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Towards a Global Assets Indicator: Re-assessing the Assets Indicator in the Global Multidimensional Poverty Index

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Abstract
This paper explains the revision of the assets indicator of the updated global Multidimensional Poverty Index (global MPI), which was launched just before the 73rd Session of the United Nations General Assembly in September 2018. The joint decision of the United Nations Development Programme (UNDP) and the Oxford Poverty and Human Development Initiative (OPHI) to revise the global MPI in 2018 to align it with the Sustainable Development Goals and to best monitor progress towards "leaving no one behind" provided the opportunity to assess the statistical validities of the assets indicator contained in the Original MPI, jointly designed by OPHI and UNDP Human Development Report Office (HDRO) in 2010, and an assets indicator included in an Innovative MPI, which was developed by UNDP HDRO in 2014. Further, considering the improvements in many Demographic and Health Surveys, Multiple Indicators Cluster Surveys and selected national surveys in recent years, from which the global MPI is constructed, the revision also offered an occasion to assess whether the inclusion of additional assets would add value to a revised asset index for the updated global MPI 2018. Taking into account a blend of inputs, including statistical test results, public consultations, normative reasoning and substantive trial measures of possible asset indices as outlined in detail in this paper, the revised assets indicator maintained the structure of the Original MPI, but added computer and animal cart as additional items. Here we explain the reasons and delineate the many decisions that were taken along the way.

Keywords: assets, assets index design, global Multidimensional Poverty Index, poverty measurement, welfare.

JEL classification: I3, I32, D63, Q2, Q15, O1

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Introduction

This paper explains the revised assets indicator of the updated global Multidimensional Poverty Index 2018 (global MPI). The global MPI was designed in 2010 as an international measure of acute poverty covering over 100 developing countries (Alkire and Santos, 2010). It was included in the 20th Anniversary *Human Development Report* in 2010 and in subsequent *HDR*s. It complements traditional income-based poverty measures by capturing the severe deprivations that each person faces at the same time with respect to education, health and living standards. Insofar as was possible at its inception, the indicators of the global MPI 2010 reflected the Millennium Development Goals.

In 2018, the United Nations Development Programme's Human Development Report Office (UNDP HDRO) and the Oxford Poverty and Human Development Initiative (OPHI) agreed to discuss improvements to the global MPI, which coincided with the start of the Third United Nations Decade for the Eradication of Poverty (2018–2027), in order to better monitor progress towards the Sustainable Development Goals (SDGs) of the 2030 Agenda for Sustainable Development.

The empirical results of the revised and updated global MPI were launched just before the 73rd Session of the United Nations General Assembly on 25 September 2018 and reflect new estimations for 105 countries. This followed a consistent theoretical and computational strategy as outlined in detail in Alkire and Jahan (2018) and Alkire and Kanagaratnam (2018), and will allow, insofar as data availability permits, monitoring of whether the commitment to "leave no one behind" is being met, the primary focus of the SDGs.

The 2018 revision of the global MPI, which eventually adjusted five of the ten indicators of the global MPI from 2010, provided the opportunity to assess more closely the assets indicator, which is one of the six indicators within the living standards dimension. The assets indicator of the Original MPI (henceforth MPI-O), jointly designed by OPHI and UNDP HDRO in 2010, differed on substantive grounds from the assets indicator of an Innovative MPI (henceforth MPI-I), which was developed by UNDP HDRO in 2014.

The MPI-O assigned a household a deprived status in assets if it did not own more than one radio, television, telephone, bicycle, motorbike or refrigerator, and if it did not own a car or truck. The MPI-I's assets indicator included additional items that were not part of MPI-O's assets indicator. These additional items were a motorboat, an animal cart, land, cattle/cow/bull, horses/donkey/mule, goats, sheep and chicken. The items were also differently grouped, namely into three dimensions (information, mobility and livelihood). A household was considered deprived in assets if it (a) did not have at least one asset related to access to information (radio, television or telephone) or (b) if it had at least one asset related to information but did not have at least one asset related to mobility (bicycle, motorbike, car, truck, animal cart or motorboat) or at least one asset related to livelihood (refrigerator, arable land (any size of land usable for agriculture) or livestock (a horse, a head of cattle, two goats, two sheep or ten chickens) (HDRO, 2016, pp.9–10).

The decision to revise the global MPI in 2018 thus provided the opportunity to assess the statistical validities of the two assets approaches and, considering the improvements in many of the Demographic and Health Surveys (DHS), Multiple Indicators Cluster Surveys (MICS) and selected national surveys in recent years, from which the global MPI is constructed, the revision also allowed the assessment of whether the inclusion of additional assets would add value to a revised asset index for the global MPI 2018.

This paper outlines in detail the conversation between statistical test results, public consultations, normative reasoning and extensive trial measures of possible asset indices that eventually underpinned the identification of the revised assets indicator of the updated global MPI in 2018. The revision is embedded in the large literature that has both debated the methodologies of asset index construction in welfare economics and used such indices to empirically analyse related phenomena, thus demonstrating their value added. The revision was informed in particular by the analytical approach adopted in the revision of the 13-item material deprivation indicator in the European Union (Guio et al. 2012, 2016, 2017).

After a concise presentation of important literature on asset index construction, this paper explains the methodology the revision employs and highlights some data challenges when constructing an internationally comparable assets indicator. It then presents key results of the statistical validation of the assets indicator of the MPI-I, and potential alternatives to the MPI-O and MPI-I. The discussion debates the lessons learned from the statistical tests, particularly in relation to the land variable, and then presents a range of so-called trial measures to empirically evaluate a range of potentially new asset indices. The last section presents the revised assets indicator of the updated global MPI 2018 and some concluding remarks about the decisions that were taken along the way.

1. Asset Index Construction

This article is concerned with the measurement of assets deprivation as a proxy for welfare.[1] To identify and aggregate asset indices, the three most commonly implemented methods found in the literature are principal component analysis (PCA), factor analysis (FA) and multiple correspondence analysis (MCA). Additionally, some papers utilised anchored regression analysis.[2] This section presents applications of these most relevant approaches and discusses the feasibility of their uptake considering the present study.

Popularising the use of PCA in asset index construction in the late 1990s and early 2000s, Filmer and Pritchett (1999, 2001) constructed a household asset index in an assessment of household wealth and children's school enrolment in India. Utilising DHS and applying PCA to 21 asset variables that included consumer durables, characteristics of the household's dwelling, and land ownership, the authors conclude that PCA "provides plausible and defensible weights" that are superior to regression weights derived from linear regression, whose coefficients only hold implicit value in predicting wealth and hence are unsuitable for constructing a robust linear index (Filmer and Pritchett, 2001, p.116; p.128).

Methodologically, the authors retained the first principal component and assigned all individuals in each household a standardized asset index score derived from normalized asset variables. The score was used to rank the sample population into quintiles ranging from the poorest to the richest. As highlighted in Alkire et al. (2015, p.90), the uptake of PCA weights was significant, and the approach of Filmer and Pritchett was applied widely (with regard to poverty and inequality studies, the following studies are noteworthy: Sahn and Stifel, 2000; McKenzie, 2005; Lelli, 2001; Roche, 2008; Nguefack-Tsague et al., 2011).

Drawing on the work of Filmer and Pritchett (2001), Sahn and Stifel (2000) and Asselin (2002), Booysen et al. (2008) used an asset index to compare poverty over time and across seven African countries. To identify variables, they opted to diverge from PCA and FA and to utilise MCA instead. The main reasons being that MCA is better suited for discrete and categorical data, while it also imposes fewer constraints on the data (ibid, p.1115). MCA was deployed to construct an indicator matrix that depicts each household's assets ownership

1 Assets encompass a wide range of tangible and non-tangible productive and durable goods, where durable goods are considered easier to measure than productive assets (Chowa et al., 2010, p. 1509). Asset ownership indices have been used as alternatives to monetary poverty measurements that are based on household consumption expenditures (Ngo and Christiaensen, 2018; Wittenberg and Leibbrandt, 2017) – especially when income or expenditure data is missing (Sahn and Stifel, 2000) or have substantial measurement errors (Ferguson, 2003; Filmer and Pritchett, 2001; Maitra, 2016).

2 Other authors also utilised regression techniques in asset index design to derive weights based on additional expenditure or price data (Stifel and Christiaensen, 2007; Ngo, 2018: see as well Ngo and Christiaensen, 2018), yet such data is not provided in the DHS, MICS and most national surveys.

and the respective category weight for each index component (following a strict pre-selection using only variables that appeared in all relevant questionnaires and that were similarly phrased). This resulted in a constructed assets index using binary indicators for four private household assets (the presence or absence of a radio, television, fridge and bicycle) and categorical indicators for the type of sanitation, the type of flooring (both with four categories each) and the main water source (five categories) (ibid: 1116). The uptake of MCA has also been significant in recent years, with applications found in Asselin and Anh (2008), Deutsch, Silber, and Verme (2012), Batana and Duclos (2010), and Ballon and Duclos (2016).

Deviating from the implementation of PCA, FA and MCA methods in asset index construction, Giesbert and Schindler (2012) utilised nonparametric, parametric and semi-parametric estimation techniques to construct comprehensive and liquidatable asset indices in an empirical application of the asset-based poverty traps theory (developed by Carter and Barrett, 2006) in rural Mozambique. Using 2002 and 2005 panel waves of the *Trabalho de Inquérito Agrícola* household surveys and drawing on Adato, Carter and May (2006), the asset indices were constructed based on a livelihood regression, whereby a household fixed-effects panel model with a second-order polynomial expansion of continuous assets and interaction effects between basic assets was utilised. Asset weights were assigned based on their marginal contribution to the household's livelihood, defined as the household's income per adult equivalent divided by the province-specific poverty line of Mozambique (ibid, p.1597).

Both asset indices were then designed by predicting the fitted values from the estimated regression coefficients and were composed of 30 assets in the comprehensive index (mostly productive assets such as land and livestock and durable household assets) and 12 potentially sellable assets in the liquidatable asset index. Findings indicated that the respective indices explain 24% and 5% of the (within) variation of the livelihood measure (ibid: 1600). The method is sophisticated yet draws its main advantage from its intuitiveness in the interpretation of the results. By scaling the asset index in poverty line units (PLU) and by depicting assets measured in different units, an easily interpretable score above one shows households with an income above the poverty line (ibid, p.1597).

Similarly, the Comparable Wealth Index (CWI) utilised regression techniques to compare wealth across countries and time (Rutstein and Staveteig, 2014). By adjusting the original DHS Wealth Index, which drew on PCA of the ownership of a household's consumer items to arrive at survey-specific relative wealth quintiles, the CWI utilised "an anchoring method" popularised by Ferguson et al. (2003) in an asset-based estimation of "permanent income"[3] (a concept traced back to Milton Friedman (1957) that postulates that consumption is a function of income and determined by physical and human resources), where a variant of the hierarchical ordered probit (DIHOPIT) model was used on items covering household ownership of durables, information on dwelling characteristics and access to services found in household surveys of Greece, Pakistan and Peru (Ferguson et al., 2003).

The reworked CWI used a sequenced statistical approach where the 2002 DHS survey from Viet Nam was chosen as a baseline survey and eight "anchoring points" were identified. Four anchoring points were derived from the unsatisfied basic needs (UBN) framework developed by the Economic Commission for Latin America and the Caribbean in the early 1980s (inadequate dwelling structure, overcrowded housing, inadequate sanitation and high economic dependency), and wealth scores were calculated for the percentage of households relative to the presence or absence of UBNs (from four points for all four UBNs present down to one point for households that had only one or more UBN). These scores were again used as anchoring points for a relative wealth index.

Four additional salient assets (ownership of a television, a refrigerator, a car/truck and a telephone) for households at the middle- and upper-end of the economic distribution were chosen as additional anchoring points, and logistic regression analysis was performed (a) to identify the wealth index score at which half of the households (the median) had each possession and (b) for each item in each DHS survey with the dichotomy for that item as the dependent variable and the wealth score as the independent variable. This sequence was applied to both the baseline and each of the 172 available DHS surveys, and was followed by a linear regression with the baseline anchor cutpoint values as the dependent variable and the specified survey's anchor cutpoint values as the independent variable. The CWI score for each survey was produced by multiplying each household's wealth index score with the coefficient β (the dispersion of the survey-specific index relative to the baseline index) and the constant term α (which represents the amount of adjustment of the level of the survey-specific wealth index). Finally, the cutpoints for the quintiles of the baseline wealth index were used on the CWI to produce comparative wealth quintiles (Rutstein and Staveteig, 2014, pp.8–10).

3 In addition to permanent income, assets ownership has also been found to allow agents to conduct asset and consumption smoothing (Filmer and Pritchett, 2001, p.116; Zimmerman and Carter, 2003). Yet asset ownership also has positive impacts beyond welfare. As shown by Chowa et al. (2010) in a systematic review of 29 studies published since the year 2000, asset ownership impacts positively on children's health conditions, advancements in schooling outcomes and decreased incidences of child labour.

The number of regression points varied between five and eight across the 172 DHS surveys (ibid: 43ff) and were used to rank countries to illustrate household wealth, and in cross-country analyses and trend analyses of young child mortality, fertility, maternal health care and child nutritional status (ibid, pp.34ff).

As highlighted by the authors, while the anchoring approach allows for the comparison of relative wealth for a large amount of countries and over time, the acknowledged normative selection of different anchoring points is likely to have an impact on country rankings. Additionally, missing values in the selected criteria are highlighted as problematic (ibid, p.37). Chakraborty et al. also underline that wealth comparisons remain relative because the CWI is benchmarked against the Vietnamese DHS 2002; they highlight further that the index "was not considered to be a viable alternative by members of the expert group, including by the comparative index creators themselves" (2016, p.150).

To conclude, each statistical method utilised in index constructions, whether descriptive, such as PCA and MCA, or model-based, such as confirmatory FA, possesses strengths and weaknesses that need to be assessed based on the underlying assumptions and axiomatic properties of each method (Alkire et al., 2015, pp.98–100). For example, while exploratory FA (EFA) makes no assumptions regarding the relationships among the observed indicators and the latent factors, confirmatory FA attempts to confirm measurement theory and assumes multivariate normality (ibid: 89). Similarly, as Townend et al. (2015, pp.8–9) highlight, while PCA has become the most popular method used to arrive at asset-based socio-economic rankings, the linearity assumption in PCA can be problematic if the model includes binary and categorical data (which led to the wider use of tetrachoric and polychoric correlations in the calculations).[4] Additionally, PCA produces standardized component scores that depend on the eigen decomposition of the corresponding datasets from which they are derived, and hence produces *relative* weights that impede robust cross-country and temporal analyses (Alkire et al., 2015, p.99). A potential uptake of component scores or similar statistical weights for the revised assets indicator would thus pose a serious limitation for the global MPI, as the index is constructed

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4 Assets indices allow inferences with welfare measures of consumption and income (Filmer and Pritchett, 2001; Wittenberg 2009; 2011; Wittenberg and Leibbrandt, 2017, p.707), yet Filmer and Scott have also shown that in settings "in which individually consumed goods are the main component of expenditures, asset indices and per capita consumption yield the least similar results" (2012, p.359). The poor correlation of asset indices with consumption data led Howe et al. (2009) to conclude that asset indices are poor proxies for consumption, while Harttgen et al. (2013) have been similarly critical when highlighting "that the relationship between growth in assets and growth in incomes or consumption is extremely weak" (2013, p.S37). While Wittenberg and Leibbrandt assumed that wealth may be more concentrated than consumption to explain observed urban-rural differences which "tend to be more marked when using asset indices than when using per capita expenditure," they further argued "that many of the household durable goods that make up asset schedules (e.g. televisions and refrigerators) require electricity, which tends to be more accessible in urban areas." They further linked this observation to the methods used in asset index design, stating that "both principal components and factor analysis will tend to extract an index which is a hybrid of 'wealth' and 'urbanness' (Wittenberg, 2009)" (Wittenberg and Leibbrandt, 2017, p.710).

from the latest available DHS, MICS and national datasets, with the objective to measure an underlying concept of *absolute* poverty (Alkire and Santos, 2014, p.252).

1.1 Proposed Method for the Revised Asset Index

Given the above review of popular methods identified in the literature on asset index construction and their respective evaluation, the analysis in this paper was informed by the analytical approach from Guio et al. (2012, 2016, 2017) who utilised a "theory based analytical framework" in their proposed and revised material deprivation indicator in the European Union. Conceptually rooted in Peter Townsend's scientific theory of relative deprivation where "people are deprived if they lack the items 'which are customary, or at least widely encouraged or approved, in the societies to which they belong'" (Guio et al., 2017, p.21), the authors deployed EFA, MCA, classical test theory (CTT, via Cronbach's Alpha) and item response theory (IRT), among other statistical techniques, to arrive at a robust indicator that is 'suitable', 'valid' and 'reliable' in measuring material deprivation for the entire population of the 28 EU member states[5].

As flagged by Guio et al. (2012, p. 9), in using statistical data reduction techniques such as EFA in asset index design one should apply such methods foremost as exploratory tools (to study the interrelations between items), and potentially less so to reduce data, or as a strict selection criterion of items per se (similar words for caution are voiced by other authors, such as Klasen (2000)[6]. The methods are nonetheless indispensable for an empirical understanding of the commonalities between items when moving forward towards a new global assets indicator.[7]

The 'suitability' criterion is essential when selecting indicator components in a multinational context (Guio et al., 2016, p.221). To define the common possessions in each society that could be potentially included in an assets indicator for a global MPI is difficult and needs to be justified on normative and empirical grounds.

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5 The identified 'optimal' material deprivation indicator in the European Union consisted of thirteen equally weighted items covering basic and social necessities, such as food, clothes, shoes, internet access and leisure activities (Guio et al., 2016, p. 219).

6 In the words of Klasen (2000), who in an empirical application of PCA designed a composite measure of deprivation based on household survey data from South Africa: "The disadvantage of such an approach is that it implicitly assumes that only components with strong correlations with each other are relevant for the deprivation measure which may be debatable in some cases" (2000, p.39).

7 Note that in the identification and revision of the EU material deprivation variables for the whole population, data-driven techniques dominated. Confirmatory FA and related confirmatory multivariate statistical procedures were largely not applied. Similarly, when designing a global asset index that is salient for rural and urban populations, there is surprisingly little measurement theory to draw on – in contrast to the global MPI, which draws on participatory work, the human development framework and Amartya Sen's capability approach (Alkire and Jahan, 2018). Given that the asset index in the global MPI is based on secondary data sources that are not purposefully designed to measure assets or material deprivation, a data-driven approach seemed more appropriate for the purposes of this study.

Items should be broadly perceived as necessary to have an "acceptable" standard of living in any given country included in the global MPI, and items should respect the homogeneity of preferences within countries. This means that items should be salient to all population subgroups, and localised items that are very specific to some contexts (e.g. to rural or urban populations, or to different age groups) should be dealt with using extra care.

The suitability criterion for the EU material deprivation indicator was established by analysing the EU-wide Eurobarometer survey on the perception of poverty and social exclusion, among other sources (Guio et al., 2016: 222-223). As a similar dataset does not exist at the global scale to determine the degree of consensus for items related to assets, a more pragmatic, and to a certain degree data driven approach, had to be taken. As point of departure, we assumed that the assets indicator of the MPI-I meets the 'suitability criterion' for assets deprivation and hence took that proposal as 'face validity' (in line with Guio et al. who highlight that "suitability" should […] be understood as the "face validity" of the measure" (2017, p. 7). The main reason for this is that the MPI-I contains all variables that were included in the global MPI from 2010 (MPI-O), but it added several items of importance for the global poor such as an animal cart, land and livestock. The items also met a minimum threshold for data availability in 75 countries and 3.5 billion people, which will be further outlined in section 2, with the exception of motorboat, where data were only available in 32 countries covering 1.1 billion people. The 11 items of the MPI-I can be classified as 'assets of the poor' or 'poor people's assets' as framed in the seminal *Voices of the Poor* series (Narayan et al., 1999; Narayan and Petsch, 2002). More specifically, all items fall into the physical capital classification, and are thus potentially valuable and sellable. The assets have multiple purposes and contribute to people's wellbeing and economic activity, and eventually can act as insurance against economic shocks (OPHI, 2018, p.19).

We then tested the MPI-I, and potential alternatives to the MPI-I and MPI-O, for their 'internal validity' and 'reliability' (the internal consistency of a scale) via tetrachoric EFA, MCA, CTT, IRT[8] and a Mokken scale procedure (MSP), which is a nonparametric IRT based on Loevinger's *H* coefficient. Results were conducted using pool of 26 countries that cover almost 3 billion people (see Table 1). Tests results are disaggregated by urban and rural populations.

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8 Cronbach's Alpha is a widely used coefficient to assess internal relations between variables, where an alpha of 0.7 or higher is assumed to depict a satisfactory internal consistency of a scale or dimension. The main weakness is that the statistic assumes equal variance among variables (Guio et al., 2017, p.29; p.32). As this assumption is hardly met in practice, we also performed IRT, which provides additional information on the reliability of each individual item in the scale (or dimension).

Table 1: Pool of 26 Countries Used in Statistical Analysis

Country	Region	Dataset	Year	Population size 2016 (thousands)
Angola	Sub-Saharan Africa	DHS	2015-16	28 813
Armenia	Europe and Central Asia	DHS	2015-16	2 925
Bangladesh	South Asia	DHS	2014	162 952
Brazil	Latin America and the Caribbean	PNAD[9]	2015	207 653
Cambodia	East Asia and the Pacific	DHS	2014	15 762
Colombia	Latin America and the Caribbean	DHS	2015-16	48 653
Congo, Democratic Republic of the	Sub-Saharan Africa	DHS	2013-14	78 736
Côte d'Ivoire	Sub-Saharan Africa	DHS	2011-12	23 696
Egypt	Arab States	DHS	2014	95 689
Ethiopia	Sub-Saharan Africa	DHS	2016	102 403
Guatemala	Latin America and the Caribbean	DHS	2014-15	16 582
Haiti	Latin America and the Caribbean	DHS	2012	10 847
India	South Asia	DHS	2015-16	1 324 171
Indonesia	East Asia and the Pacific	DHS	2012	261 115
Kenya	Sub-Saharan Africa	DHS	2014	48 462
Malawi	Sub-Saharan Africa	DHS	2015-16	18 092
Senegal	Sub-Saharan Africa	DHS	2016	15,411
Myanmar	East Asia and the Pacific	DHS	2015-16	52 885
Nepal	South Asia	DHS	2016	28 983
Pakistan	South Asia	DHS	2012-13	193 203
Peru	Latin America and the Caribbean	DHS-Continuous	2012	31 774
Philippines	East Asia and the Pacific	DHS	2013	103 320
Tajikistan	Europe and Central Asia	DHS	2012	8 735
Tanzania, United Republic of	Sub-Saharan Africa	DHS	2015-16	55 572
Uganda	Sub-Saharan Africa	DHS	2016	41 488
Zimbabwe	Sub-Saharan Africa	DHS	2015	16 150
				2,994,072

The pool of these 26 countries was purposefully selected for this study. The pool assembles countries that have wide global population coverage, and includes *at least* two countries for five of the six regions that were

9 Pesquisa Nacional por Amostra de Domicílios.

covered in the summer 2017 update of the global MPI (Alkire and Robles, 2017). Finally, the countries range from low- to lower middle-income status (according to the World Bank Atlas Method). We acknowledge the limitations of this approach, namely that the 'internal validity' and 'reliability' of the study findings presented in this paper were used to calibrate the revised assets indicator of the global MPI, which covers 104 countries (hence, 'external validity' was assumed from the 'internal validity' of 26 countries). This was a pragmatic decision[10] and on-going research is further exploring the 'external validity' of the findings from this study.

Key results of the statistical validation of the assets indicator of the MPI-I, and potential alternatives to the MPI-O and MPI-I, are subsequently discussed, particularly in light of a range of so-called trial measures to empirically evaluate the potentially new asset indices. While the trial measures were not robustness tests per se, the measures were decisive in identifying and validating the revised assets indicator of the updated global MPI 2018.

2. Data

(a) Data Availability and Constraints

We conducted a systematic review of 100 DHS, MICS and selected national surveys, covering a total population of 5.6 billion people (based on 2015 estimates), with the objective of identifying potential 'new' and 'improved' indicators to modify the global MPI while taking into account SDG indicators and improvements to surveys published in recent years (OPHI, 2018).[11] As outlined in Alkire and Santos (2014, p.254) and Ferguson et al. (2003), the DHS and MICS follow standardized guidelines and sampling frames, and provide comparable information on consumer goods, productive assets or dwelling characteristics, which are often missing in income and expenditure surveys.

The revision resulted in the identification of nearly 30 potential new household-specific assets indicators that can be grouped into 11 categories, which are presented in Table 2. For each potential new indicator, the table

10 Pooling data for such a large number of countries used in the global MPI (over 104) proved to be a challenge in its own right, and we observed that certain tests, such as the MSP, or important graphs such as the MCA dimension projection plots, were extremely slow (or not possible to construct) for very large datasets. Hence, the decision was taken to conduct the analysis on a representative pool of 26 purposefully selected countries instead.

11 The surveys were implemented in a time span from 2006 (Azerbaijan) to 2016–17 (Nigeria). Eleven countries were excluded from the revision, either due to missing dimensions (Argentina, Costa Rica, Cuba, Panama, Uruguay and Vanuatu), sampling issues (Somalia) or outdated surveys (Georgia, Libya, Syria, Uzbekistan).

presents the number of countries for which data on the indicator are available and the corresponding population covered (based on 2015 estimates).

As shown in Alkire and Santos (2014, p.255), data on assets used in the MPI-O were available in all DHS and MICS surveys (radio, television, telephone, bicycle, motorbike, car, truck and refrigerator). This is not the case for the identified potential new items, where country coverage varies considerably. For example, while data on water pumps are only available in 15 countries, 92 countries have data on livestock. Yet only 86 countries have data on the number of chickens or poultry owned, while nine of the 93 countries that have data on land ownership useable for agriculture lack data on the hectare size of the agricultural land owned.

We selected a benchmark of 75 countries and a population coverage of 3.5 billion as a critical mass for the potential inclusion of items in the revised assets index of the global MPI (see Alkire and Jahan, 2018, and Alkire and Kanagaratnam, 2018). This resulted in the exclusion of the ownership of small physical assets such as tables and beds, and the exclusion of the entire group of electrical assets except for computer. Further excluded were indicators that were not suitable to portray either physical or liquid assets. This resulted in the elimination of indicators in categories 7 to 11 listed in Table 2. For the statistical analysis we maintained, however, certain assets such as a smartphone or internet access that only met one of the two benchmarks (in the case of internet access, population coverage).

(b) Treatment of Missing Data and Missing Values

Following Tabachnick and Fidell (2007, in Yong and Pearce, 2013, p.81), missing values were dropped from the EFA and MCA to prevent overestimation (unless otherwise stated). In the trial measure analysis, where 24 potential asset specifications were compared, we report asset estimates as a lower-bound estimate of material deprivation. Hence, missing data and values were treated as deprived (this is consistent with Alkire and Santos, 2014, p.256).

(c) Treatment of Land and Livestock Variables

All potential new variables included in the paper are binary. Land and livestock are dummy variables, however, where deprivations were coded in the following way (unless otherwise stated).

Land:

a) non-deprived if household owns any sized land (even if unknown);

b) non-deprived if household owns more than 3ha (unknown land size is treated as deprived)[12];

c) non-deprived if household owns more than 6ha (unknown land size is treated as deprived);

d) non-deprived if household owns more than 10ha (unknown land size is treated as deprived).

Livestock:

a) non-deprived if household owns a horse, a head of cattle, two goats, two sheep or ten chickens (derived from MPI-I);

b) non-deprived if household owns a livestock equivalent to 1 livestock unit;

c) non-deprived if household owns a livestock equivalent to 1.5 livestock units.

Comparing livestock in the absence of price data is challenging. In order to describe livestock numbers across species and to produce a single figure indicating the total 'amount' of livestock owned, the concept of an 'exchange ratio' was developed (Njuki et al., 2011). Different species of different average sizes were converted into a unit known as a tropical livestock unit (TLU). One TLU denotes the feed requirement of a standard animal of a certain live weight (usually cows of 250 kg). With TLU the feed needs for sheep, goats, chickens and other animals are compared with those of cows (TLU = metabolic body weight for body weight X/metabolic body weight for 250kg animal) (see Njuki et al., 2011; Dida, 2017). For global comparisons, the concept of a livestock unit is preferred to that of a TLU, however, which only considers livestock raised in the tropics. In the estimation of livestock units used in this paper, we used as a benchmark Table 1 of Chilonda and Otte (2006), where it is assumed that a cow in the United States has the highest weight and hence a factor of one, and all the coefficients for the other livestock and other regions are estimated in relation to this (see also FAO, 2011, p.37). Taking Guatemala as an example, three sheep (3x0.1) and four goats (4x0.1) will have the same feed requirement as one cow (0.7), whereas in Angola three sheep (3x0.1) and two goats (2x0.1) will have the same feed requirements as one cow (0.5). The concept of a livestock unit is imperfect for the purposes of our study, as it is not conceptually aligned with a measure of human poverty or welfare,13 but it was chosen

12 Note that land size is self-reported in the DHS and MICS surveys and that the data was *not* corrected for data heaping (to be further debated in the discussion section).

13 For example, it could be that a small bird that laid very precious eggs had a miniscule food need compared to a cow, but a very high economic value; similarly, the asset value reflected by ten young goats might be far larger than that of three elderly goats even if the latter consume more.

as it is the most widely used livestock conversion unit internationally in the absence of sale prices of farm animals or data on the quantity of farm animals sold and/or consumed.

Table 2: Availability of Household-Level Assets Indicators from DHS, MICS and National Surveys

Household-level indicators				
Aim of measure		**Indicator**	**Number of countries with the indicator**	**Population covered (2015 estimate) (thousands)**
1	Household has access to information technology	Smartphone or internet access	52	4,158,855
2	Household has small physical assets	Table	31	1,923,797
		Chair	37	2,302,300
		Bed	32	2,283,582
		Cupboard	26	683,895
		Water pump	15	3,213,149
3	Household has electrical assets	Computer or laptop	82	4,983,390
		Sewing machine	27	2,066,802
		Fan/electric fan	35	2,343,743
		Air conditioner	52	3,921,487
		Water heater	16	527,542
		Washing machine	56	4,176,730
		Generator	30	532,726
4	Household has motorised and non-motorised agricultural/fishing/ farming assets	Boat without motor	32	1,065,064
		Boat with motor	68	2,096,236
		Animal-drawn cart	77	4,813,213
		Tractor	25	3,383,962
		Land (any)	93	5,445,457
		Land size	84	3,850,746
		Livestock (any)	92	4,077,684
		Number of cows/ cattle/buffalo	84	3,579,356
		Number of horses/ donkeys/ mules	82	3,478,366
		Number of goats	84	3,582,581
		Number of sheep	82	3,453,960
		Number of chicken/ poultry	86	3,678,130
		Number of camels	17	2,031,522
		Number of rabbits	21	403,650
		Number of pigs	66	1,523,622

		Number of beehives	7	146,142
5	Household has access to financial transactions	Bank account	82	3,591,511
6	Household has access to treated mosquito nets	Interior walls of dwellings are sprayed	28	597,294
		Household members sleep under insecticide- or liquid-treated nets	44	2,169,977
7	Consumption and exposure to tobacco	Smoking within household (exposure to smoke)	35	2,450,041
		Women smoke more than four cigarettes/day	71	4,525,145
		Men smoke more than four cigarettes/day	53	4,224,026
8	Overcrowding within household	Number of rooms used for sleeping	94	4,057,337
9	Household consumption of iodized salt	Presence of iodized salt in household	72	2,972,241
10	Household members have health insurance	Any household member	15	3,131,565
		Women, 15–49	39	3,761,155
		Men, 15–59	34	3,593,859
11	Household waste management	Disposal of household waste	19	2,043,989

3. Results

3.1 Statistical Validation of MPI-I

3.1.1 Exploratory factor analysis

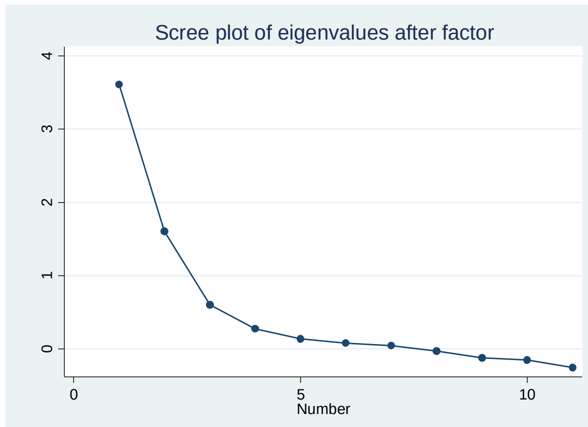
First, we performed tetrachoric EFA for binary variables to see whether the assumed three-factor solution of the MPI-I emerged (information, mobility and livelihood). FA is a model of the measurement of a latent variable. This model assumes that there are *m* underlying factors whereby each observed variable is a linear function of these factors (common variance) together with a residual variate (unique variance) (Costello and Osborne, 2005).[14] Following Guio et al. (2012, p.16) and Vaz et al. (2013, pp.6–8), factor loadings were rotated

14 A factor should consist of at least three variables; rotated factors with two variables should be highly correlated with each another (r > .70) to be considered as a factor (Tabachnick and Fidell, 2007, in Yong and Pearce, 2013, p.80). If the unique variance is beyond 0.7, the variable is not well explained by the factor. Note that due to the skewness implied by Bernoulli-distributed variables, a factor analysis of a matrix of tetrachoric correlations is more appropriate than a Pearson correlation matrix that is standardly used for continuous unimodal data (Uebersax, 2000, cited in StataCorp 2013; see as well Dekkers, 2008).

to facilitate their interpretation, and oblique rotation was used given the likely correlation between the three asset dimensions. Tetrachoric correlations were adjusted to be 'positive semidefinite'. Iterated principal-factor was chosen as the extraction method to improve communality estimates (see StataCorp, 2013).

For the pool of 26 countries, based on the EFA with oblique rotation, a three-factor solution underlying asset deprivation emerged (following the Kaiser criterion, see also the scree plot in Graph 1).

Graph 1: MPI-I: Scree Plot of Eigenvalues, Pool of 26 Countries



Eight asset items were retained using a 0.5 primary factor loading and a 0.3 cross-loading threshold (see Table 3). Factor loadings for all items were high (above 0.7), with the exception of animal cart and land, which scored factor loadings of below 0.6. The factor loadings of the first two factors explained most of the observed variance (89.6%). The model fit for sampling adequacy was mediocre (adequate at best), with the Kaiser-Meyer-Olkin (KMO) test measure amounting to 0.65. This indicates that the proportion of variance among variables is enough to interpret it as common variance, yet unique variances among variables are also strong (see StataCorp, 2013).

A lack of clustering of interrelated variables and a series of high 'uniqueness' of variables was observed (radio, bicycle and motorboat), which did not permit the retention of the proposed factor labels of information/mobility/livelihood and resulted in, at best, moderately internal consistent factor scales (Cronbach's Alpha for first factor: 0.63; for all retained items, 0.44).

Table 3: MPI-I: Exploratory Factor Analysis, Pool of 26 Countries

Pooled(1)				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	62%	27.6%	10.4%	1,470,046
Rotated Factor Loadings(2)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.8336			0.2454
Information: Television	0.8233			0.0952
Information: Radio				0.8186
Mobility: Bicycle				0.7874
Mobility: Motorbike			0.7468	0.2724
Mobility: Motorboat				0.9067
Mobility: Car	0.7220			0.5024
Mobility: Animal cart		0.5515		0.5437
Livelihood: Refrigerator	0.8906			0.1086
Livelihood: Land		0.5223		0.5852
Livelihood: Livestock		0.8195		0.3163
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	4	3	1	8
Cronbach's Alpha	0.63	0.36	.	0.44
Kaiser-Meyer-Olkin				0.65

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe. (2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.[15]

15 This trend was also observed at the country level (see Appendix 1, where we present results for DR Congo, Ethiopia, Haiti, Kenya, Nigeria and Pakistan). Based on the EFA with oblique rotation, a three-factor solution underlying asset deprivation emerged (following the Kaiser criterion), ranging between six assets items in Kenya to ten in Ethiopia that were retained using a 0.5 primary factor loading and a 0.3 cross-loading threshold (a 0.3 primary factor loading was also performed and did not yield changes in the results (it increased cross-loadings). In addition, DR Congo, Ethiopia and Haiti produced Heywood cases due to negative uniqueness values of motorboat). The factor loadings of the first two factors explained most of the observed variance, which ranged from 77% in Haiti to 92% in Ethiopia. Again, a lack of clustering of items was observed that did not permit the retention of the proposed factor structure of information/mobility/livelihood and resulted in, at best, moderately internal consistent factor scales (the alphas in the subscales ranged from moderate at best (0.69 for factor 1 [5 items] in DR Congo and

Next, we performed the same analysis for different configurations of land size and livestock. Overall, four alternatives to the MPI-I were computed.

1. Alternative 1: The first used a minimum land size cutoff of 3ha and 0.3ha, respectively, as well as one livestock unit, where missing values were dropped from the analysis.
2. Alternative 2: The second used land ownership yes/no and one livestock unit, where missing data and values on animals where treated as deprived.
3. Alternative 3: The third used a minimum land size cutoff of 3ha and 0.3ha, respectively, as well as one livestock unit, where missing data and values on animals were treated as deprived and missing data and values on land size were treated as non-deprived (this is the best comparison to the MPI-I in terms of how missing values and data on land size were treated).
4. Alternative 4: The fourth used a minimum land size cutoff of 3ha and 0.3ha, respectively, as well as one livestock unit, where missing data and values on animals were treated as deprived and missing data and values on land size were treated as deprived.

0.68 for factor 1 [five items] in Nigeria), to low (0.51 for factor 3 [five items] in Ethiopia) and poor (0.49 for factor 2 [three items] in Nigeria). Alphas for all retained items ranged from 0.62 in Ethiopia (ten items) to 0.38 for eight items in Haiti. Overall, no alpha achieved a score above 0.7, understood to be a threshold for 'satisfactory' internal consistency of a scale. In comparison, the six items of the MPI-O scored higher alphas throughout, yet never surpassed the 0.7 threshold (the highest score was 0.64 in Ethiopia). Although land and livestock scored rotated primary factor loadings of above 0.5 in five out of six countries studied, in none of the studied countries did the variables score positive rotated factor loadings of above 0.5 in the most powerful first factor (the first factor that explained most of the observed variance in all countries ranging from 51% in DR Congo to 63% in Ethiopia). In Haiti, Nigeria and Pakistan, land and livestock contributed to factor 2 and 3 quite prominently, which explained 22%, 30% and 11% of the observed variance in these countries, respectively. While these factors proportionally explain less of the overall variance than factor 1, these factors nonetheless substantially explain the cumulative variance in the countries and are thus not trivial. Rotated factors that have two or fewer variables should be interpreted with caution, however, and should only be considered reliable when the variables are highly correlated with each another ($r > .70$; Yong and Pearce, 2013). In Pakistan, land and livestock were the only variables of factor 3 with a correlation of 0.4. Thus, of six countries under individual study, only in two (Haiti and Nigeria) can land and livestock be interpreted as variables that substantially help to explain part of the cumulative variance in assets deprivation (yet this proportion is comparatively smaller as they 'only' score primary factor loadings of above 0.5 in factors 2 and 3).

Table 4: MPI-I: EFA, Pool of 26 Countries, Rural Population

Pooled(1)				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	63%	26.7%	10.3%	919,745
Rotated Factor Loadings(2)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.6081			0.3421
Information: Television	0.7350			0.1485
Information: Radio				0.8511
Mobility: Bicycle				0.7559
Mobility: Motorbike		0.7304		0.3136
Mobility: Motorboat				0.8800
Mobility: Car	0.6891			0.5071
Mobility: Animal cart				0.5758
Livelihood: Refrigerator	1.0067			0.0574
Livelihood: Land				0.8201
Livelihood: Livestock			0.7597	0.4562
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	4	1	1	6
Cronbach's Alpha	0.5763	.	.	0.5098
Kaiser-Meyer-Olkin				0.6367

(1)Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.
(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Table 5: MPI-I: EFA, Pool of 26 Countries, Urban Population

Pooled(1)				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	63.2%	22.8%	14%	550,301
Rotated Factor Loadings(2)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone		0.7154		0.4634
Information: Television		0.8923		0.1751
Information: Radio				0.9220
Mobility: Bicycle				0.8905
Mobility: Motorbike	2.6847			-6.2070
Mobility: Motorboat				0.9124
Mobility: Car		0.7222		0.4549
Mobility: Animal cart			0.5968	0.6343
Livelihood: Refrigerator		0.8784		0.2185
Livelihood: Land			0.6186	0.5917
Livelihood: Livestock			0.8386	0.2858
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	1	4	3	8
Cronbach's Alpha	.	0.5687	0.3839	0.4373
Kaiser-Meyer-Olkin			.	0.6179

(1)Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.
(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Results are presented in Appendices 2 through 8. We find that the results are akin to the MPI-I, with a KMO test measure ranging from 0.6 to 0.64 and the first factor explaining most of the observed variance, ranging from 57% to 61.3%. The first factor is composed throughout the four alternatives of telephone, television, car and refrigerator. Land is not retained in any scenario, however, with a primary factor loading of above 0.5, but instead depicts a high unique variance throughout. By using livestock units throughout all scenarios of the four alternatives, we find that this variable is retained in the second or third factor as either the only item, or as one of only two items. The second and third factors explained approximately 30% and 11% of the common variance in the various configurations. The uniqueness of livestock coded as one livestock unit was negative in five of the seven scenarios and caused several Heywood cases. Hence, in the forthcoming analysis the alternatives to the MPI-I were not further pursued.[16]

Instead, we performed the EFA of the MPI-I disaggregated for the rural and urban populations in our pool of 26 countries (see Tables 4 and 5). In contrast to the rural solution, the urban solution does produce a Heywood case (due to the negative uniqueness of motorbike); factors 2 and 3 of the urban population are a replica of factors 1 and 2 on the total population, while on the solution for the rural population land is not retained.

Overall, the EFA does not support the dimensional structure of the MPI-I and also highlights the distinctiveness of the land and livestock variables. To confirm this, we also conducted MCA.

3.1.2 Multiple correspondence analysis

Next, we performed MCA. MCA can be viewed as a generalization of PCA to ordered categorical and binary data. In contrast to FA, which is based on correlations, MCA is based on entropy (Guio et al., 2012, p.15). Since MCA is a descriptive statistical approach to model a latent concept, rather than a latent variable, MCA is useful for exploring the dimensional structure of the data further. It particularly allows analysing the individual contributions of ownership and lack of ownership of items to the variance found in the dimensions.

First, we specified a MCA of the Burt matrix for the data and used principal normalization to scale the coordinates by the principal inertias to analyse the column categories (see StataCorp, 2013). We find that two

16 We also computed the Cronbach's Alpha with all 11 items (non-categorised) of the MPI-I (0.48) and for the four alternatives. For the bigger cutoff of minimum land size, namely 3ha, the alphas are almost identical (alt.1: 0.54; alt 2: 0.49; alt 3: 0.5; alt 4: 0.5) to the alphas computed for a much smaller minimum cutoff of 0.3ha (alt.1: 0.52; alt 2: 0.49; alt 3: 0.49; alt 4: 0.5).

dimensions explain 82.94% of the total inertia (i.e. variance, see Abdi and Valenti, 2007), of which the first dimension explains 75.05% of the inertia (the third dimension only explains 0.10% of the inertia).[17]

Graph 2 plots the origin axes of the two dimensions, which helps us to see data associations. We opt to use the overlay option to obtain a combined graph of the biplot graphs for the 11 variables. The plot reveals the clustering of variables due to the relative position of their Euclidean values on a two-dimensional plot (Dijkstra et al., 2016: 84). Data points farthest away from the origin, with the horizontal axis for dimension 1 and the vertical axis for dimension 2, indicate responses to items that are more influential for the inertia of the respective dimension. Points on opposite sides of the plot indicate that a dimension contrasts the responses to items.

A pattern is emerging where ownership versus non-ownership of items are clustered together. 'No' responses to nine items are clustered more strongly and are most distant from the origin along the horizontal axis for dimension 1, with telephone and television standing out as being the farthest away from the origin. This corresponds with the relatively high contribution of these items to the inertia of dimension 1 (as can be seen in Appendix 9, which presents the statistics for column categories in principal normalization, and in Graph 3, where the MCA dimension projection plot of the column coordinates after MCA is presented, which shows that non-ownership of nine items are ordered in the first dimension before ownership). Because 'no' and 'yes' responses are on opposite sides of the origin, dimension 1 contrasts these category values. Land, livestock and animal cart ownership, on the other hand, are the farthest away from the origin of dimension 2. This is reflected in Appendix 9, as well, where the ownership of those three items are the greatest contributors to dimension 2[18]. Therefore, given that responses to the ownership of land, livestock and, to a lesser degree, animal cart, are clustered somewhat differently from the other items, their potential incompatibility with the other variables is certainly highlighted and may be interpreted as a reflection of the results obtained from the EFA presented in Table 3, where the three items were retained on the less powerful second factor.

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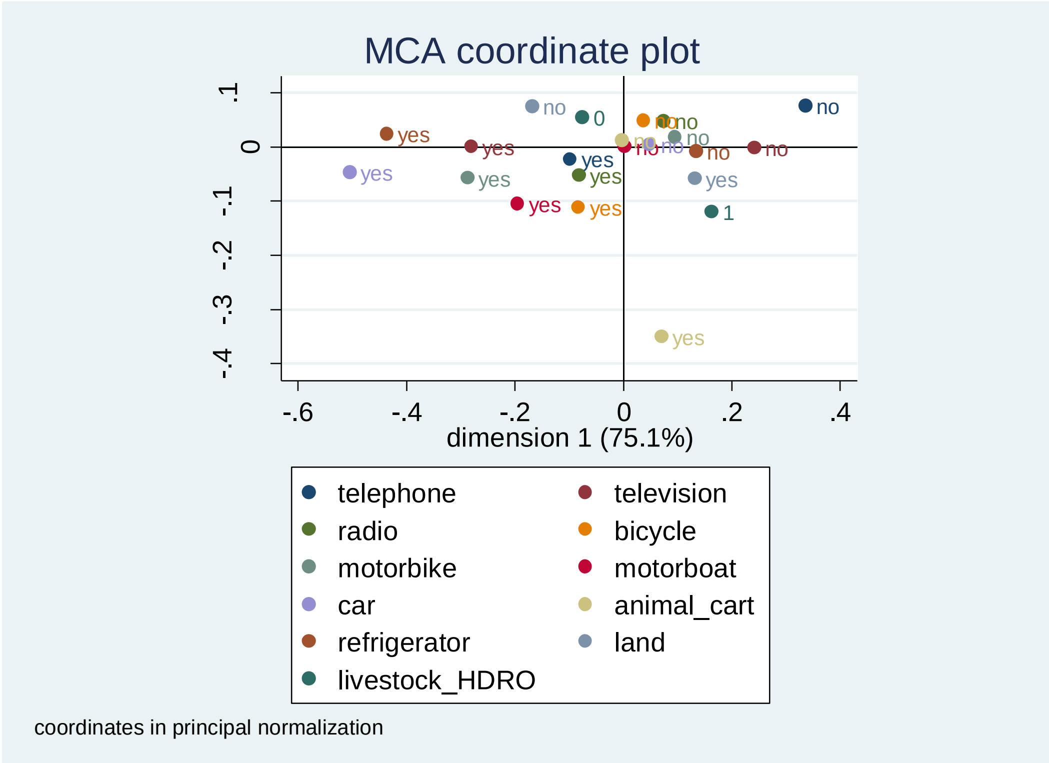
17 Number of observations: 1,470,046.

18 Ownership of a bicycle also contributes quite strongly to the inertia of dimension 2.

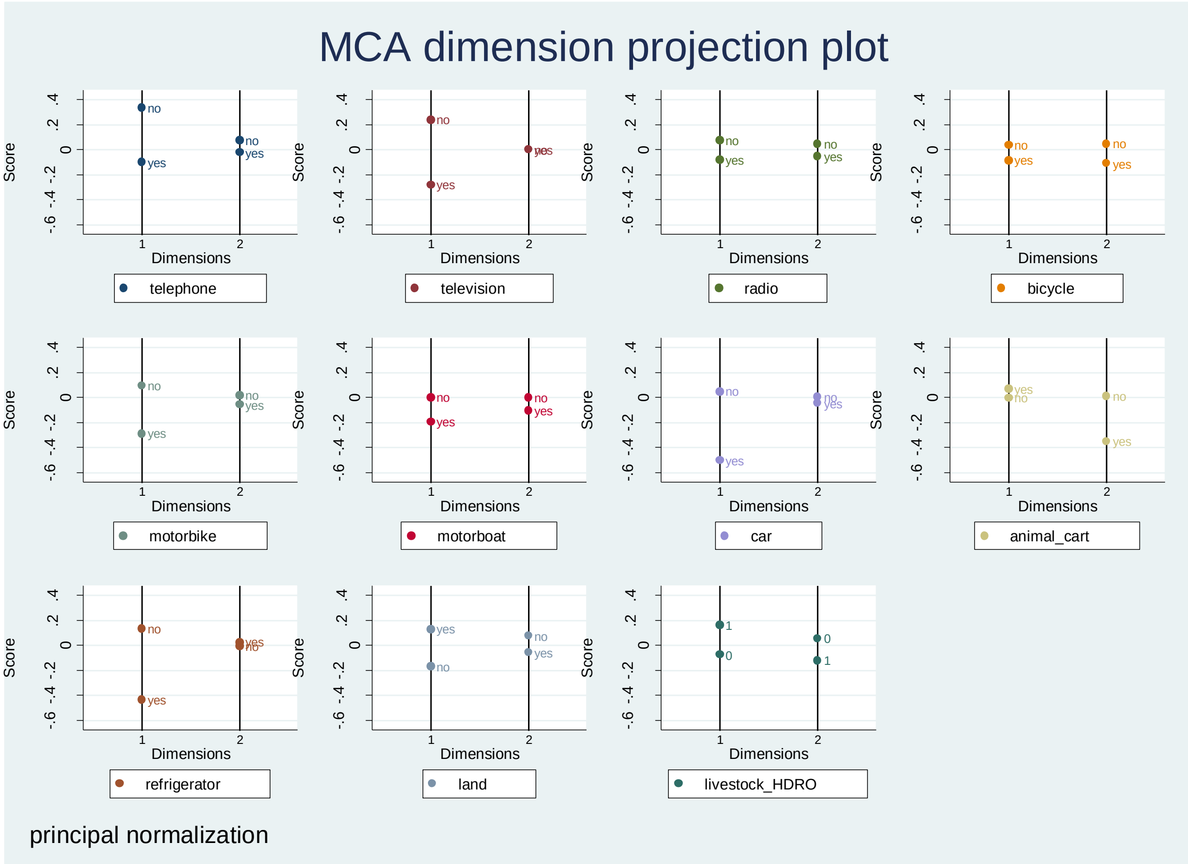
Graph 2: MPI-I: MCA Coordinate Plot, Pool of 26 Countries



As mentioned in the previous paragraph, statistics for column categories in principal normalization are presented in Appendix 9 and show that land and livestock contribute more strongly to the inertia of dimension 2 than to the inertia of dimension 1.[19] Ownership of livestock and the lack of land ownership are the strongest contributors to the inertia of dimension 2 overall (see Appendix 9). As can be seen in Graph 3, which presents a projection plot of the column coordinates after MCA, land and livestock, as well as animal cart, are indeed the only variables that show a different ordering in the *first dimension* in their projection (ownership is arrayed before non-ownership).

[19] They share that with radio, bicycle, motorbike motorboat and animal cart.

Graph 3: MPI-I: MCA Dimension Projection Plot, Pool of 26 Countries



Next, we performed the same analysis disaggregated for the rural and urban populations in our pool of 26 countries. We find a similar two-dimensional pattern. The first two dimensions for the rural population explain 81.12% of the total inertia, of which the first dimension explains 70.40% (the third dimension only explains 0.07% of the inertia).[20] For the urban population,[21] the first dimension explains 66.9%, and the second dimension 11.04% (the third explained only 0.51%).

As can be seen in the coordinate plots (presented in Graphs 4 and 5), and particularly the dimension projection plots (presented in Graphs 6 and 7), the previously identified pattern by which land and livestock, in particular, are clustered differently to the other items is confirmed. While the projection plot of the column coordinates after MCA for the urban population shows a confirmation of the results obtained for the total population, the results vary slightly for the rural population. Here, the ordering of animal cart in the first dimension in its

20 Number of observations: 919,745.

21 Number of observations: 550,301.

projection is arrayed in line with the other eight items (non-ownership is arrayed before ownership), and ownership and non-ownership of livestock seem to overlap.

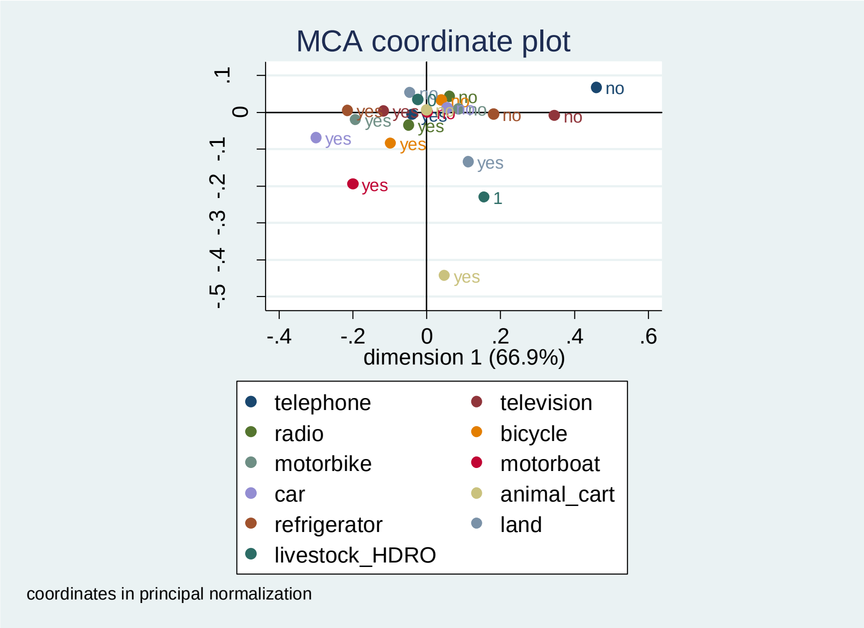
As can be seen in Appendices 10 and 11, statistics for column categories in principal normalization for the rural and urban populations show that the contribution of land and livestock to the inertia of dimension 2 is stronger than to dimension 1.[22] Ownership of livestock and the lack of land ownership are the strongest contributors to the inertia of dimension 2 overall. For the rural population, ownership of a refrigerator and lack of a telephone are the strongest contributors to the inertia of dimension 1, while for the urban population it is ownership of a refrigerator and lack of a television.

Thus, considering the analysis of the pooled data for 26 countries with reasonable sample sizes and disaggregations by rural and urban populations, and given the applied methods of EFA and MCA, we identify two dimensions (at best) in the data. This is a divergence from the measurement model proposed by the MPI-I. As the MCA reveals, the first dimension explains 75.05% of the overall 82.94% inertia. This may suggest that the available assets should be grouped in one dimension only.

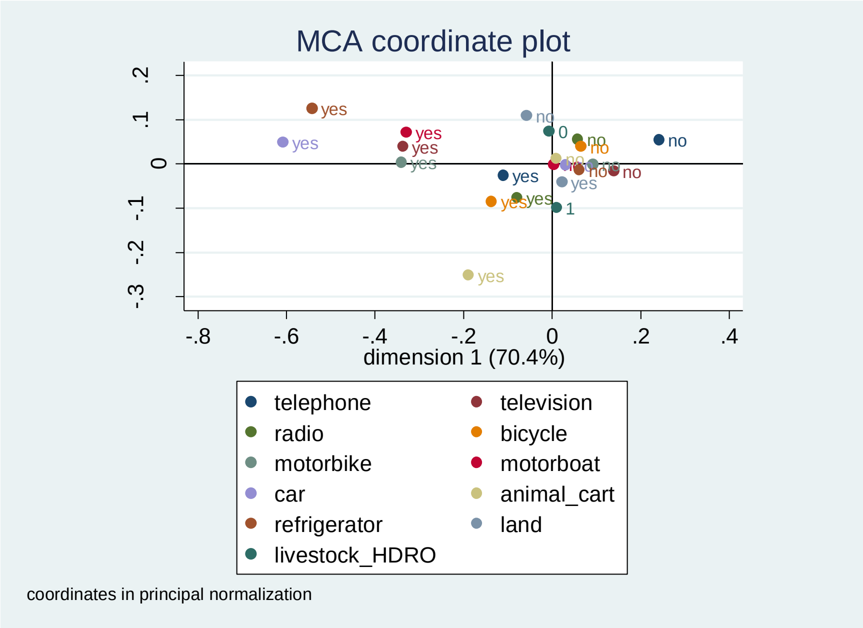
As the MCA coordinate plot in Graph 2 and the statistics for column categories in principal normalization in Appendix 9 demonstrate, there seems to be a fundamental difference between *not* having a television or a telephone, the strongest contributors to the inertia of dimension 1, and *not* having land (the strongest contributor to the inertia of dimension 2). Thus, while there is sufficient reason to assume that populations would not want *not* to have a television, a telephone or similar household durables, regardless of whether they are in an urban or rural area, a lack of land ownership may be interpreted as a livelihood choice.

22 They share this with radio, bicycle and animal cart in the rural population and radio, bicycle, motorboat and animal cart in the urban population.

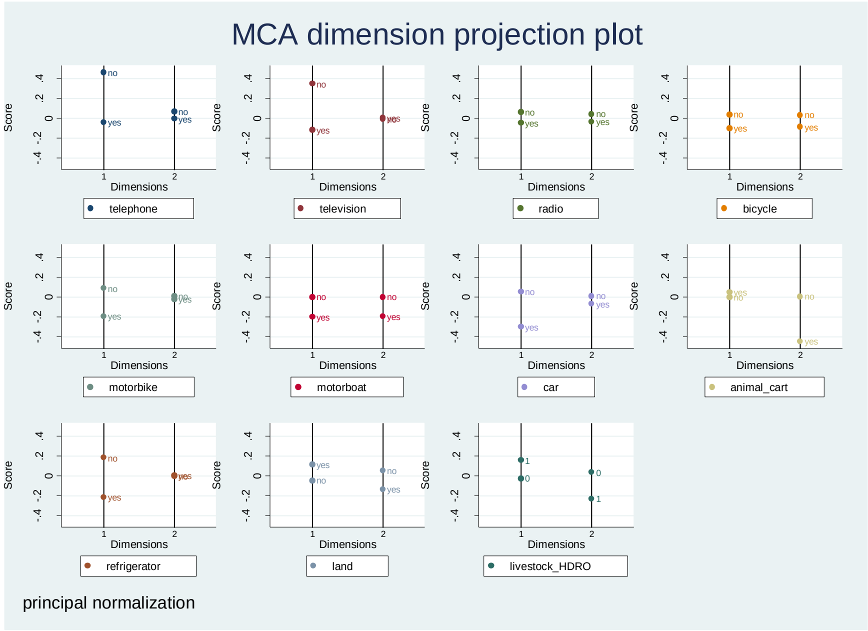
Graph 4: MPI-I: MCA Coordinate Plot, Pool of 26 Countries, Urban Population



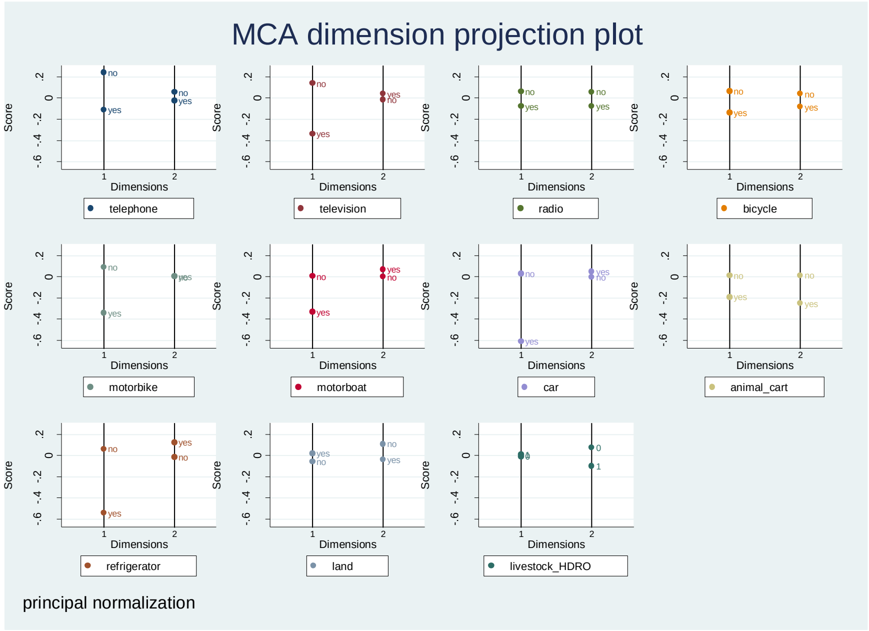
Graph 5: MPI-I: MCA Coordinate Plot, Pool of 26 Countries, Rural Population



Graph 6: MPI-I: MCA Dimension Projection Plot, Pool of 26 Countries, Urban Population



Graph 7: MPI-I: MCA Dimension Projection Plot, Pool of 26 Countries, Rural Population



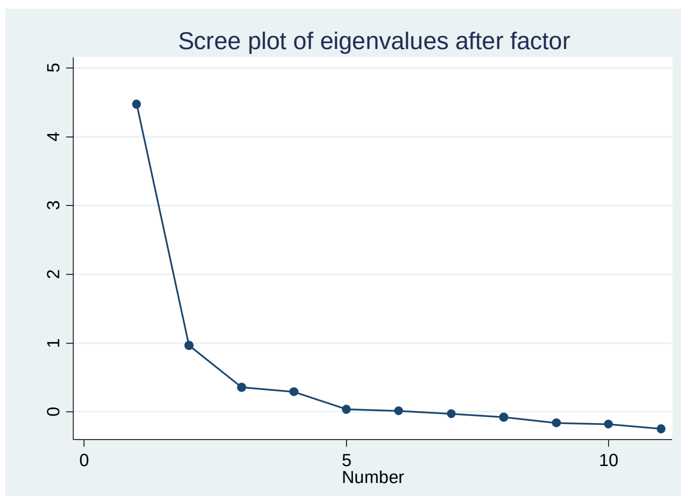
3.2 Statistical Validation of Alternatives to MPI-I and MPI-O

3.2.1 Exploratory factor analysis

Based on the systematic review of over 100 DHS, MICS and national surveys presented in section 2, we identified three additional asset variables that meet at least one of our suitability criteria (75 countries, at least 3.5 billion people), namely 'internet access', 'computer possession' and 'bank account'. Based on the preceding analysis, we excluded land and livestock variables, as well as the motorboat variable on conceptual and empirical grounds, and included the three additional variables. We performed an EFA on the pool of 26 countries, as well as for the rural and urban population.[23] For communicative purposes, we tentatively call it the 'new MPI' (MPI-N).

For the pool of 26 countries, and based on the EFA with oblique rotation, a two-factor solution underlying asset deprivation emerged (following the Kaiser criterion, see also the scree plot in Graph 8).

Graph 8: MPI-N: Scree Plot of Eigenvalues, Pool of 26 Countries



Using a 0.5 primary factor loading and a 0.3 cross-loading threshold, six items were retained in the first factor, which explained 82.2% of the variance (see Table 6). Radio, bicycle and animal cart show a high uniqueness. The alpha of the first factor is 0.74 and thus is above the minimal threshold for 'satisfactory' internal consistency, while the alpha of all retained items was also above 0.7. Note that motorbike was not retained with a primary factor loading of above 0.5; neither does it show a high uniqueness. Overall, the model fit for

[23] Note that the exclusion of the motorboat variable, which carried 70.8% missing values in the pool of 26 countries, substantially increased the number of observations (to 3.3 million).

sampling adequacy was strong (or 'meritorious', with a KMO test measure of 0.84) and better than for the three-factor solution used in the MPI-I.

Table 6: MPI-N: EFA, Pool of 26 Countries

Pooled(1)			
	Factor1	**Factor2**	**Number of observations**
Proportion of variance explained	82.2%	17.8%	3,251,694
Rotated Factor Loadings(2)			
Variable	**Factor1**	**Factor2**	**Uniqueness**
Phone	0.5223		0.3973
Television	0.7152		0.3337
Radio			0.8790
Computer	0.9014		0.2229
Internet	0.7822		0.3585
Bank		0.6859	0.4999
Bicycle			0.7809
Motorbike			0.4962
Car	0.8262		0.3625
Animal cart			0.9915
Refrigerator	0.8386		0.2321
Items retained	**Factor1**	**Factor2**	**All Items**
Items retained	6	1	7
Cronbach's Alpha	0.7445	.	0.7365
Kaiser-Meyer-Olkin	.	.	0.8395

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda, and Zimbabwe.

(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Next, we performed the EFA on the MPI-N disaggregated for the rural and urban populations in our pool of 26 countries (see Tables 7 and 8). In both cases, the KMO measure was equally as strong as the solution obtained in Table 6 (above 0.82). While the solution for the rural population replicates the solution for the total population, the solution for the urban population retains three items in the second factor (telephone, bank account and motorbike). Interestingly, television was not retained in the second factor. Overall, the same seven items were retained in Tables 6, 7 and 8, and the first factor showed satisfactory internal consistencies as measured by Cronbach's Alpha (>0.7) for the total population and the urban population.

Table 7: MPI-N: EFA, Pool of 26 Countries, Rural Population

Pooled(1)			
	Factor1	Factor2	Number of observations
Proportion of variance explained	80.9%	19.1%	2,274,428
Rotated Factor Loadings(2)			
Variable	**Factor1**	**Factor2**	**Uniqueness**
Phone	0.5353		0.4144
Television	0.6934		0.3671
Radio			0.8511
Computer	0.8511		0.3110
Internet	0.7416		0.4161
Bank		0.7635	0.4078
Bicycle			0.8292
Motorbike			0.5281
Car	0.8432		0.3493
Animal cart			0.9722
Refrigerator	0.8176		0.2771
Items retained	**Factor1**	**Factor2**	**All Items**
Items retained	6	1	7
Cronbach's Alpha	0.6659	.	0.6657
Kaiser-Meyer-Olkin	.	.	0.8280

1)Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda, and Zimbabwe.

(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Table 8: MPI-N: EFA, Pool of 26 Countries, Urban Population

Pooled(1)			
	Factor1	Factor2	Number of observations
Proportion of variance explained	79.9%	20.1%	977,266
Rotated Factor Loadings(2)			
Variable	**Factor1**	**Factor2**	**Uniqueness**
Phone		0.5228	0.4519
Television			0.4228
Radio			0.8766
Computer	0.9054		0.2019
Internet	0.7559		0.3687
Bank		0.7493	0.4524
Bicycle			0.8354
Motorbike		0.5534	0.5193
Car	0.8072		0.3738
Animal cart			0.9671
Refrigerator	0.6847		0.3115
Items retained	**Factor1**	**Factor2**	**All Items**
Items retained	4	3	7
Cronbach's Alpha	0.7479	0.4110	0.6682
Kaiser-Meyer-Olkin	.	.	0.8285

(1)Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda, and Zimbabwe.

(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

3.2.2 Classical test theory

Based on the test results obtained through EFA in section 3.2.1, we computed the Cronbach's Alpha for three possible asset versions:

1. Telephone, television, computer, internet, motorbike, car and refrigerator: 0.742,
2. Telephone, television, computer, internet, bicycle, motorbike, car and refrigerator: 0.703,
3. Telephone, television, radio, bicycle, motorbike, car, animal cart, refrigerator and computer: 0.613.

For a complete overview of the Cronbach Alphas across the various asset versions in our pool of 26 countries, see Appendix 12. Overall, we find the best solution with a combination of television, television, computer, internet, refrigerator, motorbike and car (alpha 0.74). The items are mostly consumer durables, with the exception of internet access, which is an intangible asset. Note that this combination excludes radio and bicycle. As these two items are potential assets of the poor (Narayan et al., 1999; Narayan and Petsch, 2002), we include them in the third version, in addition to animal cart, but we exclude internet. We utilised Cramer's *V* test, which measures the association between two nominal variables, to assess the potential redundancy of computer and internet. Ranging from zero to one, one indicates a strong association. We find a correlation of 0.62 between computer and internet for the pool of 26 countries.[24] Instead of merging both items, which could have been an option considering the association of the items, we decide to not use internet in the third version. We decided to exclude internet, and not computer, because data on the internet variable are only available in 52 countries, and because it is conceptually a distinct item from the otherwise tangible consumer durables.

Note that thus far we operated under the notion of using an equally weighted sum of items in the revised assets indicator, in line with Guio et al. (2012, 2016, 2017). Guio et al. consider the square root of the Cronbach's Alpha statistic as the correlation between the indicator of material deprivation and a potential 'perfect' index made from answers to an infinite set of deprivation questions. If the correlation with a perfect, infinite set of deprivation indicators is strong, there is little additional information that any differential weights could add (2017, p.51). In the presented case of the three versions above, the Cronbach's Alpha of the first version (0.74) has a square root of 0.86, of 0.84 for the second version and of 0.78 for the third version. Hence, all versions present reasonably strong correlations with what Guio et al. called "the perfect infinite set of deprivation indicators" (2012, p.110). That means that the setting of any additional weights could be considered superfluous. This would be different if we were to consider using an unweighted sum of the

[24] The Cramer's *V* ranged from 0.46 in Peru to 0.87 in Armenia.

traditional assets indicator (MPI-O) published in 2010 (telephone, television, radio, bicycle, motorbike, car and refrigerator) or the MPI-I, which had a Cronbach Alpha for the pool of 26 countries of 0.58 and 0.48, respectively. Here, the square roots are lower, namely 0.76 and 0.69; hence using additional weights would potentially change the rankings.

3.2.3 Item response theory

Classical test theory provides information on the reliability of a scale. We further explored the reliability of the potential MPI-Ns with IRT, which provides additional information on the reliability of each individual item in the scale. IRT provides information on how each individual item relates to some unobserved latent trait, where the probability of success on an item is a function of both the level of the latent trait and the properties of the item (StataCorp, 2017, p.1). Thus, IRT provides information on the severity of each item, on the difficulty to obtain that item and is thus extremely useful in making sure that the final scale encompasses items that range from low to high severity. It also provides information on the discrimination of an item, on "how fast the probability of success changes with ability near the item difficulty. An item with a large discrimination value has a high correlation between the latent trait and the probability of success on that item. […] A highly discriminating item differentiates better, around its difficulty value, between persons of similar levels of the latent trait" (ibid, p.3).

We applied IRT to two of the three versions presented in section 3.2.2. The first version is tested as it showed the highest internal consistency of all the scales, while the third is the most encompassing version that includes radio, bicycle and animal cart, but already excludes internet.

3.2.3.1 IRT on version 1 for a pool of 26 countries

First, we specify a one-parameter logistic model, a model that estimates the difficulty to obtain each of the seven items (see Table 9). The estimate of the item discrimination parameter is shared by all items and is estimated as 2.24. This suggests that the items are discriminating, that is, in the vicinity of a given difficulty estimate, any two households with distinct characteristics would have different predicted probabilities of responding that they possess an item. Based on the model, we find that a telephone is the easiest to obtain item with a coefficient of -1.53, while a car is the most difficult to obtain with a coefficient of 1.59. In other words, the probability of succeeding in obtaining a telephone is higher than for the remaining items. It is easier because members of the household would only need an ability level greater than -1.53 to be expected to succeed obtaining this item, while for a car one would need an ability level of 1.59.

Table 9: 1pl Model for Version 1, Pool of 26 Countries

Pooled(1)						
One-parameter logistic model						**Number of observations**
Log likelihood = -14813946						5,264,502
Variable	**Coefficient**	**Standard Error**	***z***	***p***	**95% CI**	
Discrimination	2.240266	.001341	1670.62	***	2.237638	2.242894
Difficulty						
Phone	-1.531712	.0010311	-1485.56	***	-1.533733	-1.529692
Television	-.3932486	.0007184	-547.41	***	-.3946566	-.3918406
Refrigerator	.4983582	.0007189	693.20	***	.4969491	.4997673
Motorbike	.6294136	.00074	850.59	***	.6279633	.6308639
Internet	1.266684	.0009861	1284.49	***	1.264751	1.268616
Computer	1.395035	.0010098	1381.45	***	1.393056	1.397014
Car	1.593675	.0010748	1482.83	***	1.591568	1.595781

(1)Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

We visualize the relationship between items and being deprived in the items of version 1 – between the items and the latent trait – by plotting the item characteristic curves (ICCs). The probabilities represent the expected scores for each item along the latent trait continuum and, as can be seen in Graph 9, shows that the probability of possessing a phone is higher than the probability of possessing all other items, with a car being the most complicated to possess.

Since ICCs based on a 1pl model plots the difficulty but not the discrimination of each item, we also plot the ICC based on a 2pl model (presented in Graph 10; Table 10 presents the results for the 2pl model).[25]

Guio et al. (2012; 2017) interpret the ICC as a measure of discrimination between the deprived and non-deprived (the more upright/vertical a curve the more the item discriminates between the deprived and non-deprived respondents) and as a measure of 'severity' of material deprivation (where a deprivation is interpreted as an 'enforced lack' of that item), set at 3 standard deviations from the mean. Several vertical 'S' shaped curves that are spread out along the X-axis and where the inflection point of each curve is between 0 and +3 on the X-axis (i.e. have a severity of between 0 and +3 standard deviations) is interpreted by the authors as a 'good' index of material deprivation.

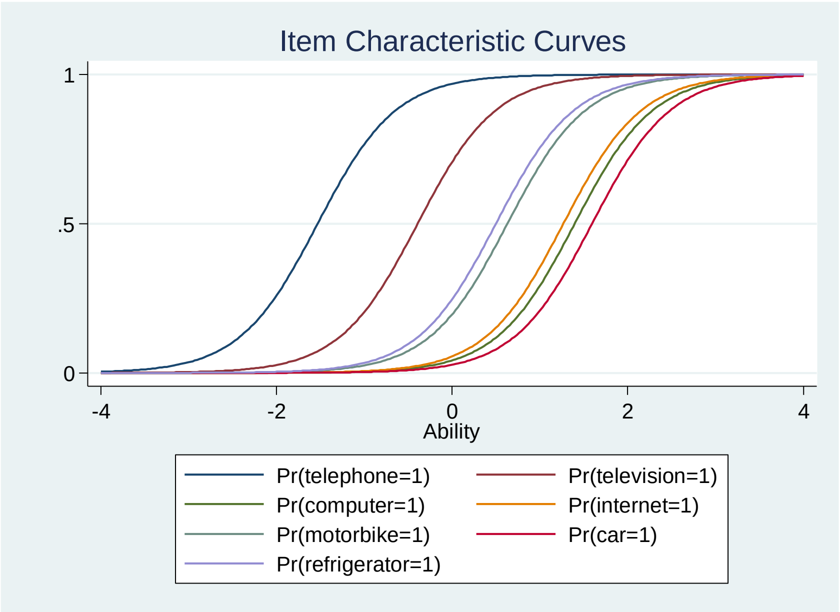
[25] We checked item fit between a 1pl and 2pl model by performing a likelihood-ratio test. The near zero significance level ($\chi 2$ (6)= 867556.80; p=0.0000) favours a 2pl model that allows for a separate discrimination parameter.

Table 10: 2pl Model for Version 1, Pool of 26 Countries

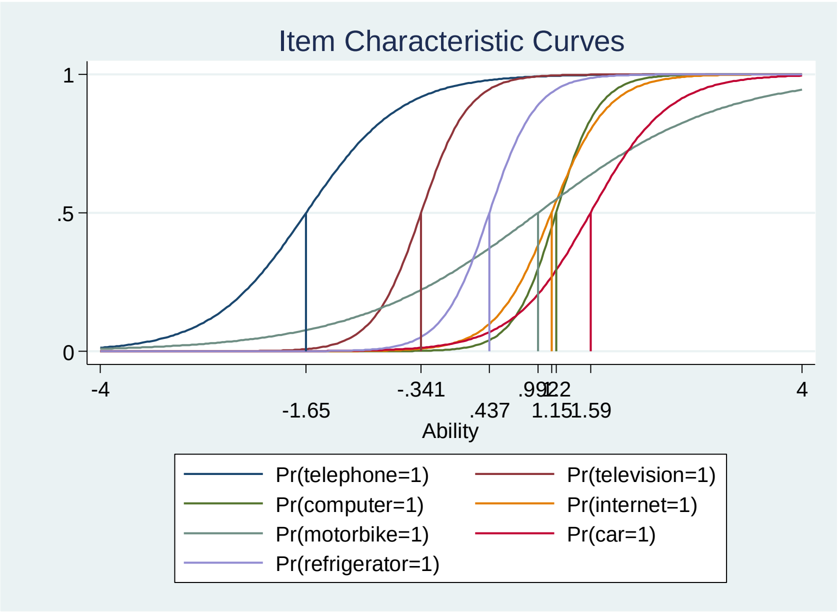
Pooled(1)						
Two-parameter logistic model						**Number of observations**
Log likelihood = -14380167						5,264,502
Variable	**Coefficient**	**Standard Error**	***z***	***p***	**95% CI**	
Phone						
Discrimination	1.846359	.0032726	564.18	***	1.839945	1.852773
Difficulty	-1.653185	.0017229	-959.52	***	-1.656562	-1.649808
Television						
Discrimination	3.691821	.0064932	568.57	***	3.679095	3.704548
Difficulty	-.3410169	.0006476	-526.57	***	-.3422863	-.3397476
Computer						
Discrimination	4.173718	.0094146	443.32	***	4.155266	4.19217
Difficulty	1.198494	.0009113	1315.21	***	1.196708	1.20028
Internet						
Discrimination	3.121696	.0055622	561.23	***	3.110794	3.132597
Difficulty	1.14542	.0009745	1175.41	***	1.14351	1.14733
Motorbike						
Discrimination	.9422919	.0014048	670.75	***	.9395385	.9450453
Difficulty	.9916142	.0015897	623.78	***	.9884985	.9947299
Car						
Discrimination	2.255033	.0036181	623.27	***	2.247942	2.262124
Difficulty	1.590109	.0014	1135.80	***	1.587365	1.592853
Refrigerator						
Discrimination	3.746449	.0064659	579.42	***	3.733776	3.759122
Difficulty	.4367549	.0006347	688.07	***	.4355109	.437999

For the presented case in this paper, since 0 is coded as not having that item (therefore, deprived) and 1 as having the item (therefore, non-deprived), the interpretation is that 0 and +3 indicates that more than half of the population do not have *the item* (it is difficult to succeed in having that item), which clearly highlights the severity of those who have the item (*severity of non-deprivation*). On the other hand, a negative coefficient indicates that more than half the population are likely *not* to suffer from this form of deprivation; it is *easy* to succeed in having this item.

Graph 9: Item Characteristics Curve, 1pl Model, Version 1



Graph 10: Item Characteristics Curve, 2pl Model, Version 1



By looking at the ICC for a 2pl model in Graph 10, we find that five out of seven items conform to the ideal pattern of depicting the severity of non-deprivation, while phone and television, less so. In terms of discrimination, all items are fairly vertical, with the exception of motorbike, which is less steep.[26]

3.2.3.2 IRT on version 3 for a pool of 26 countries

Second, we specify a one-parameter logistic model (see Table 11), a model that estimates the difficulty in obtaining each of the eight items of version 3. The estimate of the item discrimination parameter shared by all items is estimated as 1.22; hence, any two households with distinct characteristics would have predicted probabilities of responding that they possess an item that are *more similar* than in the previous model, where the discrimination parameter was estimated as 2.24.

Based on the 1pl model, we find that a phone is the easiest to obtain item with a coefficient of -2.07, while animal cart is the most difficult to obtain with a coefficient of 2.89, ahead of a car (2.17) (see also Graph 11, which presents the ICC).

Table 11: 1pl Model for Version 3, Pool of 26 Countries

Pooled(1)						
One-parameter logistic model						**Number of observations**
Log likelihood = -21635773						5,264,508
Variable	**Coefficient**	**Standard Error**	***z***	***p***	**95% CI**	
Discrimination	1.228921	.0007482	1642.55	***	1.227454	1.230387
Difficulty						
Phone	-2.068108	.0015893	-1301.29	***	-2.071223	-2.064993
Television	-.5280328	.0009737	-542.30	***	-.5299412	-.5261244
Bicycle	.2326839	.0009579	242.90	***	.2308064	.2345615
Refrigerator	.6540087	.0009904	660.35	***	.6520676	.6559499
Motorbike	.8301822	.0010339	802.97	***	.8281558	.8322085
Radio	.9983687	.0010845	920.57	***	.9962431	1.000494
Computer	1.884981	.001533	1229.61	***	1.881977	1.887986
Car	2.170364	.0016625	1305.48	***	2.167106	2.173622
Animal Cart	2.887494	.0024385	1184.11	***	2.882714	2.892273

(1)Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

[26] We also conducted the analysis with the listwise option, which handles missing values through listwise deletion (hence, observations with any missing items are dropped from the analysis (StataCorp, 2017, p.29). The number of observations dropped to 3,980,631, yet findings confirmed our test results presented in this section.

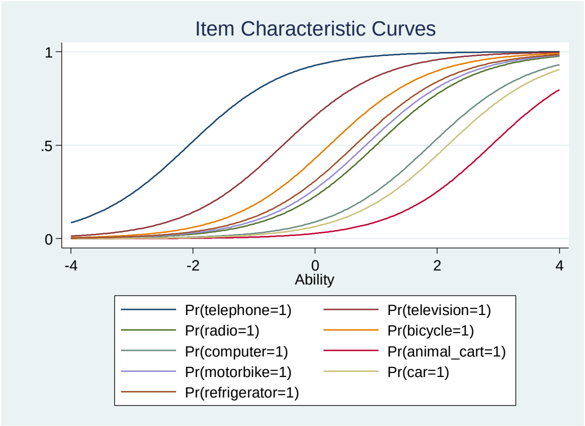
Given the lower discrimination parameter, we checked item fit between a 1pl and 2pl model by performing a likelihood-ratio test. The test result is near a zero significance level ($\chi 2$(8)=2438758.60; p=0.0000), which favours a 2pl model that allows for a separate discrimination parameter. Results are presented in Table 12, and we plot the ICC for the 2pl model in Graph 12.

Table 12: 2pl Model for Version 3, Pool of 26 Countries

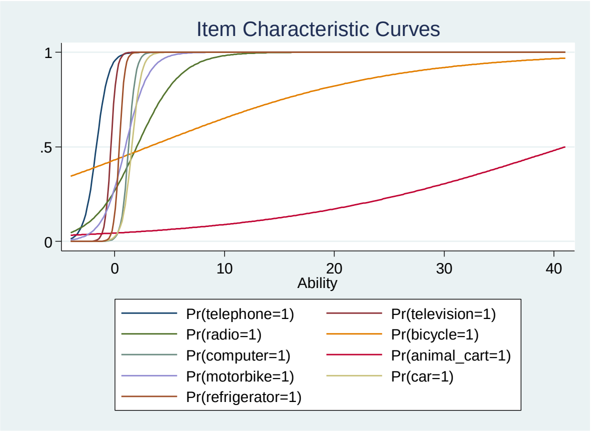
Pooled(1)						
Two-parameter logistic model						**Number of observations**
Log likelihood = -20416394						5,264,508
Variable	**Coefficient**	**Standard Error**	***z***	***p***	**95% CI**	
Phone						
Discrimination	1.820406	.0031982	569.20	***	1.814137	1.826674
Difficulty	-1.662328	.0017425	-954.01	***	-1.665743	-1.658913
Television						
Discrimination	3.846589	.007247	530.79	***	3.832385	3.860792
Difficulty	-.3390132	.0006471	-523.92	***	-.3402815	-.337745
Radio						
Discrimination	.5003772	.0012086	414.01	***	.4980083	.5027461
Difficulty	2.01035	.004819	417.17	***	2.000905	2.019795
Bicycle						
Discrimination	.0904803	.0010816	83.66	***	.0883604	.0926001
Difficulty	3.090521	.0390546	79.13	***	3.013976	3.167067
Computer						
Discrimination	3.090935	.0060115	514.17	***	3.079153	3.102718
Difficulty	1.275574	.0010543	1209.93	***	1.273508	1.27764
Animal Cart						
Discrimination	.0747796	.0026552	28.16	***	.0695754	.0799838
Difficulty	41.01983	1.458176	28.13	***	38.16186	43.87781
Motorbike						
Discrimination	.9594936	.0014354	668.44	***	.9566802	.9623069
Difficulty	.9803006	.001565	626.40	***	.9772333	.983368
Car						
Discrimination	2.345628	.0040348	581.35	***	2.33772	2.353536
Difficulty	1.571117	.0013896	1130.61	***	1.568394	1.573841
Refrigerator						
Discrimination	4.257918	.0089206	477.31	***	4.240434	4.275402
Difficulty	.4290063	.0006268	684.46	***	.4277779	.4302348

(1)Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

Graph 11: Item Characteristics Curve, 1pl model, version 3



Graph 12: Item Characteristics Curve, 2pl model, version 3



By looking at the ICC for a 2pl model presented in Graph 12, we find that seven out of nine items depict vertical S-shaped curves, of which five (refrigerator, motorbike, computer, car and radio) have an inflection point between 0 and +3 on the X-axis. While radio depicts a greater severity/difficulty than car (2.01 vs. 1.57), the discrimination of the car is greater than of radio (2.3 vs. 0.5). Television and telephone continue to depict a negative difficulty; in other words, whilst discriminating, telephone and television continue to be the easiest items to obtain. Finally, bicycle and animal cart do not depict the vertical S-shape curve of the other items.

Hence, around their respective difficult value they discriminate less well between households of similar levels of the latent trait than for the other items.[27]

Unsurprisingly, by excluding these two items from the list and redoing the Cronbach's Alpha, we see that the scales show greater reliability in all 26 countries, except for one country (Colombia, see Appendix 12, last column). For the pooled data, the alpha increased to 0.68, from 0.61 of version 3. However, given that the increase does not result in an alpha of above 0.7, the decision was taken not to exclude the items at this stage.

3.2.4 Mokken Scale Procedure

As a final step to test the reliability of the potential scales for the revised global MPI we performed the MSP, which is a nonparametric IRT based on "Loevinger's H coefficient […] that corresponds to the observed between-item covariance divided by the maximum possible covariance given the marginal distribution of the two items" (Vaz et al., 2013, p.11). This test was performed for a smaller pool of six countries only,[28] given that the procedure is extremely slow for very large datasets (van der Ark et al., 2013). The ambition was to test if the items that are supposed to measure asset deprivation are grouped in just one Mokken scale or if they are grouped in different Mokken scales.

First, we tested version 2 as identified in section 3.2.2, which is composed of eight items and has a Cronbach Alpha of 0.7 for the pool of 26 countries (telephone, television, computer, internet, bicycle, motorbike, refrigerator and car). We find that the MSP identifies *one scale* that excludes, however, bicycle (an item characterised by a high uniqueness in all EFAs). All remaining items score a Loevinger's H coefficient above 0.5, which is considered to be a strong item fit for a scale.

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[27] We also conducted the analysis with the listwise option and found that the number of observations dropped to 4,178,032. Again, findings confirmed our test results presented in this section, with two exceptions: in the 1pl model, motorbike and refrigerator changed positions in the ascending order of difficulty; second, in the 2pl model, radio joined bicycle and animal cart as a third item that does not depict the vertical S-shape curve of the other items. Hence, around their respective difficult value they discriminate less well between households of similar levels of the latent trait than for the other items.

[28] DR Congo, Ethiopia, Haiti, India, Nigeria and Pakistan. Number of observations: 3.022.474.

Next, we tested version 3 as identified in section 3.2.2, which is composed of nine items and has a Cronbach Alpha of 0.61 for the pool of 26 countries (telephone, television, radio, bicycle, motorbike, car, animal cart, refrigerator and computer). The MSP identifies *two scales*. The first scale consists of refrigerator, car, motorbike, television, telephone and computer. All six items score a Loevinger's H coefficient above 0.5. The second scale could not be constructed because no pair of items from the remaining items (radio, bicycle and animal cart) scored Loevinger's H>0.3.[29]

4. Discussion

(a) Lessons Learned from Statistical Results

In sum, the statistical results presented in section 3 indicate four major lessons:

1. Given the available data across a pool of 26 purposefully selected countries with a reasonable sample size and a wide global population coverage, we find reasons to argue that the assets that meet our suitability criterion should be grouped into *one dimension* of assets deprivation only. Any other categorisation has weak support from the statistical tests (i.e. to group items into categories such as information, mobility or livelihood – e.g. MPI-I, or to distinguish items based on their utility – e.g. to distinguish between durables and productive assets, or tangibility – e.g. tangible and intangible assets). As most items are crosscutting in nature, for example any mobility item can be a livelihood item (such as a motorboat), almost any information item can be a livelihood item (such as telephones or computers). Thus, using just one dimension makes conceptual sense.
2. Land and livestock are productive assets that should not be placed in the assets dimension unless strong conceptual reasons exist to do so. Land and livestock are tangible productive assets of the rural poor in particular, flagged as pivotal "assets of the poor" in the seminal *Voices of the Poor* series. However, serious conceptual reasons and data constraints (further outlined in discussion point b below) will need to be addressed further in order to identify a valid and reliable indicator for the global MPI.[30] If included in the future, greater data availability on productive assets of the urban poor are

[29] As a final check, we also tested the 11 items of the MPI-I. The MSP identifies two scales. Scale one consists of refrigerator, motorboat, motorbike, bicycle, television, telephone and car, yet only refrigerator, motorboat, television and telephone score a Loevinger's H coefficient above 0.5. Scale two consists of land, animal cart and livestock, yet all items have medium scale quality ($0.4 \leq H < 0.5$). We conclude that the MSR rejects the MPI-I measurement model of 11 items grouped in three dimensions.

[30] It is worth noting that the global consultation for the revision of the global MPI, which encompassed academics, UN Agencies, national statistics offices and civil society organisations (see Alkire and Jahan, 2018, and Alkire and Kanagaratnam, 2018), fetched mixed responses about whether to include land and livestock variables in the revised assets index. Forty-two percent of respondents favoured an inclusion against 58% who voted against an inclusion (N=55).

required too. Livelihoods of urban populations are diverse, and the productive assets are often not owned but rented (if owned, they tend to be associated with the employment of the household head such as equipment for small businesses – Banks, 2016, p.119). While housing is undoubtedly one of the most important physical productive assets of the urban poor (and hence captured in the 'living standards' dimension of the global MPI), research has long established that intangible social capital and labour are indispensable productive assets of the urban poor (Baharoglu and Kessides, 2002, p.124; Moser, 1998, p.1; Narayan et al., 1999, p.39). As this obviously also accounts for the rural poor (Ellis, 2000), we call for more research into the area and for greater data availability on tangible and non-tangible productive assets in DHS, MICS and national surveys.

3. A radio, bicycle and animal cart are items with weaker statistical support for inclusion in the assets indicator.
4. A computer is a salient item that should be included in the revised assets of the global MPI based on statistical and conceptual grounds.

(b) Ownership of Agricultural Land

Ownership of agricultural land is a key productive asset, particularly in rural areas, that is linked to progress in many crucial SDG targets (1.4,[31] 2.1 and 2.2). Research, for instance in Zambia, has shown that increasing smallholder farm sizes has substantial poverty reduction potential due to greater agricultural sales (Hichaambwa and Jayne, 2014, p.vii).[32] Winters' et al. meta-regression analysis covering 15 developing countries identified that greater land access is linked to increased agricultural production. The authors found a strong association between land size and crop income earned,[33] which showed a positive correlation in eight of 15 countries (2009, p.1435; p.1446).[34] Land is regarded as a stock renewable resource that fulfils various

31 SDG Target 1.4 asks that by 2030 "all men and women […] have equal rights to economic resources, as well as access to basic services, ownership and control over land".

32 Hichaambwa and Jayne (2014, p.vii) found that an increase in farm size by one hectare was associated with poverty reductions of 86% to 53% for those owning less than one hectare, and from 84% to 48% for all households in their sample, due to an increase in agricultural sales.

33 Further, increases in land ownership were linked to greater participation in so-called self-employment agricultural activities, namely crop and livestock activities (ibid, p.1445), which confirmed existing studys' findings showing a positive relationship between land size and livestock income (Yunez-Naude and Taylor 2001, cited in Winters et al., 2009, p.1437). On the other hand, Yunez-Naude and Taylor (2001) did not find a relationship between crop income and land size in a separate study on Mexico (cited in Winters et al., 2009, p.1437).

34 In two cases however, namely Pakistan and Panama, smaller land size holdings were associated with greater crop income. Winters et al. hypothesized that in specific circumstances smaller farms are more intensively farmed, leading to greater crop income and hence land size becomes less important for income-generating purposes. The authors also highlight that "in a number of cases, greater land ownership limits income from other activities, particularly wage earning activities, indicating those that have access to land tend to use labour on the farm rather than off the farm" (2009, p.1446).

functions, foremost the production of food, fibre, fuel or other biotic materials for human use (FAO and UNEP, 1999, p.8).

The importance of land as a key productive asset is not in doubt. However, the statistical test results presented in section 3 highlighted the somewhat distinct character of this crucial productive asset in comparison to other consumer durables such as telephone, television or refrigerator. In addition, further data concerns[35] that are faced when constructing an internationally comparable indicator on minimum land ownership should be highlighted.

1. Missing values on agricultural land size

As outlined in section 2, missing values and data were assumed to be signs of deprivation in this study. For the original eight items included in the MPI-O, this was of negligible concern, as most missing values were minimal (in our pool of 26 countries below 1% for example). When considering land, the relatively low percentage of missing values in land ownership (below 1% where data on the variable were available in our pool of countries) versus the very high percentage of missing values in land size (up to 69.7% in Angola or 68.9% in India) disallows this assumption (please see Appendix 13 for an overview of missing values in our pool of 26 countries). Households that own land but where members are unable to correctly quantify the land size is a well-known phenomenon in agricultural statistics. Carletto et al. (2016) outline that respondent self-reported land area size, which is one of the three main methods to measure land area in household surveys (the other two being 'compass and rope' and GPS-based measurement), are marred with measurement error that may be systematic. For example, more educated farmers and farmers for whom agriculture is their main livelihood activity have been found to quantify land areas more accurately (2016, p.6). Absentee landlords may

[35] The use of land, and by extension livestock variables, in asset indices highlights their special character. Filmer and Pritchett (2001) included land ownership in their asset index to assess household wealth and children's school enrolment in India, with a cutoff set at more than 6 acres (2.4ha); however, livestock was not included. Giesbert and Schindler (2012) used land size and livestock in their livelihood-based asset index (scaled in PLU) to empirically apply the asset-based poverty traps theory in *rural* Mozambique. Hence, the use of land size ("Size of land cultivated by household with annual crops and fallow land per adult") was justified because land is "the most important agricultural asset in rural Mozambique" (2012, p.1596). Due to the use of PLUs, no minimum land size cutoff was set. Booysen et al. (2008) used an asset index to compare poverty over time and across seven African countries. Land and livestock were not included in their measure. Ferguson et al. (2003) in an asset-based estimation of 'permanent income' used household ownership of durables, information on dwelling characteristics and access to services found in DHS surveys of Greece, Pakistan and Peru, yet land and livestock variables were not used. The Comparable Wealth Index (Rutstein and Staveteig, 2014), which adjusted the original DHS Wealth Index, refrained from using land and livestock variables as well (the original DHS Wealth Index used the number of farm animals (each animal was treated as equal) and size of agricultural land ('continuous land area variable'), yet only in the rural residence-specific wealth index and in an PCA exercise to identify statistical weights).

be less aware of the land size, while the prevalence of traditional or non-standard units challenges respondents to report land size in standardized units such as acres or hectares (ibid, p.7).

2. Data heaping in self-reported agricultural land size

Self-reported agricultural land size has been found to suffer from "data heaping at whole numbers and common fractions, such as 0.5 acres" caused by "the natural inclination of respondents to round off numbers" (Carletto et al., 2016, p.6). For the case of Malawi, Carletto et al. found that data heaping occurred at 0.5acres (0.2ha), 1acre (0.4ha), 2acres (0.8ha) and 3 acres (1.2ha) (2016, p.42). By looking at data from Senegal, Guatemala, Zimbabwe, Haiti and Malawi for example (see Table 13), we find that data heaping is also observable in these countries: in Senegal at 1ha (2.5 acres, 8.92%), in Guatemala at 0.3ha (0.7 acres, 9.5%), 0.7ha (1.7 acres, 11.5%) and 1.1ha (2.7acres, 8.7%), in Zimbabwe at 0ha (13.77%) and 1ha (2.5 acres, 31%), in Haiti from 0 to 0.4ha (0 to 1 acre, which accumulates to 89% of all responses), and in Malawi at 0.2ha (0.5 acres, 10%), 0.4ha (1 acre, 21.4%) and 0.8ha (2 acres, 15.16%). Data heaps occurred, in most of the 26 countries, up until 5ha (12 acres), and flattened afterwards.[36] In many cases data heaps occurred at round numbers, but as Guatemala in particular demonstrates, exceptions exist.

Where exactly the data heaps occur is different in any given country.[37] Data heaping[38] is problematic for the Alkire-Foster methodology, which is used in the global MPI, as the method requires binary data to identify the acutely poor (and by possible extension, the severely poor, the destitute and those vulnerable to poverty, as well). The danger of setting a global cutoff for a minimum land size that *misses* data heaps in any given country is apparent (apart from the fact that no global standard on minimum agricultural land size exists, to

[36] In Peru for example, data heaping occurred at 0ha (15.6%), 1ha (32.97%), 2ha (15.5%), 3ha (8.1%), 4ha (4.5%) and 5ha (4.9%) and again at 10ha (2.6%). In Ethiopia, at 0.5ha (17.8%), 1ha (23.8%), 1.5ha (5.5%), 2ha (12.5%), 3ha (5.2%) and 4ha (2.7%). Exceptions include Guatemala, where additional data heaps occurred at 6.2ha (4%), 7.8ha (2.9%) and 37 or more hectares (5.3%); Senegal, where another data heap was found at 10ha (4.4%); Zimbabwe, with another data heap at 6ha (4%) and Tanzania, with additional heaps at 6ha (5.1%) and 7ha (3.1%).

[37] With regards to self-reported information on income, Zinn and Würbach have highlighted that data heaping usually does not occur completely at random wherefore heaping and rounding effect the results of statistical analyses (2016, p.682). Existing statistical approaches to heaping correction have been found to lack interpretability as they rely primarily on smoothing techniques but do not impose a model for the heaping process (Groß and Rendtel, 2016, p.341). Further, Zinn and Würbach highlight that the "statistical modelling of heaping [is] mainly defined for specific applications, for example, for dealing with misreported cigarette counts" (Zinn and Würbach, 2016, p.684). Statistical modelling is similar in that it is based on a "set of rules describing the latent heaping mechanism [that] might be defined either explicitly or implicitly" and that "analysis based on heaped data can immensely be improved if heaped data are replaced by imputed ones" (ibid). However, as a) neither internal nor external rules for latent data heaping mechanisms at the global scale for self-reported land size exists (to our knowledge) and b) appropriate imputation techniques in the field of multidimensional poverty measurement are yet to be developed (Alkire et al., 2015, p.228), this means that uncorrected data heaping will continue to pose a serious problem to accurately identifying those deprived in minimum land size.

[38] Data heaping helps to explain discrepancies found between GPS area measures and farmer self-reported farm areas, with a trend where the smallest plots are "systematically" over-reported, while the largest plots tend to be under-estimated (Carletto et al., 2013; 2015; Desiere and D'Haese, 2015, cited in Carletto et al., 2016, pp.6–7).

be further debated in the subsequent discussion point (c). The interpretation of results will be complicated, and the comparability between countries will be lost.

Table 13: Hectares of Agricultural Land in Senegal, Guatemala, Zimbabwe, Haiti and Malawi

Hectares of agricultural land (1 decimal): Frequency (percentage)	Senegal	Guatemala	Zimbabwe	Haiti	Malawi
0	.	1,202 (3.25%)	**3,804(13.49%)**	**17,041 (41.34%)**	.
1	92 (0.46%)	543 (1.47%)	45 (0.16%)	**9,426 (22.87%)**	2,459 (2.65%)
2	198 (0.99%)	.	5 (0.02%)	**6,831 (16.57%)**	**9,311 (10.04%)**
3	.	**3,516 (9.51%)**	.	**2,499 (6.06%)**	1,650 (1.78%)
4	47 (0.23%)	15 (0.04%)	5 (0.02%)	927 (2.25%)	**19,808 (21.37%)**
5	910 (4.54%)	223 (0.60%)	96 (0.35%)	771 (1.87%)	3,889 (4.20%)
6	9 (0.04%)	10 (0.03%)	.	291 (0.71%)	4,874 (5.26%)
7	16 (0.08%)	**4,250 (11.49%)**	8 (0.03%)	112 (0.27%)	515 (0.56%)
8	41 (0.20%)	.	2 (0.01%)	129 (0.31%)	**14,052 (15.16%)**
9	.	150 (0.41%)	.	24 (0.06%)	404 (0.44%)
10	**2,273 (11.33%)**	.	**8,962 (31.78%)**	170 (0.41%)	6,740 (7.27%)
11	.	**3,226 (8.72%)**	6 (0.02%)	14 (0.03%)	150 (0.16%)
12	28 (0.14%)	7 (0.02%)	7 (0.03%)	26 (0.06%)	6,209 (6.70%)

Data heaps highlighted in bold font. Presented hectare sizes restricted to 1.2ha (3 acres).

The alternative is to set cutoffs at rather large hectare sizes such as 3ha, 6ha or 10ha, thus at sizes where most data heaps ceased to occur. However, this may be considered as an overestimation of deprivation, particularly in parts of Asia and Eastern Europe that are characterised by land scarcity (Winters et al., 2009: 1437) and smaller farm sizes (as found for example in Bangladesh, where 90% of the respondents owned only up to 0.2ha).

3. Strong regional variations in average farm sizes

According to the smallholders' data portrait of FAO's Family Farming Knowledge Platform, which presents "a comprehensive, systematic and standardized data set on the profile of smallholder farmers across the world" (FAO, 2018), the hectare-weighted median in farm size varies strongly both at the regional and global level. In Sub-Saharan Africa, the range was from 0.7ha in Malawi to 4.57ha in Niger, while in Latin America and the Caribbean the range was from 0.94ha in Guatemala to 9.2ha in Nicaragua. Europe and Central Asia are characterised by small average farm sizes, e.g. 0.32ha in Tajikistan, a similar pattern as found in Asia (with a range from 0.54ha in Bangladesh to 1.31ha in Cambodia). Therefore, setting land size cutoffs is meaningful at best at the regional scale, but not at the required global scale for the global MPI.

4. Lack of data on farm production in most DHS, MICS and national surveys

According to the FAO, improvements in farming systems are related to the intensification of existing patterns of farm production, the diversification of production and increased operational farm size (Dixon et al., 2001, p.29). Global farming systems are extremely diverse but can be broadly categorised into irrigated farming systems, wetland rice-based farming systems, rainfed farming systems in humid areas, rainfed farming systems in steep and highland areas, rainfed farming systems in dry or cold low potential areas, dualistic (mixed large commercial and small holders) farming systems, coastal artisanal fishing systems and urban-based farming systems, typically horticultural (ibid, p.2).

Due to a lack of data on farm productions under these various farming systems in the DHS, MICS and most national surveys, such as the value of food production per hectare and the value of crop production, we find that the quantity of land size (be it any land size as used in the MPI-I or potentially a minimum land size) as an indicator of land deprivation is too restrictive. Minimum data requirements for a *meaningful indicator of land* that is relevant to policy makers should understand the ratio of cultivated and irrigated land per person among the agricultural population in any given farming system.

In sum, in light of these four reasons we conclude that the available data on land ownership (yes/no) and land size in the DHS, MICS and most national surveys are too restrictive to design a meaningful indicator that can be included in the revised assets indicator of the global MPI.

Eventually, setting a minimum land size cutoff that is *not* linked to the sustainable use of land would also violate the *poverty focus principle* of the Alkire-Foster method, which requires that "poverty should not change if there is an improvement in any achievement of the non-poor person" (Alkire et al., 2015, p.55). An increase in ownership of land by the non-poor population is likely to affect the ownership of land of the poor population, as available arable land is finite[39] and global population growth is projected to reach 8.5 billion by 2030 (a 16.4% increase from the current world population of 7.3 billion).[40] Hence, a land indicator that may set policy incentives that potentially create trade-offs in the form of potential land conflicts among the poor and non-poor (and, by extension, also among the poor) should be avoided.

[39] According to FAO estimates, the size of the arable land worldwide in 2015 was estimated as 1.425,918.77ha (1000 ha) (FAO, 2017).

[40] According to data presented in the 2017 Revision of World Population Prospects prepared by the Population Division of the Department of Economic and Social Affairs of the United Nations Secretariat (UN DESA, 2017).

(c) Trial Analysis

As a final step, we calculated 24 trial measures of asset deprivations across our sample of 26 countries. Table 14 presents the various versions, which were grouped into seven categories. This follows global MPI practice as established in Alkire and Santos (2010, p.13), who calculated between four and eight trial measures for up to 108 countries at various stages of the identification process for the global MPI in 2010. The objective was to empirically explore and analyse certain characteristics of items that stood out during the statistical tests conducted in section 3. These trial measures were primarily concerned with the radio, bicycle and animal cart variables, but we also assessed how the car variable would behave if treated as a veto compared to considering it as any other item in an equally weighted list of items. Test results were presented to UNDP HDRO staff and statistical advisors at various meetings between March and August 2018. Comprehensive tests results are presented in the supplementary materials, together with summary statistics about the percentage of ownership of items in each country. We deliberately excluded using version one and two from section 3.2.2, but operated with version three (which in Table 14 is trial measure 23). Instead of discussing all test results in this paper, we will focus on a several observations that shaped the final selection of the revised assets indicator of the global MPI that will be presented at the end of this section.

First, we found that certain items, such as a radio or a bicycle, are owned widely in some of the countries of our pool, but not in others. For example, while more than half of the population in Kenya or Haiti owned a radio, less than 10% of the population owned this item in Bangladesh, India or Armenia. Bicycle ownership shares this fluctuating pattern. For example, ownership of bicycles in Ethiopia was less than 3%, whereas in Tanzania they were owned by almost half of the population. Consequently, excluding a radio from the set of assets used in the MPI-O (trial version 2) caused a 23.5% and 20.4% increase in the raw headcount ratio of assets in Kenya and Haiti, respectively (compared to the MPI-O, trial version 1), whereas the raw headcount ratio remained almost identical in Bangladesh, India and Armenia (with less than a 1% difference between trial version two and one). Similarly, excluding a bicycle (trial version 3) resulted in a 0.3% difference to the MPI-O in Ethiopia but a 14.4% difference in Tanzania.

Table 14: List of Asset Trial Versions

Add and Subtract

1. MPI-O
2. MPI-O minus Radio
3. MPI-O minus Bicycle
4. MPI-O plus Computer

…………………………………………………………………….

Veto of car

5. MPI-O equal weight

…………………………………………………………………….

Add two 'localised' items

6. MPI-O plus Motorboat
7. MPI-O plus Animal Cart
8. MPI-O plus Motorboat and Animal Cart

…………………………………………………………………….

Added-value of Radio

9. MPI-O Radio replaced with Computer plus Motorboat
10. MPI-O Radio replaced with Computer plus Animal Cart
11. MPI-O Radio replaced with Computer plus Motorboat and Animal Cart

…………………………………………………………………….

Land ownership[41]

12. MPI-O plus Computer, Animal Cart, Motorboat, min. land size 3ha
13. MPI-O plus Computer, Animal Cart, Motorboat, min. land size 6ha
14. MPI-O plus Computer, Animal Cart, Motorboat, min. land size 10ha
15. MPI-O plus Computer, Animal Cart, Motorboat, any land size
16. MPI-O plus Computer, Animal cart, min. land size 6ha, 1.5 Livestock Units

…………………………………………………………………….

Three new items (bank, overcrowding, livestock)

17. MPI-O plus Computer, Animal cart, min. land size 6ha, 1 Livestock Unit, Bank Account, Overcrowding (3 persons/room)
18. MPI-O plus Computer, Animal cart, min. land size 10ha, 1.5 Livestock Units, Bank Account, Overcrowding (3 persons/room)
19. MPI-O plus Computer, Animal cart, min. land size 6ha, Bank Account, Overcrowding (3 persons/room)
20. MPI-O plus Computer, Animal cart, Bank Account, Overcrowding (3 persons/room)
21. MPI-O plus Computer, Animal cart, minimum land size 10ha, Bank Account, Overcrowding (3 persons/room)
22. MPI-O plus Computer, Animal cart, Overcrowding (3 persons/room)
23. MPI-O plus Computer, Animal cart

…………………………………………………………………….

Kitchen Sink

24. 'Kitchen sink' analysis (17 items): Telephone, television, radio, computer, internet, bank, bicycle, motorbike, motorboat, car, animal cart, refrigerator, land, livestock, sewing machine, air conditioner and washing machine

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[41] The analysis also comprised computations for lower-end cutoffs of land ownership 0.3ha, 0.6ha and 1ha.

While the assumption seems justified that, for instance in Armenia, the greater prevalence of a computer (78%) and access to internet (77%), so-called high-end possessions and amenities (see Rutstein and Staveteig 2014: 1), may replaced (or substituted) a radio as a popular item to access information and entertainment in this country, no such assumption can be made in Kenya, where data on computer and internet were missing (see Appendix 13). The same is true for Haiti, where less than 5% of the population own a computer or have internet access. Hence, excluding radio from the list of items used in the revised assets indicator of the global MPI seemed unjust *if* such an exclusion causes a greater raw headcount ratio in assets in countries where either data on 'substitution items', such as a computer and/or internet access, were still missing (such as in Kenya), or where such items are still not owned widely (such as in Haiti). The same is true for bicycles, which in most of the countries in our pool seem not to be substituted by higher-end possessions such as motorbikes as of yet (ownership of motorbikes was lower than for bicycles in 19 out of the 26 countries). In contrast, adding a computer to the MPI-O list of assets resulted in little change in the raw headcount ratio (a reduction of approximately 0.5% points between trial version 4 and 1). This is due to low average ownership of a computer as an upper-end item (with less than 20% ownership in our sample).

In other words, although radio and bicycle stood out as items that fit less well into the identified dimension of asset deprivation as found in section 3, conceptual reasons led to the decision to not substitute these items, but to keep them both included in the revised assets indicator.

A second interesting observation concerns the role of a car. The IRT identified a car as one of the most difficult items to obtain in our sample and as an item that discriminates between households of similar ability levels in the latent trait – in our case, asset (or material) deprivation. Empirically we find that using a car not as a veto but as any other item in an unweighted list makes no statistical difference (the difference between trial version 5 to the MPI-O is less than 0.5 percentage points).

In other words, households that own a car also own at least two of the smaller items of the MPI-O (telephone, television, radio, bicycle, refrigerator or motorbike). It therefore seems more logical, from a conceptual and communications point of view, to continue assigning a car the veto role in the revised indicator, to highlight the exceptional status of this upper-end item.

Third, we find that an animal cart, which was identified as the item that was most difficult to obtain in the 1pl model for version 3 in the IRT analysis presented in section 3.2.3.2, is a rather *localised item*. Average ownership of an animal cart was the second lowest of all 17 items that were eventually placed into the 'kitchen sink' analysis of trial version 24 (only a motorboat was owned less frequently, on average). Senegal and Zimbabwe stood out as countries where this item was rather prevalent, where approximately one-third of the population owned the item. Unsurprisingly, adding animal cart and motorboat (trial version 8) to the MPI-O resulted in rather moderate changes in the raw headcount ratio (with decreases of 5.4% and 5% in Senegal and Zimbabwe, yet of maximum 2% in the other countries).

Since an animal cart is an item for which data are widely available (in 77 countries covering 4.8 billion people), and because an animal cart is an item that does not require electricity, it was decided to include animal cart in the revised global MPI.

We flag that an animal cart is distinctly a rural item, as highlighted by the MCA projection plot for the rural population as presented in Graph 7 of section 3.1.2. While the assets indicator aims at being salient for both urban and rural populations, including this localised item seemed just given that the raw headcount ratio in assets in rural areas of the MPI-O has been traditionally higher than in urban areas, which may be perceived as an urban bias by some (for a debate on whether the assets indicator of the MPI-O has an urban bias, please see Dotter and Klasen 2014, pp.19–20).

Fourth, operating with different land sizes changed, as expected, the raw headcount ratios considerably, with up to six and seven percentage point decreases with a 3ha cutoff in Côte d'Ivoire and Tanzania for example. African countries were particularly affected by such decreases (e.g. DR Congo and Ethiopia),[42] and fluctuations remained pronounced in some countries even when very generous cutoff points were used (e.g. 10ha, with up to six percentage points difference in Tanzania to a 3ha cutoff). Fluctuations increased even further when lower-level land size cutoffs were used, such as 0.3ha and 1ha (with 27 and 18 percentage point decreases, respectively in Ethiopia for example). The fluctuations can be best explained by the data heaping as described in section 4, but is also due to different patterns of land ownership in different countries of our pool.[43]

Fifth, the kitchen sink analysis produced reductions in the raw headcount ratio throughout, ranging from small changes to the MPI-O in Brazil (-0.02%) to decreases of up to 45% in Ethiopia. The kitchen sink approach of identifying those who are deprived in assets is distinct from identifying the 'severity of non-deprivation'

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42 Combining a generous minimum land size cutoff of 6ha with a generous livestock unit of 1.5 (trial version 16) caused substantial decreases in the raw headcount in some countries, of up to 22% in Ethiopia for example.

43 Malawi and Haiti are cases in point. Malawi is a country with land scarcity (Makombe et al., 2010), and small average farm sizes (0.7ha according to the aforementioned smallholders' data portrait of the FAO). The trial analysis revealed that with a cutoff of 3ha, 90% were deprived in land size, while the cutoff of 0.3ha resulted in a 15% deprivation rate. This resulted in a percentage difference in the raw headcount in assets of almost 15%. This was different in Haiti for example, where 80.8% were already land deprived with a 0.3ha cutoff. Hence, the percentage difference to a cutoff of 3ha was less pronounced – less than two percentage points.

which underpinned the IRT analysis presented in section 3.2.3. Whereas the latter aims at identifying the non-deprived in assets by including items that are hard to obtain,[44] the kitchen sink logic assembles as many items as possible to find those who are deprived in assets. Consequently, if a household has none or only one item in an assembled long list of possible items, it is very likely that it is either an easy to obtain item (items that are widely available in the population, such as telephones) or a localised item (animal cart and motorboat come to mind most strongly). But, if a household struggles to obtain a non-deprived status even if given the opportunity to do so through two easy to obtain items, the certainty is high that the household is indeed deprived in assets. It would be very unlikely to not have items that are owned widely and hence are easy to obtain, but to own items, almost exclusively, that are hard to obtain or localised.

Both approaches for identifying those who are deprived in assets are prone to errors. The severity of the non-deprivation approach increases the certainty about the non-deprived population in assets but may overestimate the raw headcount ratio. The kitchen sink approach increases the certainty about the population who suffer deprivations in assets but may overestimate the non-deprived population. As shown by the Ethiopian case, the reductions are substantial indeed, and 45% of those previously deprived in assets became non-deprived. As this may be a false positive, the decision was taken to eventually dismiss this kitchen sink approach for the revision of the assets indicator.

The remaining items, namely bank account and overcrowding, faced additional challenges. While ownership of a bank account relates well to such concepts as 'liquid assets' (Haveman and Wolff, 2004), a lack of data on the liquid savings households hold may mean that the ownership of a bank account results again in a false positive. Overcrowding or 'sufficient living area', as described by UN-HABITAT (2006, p.71), relates well to SDG Target 11.1 and to the Human Right to Adequate Housing (Article 25 of the Universal Declaration on Human Rights). As an indicator of overcrowding (or number of rooms in dwelling), it is often used in applications of asset or standards of living indices (e.g. Pritchett and Filmer, 2001; Angulo et al., 2016; Gallo and Roche, 2012). Although UN-HABITAT uses an operational definition of overcrowding as *three persons per room*, it is acknowledged that cultural perceptions of overcrowding vary widely, and that "there is no basis in

44 If a household owns one hard to obtain item, i.e. an item that is owned by less than half the population, the household is almost certainly non-deprived in assets. As previously highlighted, households owning a car also owned two other items in our sample. When a household owns a motorbike or a refrigerator, the likelihood is increased that the household also owns easy to obtain items, such as telephones, televisions (which were owned by more than half of the population in our sample of 26 countries; while a telephone was owned by more than 50% in each of the 26 countries, television had an ownership of more than 50% in only 16 countries). The probability of owning items that can be assumed to be available more widely, such tables or chairs, but which were not included in the MPI-O or in the analysis of this paper, given the limited data availability of these items (see Table 2 in section 2, where it is highlighted that data for tables and chairs were only available in 31 and 37 countries, respectively) is also increased.

scientific literature for choosing one standard of unacceptable overcrowding over another. Countries define the crowding indicator in different ways" (UN Habitat, 2006, p.71).

While acknowledging the normative value of the two items, the described uncertainties resulted in the decision to not include the two items in the revised assets indicator, and to the eventual decision to use trial version 23 as the revised assets indicator of the global MPI. The indicator is identical to version three as presented in section 3.2.2, with the exception that a car will continue to be used as a veto.

Overall, the difference between the revised assets indicator and the MPI-O in the pool of 26 countries was moderate. Senegal and Zimbabwe showed the greatest reductions – of approximately 5% – driven by the described greater prevalence of animal carts in the two countries.

Concluding Remarks

This paper makes two contributions to the literature on multidimensional poverty measurement. First, it explained the revision of the asset indicator of the updated global Multidimensional Poverty Index in 2018. The updated index was launched just before the 73rd Session of the United Nations General Assembly in September 2018 and is, as much as available data permits, aligned with the Sustainable Development Goals of the 2030 Agenda for Sustainable Development. The revision of the assets indicator was informed by the analytical approach adopted in the revision of the 13-item material deprivation indicator in the European Union (Guio et al. 2012, 2016, 2017). We utilised a mix of statistical tests, public consultations, normative reasoning and extensive trial measures of possible asset indices to identify a set of items that is 'suitable', 'valid' and 'reliable' to proxy assets deprivation globally for both urban and rural populations. The outcome of this conversation is that the revised assets indicator maintained the structure of the MPI-O, jointly designed by OPHI and UNDP HDRO in 2010, but added computer and animal cart as additional items.

The second contribution is the transparency about the decision-making process. By embedding the analysis in the large literature on asset index construction in welfare economics, the affirmative decision to add computer and animal cart to the list of items of the MPI-O must be seen in light of the many decisions that were taken along the way, to questions such as:

1. Should items be grouped into sub-dimensions based on their utility or some other function?
2. Should crucial productive assets such as land and livestock be included in the revised asset index, even if current data is limited?
3. Should 'assets' be renamed, for instance to 'material deprivation' or some other 'factor label' that best describes the revised assets index (given that the term 'assets' is very broad and conceptually

laden, and that it creates connotations and expectations, particularly with respect to productive assets)?

4. Should statistical weights replace the normative weights of the counting-based asset indices applied in the MPI-O and MPI-I?
5. Should conceptually strict approaches to material deprivation be adopted to identify those deprived in assets, such as the kitchen sink logic or, on the other end of the spectrum, a 'severity of non-deprivation' approach?
6. Should 'car' be treated as any other item?
7. Should the 'living standards' dimension be re-structured, as it includes electricity, housing, cooking fuel, sanitation and safe drinking water – crucial assets in the broader sense that are widely featured in empirical asset indices, such as those found in Filmer and Pritchett (2001), Ferguson, et al. (2003) or Booysen et al. (2008)?[45]

Throughout this paper we explained the empirical and normative reasons as to why these valid questions were answered in the negative. While questions one and two guided the research, the others arose in result presentations and consultations with UNDP HDRO staff and statistical advisors at various meetings between March and August 2018. We highlight that such questions are worth revisiting in future revisions. But first we re-iterate previous advocacies for a 'data revolution' in poverty[46] and further advancements in data linking, data correction, data imputation and related statistical and methodological techniques in the field of multidimensional poverty measurement, such as was voiced in Alkire and Jahan (2018), Alkire (2014) and Alkire et al. (2015, p.228).

45 Here the answer was 'no', because the assets of the revised and updated global MPI 2018 are distinct from the other items in the living standards dimension, in that a) these particular assets do not relate directly to any SDG Indicator (as 'assets of the poor' they certainly relate to well-being); and b) the alleviation of deprivations in assets may require no (or less) direct policy intervention.

46 As highlighted in Dotter and Klasen who offered a stock-take of the Multidimensional Poverty Index in 2014, better data collection on assets ownership should include data on age, current value and state of repair (2014, p. 20). The quantity of each item owned would be another useful addition.

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Appendices

Appendix 1: MPI-I: EFA on Six Individual Countries

DR Congo				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	51%	30%	18%	95703
Rotated Factor Loadings(1)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.8644			0.1867
Information: Television	1.0090			-0.0109
Information: Radio	0.5245			0.4524
Mobility: Bicycle			0.6544	0.5569
Mobility: Motorbike				0.6226
Mobility: Motorboat		1.3089		-0.7130
Mobility: Car	0.8258			0.2909
Mobility: Animal cart				0.6733
Livelihood: Refrigerator	0.7814			0.2649
Livelihood: Land	-0.5481			0.6082
Livelihood: Livestock			0.6664	0.5405
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	5	1	2	8
Cronbach's Alpha	0.69	.	0.37	0.57

(1) Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Ethiopia				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	63%	29%	0.07	75152
Rotated Factor Loadings(1)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone		0.8973		0.1366
Information: Television	0.7607			0.0085
Information: Radio		0.5331		0.6879
Mobility: Bicycle			0.5423	0.4660
Mobility: Motorbike			0.6870	0.4496
Mobility: Motorboat			1.1487	-0.1246
Mobility: Car	0.5149		0.5369	0.1847
Mobility: Animal cart			0.6618	0.4174

Livelihood: Refrigerator	0.7805			0.0258
Livelihood: Land	-0.8066			0.3654
Livelihood: Livestock	-1.0079			0.1259
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	3	2	5	10
Cronbach's Alpha	0.66	0.44	0.51	0.62

(1) Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Haiti				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	52%	25%	22%	59377
Rotated Factor Loadings(1)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.6100			0.3039
Information: Television	0.9242			0.0812
Information: Radio	0.7811			0.3982
Mobility: Bicycle				0.7654
Mobility: Motorbike				0.7298
Mobility: Motorboat		1.2092		-0.4275
Mobility: Car	0.7518			0.3808
Mobility: Animal cart		-0.5597	0.5339	0.3825
Livelihood: Refrigerator	0.8889			0.1894
Livelihood: Land			0.6278	0.4991
Livelihood: Livestock			0.9602	0.0273
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	5	2	3	8
Cronbach's Alpha	0.66	.	0.41	0.38

(1) Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Kenya				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	60%	26%	14	152242
Rotated Factor Loadings(1)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.5216	0.5330		0.3217
Information: Television	0.8416			0.2337
Information: Radio		0.5458		0.4912

Mobility: Bicycle				0.6550
Mobility: Motorbike				0.6943
Mobility: Motorboat				0.8810
Mobility: Car	0.6925			0.4293
Mobility: Animal cart			0.8795	0.2936
Livelihood: Refrigerator	1.0176			0.0517
Livelihood: Land		0.7521		0.5248
Livelihood: Livestock				0.7094
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	3	2	1	6
Cronbach's Alpha	0.59	0.31	.	0.44

(1) Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Nigeria				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	60%	31%	0.09	175208
Rotated Factor Loadings(1)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.6918			0.3520
Information: Television	0.8167			0.1011
Information: Radio	0.5719			0.5633
Mobility: Bicycle				0.7583
Mobility: Motorbike			0.8174	0.2492
Mobility: Motorboat				0.9628
Mobility: Car	0.8287			0.4102
Mobility: Animal cart		0.6175		0.6462
Livelihood: Refrigerator	0.9019			0.1645
Livelihood: Land		0.6214		0.3812
Livelihood: Livestock		0.7995		0.2750
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	5	3	1	9
Cronbach's Alpha	0.68	0.49	.	0.43

(1) Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Pakistan				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	56%	32%	12%	93541

Rotated Factor Loadings(1)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.7039			0.5065
Information: Television	0.7343			0.4154
Information: Radio				0.8628
Mobility: Bicycle				0.8364
Mobility: Motorbike	0.5790			0.6413
Mobility: Motorboat	0.5206			0.5027
Mobility: Car	0.7628			0.3994
Mobility: Animal cart		0.8838		0.1877
Livelihood: Refrigerator	0.8866			0.1833
Livelihood: Land			0.8017	0.3677
Livelihood: Livestock			0.5646	0.2309
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	6	1	2	9
Cronbach’s Alpha	0.58	.	0.53	0.42

(1) Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Appendix 2: MPI-I Alt. 1: EFA, Pool of 26 Countries

Pooled(1)				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	59.5%	29.2%	11.3%	1,429,780
Rotated Factor Loadings(2)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.7226			0.3225
Information: Television	0.8682			0.1295
Information: Radio				0.9168
Mobility: Bicycle		0.5715		0.7103
Mobility: Motorbike		0.5695		0.4887
Mobility: Motorboat				0.9102
Mobility: Car	0.7313			0.4850
Mobility: Animal cart				0.4608
Livelihood: Refrigerator	0.9926			0.0578
Livelihood: Land (3ha)				0.8238
Livelihood: Livestock			0.9944	0.0493
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	4	2	1	7
Kaiser-Meyer-Olkin				0.6060

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Appendix 3: MPI-I Alt. 1: EFA, Pool of 26 Countries

Pooled(1)				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	57.6%	29.7%	12.5%	1,429,780
Rotated Factor Loadings(2)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.7586			0.3112
Information: Television	0.9179			0.1073
Information: Radio				0.9220
Mobility: Bicycle			0.6017	0.6695
Mobility: Motorbike				0.5376
Mobility: Motorboat				0.9134
Mobility: Car	0.7090			0.5157
Mobility: Animal cart			0.5078	0.5162
Livelihood: Refrigerator	0.9780			0.0708
Livelihood: Land (0.3ha)				0.6054
Livelihood: Livestock		1.1301		-0.2334
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	4	1	2	7
Kaiser-Meyer-Olkin				0.6286

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Appendix 4: MPI-I Alt. 2: EFA, Pool of 26 Countries

Pooled(1)				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	59.8%	29.3%	10.9%	1,470,027
Rotated Factor Loadings(2)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.7431			0.3020
Information: Television	0.8906			0.1019
Information: Radio				0.9187
Mobility: Bicycle			0.5872	0.6944
Mobility: Motorbike			0.5464	0.5080
Mobility: Motorboat				0.9111
Mobility: Car	0.7280			0.5028
Mobility: Animal cart				0.5005
Livelihood: Refrigerator	0.9869			0.0664
Livelihood: Land				0.6215
Livelihood: Livestock		1.0605		-0.0451
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	4	1	2	7
Kaiser-Meyer-Olkin				0.6252

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Appendix 5: MPI-I Alt. 3: EFA, Pool of 26 Countries

Pooled(1)				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	61.3%	28.1%	10.6%	1,470,027
Rotated Factor Loadings(2)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.7430			0.3097
Information: Television	0.8432			0.1270
Information: Radio				0.9083
Mobility: Bicycle				0.7649
Mobility: Motorbike		0.6424		0.4257
Mobility: Motorboat				0.9036
Mobility: Car	0.7415			0.4722
Mobility: Animal cart			0.5591	0.3997
Livelihood: Refrigerator	0.9611			0.0798
Livelihood: Land (3ha)				0.8760
Livelihood: Livestock			0.9057	0.2207
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	4	1	2	7
Kaiser-Meyer-Olkin				0.5945

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Appendix 6: MPI-I Alt. 3: EFA, Pool of 26 Countries

Pooled(1)				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	58%	29.7%	12.3%	1,470,027
Rotated Factor Loadings(2)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.7654			0.3016
Information: Television	0.9170			0.1055
Information: Radio				0.9194
Mobility: Bicycle			0.5971	0.6731
Mobility: Motorbike				0.5389
Mobility: Motorboat				0.9123
Mobility: Car	0.7110			0.5126
Mobility: Animal cart			0.5094	0.5099
Livelihood: Refrigerator	0.9758			0.0762
Livelihood: Land (0.3ha)				0.6249
Livelihood: Livestock		1.1179		-0.2084
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	4	1	2	7
Kaiser-Meyer-Olkin				0.6116

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Appendix 7: MPI-I Alt. 4: EFA, Pool of 26 Countries

Pooled(1)				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	59.1%	29.4%	11.5%	1,470,027
Rotated Factor Loadings(2)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.7233			0.3140
Information: Television	0.8813			0.1260
Information: Radio				0.9156
Mobility: Bicycle		0.5966		0.6892
Mobility: Motorbike		0.5322		0.5158
Mobility: Motorboat				0.9143
Mobility: Car	0.7295			0.4860
Mobility: Animal cart				0.4813
Livelihood: Refrigerator	1.0002			0.0573
Livelihood: Land (3ha)				0.8207
Livelihood: Livestock			1.0328	-0.0308
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	4	2	1	7
Kaiser-Meyer-Olkin				0.6135

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Appendix 8: MPI-I Alt. 4: EFA, Pool of 26 Countries

Pooled(1)				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	57.2%	30%	12.7%	1,470,027
Rotated Factor Loadings(2)				
Variable	**Factor1**	**Factor2**	**Factor3**	**Uniqueness**
Information: Phone	0.7562			0.3038
Information: Television	0.9226			0.1052
Information: Radio				0.9181
Mobility: Bicycle			0.6131	0.6573
Mobility: Motorbike				0.5522
Mobility: Motorboat				0.9167
Mobility: Car	0.7104			0.5121
Mobility: Animal cart			0.5044	0.5301
Livelihood: Refrigerator	0.9823			0.0677
Livelihood: Land (0.3ha)				0.6130
Livelihood: Livestock		1.1538		-0.2870
Items retained	**Factor1**	**Factor2**	**Factor3**	**All Items**
Items retained	4	1	2	7
Kaiser-Meyer-Olkin				0.6419

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

(2)Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.

Appendix 9: MPI-I: MCA Statistics for Column Categories in Principal Normalization, Pool of 26 Countries

Pooled(1)									
	Overall			**Dimension 1**			**Dimension 2**		
Categories	Mass	Quality	%inert	Coord	Sqcorr	contribution	Coord	Sqcorr	contribution
Phone									
No	0.021	0.879	0.090	0.336	0.836	0.100	0.076	0.043	0.049
Yes	0.070	0.879	0.026	-0.098	0.836	0.029	-0.022	0.043	0.014
Television									
No	0.049	0.802	0.115	0.241	0.802	0.123	-0.001	0.000	0.000
Yes	0.042	0.802	0.134	-0.281	0.802	0.143	0.001	0.000	0.000
Radio									
No	0.048	0.767	0.016	0.074	0.542	0.011	0.048	0.225	0.044
Yes	0.043	0.767	0.017	-0.082	0.542	0.013	-0.053	0.225	0.049
Bicycle									
No	0.063	0.813	0.010	0.037	0.291	0.004	0.050	0.522	0.063
Yes	0.028	0.813	0.022	-0.083	0.291	0.008	-0.111	0.522	0.142
Motorbike									
No	0.068	0.870	0.024	0.095	0.837	0.027	0.019	0.033	0.010
Yes	0.023	0.870	0.072	-0.288	0.837	0.081	-0.057	0.033	0.030
Motorboat									
No	0.090	0.721	0.000	0.002	0.561	0.000	0.001	0.160	0.000
Yes	0.001	0.721	0.002	-0.195	0.561	0.001	-0.104	0.160	0.004
Car									
No	0.083	0.883	0.007	0.048	0.875	0.008	0.004	0.007	0.001
Yes	0.008	0.883	0.075	-0.505	0.875	0.087	-0.046	0.007	0.007
Animal Cart									
No	0.088	0.780	0.001	-0.003	0.030	0.000	0.013	0.750	0.006
Yes	0.003	0.780	0.017	0.070	0.030	0.001	-0.350	0.750	0.162
Refrigerator									
No	0.070	0.817	0.050	0.134	0.815	0.054	-0.008	0.003	0.002
Yes	0.021	0.817	0.162	-0.436	0.815	0.175	0.025	0.003	0.005
Land									
No	0.040	0.842	0.052	-0.168	0.703	0.049	0.075	0.139	0.091
Yes	0.051	0.842	0.040	0.131	0.703	0.038	-0.058	0.139	0.071
Livestock									
No	0.062	0.799	0.022	-0.076	0.519	0.015	0.056	0.281	0.079
Yes	0.029	0.799	0.048	0.162	0.519	0.033	-0.119	0.281	0.169

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

Appendix 10: MPI-I: MCA Statistics for Column Categories in Principal Normalization, Pool of 26 Countries, Rural Population

Pooled(1)									
	Overall			**Dimension 1**			**Dimension 2**		
Categories	Mass	Quality	%inert	Coord	Sqcorr	contribution	Coord	Sqcorr	contribution
Phone									
No	0.029	0.859	0.090	0.241	0.817	0.105	0.055	0.042	0.036
Yes	0.062	0.859	0.041	-0.110	0.817	0.048	-0.025	0.042	0.016
Television									
No	0.064	0.777	0.072	0.139	0.767	0.078	-0.016	0.010	0.007
Yes	0.026	0.777	0.175	-0.337	0.767	0.190	0.039	0.010	0.017
Radio									
No	0.052	0.761	0.020	0.058	0.396	0.011	0.056	0.365	0.068
Yes	0.038	0.761	0.027	-0.079	0.396	0.015	-0.076	0.365	0.092
Bicycle									
No	0.062	0.876	0.018	0.065	0.637	0.016	0.040	0.239	0.040
Yes	0.029	0.876	0.038	-0.137	0.637	0.035	-0.084	0.239	0.086
Motorbike									
No	0.072	0.846	0.032	0.092	0.846	0.038	-0.001	0.000	0.000
Yes	0.019	0.846	0.118	-0.341	0.846	0.142	0.004	0.000	0.000
Motorboat									
No	0.090	0.959	0.000	0.004	0.917	0.000	-0.001	0.042	0.000
Yes	0.001	0.959	0.005	-0.329	0.917	0.007	0.071	0.042	0.002
Car									
No	0.087	0.863	0.004	0.030	0.857	0.005	-0.002	0.006	0.000
Yes	0.004	0.863	0.082	-0.608	0.857	0.100	0.049	0.006	0.004
Animal Cart									
No	0.087	0.750	0.001	0.010	0.271	0.001	0.013	0.480	0.006
Yes	0.004	0.750	0.026	-0.189	0.271	0.010	-0.251	0.480	0.115
Refrigerator									
No	0.082	0.794	0.018	0.061	0.753	0.019	-0.014	0.041	0.007
Yes	0.009	0.794	0.160	-0.542	0.753	0.171	0.126	0.041	0.061
Land									
No	0.025	0.790	0.021	-0.058	0.172	0.005	0.109	0.618	0.123
Yes	0.066	0.790	0.008	0.022	0.172	0.002	-0.041	0.618	0.046
Livestock									
No	0.052	0.708	0.018	-0.007	0.007	0.000	0.074	0.701	0.118
Yes	0.039	0.708	0.024	0.010	0.007	0.000	-0.098	0.701	0.157

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

Appendix 11: MPI-I: MCA Statistics for Column Categories in Principal Normalization, Pool of 26 Countries, Urban Population

Pooled(1)									
	Overall			Dimension 1			Dimension 2		
Categories	Mass	Quality	%inert	Coord	Sqcorr	contribution	Coord	Sqcorr	contribution
Phone									
No	0.007	0.891	0.089	0.460	0.872	0.116	0.067	0.019	0.015
Yes	0.084	0.891	0.008	-0.040	0.872	0.010	-0.006	0.019	0.001
Television									
No	0.023	0.780	0.177	0.346	0.779	0.206	-0.010	0.001	0.001
Yes	0.068	0.780	0.060	-0.117	0.779	0.069	0.003	0.001	0.000
Radio									
No	0.040	0.648	0.018	0.061	0.431	0.011	0.043	0.217	0.035
Yes	0.051	0.648	0.014	-0.049	0.431	0.009	-0.035	0.217	0.027
Bicycle									
No	0.065	0.724	0.012	0.039	0.418	0.008	0.034	0.307	0.034
Yes	0.026	0.724	0.030	-0.098	0.418	0.019	-0.084	0.307	0.084
Motorbike									
No	0.063	0.792	0.030	0.087	0.783	0.035	0.009	0.009	0.002
Yes	0.028	0.792	0.067	-0.193	0.783	0.079	-0.021	0.009	0.005
Motorboat									
No	0.090	0.669	0.000	0.001	0.345	0.000	0.001	0.323	0.000
Yes	0.001	0.669	0.003	-0.201	0.345	0.002	-0.194	0.323	0.009
Car									
No	0.077	0.831	0.014	0.054	0.790	0.017	0.012	0.041	0.005
Yes	0.014	0.831	0.080	-0.300	0.790	0.094	-0.068	0.041	0.029
Animal Cart									
No	0.090	0.743	0.000	-0.001	0.009	0.000	0.007	0.734	0.002
Yes	0.001	0.743	0.018	0.048	0.009	0.000	-0.443	0.734	0.118
Refrigerator									
No	0.049	0.776	0.104	0.181	0.776	0.121	-0.004	0.000	0.000
Yes	0.042	0.776	0.124	-0.214	0.776	0.143	0.005	0.000	0.000
Land									
No	0.065	0.729	0.022	-0.045	0.303	0.010	0.054	0.426	0.085
Yes	0.026	0.729	0.055	0.113	0.303	0.025	-0.134	0.426	0.212
Livestock									
No	0.079	0.710	0.010	-0.024	0.223	0.003	0.035	0.488	0.044
Yes	0.012	0.710	0.066	0.155	0.223	0.022	-0.230	0.488	0.290

(1) Armenia, Angola, Bangladesh, Brazil, DR Congo, Côte d'Ivoire, Colombia, Egypt, Ethiopia, Guatemala, Haiti, India, Indonesia, Kenya, Cambodia, Myanmar, Malawi, Nepal, Peru, Philippines, Pakistan, Senegal, Tajikistan, Tanzania, Uganda and Zimbabwe.

Appendix 12: Cronbach's Alpha, 13 Different Asset Versions, 26 Countries

	MPI-O	**MPI-I**	**MPI-I, alt 1 (3ha)**	**MPI-I, alt 1 (0.3ha)**	**MPI-I, alt 2**	**MPI-I, alt 3 (3ha)**	**MPI-I, alt 3 (0.3ha)**	**MPI-I, alt 4 (3ha)**	**MPI-I, alt 4 (0.3ha)**	**MPI-N, version 1**	**MPI-N, version 2**	**MPI-N, version 3**	**MPI-N, version 3 minus bicycle and animal cart**
Pooled	0.583	0.4776	0.5360	0.52	0.4866	0.4970	0.4897	0.5146	0.4969	0.742	0.7034	0.6129	0.6779
Armenia	0.2356	0.2973	0.2074	0.2469	0.286	0.2233	0.2492	0.2071	0.2463	0.513	0.4982	0.3087	0.3172
Angola	0.6896	0.4964	0.5651	0.5364	0.5066	0.5319	0.5084	0.5605	0.5354	0.7627	0.7365	0.6972	0.7531
Bangladesh	0.4523	0.4667	0.4103	0.4407	0.4785	0.4103	0.4407	0.4103	0.4407	0.5727	0.5333	0.5155	0.54
Brazil	0.3685	0.3685	0.3685	0.3685	0.3685	0.3685	0.3685	0.3685	0.3685	0.5753	0.5753	0.4577	0.4577
DR Congo	0.6256	0.4759	0.518	0.4796	0.4671	0.5078	0.471	0.5152	0.48	0.6982	0.6372	0.638	0.7105
Côte d'Ivoire	0.511	0.4444	0.4932	0.4658	0.4643	0.4919	0.4644	0.4906	0.4627	0.6346	0.5586	0.5273	0.6195
Colombia	0.5625	0.5625	0.5625	0.5625	0.5625	0.5625	0.5625	0.5625	0.5625	0.6703	0.6781	0.6238	0.6073
Egypt	0.2954	0.3795	0.305	0.305	0.383	0.383	0.383	0.305	0.305	0.382	0.3601	0.3471	0.3982
Ethiopia	0.6398	0.4028	0.4883	0.4303	0.4175	0.487	0.4292	0.4876	0.43	0.6636	0.6753	0.6651	0.6814
Guatemala	0.6611	0.5167	0.547	0.5366	0.5369	0.5473	0.5367	0.5467	0.5363	0.7434	0.7291	0.6659	0.7126
Haiti	0.6338	0.4333	0.4898	0.4995	0.4432	0.4901	0.4997	0.4898	0.4995	0.691	0.6767	0.6302	0.6829
India	0.5534	0.4905	0.5255	0.515	0.4905	0.4848	0.4944	0.5195	0.5104	0.7251	0.6757	0.5795	0.6567
Indonesia	0.6811	0.4935	0.5282	0.4896	0.4868	0.5244	0.4889	0.527	0.488	0.6829	0.6821	0.6306	0.6702
Kenya	0.5833	0.5035	0.5046	0.5106	0.5019	0.5028	0.5106	0.5038	0.5089	0.5158	0.5207	0.5538	0.5755
Cambodia	0.5675	0.4429	0.4612	0.4573	0.4496	0.4611	0.4573	0.4611	0.4573	0.5739	0.5464	0.5039	0.5802
Myanmar	0.6306	0.5107	0.53	0.5233	0.5207	0.53	0.5233	0.53	0.5233	0.6674	0.671	0.6111	0.638
Malawi	0.6589	0.5629	0.6084	0.5727	0.5587	0.6048	0.5718	0.6078	0.5722	0.6673	0.6523	0.6702	0.6922
Nepal	0.5475	0.4173	0.454	0.4561	0.407	0.4436	0.4557	0.4537	0.4555	0.6423	0.6369	0.5835	0.6125
Peru	0.5431	0.2748	0.3385	0.3022	0.2888	0.3405	0.3034	0.3378	0.3010	0.7003	0.6733	0.5799	0.6295
Philippines	0.6543	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.5463	0.6332	0.6267	0.602	0.6575
Pakistan	0.5921	0.4628	0.4998	0.4921	0.4751	0.4993	0.4947	0.4979	0.4889	0.7428	0.7138	0.5962	0.6711
Senegal	0.487	0.4112	0.4265	0.4103	0.407	0.4242	0.4083	0.4167	0.3966	0.64	0.5976	0.4979	0.6073
Tajikistan	0.3994	0.3466	0.3249	0.331	0.3709	0.3255	0.3315	0.3247	0.3308	0.4831	0.4928	0.4085	0.4154
Tanzania	0.6248	0.5098	0.54	0.5058	0.5059	0.5402	0.5059	0.5394	0.5049	0.675	0.6318	0.6373	0.6901
Uganda	0.5752	0.4948	0.5403	0.5058	0.4908	0.5403	0.5058	0.5403	0.5058	0.6601	0.6024	0.6087	0.6679
Zimbabwe	0.5358	0.458	0.5204	0.4947	0.4781	0.5213	0.4952	0.5191	0.4924	0.6615	0.605	0.5679	0.6361

Appendix 13: Missing Values 26 Items (in Percentage), 26 Countries

	Armenia	Angola	Bangladesh	Brazil	DR Congo	Côte d'Ivoire	Colombia
Telephone	0	0	0	0.25	0.01	0.03	0
Mobile phone	0.02	0	0	0.25	0.07	0.04	0
Television	0	0	0	0.25	0.02	0.14	0
Radio	0.01	0	0	0.25	0.04	0.08	0
Computer	0.01	0	0	0.25	0.08	0.06	0
Internet	0	0	100	0.25	100	0.05	0
Bank	0.35	0	0.1	100	0.12	0.28	100
Bicycle	0.03	0	0.01	100	0.07	0.18	0
Motorbike	0.07	0	0.01	0.25	0.07	0.17	0
Motorboat	0.06	0	100	100	0.08	0.17	100
Car	0.02	0	0.01	0.25	0.07	0.18	0
Animal cart	0.04	0	100	100	0.07	0.2	100
Refrigerator	0.01	0	0	0.25	0.03	0.03	0
Overcrowding	0.22	0.08	0	0.25	0.47	1.88	0
Land	0.02	0	0	100	0.02	0.01	100
Land size	51.65	69.61	54.06	100	42.57	40.97	100
Livestock	0.11	0	0	100	0.02	0	100
Cattle	0	100	100	100	100	0.09	100
Cow	0	0.28	0	100	0.02	0.07	100
Horse	0	100	100	100	0.01	0.04	100
Goat	0	0.31	100	100	0.02	0.04	100
Sheep	0.03	0.03	100	100	0.02	0.07	100
Chicken	0	0.55	0	100	0.06	0.19	100
Sewing machine	0.01	100	100	100	0.17	100	100
Air conditioner	0.05	100	0	100	100	0.04	100
Washing machine	0	100	100	100	100	0.06	0

	Egypt	Ethiopia	Guatemala	Haiti	India	Indonesia	Kenya	Cambodia	Myanmar
Telephone	0.01	0	0.01	0	0	0.12	0.01	0.01	0
Mobile phone	0.02	0	0	0.01	0	0.16	0.07	0.01	0
Television	0	0	0	0	0	0.12	0.1	0.01	0
Radio	0.01	0	0.02	0.01	0	0.19	0.04	0.01	0
Computer	0.04	0	0.02	0.03	0	100	100	100	0
Internet	100	100	0.04	0.04	0	100	100	100	100
Bank	0.05	0	100	0.13	0.1	0.24	0.87	0.03	0
Bicycle	0.05	0	0.02	0.03	0	0.2	0.06	0.01	0.01
Motorbike	0.05	0	0.02	0.03	0	0.13	0.07	0.01	0
Motorboat	100	0	0.03	0.04	100	0.25	0.11	0.02	0
Car	0.05	0	0.02	0.04	0	0.2	0.07	0.02	0
Animal cart	0.04	0	0.03	0.05	0	0.27	0.09	0.01	0.01
Refrigerator	0.01	0	0.01	0.01	0	0.51	0.09	0.01	0
Overcrowding	0.05	0.1	0.13	0.59	0.03	0.4	0.35	0.15	0.08
Land	0.01	0	0.14	0.02	0	0.06	0.02	0	0
Land size	100	38.39	63.91	31.06	68.92	60.47	33.26	0.07	58.96
Livestock	0.01	0	0	0	0	0.05	0.01	0	0
Cattle	0.03	0	100	100	100	0	0.08	100	0
Cow	0.03	0.03	0	0.13	100	0.01	0.03	0	0
Horse	0.01	0	0	0.02	100	0	0.04	0	0
Goat	0.01	0.06	0	0.11	100	100	0.14	0	0
Sheep	0.01	0.02	100	0.02	100	100	0.11	100	0
Chicken	0.37	0.01	0	0.35	100	100	0.28	0.08	0.03
Sewing machine	0.04	100	100	100	0	100	100	0.03	0
Air conditioner	0.05	100	100	100	0	100	100	100	0
Washing machine	0.02	100	0.01	100	0	100	100	100	100

	Malawi	Nepal	Peru	Philippines	Pakistan	Senegal	Tajikistan	Tanzania	Uganda	Zimbabwe
Telephone	0	0	0	0.01	0.04	0	0.03	0	0	0
Mobile phone	0	0	0.01	0.02	0.12	0	0	0	0	0
Television	0	0	0	0.02	0.07	0	0.01	0	0	0
Radio	0	0	0	0.07	0.13	0	0.01	0	0	0
Computer	0	0	0	100	0.11	0	0.07	0	0	0
Internet	100	100	0	100	0.15	0	0.02	100	100	100
Bank	0	0	100	100	0.21	2	0.95	0	0	0
Bicycle	0	0	0	0.1	0.15	0	0.3	0.01	0	0
Motorbike	0	0	0	0.05	0.15	0	0.36	0	0	0
Motorboat	0	100	0	0.17	0.16	100	100	0	0	0
Car	0	0	0	0.11	0.15	0	0.19	0.02	0	0
Animal cart	0	0	0	0.17	0.22	0	0.34	0	0	0
Refrigerator	0	0	0	0.07	0.1	0	0.06	0	0	0
Overcrowding	0.03	0	0.13	0.81	0.51	0	0.81	0.02	0	0.04
Land	0	0	0	100	0.1	0	0.01	0	0	0
Land size	24.68	19.69	62.15	100	70.95	51.83	30.2	34.39	25.51	36.8
Livestock	0	0	0	100	0.08	0	0	0	0	0
Cattle	0	0	0.05	100	100	100	0	0.03	100	0.32
Cow	0	0	100	100	0.05	0.43	0	0.01	100	100
Horse	0	0	0.02	100	0.05	0.02	0	0.01	0	0.07
Goat	0.02	0	0.02	100	0.04	0.18	0	0.08	0.05	0.18
Sheep	0	0	0.06	100	0.04	0.13	0	0.03	0	0.08
Chicken	0.18	0	100	100	0.02	0.62	0	0.26	0.22	0.44
Sewing machine	100	100	100	100	0.07	100	0	100	100	100
Air conditioner	100	100	100	100	0.16	0	0.29	100	100	100
Washing machine	100	100	0	0.06	0.15	0	0.02	100	100	0