] https://ophi.org.uk/multidimensional-poverty-index/global-mpi-2019/. Note that this study makes use of 2018 data, as the 2019 dataset is available only from July 2019.

Table 1: Monetary and MPI Poverty Headcounts: Kendall Correlation Coefficients

k(%)	\$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: ***: p-value<0.001
Source: Authors' calculations based on a 90 country sample – see Appendix 1.

question emerges: how should subgroups be defined? 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 the subgroup in which a country will be situated depends on the measure and threshold chosen.

To address this, let us use three poverty lines within each of the monetary and multidimensional poverty indices to generate an *average rank* of poverty. We will focus on the same poverty lines/cutoffs as in the previous section. Our set of 90 countries will be ranked from the least to the most poor for all thresholds within each measure. Then, the mean of those ranks will be taken for each country, j, to give the *average rank*. Using this, the 90 countries can be classified into three subgroups, from least poor to most poor.

While this procedure would, in principle, be sufficient to group countries, we argue that the simple average rank neglects an important consideration, namely *volatility*. For some countries, their rank may remain largely unchanged across these measures and thresholds. However, 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 volatility.

More formally, the average rank is the mean of the six ranks, while volatility is measured as the Euclidean distance between the ranks and the average rank. The two measures are as follows:

$$Average\,Rank = \bar{r}_j = \frac{1}{6}\sum_{i=1}^{6} r_{ij} \tag{1}$$

$$Volatility = \sigma_j = \sqrt{\sum_{i=1}^{6}\left(r_{ij} - \bar{r}_j\right)^2} \tag{2}$$

Table 2 shows the results of the subgroup analysis: first, we split the countries by *average rank* into least poor, mid-poor, and poorest. Then we further split them into six groups from the interaction of *average rank* and *volatile* groups. Our results show that correlations between monetary and multidimensional poverty are strongest and most significant in the least poor countries. If we do not split the countries by volatility, we observe no significant correlations for either the mid-poor or poorest subgroups. However, when excluding the more volatile countries, we observe significant correlations – but to a lesser extent compared to the least poor countries. Interestingly, regardless of the average rank, there are no significant correlations for the volatile countries. This shows the extent to which the choice of the poverty line matters for the poverty ordering of countries for each approach.

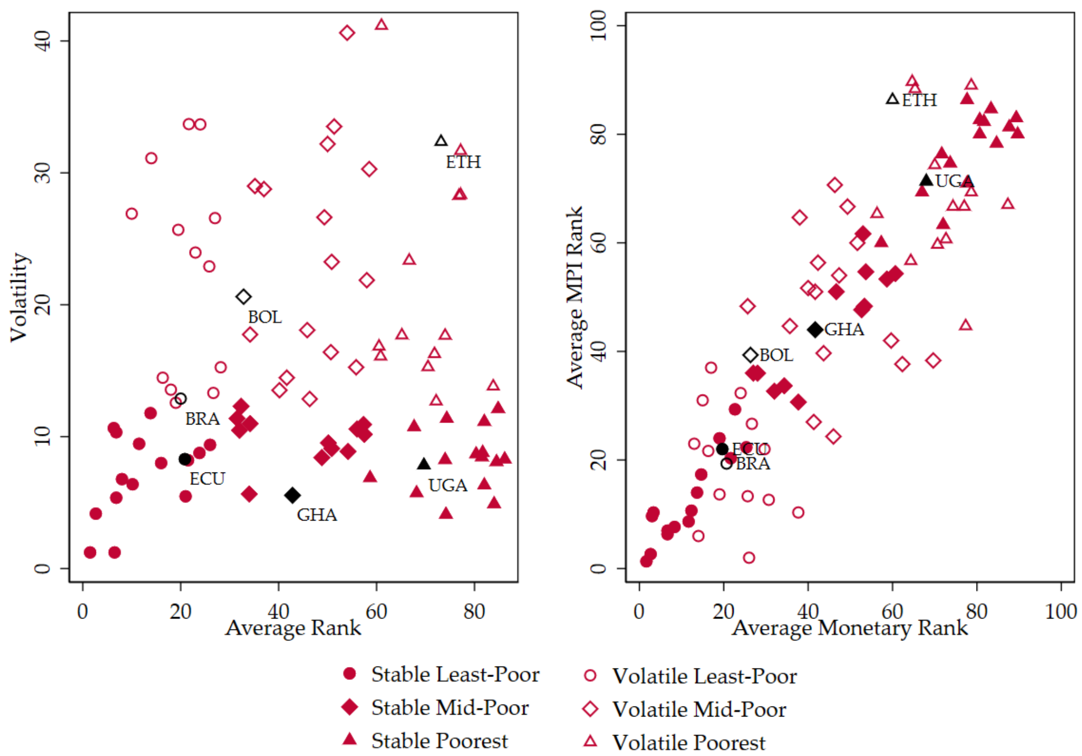
Table 2: Kendall Correlation Coefficients: Subgroups

	All			Stable			Volatile		
	$1.90	$3.20	$5.50	$1.90	$3.20	$5.50	$1.90	$3.20	$5.50
	Least Poor (n=30)			Least Poor (n=16)			Least Poor (n=14)		
MPI (0.50)	0.32*	0.34 *	0.27	0.76 ***	0.78 ***	0.61 ***	-0.21	-0.19	-0.21
MPI (0.33)	0.27	0.38 **	0.38 **	0.67 ***	0.67 ***	0.58 **	-0.28	-0.12	-0.06
MPI (0.20)	0.21	0.38 **	0.40 **	0.67 ***	0.70 ***	0.52 **	-0.39	-0.14	0.01
	Mid-Poor (n=30)			Mid-Poor (n=13)			Mid-Poor (n=17)		
MPI (0.50)	0.08	0.13	0.17	0.56 *	0.56 *	0.54 *	-0.28	-0.10	0.03
MPI (0.33)	0.11	0.20	0.24	0.51	0.56 *	0.59 **	-0.16	0.04	0.15
MPI (0.20)	0.17	0.25	0.26	0.62 **	0.62 **	0.49	-0.15	0.03	0.15
	Poorest (n=30)			Poorest (n=16)			Poorest (n=14)		
MPI (0.50)	0.06	0.08	0.18	0.48 *	0.43	0.47 *	-0.23	-0.25	-0.14
MPI (0.33)	0.14	0.16	0.21	0.48 *	0.43	0.47 *	-0.12	-0.14	-0.08
MPI (0.20)	0.19	0.24	0.28	0.52 **	0.53 **	0.53 **	-0.06	-0.08	0.03

Note: *: p-value<0.05
Source: Authors' calculations.

Overall, our aggregate results support a 'first order' finding that MPI and monetary poverty are correlated. However, the subgroup analysis has shown heterogeneity in the size and significance of these correlations. Most notably that, when making international comparisons, the correlation is weakest amongst the poorest countries. This means that understanding the underlying relationship between monetary and multidimensional poverty needs to clearly identify how the underlying distributions are correlated and when matches and mismatches matter. To do so, we need to delve into an analysis of individual-level data within a set of countries that have two characteristics. First, monetary and non-monetary variables must be available from a single survey. Second, the choice of country should take examples from each subgroup to ensure that we do not just consider 'stable' countries at a similar level of economic development/poverty prevalence.

Figure 3: Average Ranks and Volatility



Source: Authors' calculations.

The left panel of Figure 3 plots the average rank against volatility 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 taking into account the availability of data at the individual level that allows the computation of both a monetary measure and a measure of multidimensional poverty with a structure mirroring, as closely as possible, the global MPI. Thus we chose Brazil and Ecuador are within the least poor tertile, Bolivia and Ghana in the middle while Uganda and Ethiopia are in the poorest. Ecuador, Ghana, and Uganda are countries with stable rankings, while Brazil, Bolivia, and Ethiopia have a high degree of volatility. The right panel shows the plot of the average multidimensional rank against the average monetary rank. This reinforces the results of Table 2. Highlighting the close adherence to the 45 degree line for the stable countries, particularly for the least poor countries, and spread away from the 45 degree line for the volatile countries.

5 Individual Level

5.1 Data

A full and comparable analysis of monetary and multidimensional poverty matches/mismatches is limited by data deficiencies in micro-survey data (see World Bank (2018); Alkire and Santos (2014)). One key issue is the presence or lack of a set of non-monetary 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 policy used for the global MPI by UNDP-OPHI (see OPHI (2018)). 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, dhild mortality takes the full weight of the health dimension and is 1/3 instead of 1/6 of the overall measure.

Table 3 provides a summary of the micro-survey data we use, which are all representative at the national level. We use income as our monetary welfare variable in Brazil, Bolivia, and Ecuador but consumption in Ethiopia, Ghana, and Uganda. 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). Our results should be interpreted taking these data characteristics into account.

Table 3: Data Description: Individual-Level Analysis

Country	Survey	Year	N	$ Variable	Missing MPI
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	

Note: PNAD: Pesquisa Nacional por Amostra de Domicílios. EH: Encuesta de Hogares. ESS: Ethiopia Socioeconomic Survey. ECV: Ecuesta de Condiciones de Vida. GLSS: Ghana Living Standard Survey. UNPS: Uganda National Panel Survey.

5.2 Welfare analysis: Taking the whole distributions into account

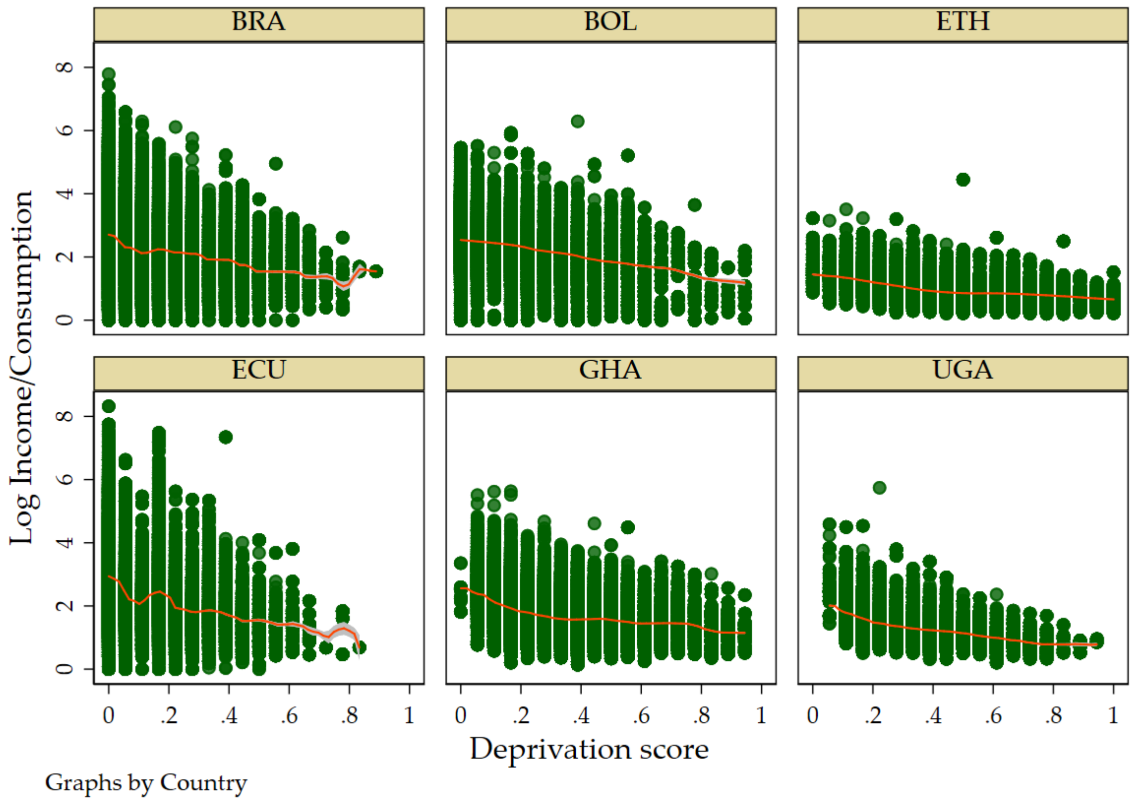
Returning to our earlier discussion in Section 2, we begin our analysis by assessing if there is a clear – but imperfect – negative relationship between the monetary welfare variables and the deprivation scores in each of the selected countries, irrespective of their ranking and volatility characteristics discussed 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 orange 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 4 and 5. 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 4, 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 4). 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 all the monetary welfare quartiles (0.20).

Figure 4: Level of Monetary Welfare vs. Deprivation Counting Scores



Source: Authors' calculations.

Table 4: Mean Deprivation Score by Income/Consumption Quartiles

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

Source: Authors' calculations.

Table 5 shows that the distribution of non-monetary deprivations across monetary welfare levels does not follow the exact same pattern. 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 5) is \$13.57/day in Ecuador and \$2.02/day in Uganda. Among the least deprived population (1st quartile in Table 5), the mean income tends to triple in both countries (\$36.78/day in Ecuador and \$6.31/day in Uganda).

Table 5: Mean per capita Income/Consumption By Deprivation Score Quartiles

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

Source: Authors' calculations.

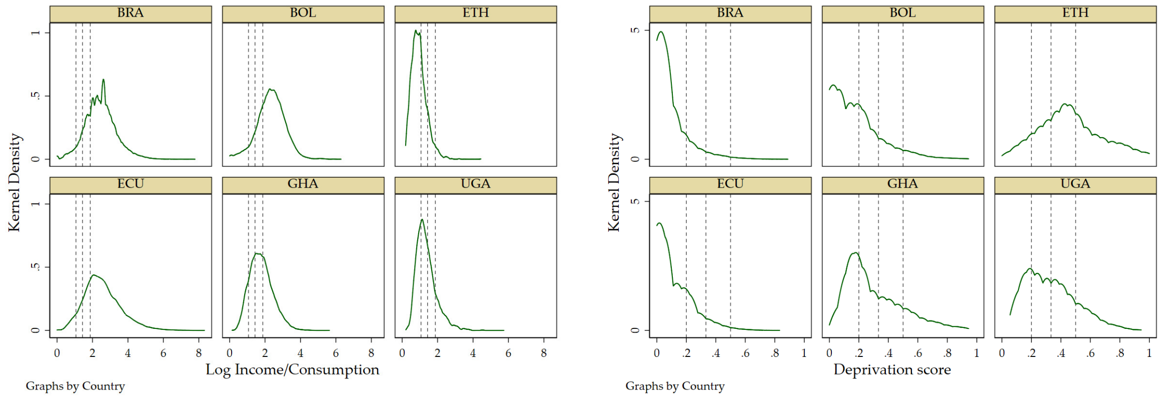
5.3 From welfare to poverty

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 as this focuses on the people sitting on selected *parts* of these distributions. This requires a sorting between the poor and non-poor population, which, as we have stated, corresponds to the first step of any poverty measurement exercise.

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 the left panel, and deprivation is shown in the right, alongside the three respective thresholds (dotted vertical lines). 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 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%.

Figure 5: Kernel Density Functions: Monetary Welfare and Deprivation Scores

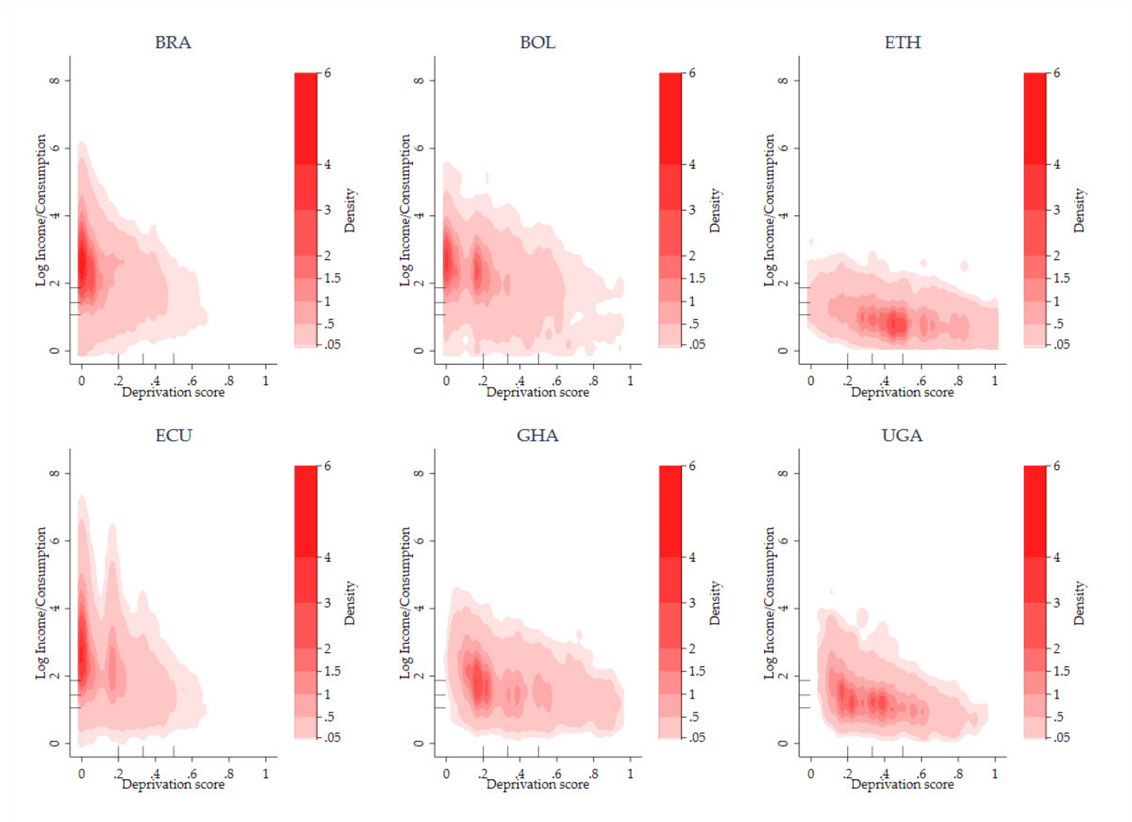


Source: Authors' calculations.

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 that gives the difference. For example, for Uganda moving from the \$1.90 to the \$3.20 threshold increases the headcount ratio by 30 percentage points, while for Brazil the increase is only 5 percentage points.

While useful, these univariate density functions reveal little of the change in matches and mismatches 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 populations 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 their populations that have deprivation scores within a much wider range (0.15–0.6) while enjoying similar levels of monetary welfare.

Figure 6: Bivariate Density



Source: Authors' calculations.

To summarise the previous figures and provide a clear link back to Figure 1, Table 6 provides measures of 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 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 are 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%.

Table 6: 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: Authors' calculations.

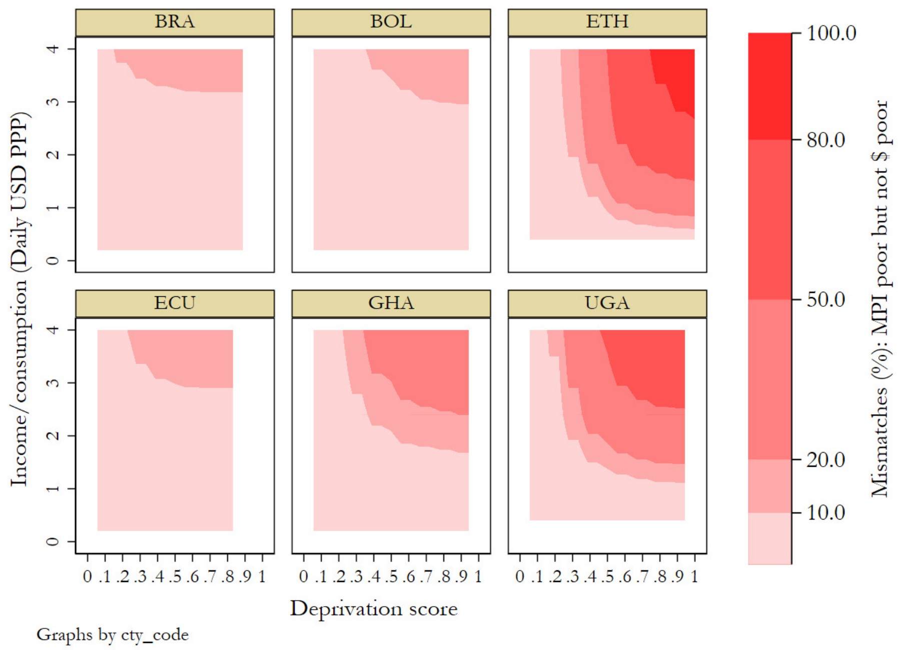
Under these circumstances, setting a pair of poverty lines (one monetary and one multidimensional) to operationalise the identification steps of a simultaneous poverty measurement analysis is a critical matter. It is evident that identification mismatches will take place to varying extents depending on the pair of chosen poverty lines, and by 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 policy-making against poverty.

To assess the extent of the mismatches, it is important to note 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 depicted in Figures 7 and 8,respectively, 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 in monetary terms is less than 10% for a wide array of poverty line pairs in Brazil and Ecuador, our less 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 as 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 range.

If we now focus on the poorer countries, Ethiopia and Uganda, comparably low levels of

Figure 7: Frequency of Mismatches: MPI Poor but Not $ Poor

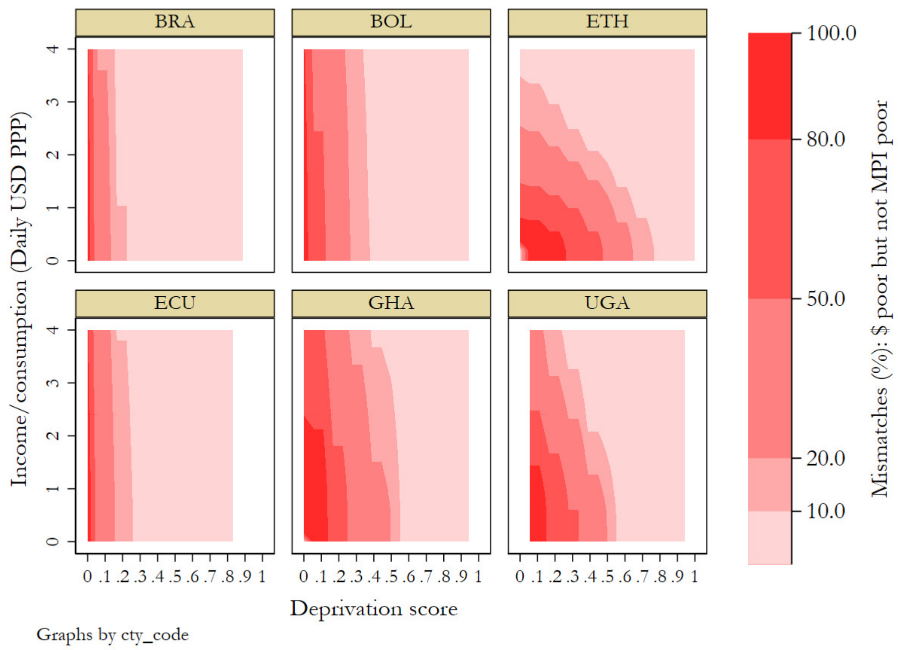


Source: Authors' calculations.

mismatches (≤ 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 (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 MPI poor people in Uganda would also be identified as being monetarily poor for *any* monetary poverty line ≤ $1.00. There is, however, a wide range of poverty line pairs for which the proportion of the population that is MPI poor while not being monetary poor is over 50%. This happens for relatively high multidimensional poverty lines (≥ 1/2 or 50%) combined with high monetary poverty lines (≥ $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, for instance, by adopting a multidimensional poverty line ≥ 7/10 (70%), while not being detected as poor by a monetary poverty line of at least $3.00, can be over 80%.

Turning now to the mismatch related to people who are monetary poor but not poor according to 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

Figure 8: Frequency of Mismatches: $ Poor but Not MPI Poor



Source: Authors' calculations.

of the population that is monetarily poor by *any* monetary poverty line ≤ $4.00 while not being multidimensionally poor by *any* poverty line ≥ 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 (60%) in Uganda and over 3/4 (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 7 represent the average proportion 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. It can be seen that average identification overlaps (either poor or non-poor by both measures) are highest for the least poor countries (85% in Brazil and 84% in Ecuador), and that this largely due to a large majority of the population being classed as non-poor by both approaches to poverty. As expected, the average identification overlaps in the poorer countries are primarily due to a prevalence

Table 7: 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** (0.2 – 4.5)	**5.8** (1.7 – 14.5)	**61.3** (33.8 – 87.5)	**3.0** (0.3 – 9.1)	**18.7** (4.8 – 42.9)	**34.5** (12.0 – 67.0)
Only $	**11.3** (3.3 – 23.2)	**8.4** (1.3 – 21.8)	**22.2** (2.7 – 54.2)	**11.2** (2.5 – 24.9)	**15.7** (2.0 – 42.7)	**25.5** (3.9 – 64.8)
Only MPI	**3.6** (0.3 – 9.2)	**13.2** (2.8 – 28.8)	**8.1** (0.4 – 25.5)	**5.1** (0.2 – 13.7)	**21.3** (4.0 – 49.1)	**13.3** (0.2 – 43.8)
Neither	**83.5** (70.1 – 94.7)	**72.6** (55.8 – 89.4)	**8.4** (1.5 – 24.3)	**80.7** (67.0 – 94.2)	**44.3** (24.4 – 72.1)	**26.6** (9.8 – 59.3)
Overlap	**85.1** (74.6 – 95.0)	**78.3** (69.9 – 91.0)	**69.7** (45.4 – 89.0)	**83.7** (74.9 – 94.5)	**63.0** (49.0 – 76.9)	**61.2** (34.9 – 76.8)

Source: Authors' calculations.

of people being classed as poor by both approaches.

In Table 7 we also show, in parentheses, 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 3% to 54%, whereas this range goes from 3% to 23% in Brazil. Similarly, the proportion of people identified only as being MPI poor can go from 0% to 26% in Ethiopia, but it goes from 0% to 9% in Brazil. These ranges are closely aligned with the volatility measures of Table 6. This evidence supports our initial concerns about the sensitivity to the monetary poverty threshold of any poverty identification 'mismatch' and our aversion to defining 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.

6 Insights from a Joint Index of Monetary and Non-monetary 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 non-monetary approaches to poverty and the large influence densities around poverty thresholds will have on matching or mismatching poor populations. This is true 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:

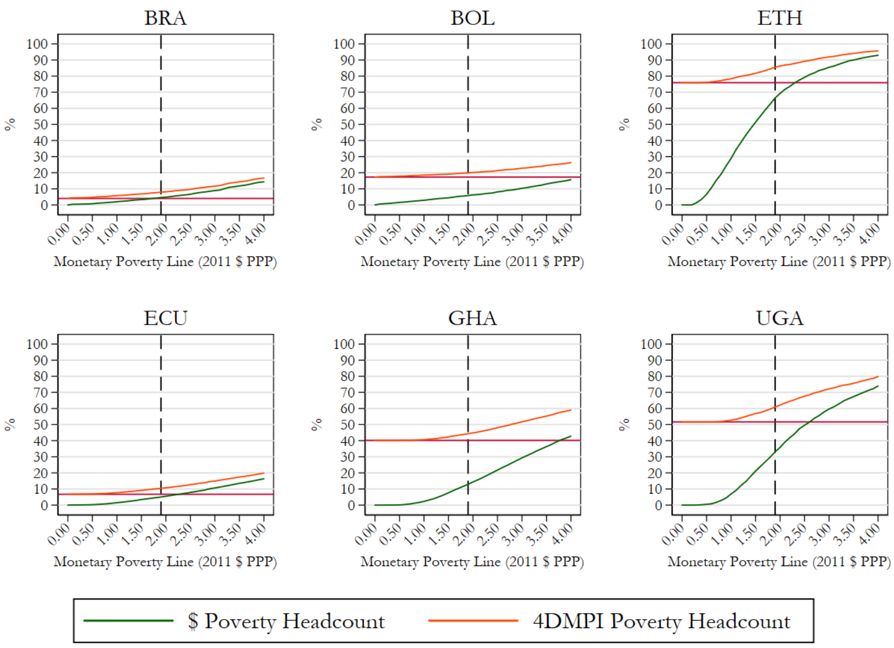
1. consumption/income is the sole indicator in the monetary welfare dimension,
2. each dimension is equally weighted (one-fourth), and the indicators are also equally weighted within dimensions,
3. the multidimensional poverty line is set to $k = 1/4$.

Under these parameters, 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. 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 would situate the 4DMPI in a rather favourable position within the active academic debate around normative choices in (multidimensional) poverty measurement (Atkinson, 2019; Alkire and Foster, 2011; 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 (at 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 why the 4DMPI headcount ratio is a non-decreasing 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 (red line) against an array of plausible monetary poverty lines between $0.00 and $4.00.

Figure 9: Poverty Headcounts by Monetary Poverty Line



Note: The red lines represent poverty headcount ratios for each country by the global MPI
Source: Authors' calculations.

In Figure 9 we can see the magnitude of the identification mismatches that can be avoided by using 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, 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 red line), we can see the proportion of the population that 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 lower poverty line 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 role in determining the 'amount' of poverty in all six countries, as measured by the 4DMPI poverty headcount ratio. But 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 the overall lower levels of poverty, the proportion of the population within the same range of monetary welfare is 4.40%, and a similar shift in 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 for the 'amount' of *multidimensional* poverty as measured by the 4DMPI, which is a combination of both monetary and non-monetary deprivations. Let us recall that, since the 4DMPI structure guarantees an 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.

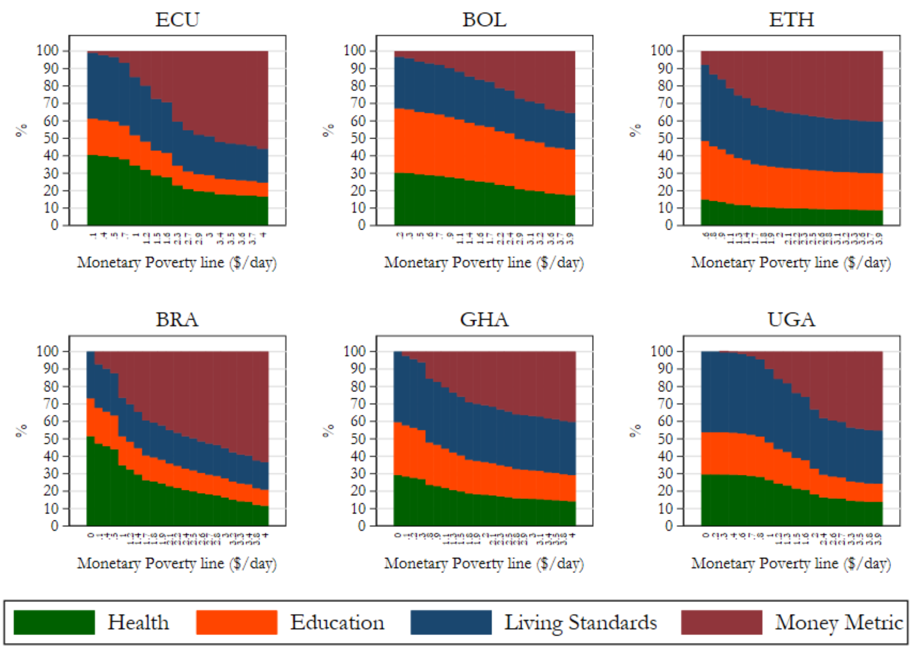
6.2 The composition of poverty and the monetary poverty line

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 us 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. We 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 non-decreasing 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 according to the 4DMPI in Brazil and Ecuador, whereas it is around 40% in the other four countries.

Figure 10: Dimensional contributions by Monetary Poverty Line

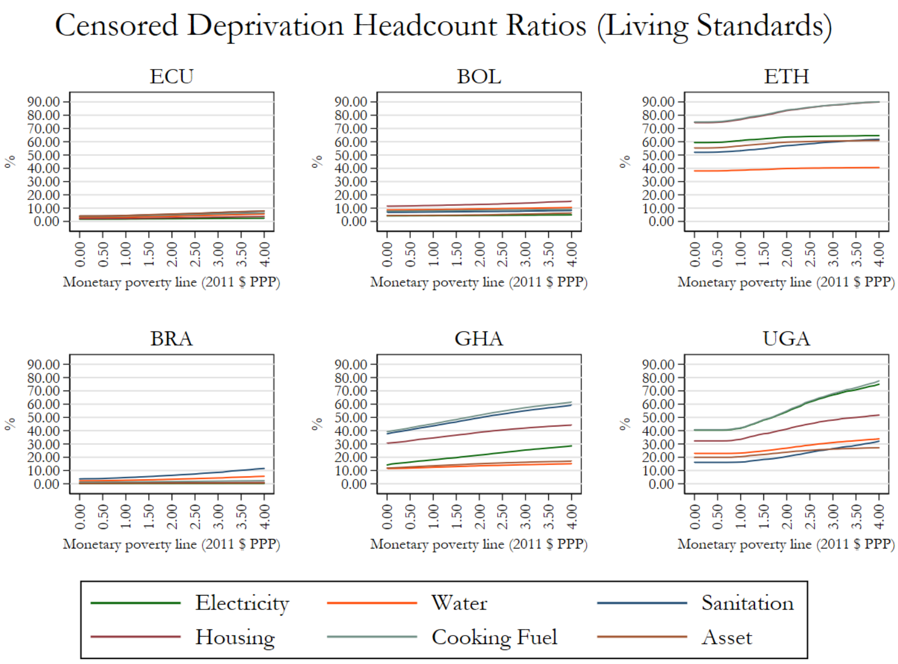


Source: Authors' calculations.

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 a 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.

Figure 11 depicts the proportion of people who are poor according to the 4DMPI and deprived in each living standard indicator (only, due to parsimony concerns). This ratio is termed the *censored* deprivation headcount ratio, as it focus on the prevalence of wellbeing shortfalls only among the people who have been identified as poor by the 4DMPI.

Figure 11: Censored Deprivation Headcount Ratios by Monetary Poverty Line



Source: Authors' calculations.

Looking at Ghana, for example, we find that around 10% and 12% of the population are poor deprived in electricity and water, respectively, through the lens of the global MPI (or, equivalently, in the 4DMPI with $0.00 as the poverty line, which can be found in the left-most side of the Ghana panel in Figure 11). If the poverty line was set to $4.00 then the proportion of people who are poor according to the 4DMPI and deprived in electricity would go up to 12%, but the proportion of people who are poor and deprived in electricity would go up to 30%. This surely has non-negligible consequences for effective policy-making combating these non-monetary aspects poverty. Adequate budgeting strategies to tackle electricity and water deprivations in Ghana would now depend on the choice of the monetary poverty line. Another example can be found in Uganda (see Figure 11), where, on average, the proportion of people who are poor and deprived in sanitation is lower those who are poor and deprived in assets *only* if the monetary poverty line is set to a value lower than $3.00. For greater values of the monetary poverty line (at least up to $4.00), we find that, on average, this statement is completely reversed.

7 Concluding Remarks

Monetary and non-monetary viewpoints differ in methods, data, and conceptual approach to poverty. Our motivation for this paper was fuelled by two concerns. First, we explored 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. Second, and as a consequence of that concern, we were then interested in the extent to which a single monetary poverty index may actually offer a clearer view.

To address these concerns we split our analysis into three parts. First, we conducted an international comparison of aggregated poverty incidence for both monetary and multidimensional poverty headcounts. Second, we used micro-data from a set of six countries to investigate individual-level relationships between welfare and poverty in monetary and multidimensional terms. Third, we considered a joint index of monetary and non-monetary deprivations.

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 the individual-level data, we observe a clear negative relationship between monetary and multidimensional welfare across six case study countries chosen to reflect differing levels of poverty and differing volatility 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 dependant 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 that have the least overlap and the most volatile responses to 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 mismatches were resolved in a combined index that 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, antipoverty policies often require 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 profiles of the individuals in the poverty set are *fundamentally* different. The intensity of their 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. Public actions against deprivation in public services such as electricity or adequate sanitation, for instance, are different from those required to sustainably improve opportunities for income acquisition. Yet both are essential to improving people's lives and to ending poverty, which is why they are prominently featured in the SDGs and in virtually every global agenda for development. Thus a measure that identifies an individual as being poor *regardless* of whether it is due to a lack of income *or* non-monetary welfare *or* both, may be less attractive.

Our analysis of a combined index has also raised important areas for future research. We suggest that more work is required on issues, such as disaggregation and decomposition of the dual-cutoff counting approach (Alkire and 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 identify upper and lower poverty lines, which can help policy-makers navigate the policy and targeting difficulties present in both monetary and non-monetary approaches to poverty measurement.

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A Appendix

Tables 8, 9, and 10 show the grouping for the 90 countries within our sample. Table 8 shows the least poor third of countries, by average rank, Table 9 the mid-poor, and Table 10 the poorest. Each table is split with the least volatile countries on the top panel and most volatile countries on the bottom. The average rank, volatility, and years difference between surveys are shown, alongside a desirability dummy. These tables highlight the preferred selection criteria, once the countries have been sorted into the six groups. The desirability criteria is such that the average rank of a country is 'close' to the middle of that group (i.e. more than three countries away from the extremes) and their volatility is 'far' from the midpoint (i.e. more than three countries away from the split between stable and volatile). Once a country has been sorted as desirable, a (weak) preference for fewer years difference is put forth.

The most crucial criteria for selecting a case study is, however, data availability. The surveys must be publicly available, and both monetary and multidimensional poverty measures must be calculable. Such data was available for Ecuador, Ghana, Uganda, and Ethiopia, so they were chosen as they are the most desirable in their group. There were issues of data availability within the volatile least poor and volatile mid-poor countries. As a result, Brazil and Bolivia were chosen, as other options were exhausted. The chosen countries are thus separated across the six groups and shown in bold.

Table 8: Least Poor

Country	AverageRank	Volatility	YearDiff	Desirable
Ecuador	21	8.3	0	1
Dominican Republic	16	8	0	1
Montenegro	8	6.8	0	1
Moldova	6.5	1.2	0	1
Viet Nam	21	5.5	0	1
Tunisia	12	9.5	-1.6	1
Palestine, State of	10	6.4	2.8	1
Jordan	6.8	5.4	-7.8	1
Thailand	6.8	10	0	0
El Salvador	26	9.4	0	0
Colombia	24	8.8	0	0
Ukraine	1.5	1.2	0	0
Mexico	22	8.2	0	0
Bosnia and Herzegovina	6.3	11	-1	0
Algeria	14	12	-1.8	0
Kazakhstan	2.7	4.2	-3	0
Kyrgyzstan	22	34	0	1
Paraguay	18	14	0	1
TFYR of Macedonia	20	26	0	1
Egypt	26	23	1	1
Mongolia	23	24	1	1
Maldives	24	34	-7.5	1
Armenia	14	31	0	0
China	19	13	0	0
Serbia	10	27	0	0
Peru	28	15	0	0
Brazil	20	13	0	0
Morocco	27	27	2.5	0
Syria	27	13	-5	0
Albania	16	14	-6	0

Table 9: Mid-Poor

Country	AverageRank	Volatility	YearDiff	Desirable
Ghana	43	5.6	-1.2	1
Comoros	49	8.4	1.5	1
Tajikistan	34	5.7	-2	1
Bangladesh	54	8.9	2	1
Zimbabwe	50	9.5	-4	1
Nepal	51	9.1	-5.8	1
Yemen	57	11	1	0
Philippines	34	11	-2	0
Nicaragua	32	10	2	0
Congo	58	10	-4	0
Laos	56	11	-4.8	0
Gabon	32	11	5	0
Iraq	32	12	-6	0
Mauritania	51	34	-1	1
Bhutan	37	29	2	1
Namibia	46	18	2.3	1
Pakistan	49	27	-2.5	1
Vanuatu	51	16	3	1
Sao Tome and Principe	54	41	-4	1
India	51	23	-4.5	1
eSwatini	50	32	-4.8	1
Cameroon	56	15	0	0
Honduras	42	14	0	0
Indonesia	34	18	0	0
Guatemala	40	14	-1	0
Myanmar	46	13	-1	0
Bolivia	33	21	-1	0
South Africa	35	29	-1.2	0
Gambia	59	30	2.3	0
Sudan	58	22	-5	0

Table 10: Poorest

Country	AverageRank	Volatility	YearDiff	Desirable
Uganda	70	7.8	0.5	1
Liberia	74	8.2	1	1
Central African Republic	84	4.9	-2	1
Benin	74	4.1	-3	1
Mozambique	80	8.7	3.4	1
Guinea-Bissau	82	8.5	-4	1
Sierra Leone	82	6.3	-6	1
Mali	82	8.8	-7.1	1
Côte d'Ivoire	59	6.9	-1	0
Burkina Faso	82	11	-1	0
Madagascar	86	8.3	1	0
Togo	68	11	1	0
Congo, D. Rep. of the	85	12	-1.6	0
Burundi	85	8.1	-3.5	0
Tanzania	74	11	-4.2	0
Senegal	68	5.7	-5.7	0
Ethiopia	73	32	-0.5	1
Rwanda	74	18	-1.3	1
Timor-Leste	67	23	-2	1
Chad	77	28	-4	1
Haiti	65	18	-5	1
Nigeria	72	16	-7.2	1
Malawi	77	28	0.3	0
Niger	84	14	-1	0
Zambia	71	15	1	0
South Sudan	77	32	-1	0
Kenya	61	17	-2.3	0
Lesotho	61	41	-4	0
Guinea	72	13	-4	0
Angola	61	16	-7.5	0