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"The many forms of poverty: Analyses of deprivation interlinkages in the developing world"

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Abstract

It is widely acknowledged that for efficient progress towards the Sustainable Development Goals (SDGs), their interlinkages have to be taken into account. The global Multidimensional Poverty Index is based on ten deprivations indicators each of which is aligned with specific SDGs, and the overlap of these deprivations already figures prominently in the way poverty is measured by this index, i.e. as multiple deprivation. In this paper we complement previous analyses with a novel account to explore how deprivations are interlinked and how these interconnections vary across the developing world. More specifically, we suggest to analyse deprivations within our measurement framework using profiles, bundles, and co-deprivations which each illuminate particular aspects of the joint distribution of deprivations. Additionally, we apply latent class analysis to corroborate our findings and to uncover additional insights. We use data for 111 countries representing 6.1 billion people to document key patterns at the global level and selected findings for world regions and countries, which may serve as a useful benchmark for more in-depth analyses. We also discuss how our approach may be adopted to different settings and how it can inform multi-sectoral policy programmes.

JEL classification: I32.

Keywords: Multidimensional poverty; Global MPI; Joint distribution of deprivations.

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1 Introduction

The adoption of the sustainable development goals (SDGs) in 2015 was a momentous achievement reflecting a wide consensus on both principal values and the broad course forward.Many of the adopted indicators directly relate to dimensions of human well-being including, for instance, the prevalence of undernourishment, the under-five mortality rate or the proportion of people having access to safe drinking water. According to several of these indicators good progress has been made over the last decade or was confidently anticipated (e.g., Lim et al. 2016; Friedman et al. 2020; WHO and UNICEF 2021; Bennett et al. 2018). More recent developments, however, suggest setbacks in several instances (e.g., United Nations 2022; World Bank 2022).

The picture provided by such an indicator-by-indicator analysis, however, remains incomplete as indicators are inherently interlinked. Indeed, the SDG framework itself recognises the importance of interactions among the individual goals. Accordingly, ways to understand these interactions and multisectoral coordinated policy programmes gained more prominence recently(e.g., Nilsson, Griggs, and Visbeck 2016; ICSU 2017; Pedercini, Arquitt, Collste, and Herren 2019).

In the case of poverty, Amartya Sen has been arguing for long that “deprivations of very different kinds have to be accommodated within a general overarching framework” as “[h]uman lives are battered and diminished in all kinds of different ways” (Sen 2000, p. 18). Angus Deaton notes that “[a] world in which the people [...] who lack education have the same ability to participate in civil affairs, would be, in many respects, a much better world than the one in which we live — and a dashboard cannot tell us which world we are in” (p. 12 Deaton 2019). In this spirit, research multidimensional poverty measurement set out to capture deprivations in otherwise diverse dimensions and proposed methods which can measure poverty understood as multiple deprivation (Bourguignon and Chakravarty 2003; Atkinson 2003; Alkire and Foster 2011).

In order to tackle multidimensional poverty in particular and to advance towards the SDGs more generally, coordinated multi-sectoral policies are essential. For instance, targeting multiply deprived households may allow to simultaneously address several deprivations and knowledge about further deprivations of a targeted household, such as a lack of education or safe drinking water access, may help to identify more effective policy measures. In spite of its crucial relevance very little is known about how these deprivations are empirically interlinked and how these interlinkages vary around the world. This impedes large-scale coordinated policy-programs and undermines the potential to learn from other countries' experience. This knowledge gap originates from several factors including a lack comparable information on indicators and the complexity of a joint distribution when having many dimensions. To close this gap is the objective of the present paper.

We illuminate interlinkages among key deprivations at a global scale using data of the global Multidimensional Poverty Index (MPI), an internationally comparable measure, which offers information for 111 countries representing 6.1 billion people (Alkire, Kanagaratnam, and Suppa 2022). The global MPI is jointly published by UNDP and OPHI and comprises ten indicators organised in three dimensions (health, education and living standards). In 2018 the global MPI was revised to better align with the SDGs (Alkire and Kanagaratnam 2021; Alkire, Kanagaratnam, Nogales, and Suppa 2022; Vollmer and Alkire 2022).

Methodologically, we propose to complement previous analyses of multidimensional poverty, which have featured prominently, for instance, in several UNDP Reports (links to gMPI reports), with a novel account to explore the interlinkage of deprivations within the well-known dual-cutoff framework for poverty measurement. Specifically, we suggest to study the interlinkage of deprivations from three distinct, complementary angles: (i) to explore the prevalence of deprivation *profiles*, which are unique combinations of deprivations, (ii) to explore the prevalence of deprivation *bundles* which are similar to profiles, but allow for several combinations of selected deprivations (we focus on pairs and triplets), (iii) to analyse *co-deprivations* for selected deprivation indicators or bundles. Moreover, we suggest latent class analyses (LCA) to corroborate previous findings and explore which deprivation interlinkages are common in groups (or classes) among the poor. We also explain how LCA results may be interpreted drawing on our introduced concepts of deprivation profiles and bundles.

Our empirical analysis covers the global level and six world regions. We also present selected country-level findings. More specifically, our results suggest that 1/3 of the global poor suffers from one of the 20 most prevalent profiles, although we observe more than 800 different deprivation profiles in our data. Moreover, we find that 60% the global poor experience simultaneous deprivation in sanitation, housing and cooking fuel. While this bundle is particular common in Sub-Saharan Africa and South Asia it is also experienced by poor in other parts of the world. Additionally, we also observe indicator-specific patterns in how co-deprivations vary (e.g., uni- versus bimodal distributions). A common thread in our analysis is that we also document substantial cross-country variations—even across countries within the same world region.

We acknowledge that a comprehensive analysis of the joint distribution of the deprivation is beyond the scope of a single paper. Such an analysis would approach the joint distribution from every possible angle, while paying due attention to both commonalities and differences in deprivation patterns and that from global to sub-

Table 1: The global MPI

Dimension of Poverty	Indicator	Deprived if ...	SDG area	Weight
Health	Nutrition	Any person under 70 years of age for whom there is nutritional information is *undernourished*.	SDG 2	$\frac{1}{6}$
	Child mortality	A child *under 18* has *died* in the household in the five-year period preceding the survey.	SDG 3	$\frac{1}{6}$
Education	Years of schooling	*No* eligible household member has completed *six years* of *schooling*.	SDG 4	$\frac{1}{6}$
	School attendance	Any school-aged child is *not attending* school *up to* the age at which he/she would complete *class 8*.	SDG 4	$\frac{1}{6}$
Living Standards	Cooking fuel	A household cooks using *solid fuel*, such as dung, agricultural crop, shrubs, wood, charcoal or coal.	SDG 7	$\frac{1}{18}$
	Sanitation	The household has *unimproved* or *no* sanitation *facility* or it is improved but *shared* with other households.	SDG 6	$\frac{1}{18}$
	Drinking water	The household's source of *drinking water* is *not safe* or safe drinking water is a *30-minute walk* or *longer walk* from home, roundtrip.	SDG 6	$\frac{1}{18}$
	Electricity	The household has *no electricity*.	SDG 7	$\frac{1}{18}$
	Housing	The household has *inadequate* housing materials in *any* of the three components: *floor*, *roof*, or *walls*.	SDG 11	$\frac{1}{18}$
	Assets	The household does *not own more than one* of these *assets*: radio, TV, telephone, computer, animal cart, bicycle, motorbike, or refrigerator, and does not own a car or truck.	SDG 1	$\frac{1}{18}$

Notes: This table is simplified based on Alkire, Kanagaratnam, and Suppa (2022).

national levels. Indeed, we emphasise the critical role of the objective in any such analysis. Policymakers or researchers may already have very specific questions or priorities which offer vital guidance on how to approach a joint distribution. For instance, national policymakers may want to analyse the most prevalent deprivation bundles in their country to exploit synergies in reducing poverty. UN agencies, instead, may have an interest in exploring the heterogeneity of co-deprivations of a given bundle across countries to identify any need for programme adjustments. Consequently, our empirical analyses can also been seen as an illustration of the analytical framework. For the same reasons we also provide (i) the raw results underlying our analysis, (ii) recommendations on how to adapt the framework to other settings, (iii) a more formal presentation, showing how the presented analysis relates to key quantities of the Alkire-Foster framework.

The paper is structured as follows: section 2 reviews the global MPI and its underlying datasets. While section 3 details our methodological approach, section 4 presents our results and section 5 offer a discussion. Finally, section 6 concludes.

2 Measuring global multidimensional poverty

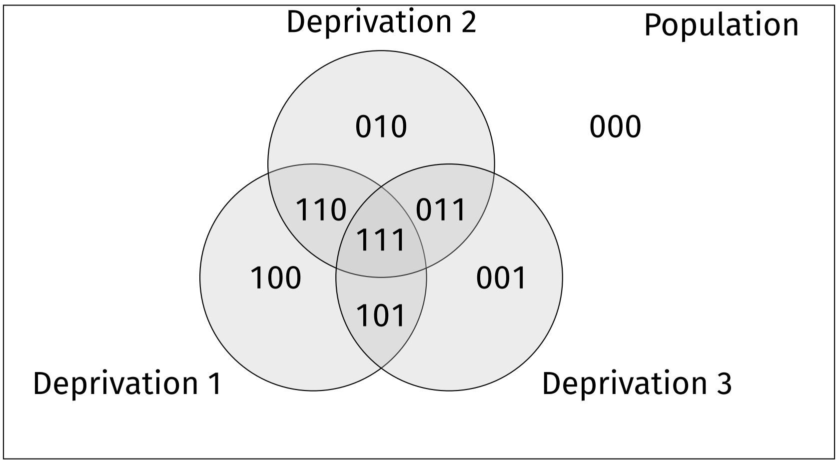
Indicators. The global MPI considers ten deprivation indicators grouped in three dimensions: Health, Education, and Living Standards. A deprivation indicator takes a value of one if a households fails to meet a critical threshold and zero otherwise. The original construction of these indicators was informed by the Millennium Development Goals (Alkire and M. E. Santos 2014). In 2018 these indicators have been revised to better align with the SDGs and the 2030 Agenda for Sustainable Development (Alkire and Kanagaratnam 2021; Alkire, Kanagaratnam, Nogales, and Suppa 2022). The three dimensions are equally weighted (1/3), reflecting an equal relative importance for measuring multidimensional poverty. Indicators are weighted equally within dimensions. See table 1 for further details on deprivation thresholds, indicator weights and related SDGs.

Identification and aggregation. The global MPI adopts the approach proposed by Alkire and Foster (2011) and draws on the joint distribution of deprivations across indicators to identify poor households using a second (cross-dimensional) cutoff. Specifically, a household and each of its members is multidimensionally poor if its sum of weighted deprivations is greater than or equal to 1/3, the poverty cutoff, which is regularly denoted by k. After identification of the poor, the headcount ratio or *incidence* of multidimensional poverty H is estimated and represents the proportion of the population who are poor. In addition, the *intensity* of multidimensional poverty, A, is estimated as the average share of weighted deprivations among the poor. The MPI value itself is then $MPI = H \times A$, the *adjusted headcount ratio*. All these estimates are regularly based upon nationally representative microdata, accounting for sampling weights and other aspects of complex survey design.

This framework also provides indicator-specific sub-indices. First, the proportion of people suffering deprivation in each of the considered indicators is called the *uncensored* headcount ratio and formally denoted as h_j for any indicator j. Moreover, the proportion of the population that is both multidimensionally poor and deprived in each indicator is called the *censored* headcount ratio and is denoted as $h_j(k)$ for any indicator j, which signifies that it is a function of the poverty cutoff, k.

Data. For our analysis we use the most recent survey data for 111 countries prepared by and documented in Alkire, Kanagaratnam, and Suppa (2022). The underlying micro datasets are largely Demographic Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS), see table B.1 for more details.

Figure 1: Deprivation overlap



Aggregation across countries. In several instances we report aggregated results for world regions or at the global level. We follow Alkire, Kanagaratnam, and Suppa (2022) and use population numbers for 2020, provided by the recently published UNDESA World Population prospects to aggregate across countries.

3 Methods

In this section we present our methods using a simplified poverty measure comprising three generic deprivation indicators; for a more formal and general presentation see appendix A. This simplified measure allows us to illustrate the newly introduced concepts (profiles, bundles and co-deprivations) and established sub-indices of the Alkire-Foster framework using a simple three set Venn diagram. This approach also allows us to pinpoint the novel insights into the joint distribution of deprivation which our proposed analyses may provide. All explanations extend to our empirically studied case of the global MPI unless mentioned otherwise.

Three indicator framework. Let our simplified poverty measure comprise three equally weighted generic indicators (deprivations 1, 2 and 3). Moreover, we require an individual to experience more than a single deprivation to be identified as poor; only people suffering from two deprivations or more are poor. Figure 1 shows how these three deprivations may overlap. Each of the three circles represents the set of individuals who are deprived in one of the three indicators. The figure shows also all the individual subsets which we denote according the overlapping deprivation indicators. For instance, individuals in the subset 100 are only deprived in indicator 1, whereas individuals in the subset 101 suffer from deprivation in indicators 1 and 3. We denote the size of a particular subset, say 101, as n_{101} where the sum of all subsets sizes is the population n. This three indicator example is useful for an intuitive explanation of our approach, but it is a substantial simplification compared with our empirically studied case of the global MPI. Specifically, our example entails $2^3 = 8$ individual subsets, where 7 subsets feature at least one deprivation and four subsets imply poverty. In contrast, the empirical analysis of the global MPI involves $2^{10} = 1024$ of which 958 imply poverty.

Selected sub-indices of the AF-framework. We can relate these subsets to selected sub-indices of our measurement framework. First, the *uncensored headcount ratio* of each indicator, which captures all individuals deprived in one particular indicator, say deprivation 1, may be obtained as $(n_{100}+n_{101}+n_{110}+n_{111})/n$. Moreover, we also see that the individuals in subsets 100, 010 and 001 are only deprived in a single deprivation and consequently not poor (subsets filled with lighter grey). Instead, people who are deprived in more than one indicator are identified as poor and thus in one of the four subsets 110, 101, 011, 111, which are depicted in darker greys. Therefore, the *headcount ratio*, which shows the proportion of poor in the population, corresponds to $(n_{110} + n_{101} + n_{011} + n_{111})/n$. Finally, the *censored headcount ratio* of a deprivation indicator shows the proportion of the population who is poor and deprived in that indicator. For deprivation 1, for instance, it can be obtained as $(n_{110} + n_{101} + n_{111})/n$. It is also this ratio which is the key ingredient to breakdown the adjusted headcount ratio into indicator-specific contributions to its value (this is termed dimensional breakdown in Alkire and Foster (2011) and Alkire, Foster, Seth, M. Santos, Roche, and Ballón (2015))[1].

What is regularly overlooked in conventional AF-based analysis are the sizes of the *individual* subsets among the poor (110, 101, 011, 111), although the AF-framework does provide sub-indices which reflect how much these subsets overlap more generally (such as intensity or censored intensity). The measures introduced below allow examine individual or particular combinations of these subsets.

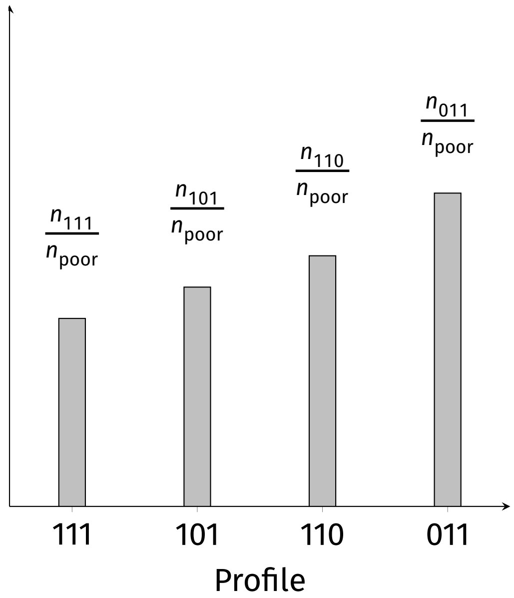
Profiles. Next, let us consider our new concepts. First, we define a *deprivation profile* as one particular combination of the individual deprivation indicators (implying 8 possible combinations, that is profiles in our three indicator example). In principle, profiles allow us to identify every single subset whether they imply poverty or not. For convenience, however, we focus on those four profiles that entail multiple deprivation and thus poverty (110, 101, 011, 111). In this simple case, we have three profiles with two deprivations and one profile with 3 deprivations.

A natural starting point for an analysis of profiles is to examine the prevalence of every single intersection of deprivations, which is illustrated in figure 2a. Related

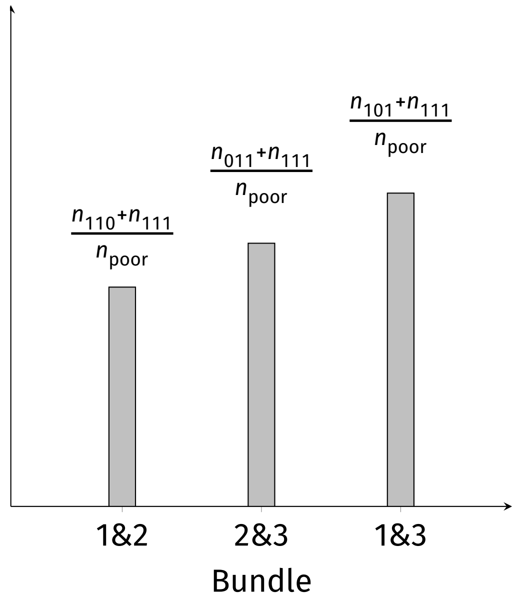
[1]Note that we can also derive the sizes of the subsets 100, 010 and 001 by taking the difference between uncensored and censored headcount ratios.

Figure 2: Illustration of analyses

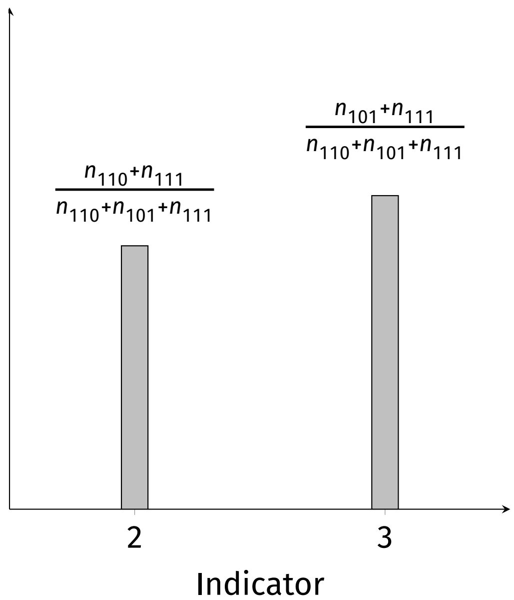
(a) Profile prevalence among poor)



(b) Bundle prevalence among poor



(c) Co-deprivation rates for poor and 1-deprived



(d) Deprivation probabilities for latent classes

		Class 1	Class 2
Indicator	1	$\frac{n_{110}+n_{101}+n_{111}}{n_{\text{class 1}}} = 1$	0
	2	$\frac{n_{110}+n_{111}}{n_{\text{class 1}}}$	$\frac{n_{011}}{n_{\text{class 2}}}$
	3	$\frac{n_{101}+n_{111}}{n_{\text{class 1}}}$	$\frac{n_{011}}{n_{\text{class 2}}}$

Notes: Let be $n_{poor} = n_{110} + n_{101} + n_{011} + n_{111}$ be the number of poor people. Moreover, we assume for this illustration the algorithm of the latent class analysis to group all profiles of the poor which feature deprivation 1 into a single class and the remaining into the other class, which then implies $n_{\text{class 1}} = n_{110} + n_{101} + n_{111}$ and $n_{\text{class 2}} = n_{011}$ for this particular illustration.

frequencies could be reported in absolute terms or relative to different reference population including the entire population, the poor population or the population deprived in at least one indicator. In this paper we report all quantities as a proportion of the poor in order to highlight how this framework can be useful to guide policies against poverty. What appears as easy-to-implement in figure 2a, turns out to be daunting in practice: instead of only four, hundreds of subsets may have to be plotted (866 in the case of the global MPI).

Bundles. One easy way to summarise the granular information offered by profiles is to select one or more deprivations into one bundle and collect all deprivation profiles which feature these deprivations *among others*. We call these deprivation bundles singletons, pairs or triplets if they contain 1, 2, or 3 deprivations, respectively. Bundles allow us to select several overlaps for analyses that have not been undertaken in depth beforehand. In our three indicator example we can only have a few bundles: one triplet (the profile 111) and three pairs: the bundle of deprivations 1 and 2 would capture the overlaps 110 and 111, the bundle of deprivations 1 and 3 would capture the overlaps 101 and 111, whereas the bundle of deprivations 2 and 3 would capture 011 and 111. We also have three singletons, one for each indicator. Note that the singleton bundle includes the same overlaps as the censored headcount ratio of an indicator would use.

Again, analysing the prevalence of bundles is a natural starting point and frequencies may be reported to different reference populations. Figure 2b illustrates such an analysis and shows how proportions for each of the three pairs may be computed. As shown in this example, having to plot one bar less compared with figure 2a may not seem worth mentioning. In the case of the global MPI, however, we can report the prevalence of 45 pairs (10-choose-2) and 120 triplets (10-choose-3) instead of some 900 profiles. Notwithstanding, a need for pre-selection of indicators and bundles according to external considerations remains.

Co-deprivations. The analysis of deprivation profiles reveals interlinkages of deprivations in the minutest detail, whereas the analysis of deprivation bundles chooses some but essentially ignores other deprivations. An intermediate angle on the joint distribution of deprivations is to examine co-deprivations of one particular bundle or indicator, which we define as deprivation rates *conditional on being multidimensionally poor and suffering from a particular deprivation bundle* (e.g., a single indicator, a pair, triplet, etc).[2]

[2] A co-deprivation rate is a conditional probability and may thus be computed for other characteristics, such as socio-demographic categories or latent class membership. In our empirical analysis, however, we focus on bundles.

In terms of figure 1, we may obtain the co-deprivation rates for being poor and, say, indicator 1-deprived as follows. First, we count the number of people in this group, which is $n_{110} + n_{101} + n_{111}$. Then we calculate how common deprivation 2 ($n_{110} + n_{111}$) and deprivation 3 ($n_{101} + n_{111}$) are within this subpopulation. Finally, we compute the co-deprivation rates as the respective ratios as illustrated in figure 2c. A helpful observation for subsequent considerations is that the co-deprivation rate of an indicator on whose deprivation status we condition on is 1 by definition (which would be indicator 1 in the example shown in figure 2c). In our three indicator case, we could alternatively also compute co-deprivation rates for the poor and indicator 2-deprived or even the poor and indicator 1 and 2 deprived (which then would only include a single co-deprivation rate for indicator 3).

Latent classes. One way to summarise the informational richness of our data on poverty profiles letting data guide the analysis entirely is by performing a latent class analysis (LCA). For a more technical discussion and selected practical considerations, see appendix A and Hagenaars and McCutcheon (2002). An LCA enables us to identify groups (or classes) of people among those that are multidimensionally poor for which we can estimate the probability (or risk or likelihood) of being deprived in each indicator. People belonging to one class are similar to each other in that they have a similar probability of facing particular deprivation profiles, which tend to be uncommon among people belonging to a different class. As we exclusively rely on deprivations indicators to determine class memberships, individuals with the same deprivation profile are considered identical and assigned to the same class. Therefore, the LCA effectively assigns deprivation profiles to classes.

Results of an LCA in our context may be reported as deprivation probabilities conditional on class membership. To illustrate the LCA in our three indicator setting, we assume that all poor people with a profile that includes deprivation 1 are assigned into a single class, and that all other people are assigned into another class. This implies for our example that the size of each class (i.e. the number of people it contains) would be $n_{\text{class 1}} = n_{110} + n_{101} + n_{111}$ and $n_{\text{class 2}} = n_{011}$. Subsequently, we can compute deprivation probabilities conditional on class membership for every indicator. More specifically, the probability of being deprived in indicator 2 conditional on being in class 1 is $\frac{n_{110}+n_{111}}{n_{\text{class 1}}}$ and conditional on being in class 2 is $\frac{n_{011}}{n_{\text{class 2}}}$; see also figure 2d.

A common challenge in LCA is to interpret what belonging to a certain class actually means (e.g., Hagenaars and McCutcheon 2002). After all, classes are latent (i.e. unobserved) and must be interpreted by the analyst in order to be meaningful. We posit an intuitive, non-arbitrary benchmark to interpret classes of poor people in our context based on the concepts proposed above. Consider the probability of being deprived in indicator 1 conditional on membership to class 1 in our example. This probability equals 1, which follows from our assumption that *only* poor people who also deprived in indicator 1 are assigned to class 1. Moreover, this assumption also implies that the probability of being deprived in indicator 1 conditional on membership to class 2 equals 0. As indicator 1 is a dominant deprivation[3] of the poor people in class 1, it seems natural to consider it for the interpretation what belonging to this class means. Specifically, as members of class 1 may be described as the set of poor people who are suffering from deprivation in indicator 1 among other deprivations, we may interpret class 1 as a specific selection or *package* of deprivation profiles. In the present simple example this package of profiles can, moreover, be interpreted as a (singleton) deprivation bundle as it contains *all* profiles with a deprivation in indicator 1. The deprivation probabilities related to the rest of the indicators may then be interpreted as co-deprivation rates of the particular deprivation package (which in the present example coincides with a singleton deprivation bundle).

For a meaningful interpretation of LCA results, the following situations can often be relevant in practice. First, we may observe probabilities *close* to 1, in which case we can interpret the underlying indicator as a dominant deprivation of a class. Accordingly, the remaining indicators in this class are only close to the exact co-deprivation rates of the package or bundle. Second, we may observe more than one dominant deprivation per class. In this case the class maybe interpreted as a package or bundle featuring those dominant indicators, whereas the remaining indicators may be interpreted as co-deprivations rates of the deprivation package or bundle defined by the dominant indicators of a class. Finally, the same indicator may be a dominant deprivation in more than one class. In this case we have to interpret a class as a profile package that features certain deprivations. The equivalence with deprivation bundles no longer holds in this case. In summary, LCA may provide an flexible view on our data and allows for an interpretation that can be related to our concepts of deprivation profiles and bundles.

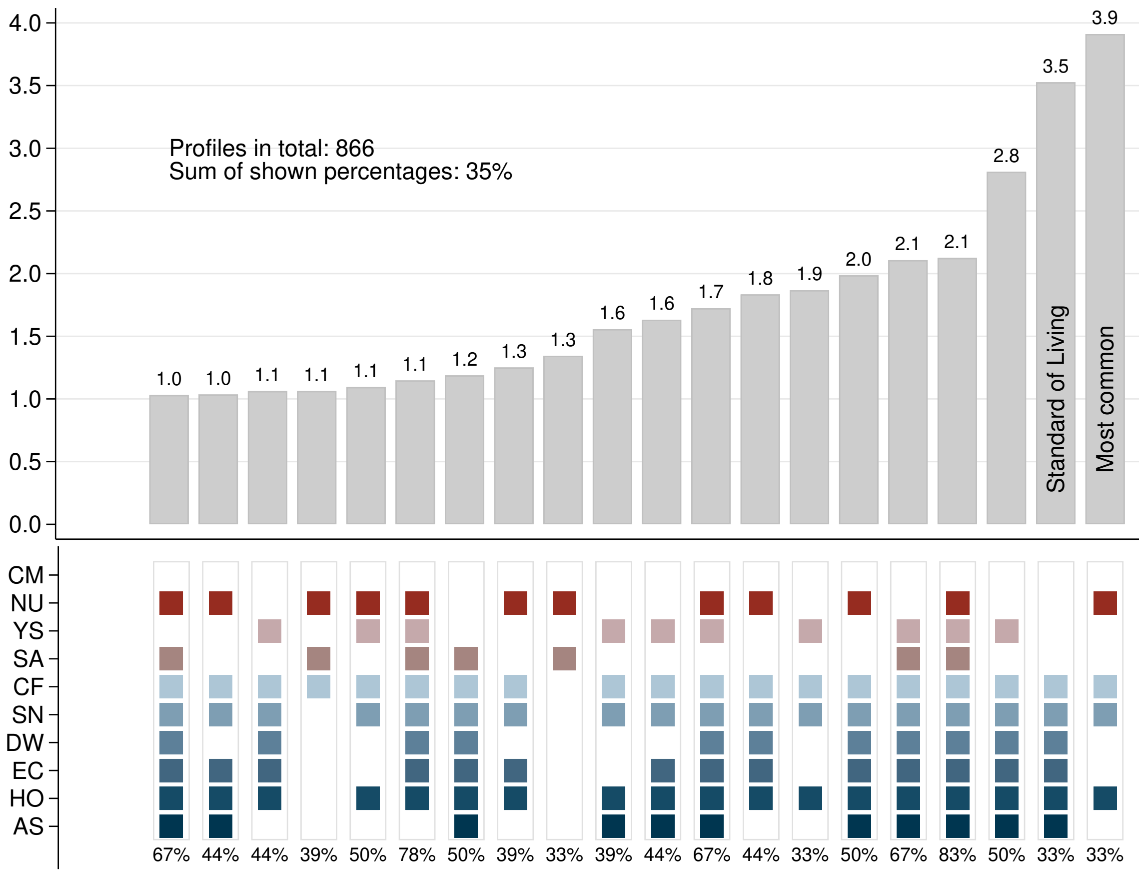
4 Results

4.1 Deprivation profiles

The ten deprivation indicators of the global MPI may be combined in $2^{10} = 1024$ ways with each other. 958 of these profiles imply poverty as their weighted deprivation score exceed the (cross-dimensional) poverty cutoff of $k = 1/3$. We do find evidence for the existence of more than 800 of those profiles among the multidimensionally poor around the globe.

[3]We adapt jargon common in the applied LCA literature, which refers to dominant traits or characteristics.

Figure 3: Deprivation profiles among the global poor



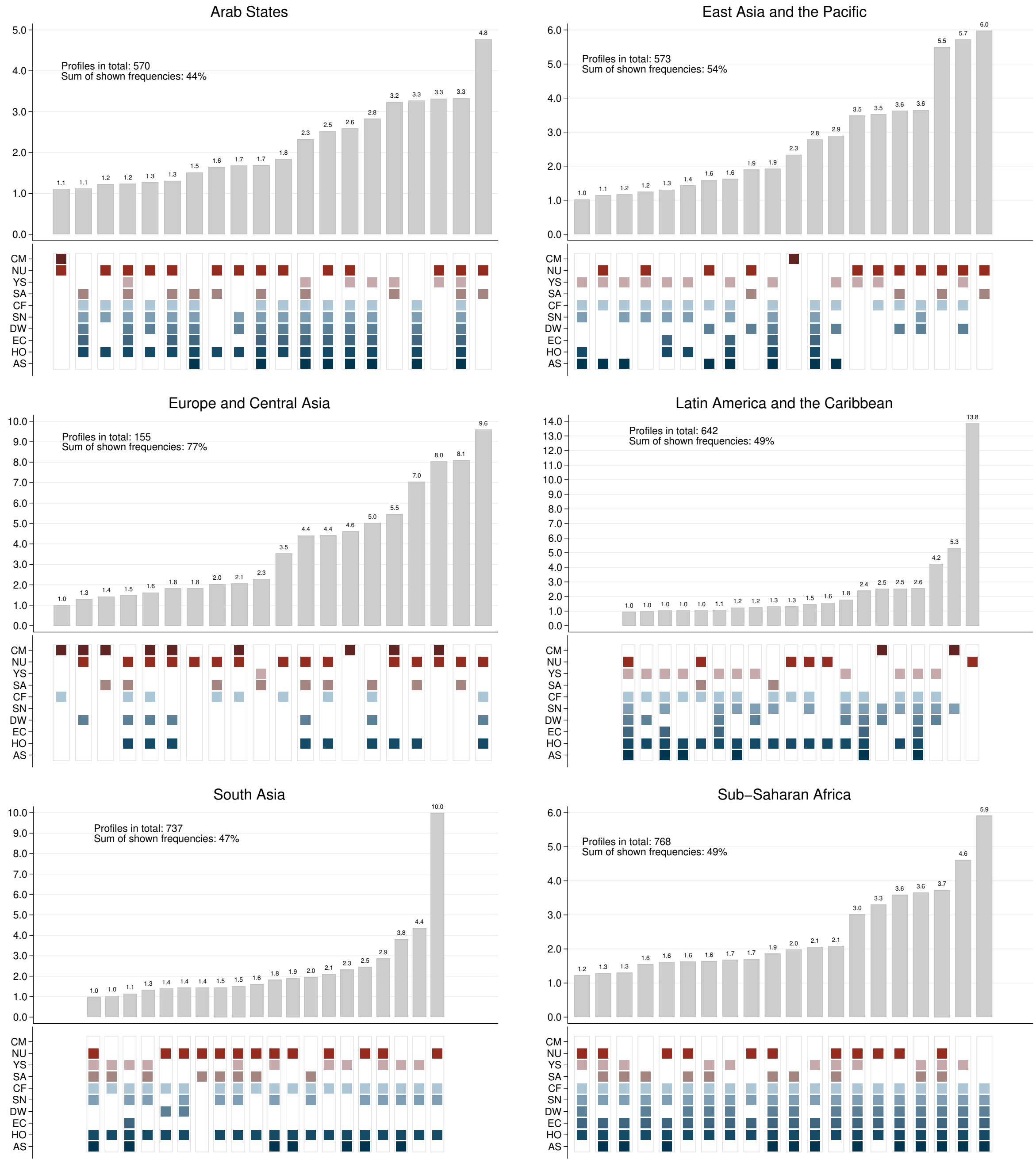
Notes: Depicted profiles are the 20 most common across the world. Deprivation indicators are child mortality (CM), nutrition (NU), years of schooling (YS), school attendance (SA), cooking fuel (CF), sanitation (SN), drinking water (DW), electricity (EC), housing (HO) and assets (AS).

A convenient graphical tool to explore the prevalence of deprivation profiles is the upset plot, which allows to identify the empirically most relevant (i.e. most frequent) deprivation profiles. The upper part of figure 3 shows the frequencies of a particular deprivation profile as a proportion among the global poor, whereas the lower part details which deprivations exactly a particular profile features. We find that 1/3 of the global poor suffer from the 20 specific profiles depicted in figure 3 and that 1/2 of the global poor suffer from 50 most common profiles (see table B.2 which shows the 130 most common profiles at the global level, their prevalence and cumulative prevalence). Moreover, we find the most common profile at the global level to be simultaneous deprivations in cooking fuel, nutrition, sanitation and housing, which is experienced by 3.9% of the global poor. The second most common profile is features deprivation in all living standard indicators and is experienced by 3.5% of the global poor. We may also look at figure 3 from a slightly different angle and consider these two profiles as bundles, thereby, allowing for additional deprivations. Figure 3 show that all but two of the depicted profiles with nutrition deprivations exhibit all four deprivations of the most common profile. Likewise, complete living standard deprivations emerge in seven other of the shown profiles. Finally, we also observe that at the global level five of the 20 shown profiles feature 8 or 9 out of the possible 10 deprivation.

Besides analysing deprivation profiles at the global level, comparisons across world regions are also instructive. Figure 4 shows the upset plot for six world regions, each containing the 20 most common profiles in each respective region. We observe, for instance, that the globally 'most common' profile (featuring deprivations in nutrition, cooking fuel, sanitation, and housing) is also the most common profile in South Asia, but less prevalent elsewhere. The 'living standard' profile is the most frequent in Sub-Saharan Africa and among the ten most abundant in Arab States, East Asia Pacific and Latin America and the Caribbean. Moreover, we find the profile with deprivation in all indicators except child mortality to be the second and third most frequent in the Arab States and Sub-Saharan Africa respectively,where it affects 3.3% and 3.7% of the poor. In terms of the implied deprivation score, we observe that profiles with a value of 0.5 or more are not among the 20 leading profiles in East Asia and Pacific or Europe and Central Asia. Finally, profiles with very high deprivation scores (over 0.75) show up in Arab States and Sub-Saharan Africa, but not in South Asia, nor in Latin American and the Caribbean. Both observations suggest that it is possible to end such heavy deprivation.

Limitations. While upset plots provide a very detailed view of the interlinkages of deprivations, they also have limitations. First, in many cases it may not even be possible to show all existing profiles (up to around 800 in our analysis). Second, it may

Figure 4: Deprivation profiles among the poor by world region



Notes: Depicted profiles are the 20 most common in respective world region. Deprivation indicators are child mortality (CM), nutrition (NU), years of schooling (YS), school attendance (SA), cooking fuel (CF), sanitation (SN), drinking water (DW), electricity (EC), housing (HO) and assets (AS).

be hard to discern differences in terms of empirical importance as many profiles may be observed with similar frequencies. Third, it may also be difficult to spot specific clusters or patterns. The larger picture or common patterns may remain hidden from immediate inspectionThese may have to be assembled by processing profiles and their frequencies in a particular way. Missing the forest for the trees seems a real risk here. Therefore, different angles of enquiry may complement the analysis of inter-linkages.

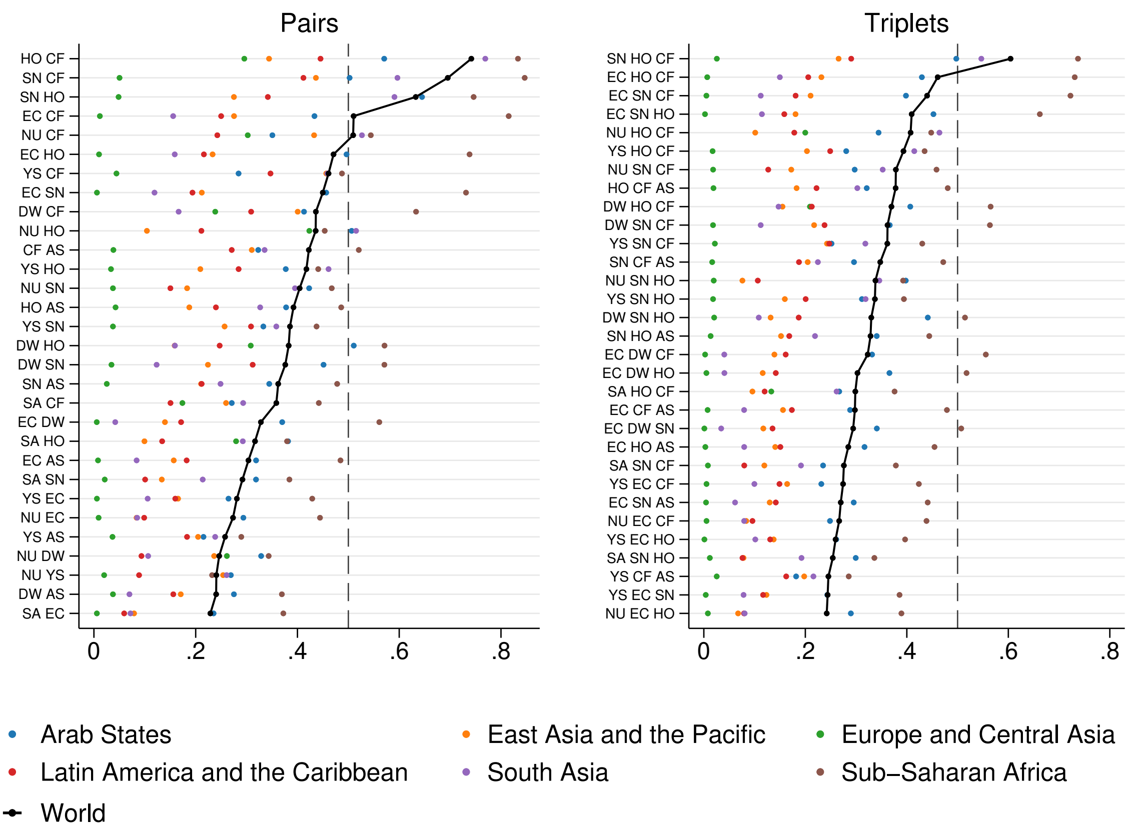
4.2 Deprivation bundles

In this section we explore deprivation bundles. We focus on pairs and triplets, which may have a particular analytical relevance, but in itself may still result in too many pieces of information. Specifically, for the global MPI with 10 indicators one would have to analyse 45 pairs (10-choose-2) or 120 triplets (10-choose-3). A natural starting point for any such analysis is, therefore, to assess their empirical relevance in the first place: How many people experience a particular bundle? What are the most common bundles at the global level? How do world regions differ from the global pattern?

Figure 5 shows the proportion of poor people experiencing a specific pair or triplet of deprivation. Black dots indicate the global prevalence (and refer to the global poor), whereas proportions for world regions are colour-coded. Salient observations include, for instance, that the top three pairs, which all comprise deprivation in housing, cooking fuel and sanitation, is experienced by 60–80% of global poor and above 50% of poor in Arab States, South Asia and Sub-Saharan Africa. In line with this, the most frequent triplet is deprivation in housing, cooking fuel and sanitation, which also afflicts 60% of global poor and over 50% in the Arab States, South Asia, and Subs-Saharan Africa. Note that this information is also consistent with the upset plot in figure 3 as 18 out of the 20 most common profiles all feature housing sanitation and cooking fuel deprivation (though not all profiles featuring the deprivations of this bundles are depicted).

Moreover, we also find considerable variation for some bundles: joint deprivation in electricity and cooking fuel affects almost 80% in Sub-Saharan Africa but close to 0% in Europe and Central Asia. In contrast, others show little variation. For example, the deprivation pair years of schooling and assets affects 20–30% of the poor for all regions except Europe and Central Asia (where it affects less than 5%). Moreover, Sub-Saharan Africa frequently exhibits the highest prevalence rates followed Arab States or South Asia whereas Europe and Central Asia often show lowest levels for the depicted bundles. Yet among the poor, several bundles such nutrition and housing, drinking water and housing, or nutrition and school attendance, are more prevalent in Europe and Central Asia than in Latin America and the Caribbean or East

Figure 5: Proportion of poor by bundles and world regions



Notes: Figure only shows 30 most common pairs and triplets among global poor; for all pairs and triplets see table B.3 and B.4, respectively.

Table 2: Censored intensities by world region

	AS	EAP	ECA	LAC	SA	SSA
CM	0.71	0.65	0.45	0.60	0.66	0.74
NU	0.63	0.51	0.42	0.56	0.54	0.66
SA	0.66	0.55	0.43	0.58	0.60	0.69
YS	0.66	0.52	0.42	0.52	0.56	0.67
EC	0.62	0.51	0.45	0.53	0.58	0.61
DW	0.60	0.48	0.41	0.50	0.55	0.61
SN	0.60	0.50	0.39	0.49	0.52	0.61
HO	0.59	0.50	0.41	0.50	0.51	0.61
CF	0.61	0.48	0.40	0.49	0.51	0.60
AS	0.62	0.50	0.43	0.52	0.53	0.61

Notes: Deprivation indicators are child mortality (CM), nutrition (NU), years of schooling (YS), school attendance (SA), cooking fuel (CF), sanitation (SN), drinking water (DW), electricity (EC), housing (HO) and assets (AS). World regions are Arab States (AS), East Asia and Pacific (EAP), Europe and Central Asia (ECA), Latin America and the Caribbean (LAC), South Asia (SA) and Sub-Saharan Africa.

Asia and Pacific (see table B.3 and B.4 for the prevalence of all pairs and triplets, respectively). Another way to explore these data would be to analyse which bundles of a given indicator are particular common. Deprivations in school attendance, for instance, is commonly observed together with deprivations in cooking fuel housing and sanitation.

An alternative way to select particular bundles is to ask whether some bundles imply systematically higher deprivation scores. One way to identify such bundles is to compute the *censored intensity* for each indicator, which reports the average deprivation for those who are poor and deprived in the particular indicator (Alkire and Foster 2019). Table 2 provides the censored intensity by world region and suggests, for instance, that deprivation scores tend to be higher in Sub-Saharan Africa than in other world regions for every indicator. Importantly, bundles which feature deprivation in child mortality imply higher deprivation scores on average than bundles featuring other indicators *within* each world region. Based on this finding one could argue that child mortality seems most prevalent among the poorest poor. An exclusive focus on prevalence of bundles would assign pairs or triplets featuring child mortality a low priority. However, as illustrated by the censored intensities, there may be good reasons to explore other deprivation patterns in depth.

We emphasise that instead of analysing all possible pairs or triplets, or only the most common bundles, development practitioners and policymakers may have a particular interest to examine the joint distribution of deprivations that include one or more specific indicators which are of particular interest for the coordination of their policy program, such as WASH which could focus on deprivation ins sanitation and drinking water access. Other similar rationales may suggest other bundles, such as households that are left behind in education which could focus on deprivations in school attendance and years of schooling.

Limitations. While deprivation bundles conflate profiles and reduce detail, they also suffer from shortcomings. For instance, the prevalence of different bundles can not be added (they may overlap) and thus there are tight limits of how they can be related to each other. Moreover, even bundles leave plenty of options for analysis (45 bundles, 120 triplets, etc).

4.3 Co-deprivations

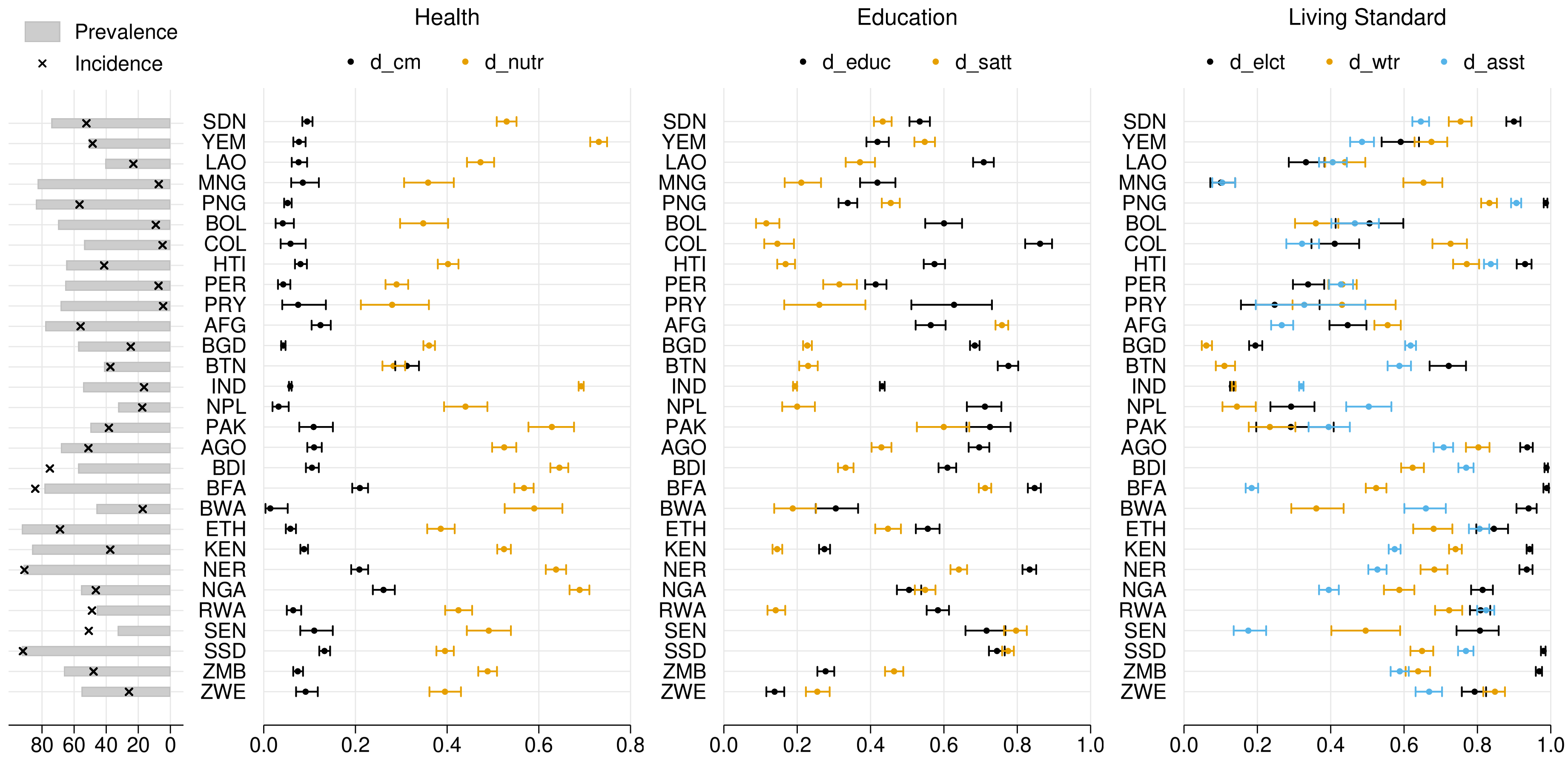
Moving to the analysis of co-deprivations changes the angle from unconditional estimates (e.g., the prevalence of a bundle) to conditional ones, which adds further nuances to our previous findings. We examine the co-deprivations of the most common triplet (joint deprivation in sanitation, housing and cooking fuel) to illustrate how this angle on the joint distribution of deprivations may complement our previous analyses. From our previous analysis, we know that this bundle afflicts more than 50% of the poor in the Arab States, South Asia and Sub-Saharan Africa. We first analyse co-deprivations for selected countries before we present findings at the global level.

Country analysis

Figure 6 shows, on the left hand side, the headcount ratio of the global MPI and the prevalence of sanitation-housing-cooking fuel triplet among the poor for selected countries. The right hand side graphs show for each country the co-deprivation rates of the remaining indicators organised by dimensions. In all the considered countries, at least 30% of the poor suffer from deprivations in this triplet, and we find a high prevalence of 60% or more in particularly poor countries located in different world regions (e.g., Afghanistan, Ethiopia, Haiti or Sudan). The salient observation from figure 6 is the considerable heterogeneity in co-deprivation rates, even for countries from the same world region, with similar headcount ratio and prevalence of the sanitation-housing-cooking fuel triplet among the poor. We also find indicator and world region specific patterns, which are, however, covered in more detail in the next section.

For health indicators, we observe that co-deprivation of *child mortality* is generally low. In some countries it is, however, experienced by 20% or more of those people who suffer from the sanitation-housing-cooking fuel triplet (e.g., Bhutan,Burkina Faso, Niger and Nigeria). Co-deprivation in *nutrition* varies between 30–70% among

Figure 6: Co-deprivation of the SN-HO-CF triplet in selected countries.



Notes: Countries sorted by name within world region; prevalence refers to among the poor; confidence intervals for 95%-level.

the considered countries. While higher values are mostly found in Sub-Saharan Africa, co-deprivation rates within this region still show a wide range of variation (40–70%). Similarly, co-deprivation rates of nutrition in South Asia are around 0.65–0.7 in Pakistan and India, which is higher than in Bangladesh or Bhutan (0.3–0.4), for instance.

In terms of education indicators we also find considerable heterogeneity within world regions. In South Asia, co-deprivation in *years of schooling* is more of an issue in Bhutan, Bangladesh, Nepal or Pakistan (0.7+) than in India (0.45). Similarly, in Sub-Saharan Africa, we find co-deprivations for years of schooling to be relatively low (<0.3) in some countries (e.g., Botswana, Kenia, Tanzania), while being relatively high (0.7+) in others (e.g., Benin, Mozambique, Senegal or Chad). Co-deprivation rates with *school attendance* are also rather low (<.2) in some countries within sub-Saharan Africa (e.g., Malawi, Rwanda or Kenia), while they are relatively high (0.7+) in others (e.g., Burkina Faso, Mauritania or South Sudan). In South Asia, Afghanistan shows particularly high co-deprivation rates with school attendance (70%+) compared to the rest of the countries in the region (20%).

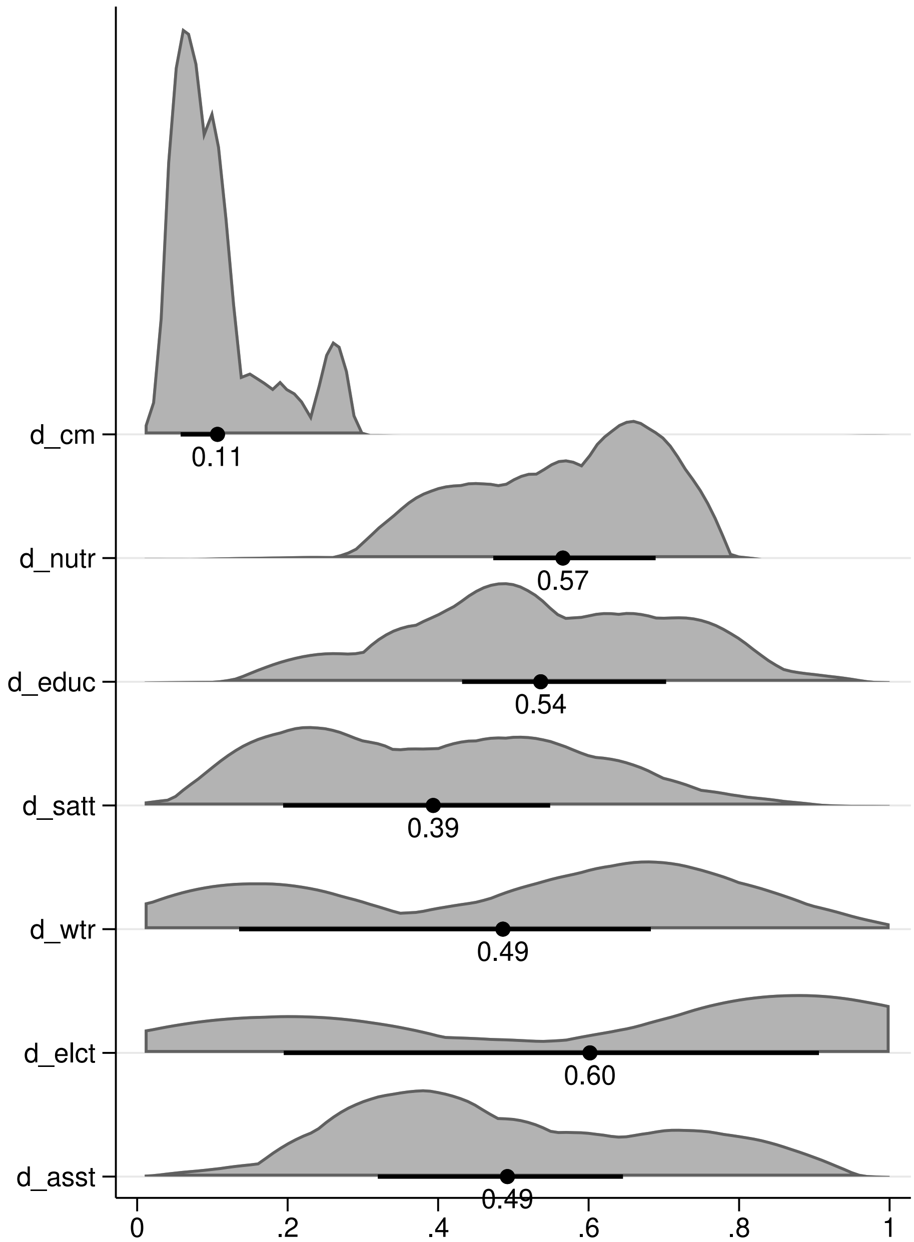
Turning to the living standard indicators, we find co-deprivation for *assets* in South Asia to range from around 30% (e.g., in Aghanistan and India) to 60% (e.g., in Bangladesh and Bhutan). Similarly, in Sub-Saharan Africa we find co-deprivation rates with assets ranging from around 20% in Burkina Faso or Senegal to around 80% in Burundi, Ethiopia or Rwanda. For many, if not most countries in Sub-Saharan Africa, *electricity* is a common co-deprivation with rates often over 90%. However, rates of 70% or more are also found in other countries of regions of the world, including the Sudan, Papua New Guinea, Haiti and Bhutan.

These findings are crucial for effective policymaking. Anti poverty programmes in Niger, for instance, must consider that is highly expected that these triplet of deprivations is encountered alongside undernourished household members, with no one having the minimum years of schooling required to be non-deprived in schooling, and most likely have no electricity. In Papua New Guinea, however, deprivation in assets, drinking water and electricity is to be expected alongside this triplet, while deprivation in education indicators is far less likely.

Global analysis

The previous analysis is based on selected countries and is particularly suited to reveal specific differences and commonalities in co-deprivation across countries. In addition, one may also ask how more general patterns may look like. To address this question, figure 7 shows the average co-deprivation rates for the sanitation-housing-cooking fuel triplet, their interquartile range and their kernel density, all at the global level and for each of the remaining 7 deprivation indicators in the global MPI.

Figure 7: Co-deprivation of the SN-HO-CF triplet



Notes: Proportions refer to people among the global poor and CF-SN-HO deprived; black dots indicate (population weighted) mean deprivation; black lines interquartile ranges, Epanechnikov kernel based on national-level estimates of co-deprivations of 111 countries.

For most deprivation indicators we find co-deprivation rates ranging between 40–60%, except for child mortality, which is with an average of 0.11 and a rather narrow interquartile range, a relatively rare co-deprivation globally. For some countries (e.g., Bhutan, Niger or Nigeria) we do, however, observe co-deprivation rates of 0.3; see also figure 6. In terms of nutrition and years of schooling, we observe 57% and 54% of the global poor and triplet deprived to also suffer from these two deprivations. The spread of both distributions is relatively low compared with the other indicators: half of the countries have co-deprivation rates between .4-.75 in these indicators. The density estimate, moreover, suggests that countries with the extreme cases of co-deprivations close to the bound 0 and 1 are rare.

Deprivations in school attendance, drinking water and electricity differ in their co-deprivation rates, (.39, .49 and .6), but all of them have both a flatter and bimodal distribution. Indeed, these three indicators are virtually absent as co-deprivations in some countries and ubiquitous in others (implying particularly wide interquartile ranges). This bi-modality suggests that other background factors such as rurality or world region heterogeneities may be at the source of this pattern. Figure 6, however, already shows that high co-deprivation with drinking water (60%+) and with electricity (80%+) can be found in several world regions. Finally, co-deprivation with assets is on average around 0.5, with a relatively low spread across the developing world.

In summary, the evidence presented in this section suggests that even when focusing on the multidimensional poor, which are suffering from joint deprivation in sanitation, housing and cooking fuel, heterogeneous patterns in terms of co-deprivations are abundant, even across countries within the same world region. The sanitation-housing-cooking fuel triplet is particularly common in Sub-Saharan and South Asia but also frequently experienced by the poor in other parts of the world. Importantly, varying co-deprivation rates across countries imply that successful policy programmes in one country have to be adapted for application in other countries to ensure effectiveness or leverage synergies. Besides the heterogeneity for any given indicator, we also observe indicator-specific patterns about how co-deprivations vary such as uni- versus bimodal distributions. These more general patterns may serve as a useful benchmark to compare world region or country-specific findings with.

4.4 Latent class analysis - LCA

The analysis of latent classes is one useful way to summarize the informational richness of our data on poverty profiles. According to this approach each deprivation profile is allocated to exactly one (latent) class. For exploratory purposes, we assume the existence of two latent classes among the poor and apply LCAs at the global level and for each world region separately. Depending on objective and set-

Table 3: Deprivation probabilities for latent classes

	World		AS		EAP		ECA		LAC		SA		SSA	
	1	2	1	2	1	2	1	2	1	2	1	2	1	2
CM	0.15	0.11	0.18	0.09	0.05	0.13	0.40	0.01	0.96	0.06	0.14	0.07	0.23	0.10
NU	0.75	0.49	0.74	0.61	0.59	0.95	0.86	0.11	0.79	0.46	0.97	0.35	0.71	0.48
SA	0.38	0.43	0.65	0.45	0.24	0.60	0.47	0.24	0.08	0.27	0.32	0.41	0.45	0.45
YS	0.45	0.58	0.52	0.48	0.63	0.36	0.05	0.87	0.21	0.65	0.30	0.80	0.33	0.58
EC	0.16	0.87	0.01	0.73	0.43	0.00	0.01	0.11	0.00	0.44	0.09	0.25	0.56	0.96
DW	0.25	0.66	0.16	0.71	0.52	0.29	0.36	0.45	0.33	0.56	0.18	0.19	0.45	0.74
SN	0.58	0.90	0.22	0.89	0.66	0.10	0.05	0.64	0.78	0.71	0.60	0.73	0.73	0.93
HO	0.70	0.94	0.36	0.99	0.82	0.18	0.55	0.50	0.06	0.74	0.77	0.92	0.59	0.97
CF	0.80	0.99	0.10	0.82	0.98	0.49	0.43	0.69	0.14	0.88	0.79	0.93	0.95	0.99
AS	0.23	0.64	0.02	0.55	0.49	0.01	0.03	0.62	0.01	0.46	0.21	0.54	0.20	0.69
N_{cl}/N	0.47	0.53	0.30	0.70	0.65	0.35	0.94	0.06	0.21	0.79	0.55	0.45	0.31	0.69
N_{cl}	530026	607858	14738	34754	71287	38014	1045	72	5856	22316	209775	169483	178154	392390
N	1137884	1137884	49492	49492	109301	109301	1117	1117	28172	28172	379258	379258	570544	570544

Notes: Deprivation indicators are child mortality (CM), nutrition (NU), years of schooling (YS), school attendance (SA), cooking fuel (CF), sanitation (SN), drinking water (DW), electricity (EC), housing (HO) and assets (AS). World regions are Arab States (AS), East Asia and Pacific (EAP), Europe and Central Asia (ECA), Latin America and the Caribbean (LAC), South Asia (SA) and Sub-Saharan Africa.

ting one may explore alternative analytical routes building from a larger number of classes. Table 3 reports the probabilities of being deprived in a particular indicator conditional on class membership at the global level and by world regions. Unsurprisingly, some of our previous findings resurface through this lens. For instance, the deprivations of previously observed 'most common profile' and the 'living standard profile' clearly dominate in one class each at the global level. Specifically, we observe high deprivation probabilities conditional on being in class 1 of 0.7 or above for nutrition, housing and cooking fuel, while sanitation exhibits a probability of almost 0.6. Deprivation probabilities for all remaining indicators are, overall, under 0.5.

Moreover, additional insights at the global level emerge. For instance, table 3 also shows that according to class 2, common co-deprivations of the 'living standard profile' are education (0.58), nutrition (0.49) and school attendance (0.44). Likewise, by analysing class 1, we find that frequent co-deprivations of the 'most common profile' are education (0.45) and school attendance (0.38).

Our previous analysis of deprivation bundles already informed about high prevalence of the sanitation-housing-cooking fuel triplet in general, which also stands out through relatively high deprivation probabilities of these indicators for *both* classes at the global level. Looking at the regional level, however, adds some variation. For instance, the sanitation-housing-cooking fuel triplet features prominently with deprivation probabilities above 0.60 in both latent classes only in South Asia and sub-Saharan Africa. In the remaining world regions, however, this triplet features prominently only in one of the latent classes.

Moreover, in South Asia the results of the LCA suggest nutrition as the dominant deprivation of class 1, which covers more than 50% of the poor in this region, and that a shortfall in the nutrition indicator is frequently accompanied by the deprivations of the sanitation-housing-cooking fuel triplet . In contrast, the dominant deprivations of class 2 are housing and cooking fuel, which are frequently accompanied by deprivation in sanitation and years of schooling.

Finally, for the Arab States we find in class 2 medium or high deprivation probabilities for all indicators except child mortality which again clearly reflects the most common profile in the Arab States (see figure 4). The most dominant deprivations of class 1 are nutrition, school attendance and education. Revisiting figure 4 above shows that indeed several profiles may correspond to this class, even though only two of the depicted profiles feature all three deprivation simultaneously.

5 A discussion on how to inform policymakers

The evidence presented thus far can be used by policymakers in a number of ways. First and foremost, it becomes evident that certain deprivations bundles must be addressed in a synergetic manner, for example through integrated policies (joint targeting), to increase impact of investments and policy efforts. This requires considering the censored headcount ratios of each indicator and the prevalence of the identified bundles to understand the extent of overlap. This way, joint targeting can benefit the jointly deprived, while single-deprivation (or alternative integrated programmes) address the singly deprived. This difference is crucial if one aims for efficient policymaking against poverty.

The problem is clear: the analysis presented in and underlying this paper is massive, with over 850 realised deprivation profiles among the poor according to the global MPI for example, and hundreds in most countries for which the global MPI is meaningful. There are different possible analytical tools that can be of help – primarily examining deprivation bundles, or co-deprivations of a particular indicator. And for deprivation bundles, it is possible to examine deprivation pairs, triplets, quartets, or higher numbers of indicators. So one need is for effective data visualisation techniques and interactive tools by which detail-oriented technicians can easily call the particular analysis of interest. We also emphasise that the appropriate angle on the data depends on the aspects a researcher or policy maker is interested, viz. the objective, which provides vital guidance for policymakers and researchers on how to approach a joint distribution.

We found evidence for larger deprivation bundles (triplets or quartets or larger bundles) across the developing world. This points to a more challenging reality for policy planners, as multisectoral policies are required. Adequate political infrastructures are required to enable coordinated actions in this case. The evidence presented in this paper makes it clear that isolated policies against one of the identified deprivations will surely help to reduce hardships, but they are far from being the first best when it comes to policy efficiency.

Having such compelling evidence on the prevalence of bundles across the developing world clearly points to the need for careful policy coordination. Importantly, this also needs to happen within countries, at the subnational levels. We must highlight then that, as any estimate from an AF-based analyses, the prevalence of the bundle can be made visible among any population subgroup for which a) the data are representative and b) the sample size for this particular analysis is sufficient. Profiling bundles subnationally acts as a cross-check to deepen and sharpen the percentage contribution information that is already used for policy design.

We also stress that if an existing multisectoral program is successfully addressing a particular deprivations (e.g. school attendance and nutrition) then a possible goal is to use this analysis to identify which other deprivations should be tackled. This is done by identifying indicators with high co-deprivation rates that we have made a case for in this paper. For instance, a high co-deprivation rate may point out a deprivation that, if ignored, may make the policy may less effective. In addition, a high co-deprivation rate may also point to potential synergies. For instance, if the deprivation bundle of housing, sanitation and cooking fuel is high, or the co-deprivation of housing with sanitation and cooking fuel are high, the impact of extending an initiative to improve housing materials to address sanitation and clean renewable energy could also be high, because the households who have already been targeted anyway tend to be deprived in these indicators also. Conversely, some deprivations may actually not intersect regularly with a given bundle (for example because they primarily affect urban dwellers, whereas the given bundle is prevalent in rural areas). Either the deprivation bundle frequency or the co-deprivation formatting easily provide information that could improve programme efficiency.

Clearly, the interlinked nature of deprivations that is so evident in our results can also be used to assess the probability of success and replication of programmes in a new context. For example, if a policy was highly successful in region (or country) A, it may be that part of the success was because in region A, a given deprivation bundle, which that policy addressed, was prevalent among the poor. In region B, where the programme is to be replicated, perhaps that deprivation bundle is actually not common. This could limit the reach or success of the replicated programme. If such analysis is conducted often it will build up a useful body of empirical analysis to guide future programme replication.

Finally, let us highlight that if common bundles, or (sets of) profiles are not evident among the poor, an LCA can help uncover them. Cross-checking and analysing the LCA and its component bundles will enable a technician or policymaker to find deprivation bundles or patterns more easily, that could improve policy impact. Naturally, LCA has many potential contributions to the understanding of interlinkages and has been only briefly introduced here. This analysis could be implemented more extensively and iteratively with the deprivation bundle analysis. This is particularly useful if one wishes to contrast already existing multisectoral policy programmes with empirical evidence about, not only how interlinked deprivations are, but also with what degree of imperfection and error.

6 Concluding remarks

Summary and relevance. This paper proposes a novel account to explore the interlinkage of deprivations within a multidimensional poverty measurement framework. In our empirical analysis we analyse the prevalence of deprivation profiles, bundles and co-deprivation rates using global MPI data for 111 countries. While we do observe more than 800 different profiles in our data, we find that more than 1/3 of the global poor suffer from one of the 20 most prevalent profiles and some 50% of the global poor suffer from one of the 50 most common profiles. Moreover, we also find evidence that 60% of the global poor suffer from simultaneous deprivation in sanitation housing and cooking fuel. In terms of co-deprivations for this bundle we observe indicator-specific patterns at the global level such as bimodal distributions for drinking water access and electricity, which calls for further research. Despite these and other commonalities at aggregated levels, a common thread through all of our analyses is the heterogeneity in deprivation patterns across countries—even within the same world region.

The presented findings may serve as a benchmark and starting point for more in-depth analysis at the country-level or analyses focusing on a particular set of deprivation indicators. Moreover, knowledge about deprivation patterns in other countries may, allow national policymakers to identify better policies for their own country. Pertinent evidence may, for instance, allow policymakers to assess potential reach and synergies of a program or to identify the need for programme adjustments due to specific co-deprivations already during the decision-process.

Selectivity of Evidence. The presentation of evidence in this paper is very selective, which largely follows from the complexity of the joint distribution of deprivations and the particular angle on it one seeks to take. By looking at the most prevalent profiles and bundles at global and world region level, we only scratched the surface: we had to ignore, among others, less common patterns and national level analysis. Codeprivations were only studied conditional on one particular bundle, the sanitation, housing cooking fuel triplet).

While an analysis along the suggested lines may produce many intriguing insights, we also emphasise that the appropriate angle on the data depends on the aspects a researcher or policy maker is interested, viz. the objective. For instance, if one were to improve the lives of people left behind in education, one could explore (i) the prevalence of joint deprivation in both education indicators and its variation by country or region, (ii) the leading pairs or triplets involving at least one deprivation indicator of education, or (iii) the most frequent co-deprivations of those who are deprived in both education indicators.

Cautionary note. An important limitation of this paper is that most of the underlying micro data reflect a pre-pandemic state of affairs. Consequently, our analysis largely ignores recent setbacks related to the pandemic or the currently deepening food crises. Previous research suggests that due to the covid-19 pandemic and related policy responses almost ten years of poverty reduction could be undone (Alkire, Nogales, Quinn, and Suppa 2021). Moreover, one may expect deprivation indicators to be unevenly affected, which is pertinent to the presented findings. In particular, deprivation in school attendance and nutrition may have increased in many countries.

Future research. Future research may advance the presented analyses in several directions. First, by extending the analysis to alternative poverty cutoffs one may uncover interlinkages for poverty intensity gradients. Moreover, understanding how interlinkages change over time can be particularly useful for effective policymaking; strict microdata harmonisation exercises can pave the way for such analysis. Additionally, distinguishing which poverty bundles can (or should) be tackled to accelerate poverty reduction can be useful for efficient policymaking; this is of course not a focus on low hanging fruit, but rather maximising benefits with scarce resources. Finally, ex post evaluations about how successful (or not) were policy programmes to tackle prevalent bundles can yield useful novel insights. Likewise ex ante evaluations of how bundles can respond to programming can also lead to critical information for policy actors and international organisations.

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A Technical appendix

The measurement framework

We consider $i = 1, \dots, n$ individuals and $j = 1, \dots, d$ dimensions where i and $d \geq 2$ are positive integers. Let $\boldsymbol{y}$ be the $n \times d$ achievement matrix with the typical element $y_{ij} \in \mathbb{R}^{+}$ and $\boldsymbol{z}$ a $1 \times d$ vector containing a deprivation threshold z_j for every dimensions j. The $n \times d$ deprivation matrix is $\boldsymbol{g}$ with the typical element $g_{ij} = 1$ if $y_{ij} < z_j$ and 0 otherwise.[4] Let $\boldsymbol{g}_{i\bullet}$ denote the row vector containing the deprivation status for all indicators of an individual i. Let $\boldsymbol{w}$ be a $1 \times d$ weighting vector with elements $0 \leq w_j \leq 1$ and $\sum_j w_j = 1$. Then we obtain the $n \times 1$ counting vector as the inner product of deprivation matrix and weighting vector $\boldsymbol{c} = \boldsymbol{g} \cdot \boldsymbol{w}$, with its typical element being the deprivation score $c_i = \sum_j g_{ij} \times w_j$ for each individual. Based on the deprivation score and the cross-dimensional poverty cutoff $0 < k \leq 1$ we can assert whether an individual is poor using the identification function $\rho(k) = \mathbb{I}(c_i \geq k)$ where $\mathbb{I}(\cdot)$ is the indicator function. We obtain the censored deprivation matrix by multiplying its typical element with the identification function $g_{ij}(k) = g_{ij}\rho(y_{ij}, k)$.

We now turn to selected sub-indices of the Alkire-Foster framework. First, the *headcount ratio* is proportion of the population which is multidimensionally poor (suffering from multiple deprivations) and can be written as $H = \frac{q}{n}$ where $q = \sum_i^n \rho(y_{ij}, k)$ is the number of poor people. The *intensity*, which is the average deprivation among the poor, can be written $A = \frac{1}{q} \sum c_i \times \rho(y_{ij}, k)$. The *adjusted headcount ratio* is the product of both sub-indices $M = HA$. Let $q_j = \sum_i g_{ij}$ be the number of j-deprived people then the *uncensored headcount ratio* of indicator j is $h_j = \frac{q_j}{n}$ which is the proportion of the population deprived in indicator j. The *censored headcount ratio*, instead, shows the proportion of the population which is poor and deprived in a particular indicator, which may be written as $h_j(k) = \frac{q_j(k)}{n}$ with $q_j(k) = \sum_i g_{ij}(k)$ being the number of poor and j-deprived people.

Profiles, bundles and co-deprivations

We define a *deprivation profile* as any unique combination of deprivations. Specifically, let $\Pi = \{0, 1\}^d$ be the set of all binary row vectors of dimension d and let $\boldsymbol{\pi}_p \in \Pi$ be a $1 \times d$ vector describing deprivation profile $p = 1, \dots, 2^d$. While the set Π contains vectors for all possible deprivation profiles, sometimes one may wish to restrict the analysis to those implying poverty. Therefore, we define and subsequently focus on the set $\Pi^{\text{poor}} = \{\boldsymbol{\pi}_p \in \Pi | \boldsymbol{\pi}_i \cdot \boldsymbol{w} \geq k\}$ where $\boldsymbol{\pi} \cdot \boldsymbol{w}$ is the inner product and thus $\sum_j \pi_{pj} w_j$.

[4] In Alkire, Foster, Seth, M. Santos, Roche, and Ballón (2015) the deprivation matrix carries a superscript 0, which we drop here for notational convenience.

The *prevalence of a profile p* among the poor[5] can now be written as

$$h_p^P(k) = \frac{1}{q(k)} \sum \mathbb{I}(g_{i\bullet}(k) = \pi_p) \qquad \forall \pi_p \in \Pi^{poor}. \tag{1}$$

We define a *deprivation bundle* of a particular profile p^* as the set of all deprivation profiles which feature the deprivations in π_{p^*} among others or formally as $\{\pi_p \in \Pi | \pi_p \geq \pi_{p^*}\}$. The prevalence the bundle p among the poor is

$$h_p^B(k) = \frac{1}{q(k)} \sum \mathbb{I}(g_{i\bullet}(k) \geq \pi_p) \qquad \forall \pi_p \in \Pi. \tag{2}$$

We refer to π_{p^*} as a deprivation singleton if $\sum_j \pi_{p^*j} = 1$, a deprivation pair if $\sum_j \pi_{p^*j} = 2$, a triplet if $\sum_j \pi_{p^*j} = 3$ and so forth.

Finally, we define the *co-deprivation rate* as the proportion of poor people deprived in a particular indicator given that they already suffer from a specific deprivation bundle.[6] Formally,

$$h_j^C(k, \pi_p) = \frac{1}{q_p(k)} \sum_i^n g_{ij}(k) \mathbb{I}(g_{i\bullet} \geq \pi_p) \qquad \forall \pi_p \in \Pi. \tag{3}$$

where $q_p(k) = \sum_i \mathbb{I}(g_{i\bullet}(k) \geq \pi_p)$ is the number of poor people experiencing a particular deprivation bundle. Note that for $p_{pj} = 1$ it follows that $h_j^C = 1$ as a special case.

Latent class analysis

Let us now present some formal aspects of LCA. Let N be the variable indicating the latent, unobserved class variable. If we have C pre-defined classes among the poor people, then $X = 1...C$. In a framework with D deprivation indicators, let I_j be an indicator variable where a unity value denotes deprivation in indicator j while being poor. In a parametric approach to this analysis, the likelihood of facing a deprivation in indicator j conditional on membership to class x can be defined by a logistic function as

$$P(I_j = 1 | X = x) = \frac{e^{\alpha_{jx}}}{1 + e^{\alpha_{jx}}}, \qquad \forall j; x \tag{4}$$

.

where α_{jx} are unknown parameters. The probability of class membership is esti-

[5]Depending on the context one may wish to include profile which do not imply poverty and report a prevalence within the entire population.

[6]Technically, the co-deprivation rate is simply a conditional probability, which we define for deprivation bundles. Naturally, we may calculate and use conditional probabilities in other instances too, including socio-demographic characteristics latent classes, for instance.

mated through a multinomial logistic regression as follows:

$$P(X = x) = \frac{e^{\gamma_x}}{\sum_{l=1}^{C} e^{\gamma_l}}, \qquad \forall x \tag{5}$$

where γ_x are also unknown parameters. The unconditional probability of facing a deprivation in indicator j is then

$$P(I_j = 1) = \sum_{x=1}^{C} P(X = x)P(I_j = 1|X = x) \qquad \forall j \tag{6}$$

The frequency of deprivation in indicator j while being poor is effectively the censored headcount ratio in the sample, $h_j(k)$. Thus the likelihood function of the LCA model in this context can be defined as

$$L = \prod_{j=1}^{D} P(I_j = 1)^{h_j(k)} \tag{7}$$

The above function - or its log - is maximised to solve for all the unkown parameters

B Additional results

Table B.1: Datasets

Country	Survey	Year
AFG	DHS	2015-2016
AGO	DHS	2015-2016
ALB	DHS	2017-2018
ARG	MICS	2019-2020
ARM	DHS	2015-2016
BDI	DHS	2016-2017
BEN	DHS	2017-2018
BFA	DHS	2010
BGD	MICS	2019
BIH	MICS	2011-2012
BLZ	MICS	2015-2016
BOL	EDSA	2016
BRA	PNAD	2015
BRB	MICS	2012
BTN	MICS	2010
BWA	BMTHS	2015-2016
CAF	MICS	2018-2019
CHN	CFPS	2014
CIV	MICS	2016
CMR	DHS	2018
COD	MICS	2017-2018
COG	MICS	2014-2015
COL	DHS	2015-2016
COM	DHS	2012
CRI	MICS	2018
CUB	MICS	2019
DOM	MICS	2019
DZA	MICS	2018-2019
ECU	ENSANUT	2018
EGY	DHS	2014
ETH	DHS	2019
GAB	DHS	2012
GEO	MICS	2018
GHA	MICS	2017-2018
GIN	DHS	2018
GMB	DHS	2019-2020
GNB	MICS	2018-2019
GTM	DHS	2014-2015
GUY	MICS	2019-2020
HND	MICS	2019
HTI	DHS	2016-2017
IDN	DHS	2017
IND	DHS	2019-2021
IRQ	MICS	2018
JAM	JSLC	2018
JOR	DHS	2017-2018
KAZ	MICS	2015
KEN	DHS	2014
KGZ	MICS	2018
KHM	DHS	2014
KIR	MICS	2018-2019
LAO	MICS	2017
LBR	DHS	2019-2020
LBY	PAPFAM	2014
LCA	MICS	2012
LKA	SLDHS	2016

Country	Survey	Year
LSO	MICS	2018
MAR	PAPFAM	2017-2018
MDA	MICS	2012
MDG	MICS	2018
MDV	DHS	2016-2017
MEX	ENSANUT	2020
MKD	MICS	2018-2019
MLI	DHS	2018
MMR	DHS	2015-2016
MNE	MICS	2018
MNG	MICS	2018
MOZ	DHS	2011
MRT	DHS	2019-2021
MWI	MICS	2019-2020
NAM	DHS	2013
NER	DHS	2012
NGA	DHS	2018
NIC	DHS	2011-2012
NPL	MICS	2019
PAK	DHS	2017-2018
PER	ENDES	2019
PHL	DHS	2017
PNG	DHS	2016-2018
PRY	MICS	2016
PSE	MICS	2019-2020
RWA	DHS	2019-2020
SDN	MICS	2014
SEN	DHS	2019
SLE	DHS	2019
SLV	MICS	2014
SRB	MICS	2019
SSD	MICS	2010
STP	MICS	2019
SUR	MICS	2018
SWZ	MICS	2014
SYC	QLFS	2019
TCD	MICS	2019
TGO	MICS	2017
THA	MICS	2019
TJK	DHS	2017
TKM	MICS	2019
TLS	DHS	2016
TON	MICS	2019
TTO	MICS	2011
TUN	MICS	2018
TUV	MICS	2019-2020
TZA	DHS	2015-2016
UGA	DHS	2016
UKR	MICS	2012
VNM	MICS	2020-2021
WSM	MICS	2019-2020
YEM	DHS	2013
ZAF	DHS	2016
ZMB	DHS	2018
ZWE	MICS	2019

Table B.2: Prevalence of deprivation profiles at global level

No.	Perc.	Cum. Perc.	NU	CM	YS	SA	CF	SN	DW	EC	HO	AS
1	3.91	3.91	•				•	•			•	
2	3.53	7.44					•	•	•	•	•	•
3	2.81	10.25			•		•	•	•	•	•	•
4	2.12	12.37	•		•	•	•	•	•	•	•	•
5	2.11	14.48			•	•	•	•	•	•	•	•
6	1.99	16.47	•				•	•	•	•	•	•
7	1.87	18.34			•		•	•			•	
8	1.83	20.17	•				•	•	•	•	•	
9	1.72	21.89	•		•		•	•	•	•	•	•
10	1.63	23.52			•		•	•		•	•	•
11	1.56	25.08			•		•	•			•	•
12	1.34	26.43	•			•						
13	1.25	27.68	•				•	•		•	•	
14	1.19	28.86				•	•	•	•	•	•	•
15	1.15	30.01	•		•	•	•	•	•	•	•	
16	1.09	31.11	•		•		•	•			•	
17	1.06	32.17	•			•	•					
18	1.06	33.23			•		•	•	•	•	•	
19	1.03	34.27	•				•	•		•	•	•
20	1.03	35.30	•			•	•	•	•	•	•	•
21	1.02	36.32	•				•	•			•	•
22	1.00	37.31			•	•	•	•	•	•	•	
23	0.97	38.28	•				•	•	•		•	
24	0.96	39.24				•	•	•			•	
25	0.93	40.18	•		•	•	•	•		•	•	•
26	0.93	41.10				•	•	•	•	•	•	
27	0.92	42.02	•			•	•	•	•	•	•	
28	0.91	42.93			•	•	•	•		•	•	•
29	0.88	43.81	•				•	•	•			
30	0.88	44.68			•		•				•	•
31	0.87	45.55	•		•		•	•		•	•	•
32	0.84	46.39			•		•	•		•	•	
33	0.78	47.17	•		•							
34	0.77	47.94	•		•		•				•	
35	0.71	48.66	•		•		•	•	•	•	•	
36	0.71	49.36	•				•				•	•
37	0.70	50.06	•		•	•	•	•		•	•	
38	0.68	50.75	•		•		•	•			•	•
39	0.67	51.42	•				•		•		•	
40	0.67	52.09	•			•	•				•	
41	0.66	52.75	•			•	•	•			•	
42	0.66	53.41			•	•	•	•		•	•	
43	0.60	54.00				•	•	•		•	•	
44	0.59	54.59	•		•	•	•	•			•	
45	0.58	55.17			•	•	•	•			•	
46	0.58	55.75	•		•		•					
47	0.57	56.33	•		•		•		•			
48	0.57	56.90	•		•		•	•		•	•	
49	0.57	57.46				•	•	•		•	•	•
50	0.52	57.98	•				•			•	•	
51	0.46	58.45			•		•	•	•		•	
52	0.46	58.91			•		•	•				•
53	0.45	59.36	•									
54	0.43	59.79	•			•	•	•		•	•	•
55	0.43	60.22	•			•	•		•			
56	0.43	60.65	•			•	•	•		•	•	
57	0.41	61.06				•	•	•	•		•	
58	0.41	61.48			•	•	•				•	
59	0.41	61.88	•				•	•				•
60	0.40	62.28			•		•			•	•	•
61	0.39	62.68	•				•	•		•		
62	0.39	63.06	•	•								
63	0.38	63.45	•		•		•	•				
64	0.38	63.82	•				•	•	•	•		
65	0.37	64.20			•		•	•	•		•	•

Table continues on next page.

Table B.2 continued.

No.	Perc.	Cum. Perc.	NU	CM	YS	SA	CF	SN	DW	EC	HO	AS
66	0.37	64.56			•	•						
67	0.37	64.93			•	•	•	•			•	•
68	0.36	65.30	•		•	•	•	•			•	•
69	0.36	65.66				•	•	•			•	•
70	0.36	66.02			•		•	•	•			
71	0.36	66.37	•	•	•	•	•	•	•	•	•	•
72	0.35	66.72	•	•	•	•	•	•	•	•	•	
73	0.35	67.07	•				•		•	•	•	
74	0.33	67.40	•			•	•	•				
75	0.33	67.73	•				•	•	•		•	•
76	0.33	68.06	•		•		•				•	•
77	0.31	68.37	•		•	•	•				•	
78	0.31	68.67			•		•		•	•	•	•
79	0.31	68.98			•		•		•			•
80	0.29	69.27			•		•			•	•	
81	0.29	69.55	•	•			•				•	
82	0.27	69.82	•			•					•	
83	0.26	70.08	•				•			•	•	•
84	0.26	70.34	•				•		•	•	•	•
85	0.25	70.59	•		•						•	
86	0.25	70.84	•			•	•	•	•		•	
87	0.25	71.10			•	•	•	•	•		•	
88	0.25	71.35		•			•	•			•	
89	0.25	71.59			•			•			•	•
90	0.25	71.84		•								
91	0.25	72.09	•		•		•	•	•		•	
92	0.24	72.32	•	•			•	•			•	
93	0.23	72.56				•	•				•	•
94	0.23	72.79	•		•			•			•	
95	0.23	73.01	•	•			•					
96	0.22	73.24	•			•		•				
97	0.22	73.46		•			•	•	•	•	•	
98	0.22	73.68	•		•			•				
99	0.22	73.90	•			•			•			
100	0.22	74.12		•	•	•	•	•	•	•	•	•
101	0.22	74.33			•	•	•					
102	0.22	74.55	•	•	•		•	•	•	•	•	•
103	0.21	74.77			•	•	•	•				
104	0.21	74.98	•	•			•	•	•	•	•	
105	0.21	75.19	•		•	•	•	•				
106	0.21	75.40	•		•	•						
107	0.21	75.60	•					•	•		•	
108	0.20	75.81	•		•	•	•	•	•		•	
109	0.20	76.01	•	•			•	•				
110	0.20	76.21				•	•			•	•	
111	0.20	76.41			•		•		•		•	
112	0.20	76.61	•			•	•	•			•	•
113	0.20	76.81		•			•	•	•	•	•	•
114	0.20	77.01	•		•	•	•					
115	0.20	77.20	•				•		•			•
116	0.20	77.40		•				•				
117	0.20	77.60	•		•		•	•	•		•	•
118	0.19	77.79	•	•			•	•	•	•	•	•
119	0.19	77.98	•				•	•		•		•
120	0.19	78.17	•	•			•	•		•	•	
121	0.19	78.36	•		•		•			•	•	•
122	0.19	78.54		•	•	•	•	•	•	•	•	
123	0.19	78.73	•	•	•	•	•	•		•	•	
124	0.18	78.91				•	•	•	•			
125	0.18	79.09	•	•		•	•	•	•	•	•	
126	0.18	79.27				•	•		•		•	
127	0.18	79.45		•	•		•	•	•	•	•	•
128	0.18	79.63			•	•	•	•	•		•	•
129	0.17	79.80	•		•		•		•	•	•	•
130	0.17	79.97				•	•	•	•		•	•

Notes: Deprivation indicators are child mortality (CM), nutrition (NU), years of schooling (YS), school attendance (SA), cooking fuel (CF), sanitation (SN), drinking water (DW), electricity (EC), housing (HO) and assets (AS).

Table B.3: Prevalence of all deprivation pairs by world region

	AS	EAP	ECA	LAC	SA	SSA	World
HO CF	0.57	0.34	0.30	0.45	0.77	0.83	0.74
SN CF	0.50	0.44	0.05	0.41	0.60	0.85	0.70
SN HO	0.64	0.28	0.05	0.34	0.59	0.75	0.63
EC CF	0.43	0.28	0.01	0.25	0.16	0.82	0.51
NU CF	0.35	0.43	0.30	0.24	0.53	0.54	0.51
EC HO	0.50	0.23	0.01	0.22	0.16	0.74	0.47
YS CF	0.28	0.46	0.04	0.35	0.46	0.49	0.46
EC SN	0.46	0.21	0.01	0.19	0.12	0.73	0.45
DW CF	0.41	0.40	0.24	0.31	0.17	0.63	0.44
NU HO	0.51	0.10	0.42	0.21	0.52	0.45	0.44
CF AS	0.32	0.31	0.04	0.27	0.34	0.52	0.42
YS HO	0.38	0.21	0.03	0.28	0.46	0.44	0.42
NU SN	0.42	0.18	0.04	0.15	0.40	0.47	0.40
HO AS	0.38	0.19	0.04	0.24	0.33	0.49	0.39
YS SN	0.33	0.26	0.04	0.31	0.36	0.44	0.39
DW HO	0.51	0.16	0.31	0.25	0.16	0.57	0.38
DW SN	0.45	0.22	0.03	0.31	0.12	0.57	0.38
SN AS	0.34	0.21	0.03	0.21	0.25	0.48	0.36
SA CF	0.27	0.26	0.17	0.15	0.29	0.44	0.36
EC DW	0.37	0.14	0.01	0.17	0.04	0.56	0.33
SA HO	0.38	0.10	0.28	0.13	0.29	0.38	0.32
EC AS	0.32	0.16	0.01	0.18	0.08	0.48	0.30
SA SN	0.32	0.13	0.02	0.10	0.21	0.38	0.29
YS EC	0.26	0.17	0.01	0.16	0.11	0.43	0.28
NU EC	0.29	0.08	0.01	0.10	0.08	0.44	0.27
YS AS	0.22	0.20	0.04	0.18	0.24	0.29	0.26
NU DW	0.33	0.24	0.26	0.09	0.11	0.34	0.25
NU YS	0.27	0.25	0.02	0.09	0.26	0.23	0.24
DW AS	0.28	0.17	0.04	0.16	0.07	0.37	0.24
SA EC	0.24	0.08	0.01	0.06	0.07	0.37	0.23
YS DW	0.25	0.23	0.03	0.24	0.09	0.32	0.23
NU SA	0.31	0.23	0.32	0.07	0.20	0.24	0.22
NU AS	0.22	0.10	0.02	0.11	0.19	0.26	0.21
SA YS	0.24	0.11	0.04	0.07	0.19	0.25	0.21
SA DW	0.25	0.13	0.15	0.07	0.07	0.28	0.19
SA AS	0.17	0.08	0.01	0.06	0.11	0.22	0.16
CM CF	0.05	0.05	0.09	0.05	0.07	0.14	0.10
CM HO	0.08	0.03	0.15	0.04	0.07	0.11	0.09
CM SN	0.06	0.03	0.01	0.15	0.05	0.12	0.09
CM NU	0.07	0.01	0.24	0.02	0.07	0.09	0.07
CM EC	0.04	0.02	0.00	0.02	0.01	0.11	0.06
CM DW	0.05	0.02	0.08	0.07	0.02	0.09	0.05
CM YS	0.04	0.01	0.01	0.05	0.04	0.06	0.05
CM SA	0.04	0.01	0.05	0.02	0.03	0.07	0.05
CM AS	0.03	0.02	0.01	0.02	0.02	0.05	0.04

Notes: World regions are Arab States (AS), East Asia and Pacific (EAP), Latin America and the Caribbean (LAC), South Asia (SA) and Sub-Saharan Africa).

Table B.4: Prevalence of all deprivation triplets by world region

	AS	EAP	ECA	LAC	SA	SSA	World
SN HO CF	0.50	0.27	0.03	0.29	0.55	0.74	0.60
EC HO CF	0.43	0.23	0.01	0.21	0.15	0.73	0.46
EC SN CF	0.40	0.21	0.01	0.18	0.11	0.72	0.44
EC SN HO	0.45	0.18	0.00	0.16	0.11	0.66	0.41
NU HO CF	0.34	0.10	0.20	0.18	0.46	0.45	0.41
YS HO CF	0.28	0.20	0.02	0.25	0.41	0.44	0.39
NU SN CF	0.30	0.17	0.02	0.13	0.35	0.46	0.38
HO CF AS	0.32	0.18	0.02	0.22	0.30	0.48	0.38
DW HO CF	0.41	0.16	0.21	0.21	0.15	0.57	0.37
DW SN CF	0.37	0.22	0.02	0.24	0.11	0.56	0.36
YS SN CF	0.25	0.24	0.02	0.25	0.32	0.43	0.36
SN CF AS	0.30	0.20	0.02	0.19	0.22	0.47	0.35
NU SN HO	0.40	0.08	0.02	0.11	0.35	0.39	0.34
YS SN HO	0.31	0.16	0.02	0.20	0.32	0.39	0.34
DW SN HO	0.44	0.13	0.02	0.19	0.11	0.51	0.33
SN HO AS	0.34	0.15	0.01	0.17	0.22	0.44	0.33
EC DW CF	0.33	0.14	0.00	0.16	0.04	0.56	0.32
EC DW HO	0.37	0.12	0.01	0.14	0.04	0.52	0.30
SA HO CF	0.27	0.10	0.13	0.12	0.26	0.38	0.30
EC CF AS	0.29	0.16	0.01	0.17	0.08	0.48	0.30
EC DW SN	0.34	0.12	0.00	0.14	0.03	0.51	0.29
EC HO AS	0.32	0.14	0.00	0.15	0.08	0.45	0.28
SA SN CF	0.23	0.12	0.01	0.08	0.19	0.38	0.28
YS EC CF	0.23	0.16	0.01	0.15	0.10	0.42	0.27
EC SN AS	0.30	0.13	0.00	0.14	0.06	0.44	0.27
NU EC CF	0.25	0.08	0.01	0.10	0.08	0.44	0.27
YS EC HO	0.26	0.14	0.00	0.13	0.10	0.40	0.26
SA SN HO	0.30	0.08	0.01	0.08	0.19	0.34	0.25
YS CF AS	0.18	0.20	0.03	0.16	0.22	0.29	0.25
YS EC SN	0.24	0.12	0.00	0.12	0.08	0.39	0.24
NU EC HO	0.29	0.07	0.01	0.08	0.08	0.39	0.24
DW CF AS	0.25	0.17	0.02	0.14	0.07	0.37	0.24
NU DW CF	0.24	0.21	0.15	0.09	0.10	0.34	0.23
YS HO AS	0.21	0.11	0.02	0.15	0.21	0.27	0.23
NU EC SN	0.26	0.06	0.00	0.07	0.06	0.39	0.23
SA EC CF	0.21	0.08	0.00	0.06	0.07	0.37	0.22
DW HO AS	0.27	0.10	0.03	0.13	0.06	0.35	0.22
YS DW CF	0.20	0.21	0.02	0.20	0.08	0.31	0.22
DW SN AS	0.25	0.11	0.01	0.13	0.05	0.34	0.21
NU YS CF	0.15	0.20	0.00	0.08	0.21	0.23	0.21
YS SN AS	0.19	0.13	0.02	0.13	0.17	0.26	0.21
SA EC HO	0.23	0.07	0.00	0.05	0.07	0.33	0.21
EC DW AS	0.25	0.09	0.00	0.12	0.02	0.35	0.20
NU CF AS	0.18	0.10	0.01	0.11	0.17	0.25	0.20
SA EC SN	0.21	0.06	0.00	0.04	0.05	0.33	0.20
NU DW HO	0.31	0.04	0.23	0.07	0.09	0.30	0.20
YS DW HO	0.23	0.08	0.01	0.15	0.08	0.29	0.19
NU DW SN	0.27	0.08	0.02	0.06	0.06	0.30	0.19
NU SA CF	0.16	0.14	0.10	0.06	0.15	0.23	0.19
SA YS CF	0.14	0.09	0.01	0.06	0.16	0.24	0.19
YS DW SN	0.21	0.10	0.01	0.19	0.06	0.29	0.19
NU YS HO	0.21	0.04	0.01	0.07	0.21	0.21	0.19
NU HO AS	0.21	0.04	0.02	0.09	0.17	0.23	0.19
SA DW CF	0.19	0.10	0.08	0.06	0.06	0.28	0.18
SA YS HO	0.18	0.04	0.01	0.05	0.16	0.22	0.18
YS EC AS	0.18	0.09	0.01	0.11	0.06	0.27	0.17
NU SN AS	0.19	0.05	0.00	0.07	0.13	0.23	0.17
YS EC DW	0.19	0.07	0.00	0.10	0.03	0.29	0.17
NU YS SN	0.18	0.07	0.00	0.05	0.16	0.20	0.17
NU EC DW	0.21	0.03	0.00	0.06	0.02	0.29	0.17

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Table B.4: ... continued.

	AS	EAP	ECA	LAC	SA	SSA	World
SA DW HO	0.24	0.04	0.14	0.05	0.06	0.25	0.16
SA YS SN	0.16	0.07	0.01	0.04	0.12	0.22	0.16
NU SA HO	0.23	0.02	0.19	0.05	0.15	0.20	0.16
SA DW SN	0.21	0.05	0.00	0.05	0.05	0.25	0.16
SA CF AS	0.15	0.07	0.01	0.06	0.10	0.21	0.16
SA HO AS	0.17	0.06	0.01	0.05	0.10	0.20	0.15
NU SA SN	0.19	0.04	0.01	0.03	0.10	0.20	0.15
SA EC DW	0.17	0.04	0.00	0.03	0.02	0.25	0.14
NU EC AS	0.17	0.03	0.00	0.07	0.04	0.23	0.14
SA SN AS	0.15	0.06	0.00	0.04	0.08	0.20	0.14
SA YS EC	0.13	0.04	0.00	0.03	0.05	0.22	0.13
YS DW AS	0.15	0.10	0.02	0.10	0.04	0.20	0.13
NU YS EC	0.14	0.04	0.00	0.04	0.04	0.20	0.13
SA EC AS	0.14	0.05	0.00	0.04	0.03	0.20	0.12
NU SA EC	0.13	0.02	0.00	0.02	0.03	0.19	0.12
NU DW AS	0.15	0.04	0.02	0.05	0.04	0.17	0.11
NU YS AS	0.11	0.05	0.00	0.05	0.09	0.13	0.11
NU SA YS	0.12	0.04	0.00	0.02	0.09	0.13	0.11
NU YS DW	0.13	0.10	0.01	0.04	0.03	0.15	0.10
SA YS DW	0.12	0.03	0.01	0.03	0.04	0.16	0.10
SA YS AS	0.10	0.04	0.00	0.03	0.07	0.13	0.10
NU SA DW	0.15	0.07	0.08	0.02	0.03	0.15	0.10
SA DW AS	0.12	0.03	0.01	0.03	0.03	0.15	0.09
CM HO CF	0.05	0.02	0.05	0.03	0.06	0.11	0.08
NU SA AS	0.10	0.02	0.00	0.02	0.05	0.11	0.08
CM SN CF	0.04	0.03	0.01	0.04	0.04	0.11	0.08
CM SN HO	0.06	0.02	0.00	0.03	0.04	0.10	0.07
CM EC CF	0.04	0.02	0.00	0.02	0.01	0.11	0.06
CM NU CF	0.03	0.01	0.06	0.01	0.05	0.08	0.06
CM EC HO	0.04	0.01	0.00	0.01	0.01	0.09	0.05
CM EC SN	0.04	0.01	0.00	0.01	0.01	0.09	0.05
CM NU HO	0.05	0.00	0.11	0.01	0.05	0.06	0.05
CM DW CF	0.04	0.01	0.04	0.03	0.01	0.08	0.05
CM NU SN	0.04	0.01	0.00	0.01	0.03	0.07	0.05
CM DW SN	0.04	0.01	0.00	0.06	0.01	0.07	0.04
CM DW HO	0.05	0.01	0.06	0.02	0.01	0.07	0.04
CM YS CF	0.02	0.01	0.00	0.02	0.03	0.06	0.04
CM SA CF	0.02	0.01	0.02	0.01	0.03	0.06	0.04
CM YS HO	0.03	0.01	0.00	0.01	0.03	0.05	0.04
CM EC DW	0.03	0.01	0.00	0.01	0.00	0.07	0.04
CM SA HO	0.03	0.00	0.03	0.01	0.03	0.05	0.04
CM YS SN	0.03	0.01	0.00	0.03	0.02	0.05	0.04
CM CF AS	0.02	0.02	0.00	0.02	0.02	0.05	0.04
CM NU EC	0.02	0.00	0.00	0.01	0.01	0.06	0.04
CM SA SN	0.03	0.01	0.00	0.01	0.02	0.05	0.03
CM HO AS	0.03	0.01	0.01	0.01	0.02	0.05	0.03
CM SN AS	0.03	0.01	0.00	0.01	0.02	0.05	0.03
CM YS EC	0.02	0.01	0.00	0.01	0.01	0.05	0.03
CM SA EC	0.02	0.00	0.00	0.00	0.01	0.05	0.03
CM NU DW	0.03	0.00	0.06	0.01	0.01	0.05	0.03
CM EC AS	0.02	0.01	0.00	0.01	0.01	0.05	0.03
CM NU SA	0.02	0.00	0.01	0.00	0.02	0.04	0.03
CM NU YS	0.02	0.00	0.00	0.01	0.02	0.04	0.03
CM SA YS	0.02	0.00	0.00	0.00	0.02	0.04	0.03
CM SA DW	0.02	0.00	0.01	0.01	0.01	0.04	0.02
CM YS DW	0.02	0.00	0.00	0.02	0.01	0.04	0.02
CM DW AS	0.02	0.01	0.01	0.01	0.00	0.04	0.02
CM NU AS	0.02	0.00	0.01	0.01	0.01	0.03	0.02
CM YS AS	0.02	0.01	0.00	0.01	0.01	0.03	0.02
CM SA AS	0.01	0.00	0.00	0.00	0.01	0.02	0.02

Notes: World regions are Arab States (AS), East Asia and Pacific (EAP), Latin America and the Caribbean (LAC), South Asia (SA) and Sub-Saharan Africa).