2019

IARIW-World Bank

Special IARIW-World Bank Conference "New Approaches to Defining and Measuring Poverty in a Growing World" Washington, DC, November 7-8, 2019

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Martin Evans

Ricardo Nogales

Matthew Robson

Paper Prepared for the IARIW-World Bank Conference

Washington, DC, November 7-8, 2019

Session 1B: Comparisons of Monetary and Multidimensional Poverty

Time: 11:00 – 13:00, September 7

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Martin Evans[†] Ricardo Nogales[‡] Matthew Robson[§]

Working Paper - Preliminary Draft[¶]
October 15, 2019

Abstract

This paper considers the relationships between multidimensional (MPI) and monetary poverty indices in international and national poverty profiles, and evaluates the trade-offs in separate individual poverty profiles that include monetary poverty as a dimension. The paper has three analytical parts. First, it considers the change in national aggregate poverty that arise for different monetary poverty thresholds and how this relates to poverty incidence by the MPI. The results suggest correlation between poverty headcounts across both indices using a range of thresholds, but that this correlation breaks down in poorer countries and when alternative rankings are used. The second part uses microdata to investigate how the distribution of monetary and multidimensional welfare differs in a range of six countries. This analysis shows the extent to which deprived households are poorer in monetary terms than non-deprived households, and how far monetary and deprivation poverty status aligns with poverty lines. The final part takes forward the evidence from the first two analyses to show how different assumptions about the level of monetary poverty thresholds affect 'a combination of MPI and monetary poverty'. The paper concludes by discussing the results and some sensitivity issues that need to be addressed in order to understand the behaviour of an MPI that includes monetary poverty as a dimension.

Keywords: Poverty, Mismatch, Monetary, Multidimensional.

[†]ODI and OPHI, University of Oxford. Email: m.evans@odi.org.uk.
[‡]OPHI, University of Oxford. Email: ricardo.nogales@qeh.ox.ac.uk.
[§]EQUIPOL, University of York. Email: matthew.robson@york.ac.uk.

[¶]This paper is in draft form and some estimates and computations will be revised for a final draft for presentation at the conference. Please do not cite or share beyond discussants and conference organisers.

1 Introduction

Our motivation comes from pressing issues of poverty measurement policy. The recent and rapid adoption of multidimensional poverty measures in developing countries is now formally entrenched in the Sustainable Development Goals (SDGs)[1] and has, more recently, been taken forward by the World Bank (World Bank, 2018) to accompany the longer-standing global Multidimensional Poverty Index (MPI) produced by the UNDP and the Oxford Poverty & Human Development Initiative (OPHI) since 2010 (Alkire and Santos, 2014; OPHI, 2018). Moreover, this internationally comparable poverty index is supplemented with an increasing number of nationally tailored indices to inform policy-making against poverty in their societies (UNDP-OPHI, 2019). Furthermore, following the Atkinson report (Atkinson, 2017) the World Bank put forward a proposal of a multidimensional indices that included both deprivation-based dimensions and a dimension for monetary poverty (World Bank, 2018). These developments drive our research and underlie our two key research questions: How do these two approaches to measuring poverty relate to each other? And, in the light of these relationships, what are the issues that may surround the creation of a 'combined' multi-dimensional index that includes monetary poverty as one of its component indicators?

The discussion of the relationship between monetary and non-monetary indicators and indices of poverty is, by far, not new. Largely, discussion in high income countries focused on how far measures of material deprivation could be used alongside poverty thresholds for income that were set in relative terms. During the long period of economic growth in the 1990s and early 2000s median income was rising in real terms globally, and thus dragged poverty thresholds based on a percentage of the median upwards with no reference to any understanding of underlying lack of material welfare in terms of households' access to, or holdings of, a set of material goods and services (Nolan, Whelan, et al., 1996). This led the EU to measure poverty and social inclusion adopting a dual approach that captures both relative income and a set of material deprivations *as separate indicators* (Atkinson et al., 2002). Household surveys were then designed and implemented across the EU and associate countries to capture both monetary poverty and material deprivation.

The evolution of multidimensional measures of poverty for developing countries has been different. The intellectual driver for multidimensional poverty was fundamentally

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

grounded on alternative approaches to capturing human development and welfare, inspired by Sen (1976). A few countries, particularly in Latin America and the Caribbean, began to explore national approaches to a non-monetary multidimensional measure, but global-level progress on an international multidimensional measure did not evolve until 2010 and the development of Human Development Report's global MPI that used household survey data to measure poverty by the three dimensions set out earlier in the Human Development Index (HDI). These are education, health and living standards.

The uncertainty about whether to include multidimensional poverty into global measures for the SDGs meant that monetary approaches were adopted solely in 2015. However, since then the uncertainty about the appropriateness and usefulness of MPI has largely evaporated and all of the major UN agencies concerned with poverty including the World Bank, UNDP and UNICEF have accepted the need for both visions to effectively improve people's lives. For the World Bank, this has meant adopting the recommendations of the Atkinson report (Atkinson, 2017) for a 'counting index' for multidimensional poverty as one of a range of fundamental reforms to measuring global poverty that has been accepted to inform future approaches.

The expansion of multidimensional poverty measurement to developing countries meant that indicators captured publicly provided public goods as well as private consumption and assets. This necessarily means that resulting poverty is often less reflective of household level income and expenditure than of state and community-based provision of services. This also means that countries differ a great deal in their levels of public sector provision and investment. If one thinks of this at the extreme, then examples are state socialist countries such as Cuba who provide health, sanitation, water and education to all, but where wages are not market based and flat – resulting in the potential to observe monetary poverty and non-monetary material poverty as a large mismatch. On the other hand, the poorest low-income countries will have a combination of poor public services and very low incomes, especially for the rural populations relying largely on subsistence agriculture and high levels of production on non-market staple foods for their own consumption. Of course, countries lie on a large continuum on both monetary and non-monetary welfare distributions and neither monetary nor non-monetary factors dominate entirely. Understanding the mismatch empirically is thus important, rather than relying on the assumptions that each measure captures entirely different types of material welfare. Advocates of each approach tended to be binary in their appreciation of difference as well as methodologically adversarial (Alkire, Foster, and Santos, 2011; Ravallion, 2011).

Thus, monetary and multidimensional poverty valuations coexist in a context where there continues to be real differences in approach, data and method. In terms of approach, both perspectives seek to identify populations who have low levels of material welfare, but in different ways. 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, as represented by the global MPI, is based on an array of deprivations that reflect a smaller set of defined 'dimensions' of well-being, 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).

In terms of data, the monetary approach based on household consumption in most developing countries outside of Latin America & the Caribbean. These data come from specific surveys of household expenditure and incomes, or from general surveys that have a complete income and/or consumption module. Constructing the global MPI necessarily had to come from a consistent set of deprivation indicators that were not well represented in the household expenditure and income surveys for monetary poverty, particularly pertaining the health dimension. In fact, the most consistent and comprehensive set of indicators came from very different surveys that did not collect data on consumption or income, such as Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS) surveys (Alkire and Santos, 2014). These surveys were designed to capture maternal and child well-being and for monitoring progress on the MDGs in the most part. This leads to the current position outlined in the recent World Bank Poverty and Shared Prosperity report (World Bank, 2018), where only a minimal set of deprivations are observed in monetary poverty surveys and the ability to capture combined monetary and multidimensional data on global poverty relies on different and non-related survey sources.

In terms of method, the underlying welfare variable in each approach are different. Consumption in the monetary approach is a continuous variable reflecting self-reported consumption patterns in each household, which are then valuated into a money metric using domestic market prices (Haughton and Khandker, 2009). Income in the monetary approach is also a continuous variable constructed from self-reported amounts of money received from each household from predefined sources in each country (ibid). It regularly considers labour compensations, capital and financial gains, remittances and transfers. If any of these benefits are received in kind, they are rendered comparable by being translated to the money metric. The global MPI, on the other hand, is based on the dual cutoff counting approach pioneered by Alkire and Foster (2011). It considers binary deprivations across ten indicators pertaining to three dimensions (two indicators of health, two of education and six of living standards) to build up an individual score of weighted deprivations. Each dimension is given the same weight (one-third) and each indicator is given the same weight within dimensions. The collection of these individual scores, termed the counting vector (Alkire and Santos, 2014; Alkire, Roche, et al., 2015) and it does not match the continuous nature of income or consumption. Thus, the underlying welfare variable in the monetary approach is a measure of welfare *advantage*, whereas that non-monetary welfare measure reflects a *disadvantage*.

Taking into account these considerations, we empirically revisit the relationship between monetary and multidimensional poverty - as measured by the global MPI - in order to set solid grounds for an empirical discussion about a measure that combines both. As any poverty measurement analysis, both approaches consist of *identifying* the poor population and then *aggregating* the poverty characteristics of different people into one overall measure. Therefore, our revision will take two complementary perspectives to gauge the extent to which both approaches coincide in these two basic steps of poverty measurement. We first assess their relationship at the aggregate level in terms of the stability of orderings among 90 countries for which there is comparable information. The relationship of both approaches in terms of poverty identification will focus on microdata from six countries (Bolivia, Brazil, Ecuador, Ethiopia, Ghana and Uganda) to assess the similarity of poverty sets defined by both approaches using joint distribution and model-based analyses. Naturally, the latter analysis is limited to countries where similar versions of the global MPI can be constructed from datasets that also include information on monetary welfare. Finally, we apply the dual cutoff counting approach to Ethiopian and Ecuadorian microdata to construct a multidimensional index that includes income/consumption deprivation as the sole indicator of a fourth dimension, namely monetary poverty, alongside the other three dimensions included in the global MPI. This will allow us to discuss some empirical characteristics of such a combined index.

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 complementary to each other. In Section 3 we present the empirical relationship between both approaches at the aggregate level. In Section 4 we assess the similarity of poverty sets identified by both approaches. In Section 5 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 and the weight give to that dimension in the overall index. We discuss the findings in a concluding section that lays out further issues to be explored in future research.

2 Relationship Between Monetary and Non-monetary Material Well-being

What would be expected from different approaches to capturing 'material well-being'? One approach uses a continuous variable that captures the monetary resources of the household, the other uses a range of indicators to produce a score for counting incidence of deprivations. One first assumption is that there is a common underlying purpose: to capture material well-being. If the multidimensional measure is trying to have a wider role and capture non-material aspects of well-being that are not related to material aspects (for instance, 'spiritual and emotional well-being' (UNICEF, 2005; Ura et al., 2012), then the underlying presumption that 'poverty' is solely a measure of material well-being will break down. But on the other hand, if the material deprivation indicators follow an underlying approach to capturing key aspects of material outcomes – such as attending school, having books or toys in the household, being able to afford holidays or religious or other celebrations – then there is an underlying justification to hypothesise that there will be a clear relationship, and perhaps strong correlation, between a monetary and non-monetary approach. One approach measures the ability to purchase/participate, the other approach measures the things purchased, or activities participated in, and/or the human capital attributes that affect productivity and earnings and the ability to purchase and participate. This suggests that underlying the level in the presence of 'things' and 'participation' observed in households there will be a gradient of monetary resources. But this assumption may not apply in countries that have different approaches to public provision of education, health and other core services. If the primary determinant of receiving those services is monetary then we can expect a clear 'gradient' that reflects the ability to purchase or participate. On the other hand, if income or wealth does not determine access we should see no or little gradient – all will have non-material welfare from public services irrespective of their households' monetary resources. This means that there is no empirical reasons why we expect the two measurement approaches to produce duplicate distributions that are parallel or lie on top of each other for underlying policy reasons.

Moreover, there are also several reasons that reflect measurement dissimilarities. Monetary welfare is measured in the short-term - annually or less - and will fluctuate and such fluctuation is biased to poverty because it is linked to low income, which is more likely to be volatile (Jolliffe and Ziliak (2008) and others). On the other hand, non-monetary indicators are less likely to be based on fluctuating or volatile goods and are more likely to be fixed or inelastic if they are 'stock' indicators – such as the education levels of adults, which tend to be fixed, or on 'inelastic' goods – stunting for children is a medium to long-term condition, while water and sanitation provision represent investments by the community or the equivalent of large one-off outlays or borrowings by the household. On the other hand, some indicators of material well-being may be elastic and fluctuate more - for instance, sending children to school, purchases of food and dietary intake, presence of books or toys etc.

These two different profiles of fluctuating and volatility are however further confounded when we measure poverty solely using snap-shots. Repeated cross-sectional data are basis for poverty monitoring across both measures. The low coverage of longitudinal evidence means that we mainly miss important dynamics that may underlie differences between monetary and non-monetary measures. For example, a household may be poor today but still have the dwelling, car, and stock of durable goods and possessions they had previously when they were not poor. If one measures their non-monetary material goods one month after the point at which they became monetary poor it may differ from two years after. The opposite is also true, households who were monetarily poor recently may wait until they invest in the stocks of goods or participate in activities that are costly – they may repay loans instead of purchasing or simply save to avert the risk of income volatility rather than change consumption behaviour greatly on material goods and participation. Cognitive perceptions are also affected by anxiety associated with poverty (see e.g. Freimuth and Hovick (2012)) and risk aversion can be high – and such risk aversion is not tied to a fixed monetary threshold but can apply to the poor and near-poor alike.

There are also other measurement factors related to the nature of the underlying welfare variables and the role played by poverty lines/cutoffs. The approaches capture change and difference in poverty status in quite dissimilar ways. In the monetary approach, a person is currently identified as poor if their monetary valuation of wellbeing is below \$1.90/day. In the global MPI, a person is identified as poor if they experience a sum of weighted deprivations that is equal or greater than 1/3 (i.e. the equivalent of one dimension or more). Crucially, changes in monetary welfare can be captured in units of a continuous currency variable (a cent, for instance), but changes in non-monetary welfare in the global MPI counting vector of weighted deprivations are of a more discrete nature. A change from deprived to non-deprived status in an indicator of the MPI may give rise to a change of 0.056 or 0.166 in the deprivation score. Clearly, the likelihood of change in poverty status varies greatly – 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 or currency unit). There is also measurement error, and measuring consumption and income is inherently more likely to include errors of response that affect 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 and values given to imputed elements such as rent and use-rents of durable goods, and the valuation of production for home use.

All of these factors mean that identifying a common underlying relationship from a monetary gradient for levels of deprivation will not play out consistently in any comparison – both across the distributions but also, importantly, at the points in those distributions where poverty thresholds are set.

Importantly, in practice, the use of a poverty threshold reduces each distribution into a binary comparison: poor and non-poor in both approaches. Comparison across both distributions using a common data set that can measure both approaches produces a four-cell matrix based on these binary states. Each cell will be represented by different populations, and many commentators have found that the 'overlap' population between multi-dimensional and monetary poverty can be small compared to the population who are poor using multidimensional approach alone (Tran, Alkire, and Klasen (2015); Roelen (2017); Ballón et al. (2018) and others). We show this four-cell matrix in Figure 1 and label the 'overlap' population who are identified as poor in both monetary and multi-dimensional terms, and the two areas of 'mismatch' where populations are poor using one measure but not poor using the other. Our earlier discussion suggests that the boundaries between these groups may not be as certain due to inherent measurement characteristics, measurement error and sensitivity around the thresholds that distinguish each status of overlap and mismatch. We show these issues diagrammatically as the grey shaded areas at the boundaries of each cell. Furthermore, the distinction between the cells is only defined by a single characteristic: poverty status. The underlying characteristics of populations may not be so clearly different. 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, Ravallion, and Van de Walle, 2016; Fortin et al., 2015).

Figure 1: Overlap and Mismatch
Source: Own

But when we consider the underlying distributions, we can assume that the size of the populations described as mismatch is dependent on where in the distributions the thresholds for the poverty measures are set. A monetary poverty line at a higher value threshold may well increase the population size of the overlap and reduce those in the mismatch groups, for instance. There are thus two forms of uncertainty. The first comes from the setting of the threshold itself, often arbitrary. The second comes from our earlier discussion of approaches and measurement issues and of sensitivity around any threshold.

The underlying difference in the measures themselves will create different margins around the poverty line – as discussed earlier. For monetary poverty many can be just 'cents' away from poverty levels and thus have small 'gaps' or 'clearance' compared to the line. For those at the margins of multi-dimensional poverty the differences are characterised by larger margins: a single change in indicator can represent 17% or 50% of the value of the poverty line. These theoretical measurement sensitivities are heightened when we consider what we know empirically about monetary welfare distributions: they are left centred and right skewed, meaning that the poverty line will cut the distribution at or near the densest portion. This results in sensitivity: a small change in monetary threshold or welfare value can lead to a disproportionately large change in poverty incidence as a considerable proportion of the population will cross the poverty threshold as a result. Interpreting this sensitivity as producing ‘difference’ in welfare level and characteristics is further hindered when we additionally consider the underlying measurement error, and/or the differences in measurement approaches to the monetary welfare aggregate.

3 Monetary poverty and the global MPI at the aggregate level

Several analyses of international poverty measures across developing countries or regions within countries focused on a comparison to the ‘extreme poverty’ in monetary and non-monetary terms (see e.g. Kim (2019); Lemmi et al. (2019) for recent evidence and Dotter and Klasen (2017); Atkinson (2019) for a discussion on this issue). We follow that approach. However, in the light of our discussion above, we change the fundamental basis of comparison by having a set of poverty thresholds set by consistent increments. This reflects our underlying assumption that comparing single thresholds for each measure is potentially misleading if one is assessing an underlying relationship between the distributions of welfare.

Our data comes from a sample of 90 countries defined by data availability. These are countries represented in both the World Bank PovCalNet database[2] and in the 2018 global MPI data set.[3] 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. The final sample consists of 27 Low Income Countries, 39 Lower-Middle-Income Countries, 24 Upper-Middle-Income Countries when defined by World Bank 2018 income group classification (World Bank 2019).

We choose poverty thresholds that match to existing measurement and policy approaches to make our results more interpretable and in line with existing comparisons and datasets (see Atkinson (2019) for a comprehensive review). Different monetary poverty lines have been proposed by the World Bank depending on the level of aggregate income. The global MPI, however, has only one poverty line (1/3 of the weighted deprivations). For analytical purposes, we draw inspiration from OPHI (2018) to scrutinize alternative poverty lines around 1/3, namely 1/5 and 1/2.

Monetary Poverty:

[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.

- $1.90 per capita per day ('extreme poverty' in SDG goal 1 and poverty line for Low-Income country group (LIC))
- $3.20 per capita per day (poverty line for Lower-Middle Income country group (LMIC))
- $5.50 per capita per day (poverty line for Upper-Middle Income country group(UMIC))

Multidimensional Poverty:

- 2018 Global MPI – headcount at the 1/5 poverty cutoff
- 2018 Global MPI – headcount at the 1/3 poverty cutoff (the standard MPI threshold reported in summary poverty statistics)
- 2018 Global MPI – headcount at the 1/2 poverty cutoff

Table 1 shows the overall correlation of the two poverty measures using the six different thresholds for the whole 90 country sample ranked by their $1.90 poverty headcount using Kendall rank correlation coefficients. We observe high and significant coefficients with nearly all the coefficients between 0.6 and they go as high as 0.67. However, it is not clear if country orderings are stable across poverty measures for our sample and how far this would affect interpretations of correlation.

Table 1: Monetary and MPI Poverty Headcounts: Kendall correlation coefficients

k(%)	$1.90	$3.20	$5.50
50	0.598***	0.621***	0.606***
33	0.616***	0.656***	0.645***
20	0.623***	0.671***	0.659***

Source: 90 country sample – see Appendix 1

We uncover further nuances by dividing our sample into three terciles based on their headcount rates for $1.90 poverty. Table 2 shows these results and clearly suggests that correlation is weakest for the poorest countries in monetary terms (those with the highest $1.90 poverty rates) and becomes much stronger and more robust for the countries with less poverty at $1.90.

We earlier suggested that country level development of public services could alter the mismatch between measures, but we have no independent measure of country level investment in services that is not tautologous to MPI indicators to assess this. However, if we

Table 2: Monetary and MPI Poverty Headcounts by Tertile: Kendall Coefficients

	$1.90		$3.20		$5.50	
	Poorest tercile of countries (n=30)					
MPI (k=0.50)	0.181		0.190		0.238	
MPI (k=0.33)	0.222		0.246		0.254	
MPI (k=0.20)	0.258		0.315	*	0.315	*
	Middle tercile of countries (n=30)					
MPI (k=0.50)	0.300		0.423	***	0.448	***
MPI (k=0.33)	0.290		0.440	***	0.464	***
MPI (k=0.20)	0.270		0.440	***	0.488	***
	Richest tercile of countries (n=30)					
MPI (k=0.50)	0.470	***	0.451	***	0.382	***
MPI (k=0.33)	0.410	***	0.452	***	0.444	***
MPI (k=0.20)	0.385	***	0.468	***	0.452	***

use GNI-per capita as a crude comparator, our initial findings in Tables 1 and 2 may be sensitive to both the composition of the sample and the chosen ordering variable. Figure 2 shows that the influence of sample composition may be considerable if the 90 countries are ranked by their GNI Per-capita. Our sample is very skewed in terms of underlying values of national GNI per capita. The countries with lower poverty rates form an extended tail with a much larger range of values. This helps explain why the correlations in Table 2 are weaker and non-significant for the bottom third of our sample.

We know that high levels and high global shares of monetary poverty are not solely found in the LIC sample, but also in MICs (Coulson 2011). The relationship between monetary indicators: PPP poverty rates and GNI per capita is thus not linear. There is a group of countries who are 'middle income' but who have 'low income' levels of poverty, for instance Nigeria and Zambia. GNI is also not linked necessarily to public-services, and we show this by a comparison of ranking variables in Figure 2. While the ranking of GNI and $ppp monetary poverty shows reduced correlation, the ranking of countries by MPI is shown to have even more radical effects on any interpretation of underlying relationships.

Table 3 repeats the earlier production of Kendall correlation coefficients shown in Tables 1 and 2 but does so for our other two ranking variables: GNI per capita and MPI poverty rates at the cutoff of 1/3.

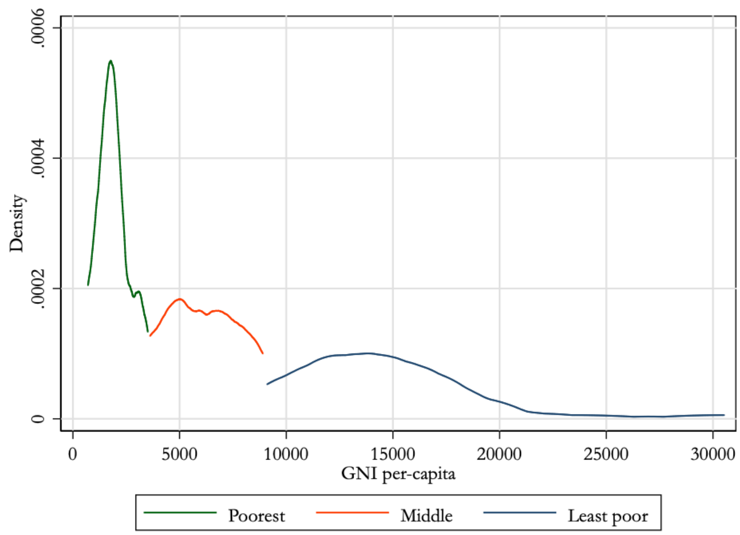


Figure 2: Kernel Density of GNI per-capita for 90 Country Sample
Source: World Development Indicators for 90 Country Sample.

We see that overall coefficients of correlation weaken when using the alternative rankings compared to ranking by $1.90 poverty headcount. However, we see that correlation is weakest in the poorest terciles of both alternative rankings, duplicating what we saw for the original ranking.

Overall our results for a comparison using the international measures support a 'first order' finding that MPI and monetary poverty are correlated, but that this correlation is not strong and is unreliable as it is highly dependent on two things: the choice of the ranking variable and the non-linearity of correlation that consistently shows that the 'poorest' countries, by any ranking, have the weakest. 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 move to the second part of our analysis and consider country level survey data that contain both monetary and non-monetary variables that can be used for consistent comparison.

Table 3: Monetary and MPI Poverty Headcounts by Tertiles: Kendall Coefficients

	Ranked by GNI per capita						Ranked by MPI (k=0.3333)					
	$1.90		$3.20		$5.50		$1.90		$3.20		$5.50	
	Poorest tercile of countries (n=30)						Poorest tercile of countries (n=30)					
MPI (k=0.50)	0.258		0.250		0.298		0.145		0.137		0.198	
MPI (k=0.33)	0.29		0.290		0.315	*	0.246		0.246		0.266	
MPI (k=0.20)	0.323	**	0.331	*	0.347	**	0.306	*	0.339	*	0.251	*
	Middle tercile of countries (n=30)						Middle tercile of countries (n=30)					
MPI (k=0.50)	0.496	**	0.500	***	0.5	***	0.278		0.298		0.286	
MPI (k=0.33)	0.556	***	0.544	***	0.544	***	0.310		0.355	*	0.359	**
MPI (k=0.20)	0.597	***	0.601	***	0.601	***	0.375		0.411	***	0.391	**
	Richest tercile of countries (n=30)						Richest tercile of countries (n=30)					
MPI (k=0.50)	0.285		0.341	**	0.263		0.329	*	0.264		0.15	
MPI (k=0.33)	0.252		0.368	**	0.308	*	0.298		0.343	**	0.298	
MPI (k=0.20)	0.213		0.329	**	0.303		0.262		0.363	**	0.319	*

4 Monetary poverty and the global MPI: Microdata Analyses

Let us now delve deeper and transcend aggregate information by scrutinizing the relationship between the underlying welfare variables in both approaches, namely the income/consumption distribution and the counting vector. Naturally, our choice of countries for this analysis is constrained by data availability, but we wish to make a detailed case about the selection of this in-depth case studies in order to put our results in a clear context. This also allows us to complement the findings of the 90 sample countries.

When measuring the incidence of poverty and its intensity, a poverty line or a poverty cutoff must both be chosen in both approaches to poverty. This choice will, to some extent, determine the incidence of poverty of a particular country and the respective ranking of that country when compared to others. Regardless of that choice, however, we find that some countries are consistently situated amongst the poorest, while others are consistently found to be amongst the least-poor. But, the extent of that consistency depends also on how volatile poverty incidence rates are. This poses difficulties when trying to classify countries that have to be acknowledged, as the group in which a country will be situated depends on the measure and poverty line/cutoff chosen. The selection of case studies in this context deserves a careful consideration.

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: \$1.90 , \$3.20 and \$5.50 for monetary poverty and 1/2, 1/3 and 1/5 for multidimensional poverty. Our set of 90 countries will be ranked the least to the most poor, for each poverty line/cutoff within both measures. 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 categories, least poor to most poor.

While this procedure would, in principle, be sufficient for us to group countries, from which to choose case studies for individual-level analysis, we argue that the simple average rank neglects an important consideration: *volatility*. For some countries their cross-country rank may remain largely unchanged across these indices and poverty lines. However, for others the choice may dramatically change their rank. We highlight these points because, in their own, they also provide useful information about the extent to which choice of an aggregate measure matters to understand poverty across the world.

When identifying case studies, volatility of a country's rank is of interest. In effect, there may be useful lessons which can be drawn from delving into individual-level data for less and more volatile countries. Combining the average rank and the volatility around it, we split the 90 countries into six groups, which are made from the least-poor, mid-poor and most-poor classification interacted with stable and volatile countries.

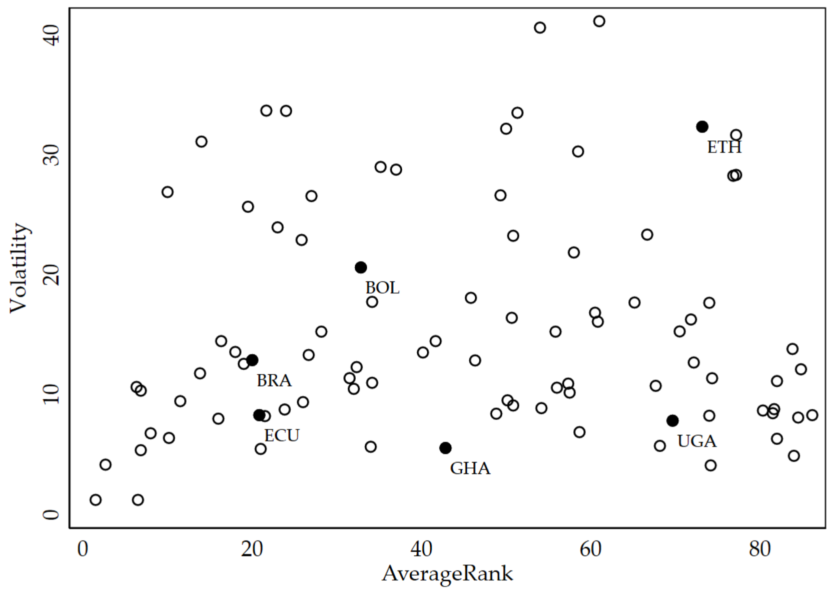
More formally, the average rank is the mean of the six ranks, while volatility is measured as the Euclidean distance between the ranks and the average rank. The two measures are as follows:

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

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

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.1, aims to ensure an even spread across these two dimensions. 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.

Figure 3: Average Rank and Volatility

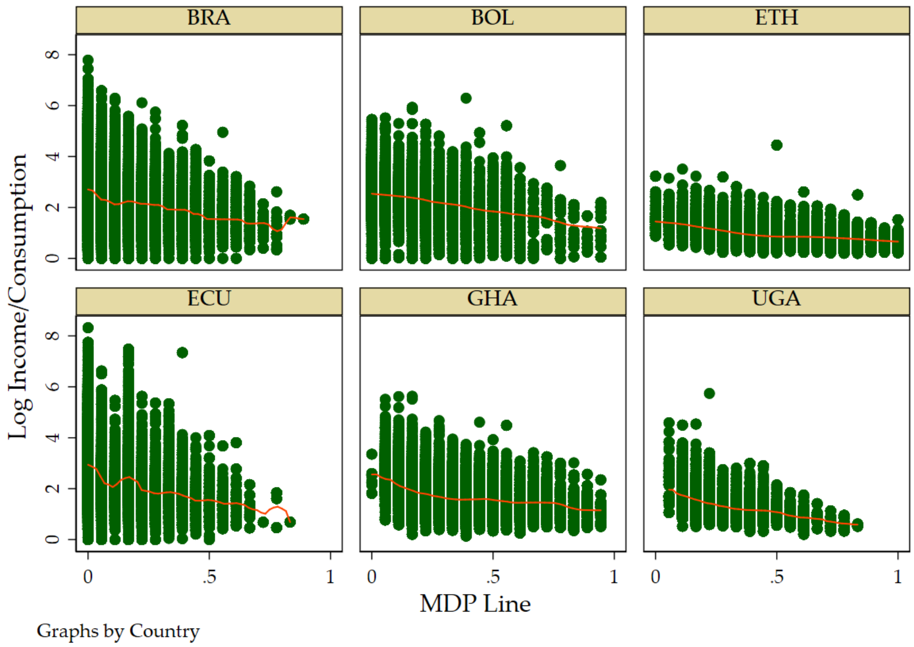


4.1 A preliminary descriptive analysis

Let us start our analysis by making a case for the fact that there is clear (negative) relationship between the monetary-welfare variable and the counting deprivation vector in each of the selected countries.

Evidently, on average, people with low levels of monetary welfare tend to suffer a greater number of non-monetary deprivations. As can be seen in Figure 4, higher levels of monetary welfare (up in the vertical axes) are more frequent among the population suffering the least amount of non-monetary deprivations (left in the horizontal axes). The converse is also true, but 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 score a 0 in the deprivation counting vector (horizontal axis) can have levels of monetary welfare ranging *from the lowest to the highest level*. This dispersion reduces gradually for countries with higher levels of overall poverty, such as Ethiopia and Uganda.

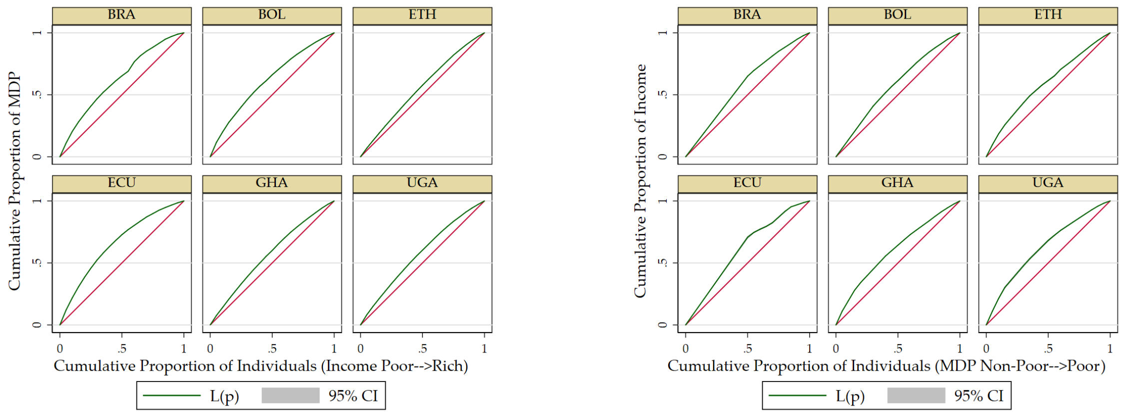
Figure 4: Scatter



Another way of seeing this pattern, and complementing it, is by assessing how 'equal' the distributions of both underlying welfare variables are. In Figure 5 we present a set of concentration curves grouped in two panels. In the left panel we plot the concentration of non-monetary deprivations (green line) with respect to monetary welfare. It represents proportion of the total non-monetary deprivations in each country (i.e. the part of the sum of individual deprivation scores) experienced by the $p-th\%$ poorest people in monetary terms. Thus, the closer the green line is to the 45^0 line (in red), the more equal both distributions are. The larger the distance between the concentration curve is the reference line, the higher the concentration of non-monetary deprivations.

Hence, non-monetary deprivations are found to be more concentrated in the least poor countries. In Ecuador for instance, 75% of the sum of deprivations in the society is born by the 50% poorest people in monetary terms. This proportion reduces to around 55% in Ethiopia. Interestingly, this relationship is not symmetric. In the right panel of Figure 5 we can see that the concentration of monetary welfare with respect to non-monetary deprivations is considerable, *and* it does not seem to depend on the level of aggregate poverty. For instance, in Ecuador, Ghana and Uganda, around 75% of monetary welfare is concentrated in people suffering 50% least deprived population in each country by non-monetary terms.

Figure 5: Concentration Indices: Income and MPI



These visual results are complemented by the information presented in Tables 4 and 5. The mean deprivation score among people in the 1st quintile of the income schedule (the poorest) is 0.17 in Ecuador and 0.58 in Ethiopia. For people in the 5th quintile (the richest), this mean score goes down to 0.03 (nearly half) in Ecuador and 'only' to 0.32 (around a fourth) in Ethiopia. The concentration of non-monetary hardships among the monetary poor population is clearly greater in the least poor countries. As we have stated, however, the concentration of low levels of monetary welfare among the most deprived population (non-monetarily) is practically invariant with respect to the aggregate level of poverty. For instance, the mean income among the most deprived population non-monetarily is \$11.11/day in Ecuador and \$1.97/day in Uganda. Among the least deprived population, the mean income more than triples in both countries (\$36.39/day in Ecuador and \$6.71/day in Uganda).

Table 4: Mean deprivation score by income quintiles

	BRA	BOL	ETH	ECU	GHA	UGA
1 ($ poorest)	0.11	0.27	0.58	0.17	0.41	0.39
2	0.07	0.18	0.52	0.11	0.35	0.33
3	0.07	0.14	0.47	0.08	0.31	0.29
4	0.05	0.12	0.43	0.05	0.25	0.25
5 ($ richest)	0.03	0.09	0.32	0.03	0.20	0.18
Total	0.07	0.16	0.46	0.09	0.30	0.29
N	348258	36876	26670	108093	71277	17465

Table 5: Mean income by deprivation score quintiles

	BRA	BOL	ETH	ECU	GHA	UGA
1 (least deprived)	21.52	17.89	2.98	36.39	11.17	6.71
2	22.06	16.02	2.02	36.10	7.01	4.29
3	18.52	12.40	1.60	25.31	5.67	3.38
4	12.28	11.09	1.46	17.62	4.82	2.50
5 (most deprived)	9.84	7.86	1.30	11.11	4.04	1.97
Total	16.83	13.05	1.88	25.31	6.54	3.77
N	348258	36876	26670	108093	71277	17465

Our key messages are corroborated in light of all three considered variants. There is a heavy concentration of non-monetary deprivations among the the monetary poor population, but this is true to a greater extent in the least poor countries than in the poorest ones.

4.2 A model-based analysis

So far, our results are not taking into consideration the host of measurement errors and the intrisic heterogeneities in the distributions of both welfare variables. To show that this undeniably present confounders do not alter our qualitative results, we performed a set of quantile regressions of monetary welfare on the counting deprivation scores. This approach allow us to include error terms in an attempt to use non-monetary deprivations as a predictor monetary welfare. To be clear, no causal claim is posited whatsoever, and the latter is privileged as the dependent variable in this analysis only due to its continuous nature. We estimated two variants of these regressions: variant (a) using the non-monetary deprivation score, and (b) with additional characteristics as controls (urban/rural, household size, and age and gender of individuals within each household). The results of each variant are present in Tables 6 and 7, respectively.

In both variants, our key message is unchanged. As every single coefficient associated with the deprivation score is negative and (highly) significant all across the set of regression, there is a clear negative relationship between non-monetary deprivations and monetary welfare all cross the distribution of the latter variable. Yet, we corroborate that (a) non-monetary deprivations are heavily concentrated among the poor population, while (b) this is particularly true in the least poor countries. For instance, after controlling for socioeconomic characteristics, a marginal increase in the deprivation score can be associated to a \$0.58/day

Table 6: Variant (a): Quantile Regression of Income/Consumption on Deprivation Score

	(1) **BRA** Coef./S.E.	(2) **BOL** Coef./S.E.	(3) **ETH** Coef./S.E.	(4) **ECU** Coef./S.E.	(5) **GHA** Coef./S.E.	(6) **UGA** Coef./S.E.
q10						
Dep. Score	-8.1096***	-7.7424***	-0.7917***	-9.0124***	-2.4437***	-1.9280***
	(0.0656)	(0.1443)	(0.0175)	(0.1137)	(0.0382)	(0.0509)
Constant	4.0226***	4.7314***	1.0151***	4.2642***	2.6115***	1.8061***
	(0.0000)	(0.0541)	(0.0114)	(0.0275)	(0.0145)	(0.0250)
q30						
Dep. Score	-12.4903***	-11.7392***	-1.3536***	-15.9331***	-4.2857***	-3.3929***
	(0.0580)	(0.1548)	(0.0170)	(0.1315)	(0.0572)	(0.1119)
Constant	7.5988***	8.4918***	1.7151***	8.1827***	4.5986***	2.9528***
	(0.0173)	(0.0430)	(0.0106)	(0.0342)	(0.0255)	(0.0423)
q50						
Dep. Score	-17.8517***	-15.1159***	-1.6784***	-26.0001***	-6.4042***	-5.2580***
	(0.0946)	(0.2163)	(0.0245)	(0.2327)	(0.0627)	(0.1473)
Constant	11.7944***	12.1106***	2.2780***	13.3688***	6.7964***	4.2639***
	(0.0204)	(0.0723)	(0.0110)	(0.0529)	(0.0315)	(0.0644)
q70						
Dep. Score	-25.6322***	-19.0370***	-2.2541***	-44.4003***	-9.0181***	-7.6463***
	(0.1686)	(0.1376)	(0.0341)	(0.3941)	(0.1089)	(0.1481)
Constant	18.0858***	17.4271***	3.1331***	23.1560***	9.8136***	6.0644***
	(0.0379)	(0.0858)	(0.0240)	(0.0960)	(0.0546)	(0.0684)
q90						
Dep. Score	-58.3472***	-30.0063***	-3.8030***	-103.1813***	-16.6450***	-14.7848***
	(0.4170)	(0.3398)	(0.0876)	(0.9152)	(0.1640)	(0.2611)
Constant	37.4105***	29.7025***	5.1748***	58.2966***	17.8107***	11.2224***
	(0.1844)	(0.2312)	(0.0544)	(0.2815)	(0.0820)	(0.1342)
N	348258	36876	26670	108093	71277	17465

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and a $6.42/day monetary welfare reduction for the average person in the 10-th percentile in Ecuador and Ethiopia, respectively. The same marginal increase can be associated to a $1.50/day and a $47.48/day reduction for the average person in the 90-th decile in Ecuador and Ethiopia, respectively. These coefficients are around 2.5 and 7.4 stronger for the richer households.

These model-based analyses not only suggest the robustness behind our claims, but also point out to the fact that socioeconomic characteristics do play an important role. Our analyses here focus on anonymous poverty ordering among the population, but we cannot omit to mention, that after controlling for non-monetary deprivations, the gender is no longer a significant predictor of the level of monetary welfare in the richest quantiles in the poorest countries, namely Ethiopia and Uganda.

Table 7: Variant (b): Quantile Regression of Income/Consumption on Deprivation Score including controls

	(1) BRA Coef./S.E.	(2) BOL Coef./S.E.	(3) ETH Coef./S.E.	(4) ECU Coef./S.E.	(5) GHA Coef./S.E.	(6) UGA Coef./S.E.
q10						
Dep. Score	-5.8758***	-3.6100***	-0.5803***	-6.4180***	-1.7183***	-1.9128***
	(0.0793)	(0.1658)	(0.0146)	(0.1516)	(0.0384)	(0.0798)
Urban	1.1246***	2.2083***	0.4639***	1.9474***	1.4254***	0.5849***
	(0.0197)	(0.0515)	(0.0180)	(0.0395)	(0.0253)	(0.0263)
Household Size	-0.5329***	-0.2785***	-0.0398***	-0.1876***	-0.1285***	-0.0473***
	(0.0074)	(0.0131)	(0.0022)	(0.0068)	(0.0036)	(0.0040)
Age	0.0438***	0.0063***	-0.0001	0.0087***	0.0018***	0.0019***
	(0.0005)	(0.0015)	(0.0002)	(0.0007)	(0.0005)	(0.0006)
Male	0.2200***	0.2128***	0.0146***	0.1574***	0.0218	0.0120
	(0.0174)	(0.0497)	(0.0057)	(0.0328)	(0.0142)	(0.0134)
Constant	4.0370***	3.7087***	1.1142***	4.0797***	2.9662***	2.0671***
	(0.0501)	(0.1103)	(0.0209)	(0.0458)	(0.0358)	(0.0482)
q30						
Dep. Score	-9.2681***	-6.3988***	-0.7632***	-11.6750***	-2.4892***	-3.2161***
	(0.1151)	(0.1208)	(0.0183)	(0.1575)	(0.0608)	(0.0755)
Urban	1.7126***	2.9984***	0.7834***	3.5444***	2.0783***	0.8840***
	(0.0262)	(0.0617)	(0.0209)	(0.0568)	(0.0375)	(0.0575)
Household Size	-0.9386***	-0.4387***	-0.0581***	-0.3201***	-0.2049***	-0.0616***
	(0.0074)	(0.0110)	(0.0028)	(0.0112)	(0.0046)	(0.0037)
Age	0.0730***	0.0210***	0.0001	0.0210***	0.0054***	0.0046***
	(0.0005)	(0.0016)	(0.0003)	(0.0010)	(0.0006)	(0.0009)
Male	0.3676***	0.3320***	0.0097	0.2573***	0.0621***	-0.0139
	(0.0221)	(0.0742)	(0.0111)	(0.0422)	(0.0213)	(0.0256)
Constant	7.6785***	6.8058***	1.6575***	7.5334***	4.6832***	3.1629***
	(0.0474)	(0.1293)	(0.0250)	(0.0891)	(0.0469)	(0.0615)
q50						
Dep. Score	-14.3545***	-8.7627***	-0.9321***	-17.0514***	-3.0421***	-4.1772***
	(0.1237)	(0.1667)	(0.0303)	(0.2517)	(0.0677)	(0.0882)
Urban	2.0091***	3.3161***	1.0019***	6.1191***	2.6813***	1.4368***
	(0.0323)	(0.0938)	(0.0349)	(0.1115)	(0.0275)	(0.0343)
Household Size	-1.2068***	-0.6391***	-0.0744***	-0.4095***	-0.2639***	-0.0824***
	(0.0089)	(0.0196)	(0.0042)	(0.0107)	(0.0051)	(0.0030)
Age	0.0843***	0.0451***	-0.0004	0.0463***	0.0086***	0.0072***
	(0.0008)	(0.0019)	(0.0003)	(0.0016)	(0.0007)	(0.0007)
Male	0.4954***	0.6085***	0.0095	0.4559***	0.1030***	-0.0021
	(0.0376)	(0.0897)	(0.0144)	(0.0492)	(0.0250)	(0.0222)
Constant	11.6036***	10.2064***	2.2111***	10.8069***	6.2769***	4.1377***
	(0.0624)	(0.1406)	(0.0385)	(0.0930)	(0.0517)	(0.0584)
q70						
Dep. Score	-19.6719***	-11.9197***	-0.9992***	-25.7299***	-4.0084***	-5.4198***
	(0.2282)	(0.1953)	(0.0337)	(0.3220)	(0.0976)	(0.0940)
Urban	3.5755***	3.6410***	1.4372***	12.4888***	3.7653***	2.4970***
	(0.0478)	(0.1437)	(0.0384)	(0.1685)	(0.0484)	(0.1060)
Household Size	-1.6519***	-0.9614***	-0.0935***	-0.5604***	-0.3313***	-0.1005***
	(0.0133)	(0.0243)	(0.0040)	(0.0200)	(0.0077)	(0.0046)
Age	0.1191***	0.0751***	0.0001	0.0835***	0.0184***	0.0109***
	(0.0012)	(0.0035)	(0.0004)	(0.0025)	(0.0014)	(0.0016)
Male	0.6216***	0.8036***	0.0114	0.6523***	0.2494***	0.0222
	(0.0548)	(0.1363)	(0.0196)	(0.1082)	(0.0436)	(0.0274)
Constant	16.3069***	15.5238***	2.7825***	16.4354***	8.3495***	5.3608***
	(0.1042)	(0.1752)	(0.0408)	(0.1547)	(0.0724)	(0.0693)
q90						
Dep. Score	-31.6654***	-18.2277***	-1.4964***	-47.4794***	-7.0289***	-9.3525***
	(0.5917)	(0.5533)	(0.0765)	(0.7146)	(0.2148)	(0.2293)
Urban	8.8707***	3.6026***	2.2150***	37.1413***	6.9179***	5.6606***
	(0.1623)	(0.2457)	(0.1161)	(0.9335)	(0.1343)	(0.1657)
Household Size	-2.6708***	-1.6897***	-0.1625***	-1.2491***	-0.4113***	-0.1254***
	(0.0185)	(0.0505)	(0.0049)	(0.0522)	(0.0102)	(0.0199)
Age	0.2550***	0.1202***	0.0010	0.2211***	0.0443***	0.0242***
	(0.0047)	(0.0125)	(0.0010)	(0.0187)	(0.0033)	(0.0023)
Male	0.7805***	1.1982***	0.0274	1.2411***	0.6045***	0.0933
	(0.1535)	(0.2423)	(0.0225)	(0.3227)	(0.0829)	(0.0813)
Constant	27.9711***	28.1778***	4.4059***	35.3280***	12.7569***	8.4190***
	(0.2301)	(0.5225)	(0.0625)	(0.4877)	(0.1437)	(0.1734)
N	348258	36876	22823	108063	71276	17298

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 Poverty lines and cutoffs as thresholds for the welfare distributions

So far, our results have not considered any poverty line or cutoff. In that sense, we argue that they are powerful in that they hold irrespective of if and how we identify poor people. However, when it comes to a full-fledged practical poverty analysis, identification *needs* to take place. Among others, aggregation becomes impossible if one fails to sort the poor out of the non-poor population.

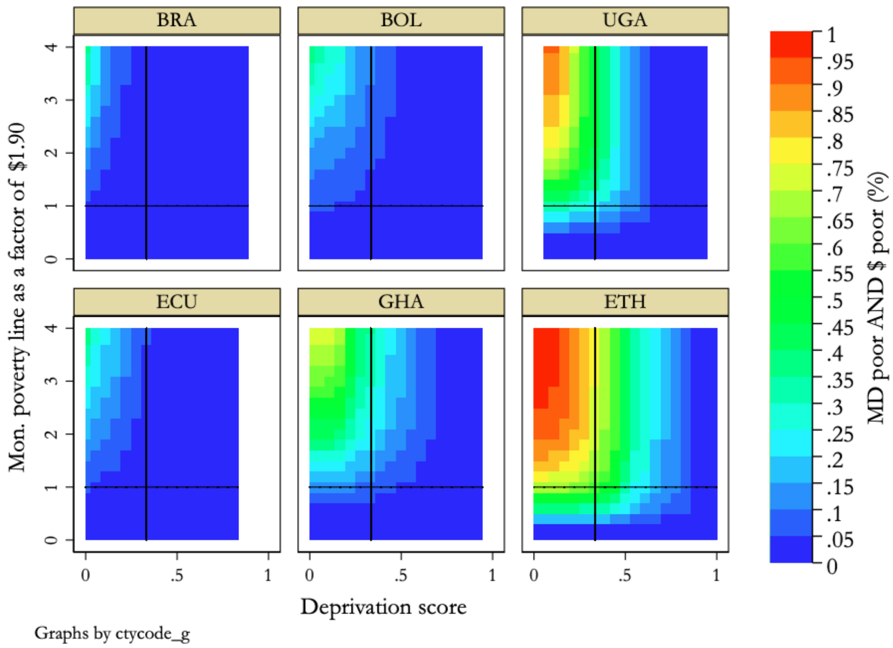
To complement our analyses above while bringing in poverty identification thresholds we will assess the likelihood of a combination of two events. The first is person i being identified as poor in non-monetary terms by the multidimensional poverty cutoff k. Denoting person's i deprivation score as c_i, the likelihood of this event is $P(c_i \geq k)$. The second event is the same person i being identified as poor in monetary terms by monetary poverty line p. Denoting individual's i level of monetary welfare as y_i, this likelihood can be written as $P(y_i \leq p)$. Among all the possible poverty lines, \$1.90 is a global reference, so for the ease of interpretation, we rescale y_i to be interpreted as multiples of \$1.90. The rescaled variable is $\tilde{y}_i \equiv y_i/1.90$ and the likelihood of our second event of interest is $P(\tilde{y}_i \leq \tilde{p})$, with $\tilde{p} = p/1.90$.

Let us define an indicator function taking a unity value if an individual is identified as poor by both measures under the couple of cutoff/poverty line $\{k, \tilde{p}\}$: $\mathbb{1}(c_i \geq k, \tilde{y}_i \leq \tilde{p}), \forall i$. The frequency of individuals for which this is the case is a simple empirical estimator of the likelihood of a poverty population subset *overlap* under $\{k, \tilde{p}\}$. Higher frequencies represent a higher *match* between both measures for this couple of cutoff/poverty line. Lower frequencies represent higher *mismatch*. These frequencies are plotted in Figure 6. In the horizontal axes, we cover the whole range of k, i.e. $[0, 1]$ in all the possible 18 steps corresponding to the combinations of weights defined in the global MPI structure. In the vertical axes we cover the range of $\tilde{p}$ in $[0, 4]$ in steps of 0.2. This corresponds to covering a range of $[0, 7.6]$ in money metrics (\$/day).

Figure 6 shows that around the largely preferred combination $p =$ \$1.90 (i.e. $\tilde{p} = 1$) and $k = 1/3$ we observe that (a) the *joint* poverty status of individuals appears to be more responsive to changes in the *monetary* poverty line than the multidimensional poverty cutoff, and (b) that this seems to be particularly true in contexts of high overall poverty.

To see this, let us first focus in the context of our two low-poverty countries, Brazil and Ecuador. Overall, both measures coincide in stating that poverty levels are low. The proportion of people that are poor by both approaches is lower than 5% (darkest blue)

Figure 6: Frequency of matches for different $\{k, \tilde{p}\}$



for a wide array of $\{k, \tilde{p}\}$ combinations. Note first that in both cases, the joint poverty incidence remains under 5% for every combination of a poverty line equal to \$1.90 and *any* multidimensional cutoff. Actually, this holds true for every poverty line below \$1.90, and there is a symmetry to this result, as poverty remains under 5% for virtually all combinations of a 1/3 multidimensional poverty cutoff and *any* monetary poverty line between 0 and 4 times \$1.90.

However, turning to Ghana, a context where poverty is more prevalent overall, we find that a slight upshift of the poverty line over \$1.90 would imply a jump of the joint poverty incidence from the $[5\%, 10\%]$ to the $[10\%, 15\%]$, whereas the incidence would remain stable by changing the multidimensional poverty cutoff from 1/3 to 1/2. The general pattern seems to be that there is more variation in the vertical sense of our graphs than in the horizontal sense. This becomes more evident if we turn to Ethiopia, one of poorest countries. In the \$1.90, $k = 1/3$ combination, the joint poverty incidence is around 50%. It could be between 25% and 80% by changing, ceteris paribus, the poverty line to a value between 0.5 and 1.5 times \$1.90. The incidence 'only' changes to the range 35% to 70% by changing the multidimensional poverty cutoff to a value between 1/5 and 1/2.

5 A joint index of monetary and non-monetary deprivations (?)

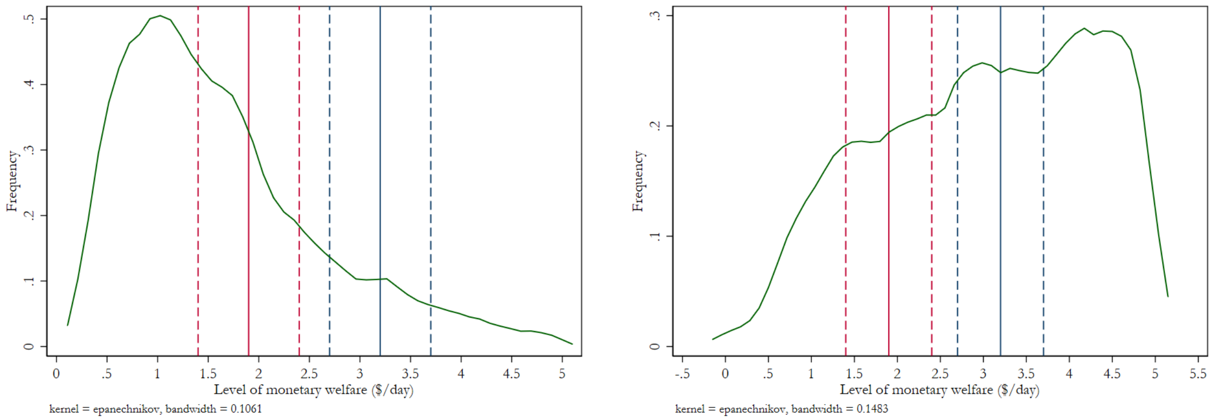
Our preliminary analyses have given clear hints of the related, yet fundamentally different empirical nature of the underlying welfare variables in the monetary and non-monetary approaches to poverty. Moreover, our last descriptive analysis seems to point to a non-negligible sensitivity of the overall *joint* poverty incidence to changes in the monetary poverty line. Although this is expected, to the best of our knowledge, it has never been empirically tested. We argue that this is a relevant matter because there is a stark contrast between the responsiveness of the poverty incidence to the monetary poverty line and its sensitivity to changes in the multidimensional poverty cutoff. It is related to the *continuous* nature of the monetary welfare variable. In effect, one can empirically come across infinitesimal variations of income and/or consumption in real data, but only discrete changes are effectively observed in the counting deprivation score vector.

Let us now empirically test this considering a joint index of monetary and non-monetary deprivations. For the sake of brevity, we will only focus on the cases of Ethiopia (one of the poorest countries) and Ecuador (one of the least poor countries). We will employ the dual-cutoff counting approach (Alkire and Foster, 2011) to construct an index that extends the global MPI to include one additional dimension, namely *Monetary Poverty*. Thus our four-dimension MPI (4DMPI) includes education, health, living standards and monetary poverty. Each of them is given the same relative importance (1/4) and we take the monetary poverty status (1 if income/consumption is below the chosen poverty line, and 0 otherwise) as the only indicator relevant to measure monetary poverty. This structure is not identical, but very closely mimics the one that is proposed in (World Bank, 2018). Note that by construction, a change in *monetary* poverty status (induced for instance, by a change in the monetary poverty line) shifts the deprivation score of the 4DMPI by 0.25 points.

Let us start our analysis by pointing out that the proportion of the population around the monetary poverty line is considerable. In Ethiopia 30.22% of the population has a level of monetary welfare between \$1.40 and \$2.40/day. Due to lower levels of poverty this proportion is 4.40% in Ecuador. Around 9.4% of the population in Ethiopia has a level of welfare between \$2.70 and \$3.70, and this proportion is 5.70% in Ecuador.

In the spirit of the global MPI, we identify here a person as being poor in light of the 4DMPI, we adopt a multidimensional poverty cutoff of 0.25 for the corresponding deprivation

Figure 7: Monetary welfare kernel density functions (capped > \$5 /day)
(Ethiopia to the left, Ecuador to the right)

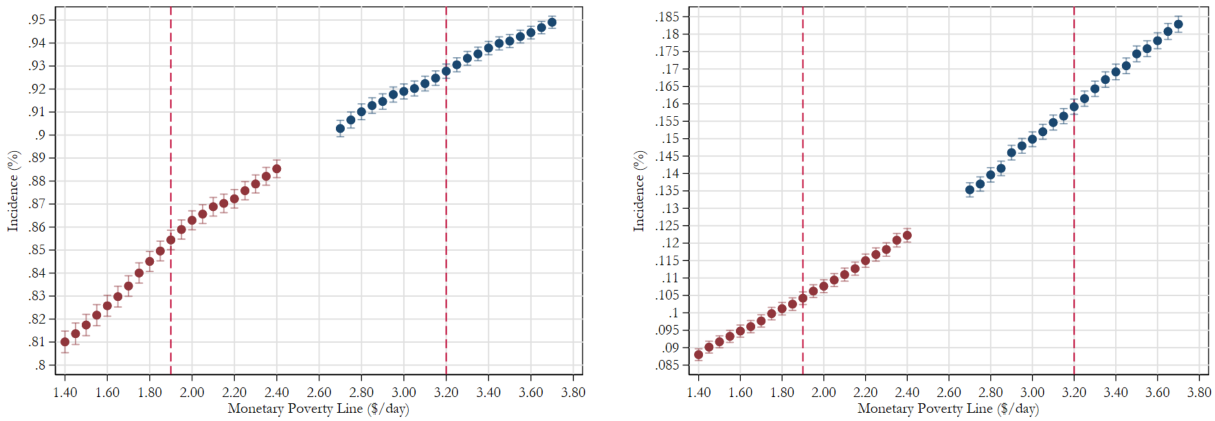


score. That is, we maintain the principle that somebody is poor if they face a number of weighted deprivations equivalent to one dimension or more. By construction, the mismatch between both approaches is mitigated, as every poor person by purely monetary terms will also be poor by the 4DMPI. Similarly, every person who was identified as poor by the regular global MPI structure, will also be poor by the 4DMPI. Thus, by construction, the poverty incidence obtained by the 4DMPI can only higher or equal than the *maximum* between the monetary poverty headcount ratio and the poverty incidence by the global MPI. In light of the 4DMPI, there cannot be an individual who is poor by one approach, but non-poor by the other.

The above feature 'solves' one of the matrix cells of 'mismatch' earlier observed in Figure 1 and is undeniably an attractive feature of this 'combined' index. One crucial element, however, is that even if the mismatch mitigated, the poverty *sets* vary greatly. That is, the group of the population that is identified as poor by the 4DMPI suffer a mixture of conditions of poverty (monetary and non-monetary) depicting a level of intensity that can hardly be compared to the structure of poverty intensity in each of the poverty measures separately.

Furthermore, the monetary poverty line, which now, strictly speaking corresponds to a deprivation threshold in the 4DMPI, is the only *continuous* element in the set of deprivation thresholds of this combined index. As a result, the poverty incidence obtained by the 4DMPI becomes particularly responsive to marginal changes in the monetary poverty line (see Figure 8)

Figure 8: Monetary welfare kernel density functions (capped at >$5/day)
(Ethiopia to the left, Ecuador to the right)



Not only do changes in the monetary poverty line induce variations in the poverty incidence (as is evident in light of Figure 8), it also reshuffles the entire poverty set. The mismatch that we made a case for in previous sections allows to posit that people who are sorted in or out of the poverty *only* because of a change in the monetary poverty line may have distinctive non-monetary deprivation profiles. To see this, we conduct a two sets of formal hypothesis tests.

The first one is concerned with a change in the monetary poverty line to a lower value, while everything else is held constant. Unambiguously, this revision shifts people out of poverty by the 4DMPI, and the ensuing poverty set differs from the previous one because it no longer contains these persons. In this context we ask: is the average non-monetary deprivation profile of these people similar to the ones that were poor by the 4DMPI with the *previous* monetary poverty line? We test this hypothesis for all the elements that make up the non-monetary deprivation profile (i.e. the ten non-monetary indicators included in the structure of the global MPI). The results of these tests are found in Table 8 for a change from $1.90 to $1.65/day (i.e. -25 cents) and in Table 9 for a change from $3.20 to $2.95 (again, -25 cents). Not one single element of the non-monetary deprivation poverty profile is similar. This means that the poverty sets have been reconfigured considerably.

The second set of tests are similar but are concerned with an increase of the monetary poverty line. In this case, the poverty set is expanded, as people who were not poor by the 4DMPI are now considered as poor due to this revision. In this context we ask if the non-monetary deprivation profile of these 'newly' poor people by the 4DMPI is similar, on

Table 8: t-tests: shifting the monetary poverty from \$1.90 to \$1.65

	Ethiopia			Ecuador		
	Reference group : 4DMPI poor with \$1.90	Previously 4DMPI poor with \$1.90; Now 4DMPI non-poor with \$1.65	pvalue	Reference group : 4DMPI poor with \$1.90	Previously 4DMPI poor with \$1.90; Now 4DMPI non-poor with \$1.65	pvalue
Proportion of pop.	84.55	1.57		10.42	0.82	
Mean Dep. Score	52.08	20.84	0.000	32.27	13.12	0.000
Nutrition	24.69	0.00	0.000	48.23	25.17	0.000
School Attendence	51.26	34.70	0.000	16.37	3.97	0.000
Education	59.80	0.61	0.000	21.30	5.22	0.000
Electricity	75.55	27.85	0.000	20.55	5.56	0.000
Water	47.39	16.74	0.000	38.25	15.65	0.000
Sanitation	66.92	48.71	0.000	52.73	23.92	0.000
Housing	97.39	77.63	0.000	26.17	14.17	0.000
Cooking Fuel	97.94	75.19	0.000	47.69	19.16	0.000
Assets	70.99	23.14	0.000	54.23	32.88	0.000

Table 9: t-tests: shifting the monetary poverty from \$3.20 to \$2.95

	Ethiopia			Ecuador		
	Reference group : 4DMPI poor with \$3.20	Previously 4DMPI poor with \$3.20; Now 4DMPI non-poor with \$2.95	pvalue	Reference group : 4DMPI poor with \$3.20	Previously 4DMPI poor with \$3.20; Now 4DMPI non-poor with \$2.95	pvalue
Proportion	92.78	1.02		15.92	1.12	
Mean Dep. Score	48.97	16.22	0.000	25.16	11.74	0.000
Nutrition	22.33	0.00	0.000	37.68	16.24	0.000
School Attendence	49.50	42.44	0.021	11.45	2.64	0.000
Education	54.28	1.48	0.000	16.53	8.74	0.000
Electricity	70.04	4.06	0.000	15.30	4.95	0.000
Water	43.97	4.43	0.000	32.06	16.49	0.000
Sanitation	65.19	46.49	0.000	44.59	29.02	0.000
Housing	95.39	42.44	0.000	21.72	9.81	0.000
Cooking Fuel	95.51	54.98	0.000	38.26	18.55	0.000
Assets	66.02	7.75	0.000	45.18	28.85	0.000

average, compared to the set of poor persons as defined by the *revised poverty line*. The results of these tests are found in table 10 for a change from \$1.90 to \$2.15/day (i.e. +25 cents) and in table 11 for a change from \$3.20 to \$3.45 (again, +25 cents).

Once more, none of the element in the non-monetary deprivation profile is found to be similar.

Table 10: t-tests: shifting the monetary poverty from $1.90 to $2.15

	Ethiopia			Ecuador		
	Reference group: 4DMPI poor with $2.15	Now 4DMPI poor with $2.15; previously 4DMPI non-poor with $1.90	pvalue	Reference group: 4DMPI poor with $2.15	Now 4DMPI poor with $2.15; previously 4DMPI non-poor with $1.90	pvalue
Proportion of pop.	84.55	2.48		10.42	0.85	
Mean Dep. Score	51.18	20.56	0.000	30.77	12.86	0.000
Nutrition	23.98	0.00	0.000	46.42	18.65	0.000
School Attendence	50.78	33.02	0.000	15.40	2.07	0.000
Education	58.09	1.18	0.000	20.04	6.32	0.000
Electricity	74.17	22.17	0.000	19.37	5.02	0.000
Water	46.50	12.74	0.000	36.48	23.77	0.000
Sanitation	66.39	40.80	0.000	50.47	34.68	0.000
Housing	96.82	86.79	0.000	25.23	19.63	0.000
Cooking Fuel	97.28	81.13	0.000	45.45	27.04	0.000
Assets	69.61	23.82	0.000	52.56	27.81	0.000

Table 11: t-tests: shifting the monetary poverty from $3.20 to $3.45

	Ethiopia			Ecuador		
	Reference group: 4DMPI poor with $3.45	Now4DMPI poor with $3.45; previously 4DMPI non-poor with $3.20	pvalue	Reference group :4DMPI poor with $3.45	Now4DMPI poor with $3.45; previously 4DMPI non-poor with $3.20	pvalue
	92.78	1.21		15.92	1.18	
Mean Dep. Score	48.61	18.58	0.000	24.21	10.81	0.000
Nutrition	22.08	0.00	0.000	36.17	18.88	0.000
School Attendence	49.42	37.27	0.000	10.83	2.75	0.000
Education	53.70	0.00	0.000	15.98	8.81	0.000
Electricity	69.31	8.39	0.000	14.57	3.23	0.000
Water	43.53	8.39	0.000	30.96	15.18	0.000
Sanitation	64.99	53.73	0.000	43.50	23.76	0.000
Housing	94.81	75.47	0.000	20.88	11.80	0.000
Cooking Fuel	95.06	67.70	0.000	36.87	14.71	0.000
Assets	65.39	9.01	0.000	44.02	24.55	0.000

6 Concluding Remarks

Poverty measurement has always been as much a fundamental issue for policy making as a heavily debated subject in academic spheres. Monetary and non-monetary viewpoints differ in methods, data and conceptual approach to poverty. In this context, our motivation for this paper was fueled by two concerns. We explored the differences or correlation between household welfare distributions produced by monetary and multi-dimensional welfare approaches as opposed to solely considering the differences produced from poverty thresholds set within them. As a consequence of that concern, we were then interested in how a single poverty index using both approaches solved or worsened mismatch between the two measures.

To address these concerns our analysis is split 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.

At the aggregate level we find an overall correlation across a range of poverty headcounts using differing MPI and $ppp thresholds across the whole sample of 90 countries. However, this correlation is not observed for the poorest third of countries (when using the $ppp ranking).

By delving deeper into a individual-level data we observe a clear negative relationship between monetary and multidimensional welfare, but find that dispersion around this relation 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 find that mismatches in poverty status of individuals appear more responsive to changes in the monetary poverty line and that this seems particularly true in contexts of high overall poverty.

A combined index has some desirable features, which are however, counterbalanced by 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. 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.

It is also important to recognize that some important properties of the dual-cutoff counting approach, such as disaggregation and decomposition (Alkire and Foster, 2011), may be explored as a possible way to mitigate the drawback that we mention. This can and perhaps should be the object of future research. 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 in both high (Ethiopia) and low (Ecuador) overall poverty contexts.

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A Appendix

A.1 Six Categories of Countries

Tables 12, 13 and 14 show the grouping for the 90 countries within our sample. Table 12 shows the least-poor third of countries, by average rank, Table 13 the mid-poor and Table 14 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 out forth.

The most crucial criteria to be a case-study is, however, data availability. The surveys must be publicly available and both monetary and multidimensional poverty measures must be calculable. For each Ecuador, Ghana, Uganda and Ethiopia data was available, so they are 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 12: 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 13: 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 14: 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