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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 article demonstrates how the revised assets indicator of the updated global Multidimensional Poverty Index (global MPI), launched in September 2018, consolidated and improved the measurement of assets deprivation at the global level. The revision combines normative and statistical methods to assess the validity of the 7-item assets schedule contained in the Original MPI, jointly designed by the Oxford Poverty and Human Development Initiative and the UNDP Human Development Report Office (HDRO) in 2010, and an 11-item schedule of an Experimental MPI, which was developed by the UNDP HDRO in 2014. It also analysed whether the inclusion of additional items identified in a review of over 100 Demographic and Health Surveys, Multiple Indicators Cluster Surveys and national surveys from which the global MPI is constructed, would add value to a revised assets indicator. Drawing on the analytical framework developed for the European Union material deprivation indicator, complemented by normative assessment, this paper applies tetrachoric exploratory factor analysis, multiple correspondence analysis, classical test theory, item response theory and alternative measures to identify a set of items that proxy assets deprivation globally. In using a set of 26 purposefully selected countries, test results were used to rule out infeasible assets, and finally to justify the addition of computer and animal cart to the assets schedule of the Original MPI. Based on this statistically validated expansion, and greater reliability of the items in the schedule, we conclude that the consolidated and revised indicator measures assets deprivation more accurately at the global level.

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1. Introduction

This article outlines the consolidation and improvement of the assets indicator of the updated global Multidimensional Poverty Index (global MPI).[1] 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 (HDR) in 2010 and in subsequent HDRs. 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, 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 revise the global MPI, at the start of the Third United Nations Decade for the Eradication of Poverty (2018–2027), in order to better align its indicators with the Sustainable Development Goals (SDGs) and 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 in September 2018 and reflect new estimations for 105 countries home to 77 per cent of the world's population, or 5.7 billion people. The consistent theoretical and computational strategy is outlined in detail in Alkire and Jahan (2018) and will allow, insofar as data permits, monitoring of the Third Decade of Poverty reduction's aim to "leave no one behind" in terms of poverty, a 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 Experimental MPI (henceforth MPI-E), 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 (also referred to as small assets[2]), and if it did not own a car or truck. The MPI-E's assets indicator included additional items: a motorboat, an animal cart, land, cattle/cow/bull, horses/donkey/mule, goats, sheep and chicken. The items

[1] This paper draws on Vollmer and Alkire (2018) that comprehensively presents all test results conducted in the identification of the revised assets indicator in the updated global MPI 2018.

[2] See Dotter and Klasen, 2014, p.4.

were also grouped 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 (at least one cattle or horse, or at least two goats or sheep, or at least 10 chicken) (HDRO, 2016, pp.9–10). Put differently, a household had to own a radio, television or telephone, plus at least one non-information asset to be considered non-deprived, whereas if a household lacked all three information items, a household is deprived in assets no matter the ownership of items related to mobility and livelihood.

The MPI-E was proposed because: a) the number of items the assets indicator in the MPI-O is based on was perceived to be limited (seven, whereas the MPI-E was based on eleven items); b) the MPI-O was perceived to be urban biased as it lacked productive assets of the rural poor such as the ownership of arable land and livestock (Kovacevic, 2015); c) items were not grouped into sub-dimensions (or categories) based on their utility, such as items of information, mobility and livelihood; and d) the threshold for being non-deprived in the MPI-O was *not* conditioned on the possession of items of different categories. Whereas the MPI-O required the ownership of *any* two small assets or a car/truck for being non-deprived, the MPI-E set a threshold at the ownership of two items from two categories, with the caveat that one category had to be information.

While empirically the results between the MPI-O and MPI-E matched closely, as noted in Alkire and Jahan (2018), the 2018 revision needed to either select between these or improve upon them. The assets indicator in the global MPI sets standards for National Multidimensional Poverty Indexes that are increasingly being adopted as official permanent poverty statistics, usually standing alongside and complementing national monetary poverty statistics (see World Bank, 2018, p. 122). As shown in UNDP and OPHI (2019), an assets indicator is commonly used in national MPIs (where it is profiled in nine national MPIs), while land livestock variables feature alongside an assets indicator in the national MPIs of Bhutan and Pakistan.

The decision to revise the global MPI in 2018 thus provided the opportunity to revisit the normative and statistical validity of the existing assets indicators, in particular the MPI-E. Further, 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 decision was taken to explore systematically whether the inclusion of other asset items would improve the measurement of assets deprivation at the global level.

Hence, the objective of the research was to build on former work and create a statistically and normatively validated indicator of assets deprivation.

This paper outlines in detail the conversation between statistical test results, normative reasoning and trial measures of possible asset indices that eventually underpinned the revised assets indicator of the updated global MPI in 2018. The revision drew substantively on the large literature that 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. In particular, the revision 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).

After a concise overview of the considerable literature on asset index construction, this paper sets out the methodology and the results of a systematic review of over 100 DHS, MICS and national surveys to identify potentially new household asset items. It enumerates the data challenges when constructing an internationally comparable assets indicator, then presents the results of the statistical assessments of the assets indicator of the MPI-E, and potential alternatives to the MPI-O and MPI-E. The discussion draws on normative reasoning as well as interpretation of the statistical tests, and then presents a range of so-called trial measures to evaluate a range of potentially new asset indices empirically. The last section presents the revised assets indicator of the updated global MPI 2018 and some concluding remarks.

2. Asset Index Construction

Asset indices are troublesome to design well for conceptual as well as data reasons. The term assets can cover a wide range of tangible and non-tangible productive and durable goods. The accuracy of their measurement varies: 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, or do not reflect permanent income (Ferguson, 2003; Filmer and Pritchett, 2001; Maitra, 2016).

Existing asset indices typically aggregate across a vector of asset ownership using, or informed by, methods such as principal component analysis (PCA), factor analysis (FA), and/or multiple correspondence analysis (MCA). Additionally, some papers utilised anchored regression analysis.[3] 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 data 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) as well as 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 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).

[3] 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.

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" [4] (a concept traced back to Milton Friedman (1957) that postulates that consumption is a function of income and determined by physical and human resources). 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. 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). The method is sophisticated and as highlighted by

[4] In addition to permanent income, asset ownership has also been found to allow agents to conduct asset and consumption smoothing (Filmer and Pritchett, 2001, p.116; Zimmerman and Carter, 2003). In addition, in a systematic review of 29 studies published since 2000, Chowa et al. (2010) find that asset ownership impacts positively on children's health conditions, schooling outcomes and decreased child labour.

Chakraborty et al., unsuitable to derive at absolute wealth comparisons as the CWI is benchmarked against the Vietnamese DHS 2002 and hence remains a relative measure of wealth; the authors 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).

Each of the applied statistical methods possesses strengths and weaknesses based on their underlying assumptions, and on precise details of how each method is implemented. These need to be understood in order to assess how they could add value to the revision of the assets indicator in the global MPI. 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 (Alkire et al., 2015, p.89). Similarly, as Townend et al. (2015, pp.8–9) highlight, while PCA has become a popular method used to arrive at asset-based socio-economic position 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, and MCA). In implementing these statistical techniques the researcher also takes many technical decisions that drive the results and include, for example, whether to "compel" all included variables in the model to contribute to the latent component variable such as in PCA or MCA, with weights emphasising some variables more than others, or to opt for a method that allow variables to retain unique variance that is unexplained by the latent variable, such as in FA (Grace-Martin, 2017). The biggest challenge however is that statistical approaches reflect the relationships within a given dataset (or a set of collapsed datasets), so produce weights that are *relative* to that particular dataset. This implies that the weights could change every update, which would impede robust cross-country and intertemporal analyses (Alkire et al., 2015, p.99). A direct uptake of component scores or similar statistical weights for the revised assets indicator of the global MPI would generate a serious limitation for the updated global MPI, as the index is constructed 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). In conclusion, statistical data reduction and latent trait techniques such as EFA in asset index design are important to obtain an empirical understanding of the commonalities between items and the dimensional structure of the data (Klasen, 2000, p. 39)[5]. Thus we use statistical analyses to

[5] 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).

understand the structure of the data, to explore the possibilities of including different items in the asset indicator, and to inform the selection of normative weights.

2.1 Methodology

In assessing indicators for potential inclusion in an asset index, we chose to follow 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. In particular, the authors deployed EFA, MCA, classical test theory (CTT, via Cronbach's Alpha), item response theory (IRT), and other statistical techniques, to choose which indicators to include in (and subsequently, add to) a counting-based, equally weighted indicator of material deprivation for the 28 EU member states[6]. Their project was thus similar to our own.

Following Guio et al. (2012, p. 9) and Klasen (2000), we used statistical data reduction techniques such as EFA primarily as exploratory tools in asset index design (to study the interrelations between items), and less as a strict selection criterion of item inclusion, or as a data reduction technique[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). Although improved, the DHS, MICS and most national surveys still lack a thematic module on assets or material deprivation, such as was included in the 2009 wave of the EU Statistics on Income and Living Conditions (EU-SILC) to purposefully improve the EU material deprivation indicator. While the DHS surveys for example include "easy-to-collect data on a household's

[6] 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). The original MD indicator was designed in 2009 and consisted of nine items, which were perceived as too few (Guio et al., 2017, p. 1) and hence faced similar criticism as the MPI-O. In main difference to the measurement of assets deprivation in the global MPI, the EU material deprivation indicator focuses on preferences and affordability of items, such as the inability of households to afford a meal with meat, chicken or fish every second day. Thus, 'items' capture "an enforced lack of socially perceived necessities" (Guio et al., 2016, p. 222), and interestingly, of the tested 50 possible items (Guio et al., 2012, pp.11-13), several items were considered unreliable to measure material deprivation including "some basic durables (TV, telephone, washing machine) and basic amenities" (Guio et al., 2016, p. 224). Overall, of the 50 tested items none could be considered a productive or capital asset.

[7] Our approach is thus also in line with Steinert et al. (2018) who cautioned against the assumption that a "'one size fits all' measurement model yields valid results in the design of composite poverty indices.

ownership of selected assets" (DHS, 2018), the thematic focus of the surveys is on population, health and nutrition. Data on prices of assets, their quality and age, the quantity of each item owned per household or data on preferences and the affordability of items, are lacking (see Dotter and Klasen, 2014, p.20). Therefore, given that the asset index in the global MPI is based on data sources that are not purposefully designed to measure assets or material deprivation, a data- rather than theory-driven research approach seemed more appropriate for the purposes of this study. As these techniques explore the statistical commonalities between data a word of caution is appropriate that one can expect higher levels of data commonalities in purposefully designed data, such as in data collected in the thematic module on material deprivation in the EU-SILC, in contrast to results obtained when such methods are applied to ad-hoc or non-purposefully collected data.

Our approach differs from that of Guio et al. in that the selection of indicators was not based on perceptual data, nor did it make assumptions that preferences were homogenous within countries. Rather, we first established a minimum threshold for data availability in 75 countries and 3.5 billion people, which will be further outlined in section 3, with the exception of motorboat, where data were only available in 32 countries covering 1.1 billion people. In addition to data availability, the potential indicators must be recognised as 'assets of the poor' or 'poor people's assets' in the literature such as the seminal *Voices of the Poor* series (Narayan et al., 1999; Narayan and Petsch, 2002). More specifically, all old and potential new asset items fell 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.20).

We then tested the MPI-E and a set of Alternative measures, for their dimensional structure and 'reliability' (the internal consistency of a scale of items) 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 a set of 26 countries that cover almost 3 billion people (see Table 1).

The trial measures utilised the structure of the MPI-O with different vectors of asset items to observe certain characteristics of selected items and how they affect the uncensored headcount ratio of assets, that is the percentage of people in the population who are classified as deprived in

[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).

assets (Alkire et al., 2015). While the trial measures were not rank robustness analyses per se, the measures had a sensitivity test character to empirically validate the potential asset indices that were identified during the preceding statistical analysis, and to identify upfront potential false positives in the uncensored headcount ratio when new items are included, or existing items of the MPI-O and MPI-E were to be excluded or substituted.

A set of 26 countries covering roughly 3 billion people was purposefully selected for this study. The set assembles countries that have a large population coverage, with using DHS datasets fielded in 2012-16, and includes *at least* two countries for five of the six regions that are covered by the global MPI. The countries range from low- to lower middle-income status (according to the World Bank Atlas Method). We acknowledge the potential 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 105 countries (hence, 'external validity' was assumed from the 'internal validity' of 26 countries). This was a pragmatic decision[9] and on-going research is further exploring the 'external validity' of the findings from this study (see Alkire, Kanagaratnam and Suppa (2018) that presents a methodological note on the revised global MPI with notes on each item that was missing in the assets indicator for each of the 105 countries; see as well Alkire et al. (2019) for a systematic comparison of the revised 2018 and the original 2010 specifications of the global MPI which found that aggregate results and the ranking of countries remained similar under both specifications).

The analytical advantages of this approach are considerable in that it became feasible to revise the asset indicators in the light of statistical tests, thus improving upon the MPI-E and MPI-O that were based mainly on theoretical and normative reasoning[10].

[9] Pooling data for such a large number of countries used in the global MPI (over 105) proved challenging, and certain tests or important graphs, such as the MCA dimension projection plots, were extremely slow (or not possible to construct). Hence, the decision was taken to conduct the analysis on a representative set of 26 purposefully selected countries.

[10] Statistically, the MPI-O was compared via Spearman correlation coefficients with the DHS Wealth Index, an index that uses PCA weights and information on different household assets (access to services and amenities), many of which are contained in the Living Standards dimension of the MPI (Alkire and Santos, 2010, p. 44). While the global MPI was presented as a robust measure of acute poverty in 2014 (Alkire and Santos, 2014), indicator specific robustness tests focused on child nutrition, child mortality, school attendance, water, sanitation and flooring. Tests on the years of education, cooking fuel and the assets indicator were "left for further research" (Alkire and Santos, 2014, p. 268), and with regards to the assets indicator, is picked up in this study. The MPI-E was first presented in 2014 (Kovacevic and Calderon, 2014) as a follow-on from two HDRO organised conferences in 2012 and 2013 based on theoretical delineations as outlined in Kovacevic and Calderon (2014) and Kovacevic (2015).

Table 1. 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[11]	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

[11] Pesquisa Nacional por Amostra de Domicílios.

3. Data

(a) Data Availability and Constraints of Potential New Household Asset Items

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 population estimates), with the objective of identifying potential 'new' and 'improved' household asset items, taking into account that many surveys that were published in recent years have improved (OPHI, 2018).[12] 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 review resulted in the identification of nearly 30 potential new household-specific assets 'items' that can be grouped into 11 categories, which are presented in Table 2. For each potential new item, the table presents the number of countries for which data on the item are available and the corresponding population covered (based on 2015 population estimates). At the review stage, we utilised a generous definition of asset ownership that includes the ownership of consumer durables and productive assets such as farm animals owned, as well as the consumption of goods, such as iodized salt; demerit goods, such as tobacco; as well as access to liquid assets (financial transactions) and treated mosquito nets. We also considered a household's waste management. Many of these items might be used to construct country specific DHS Wealth Indices (Rutstein, n.d.) and were used in Ferguson, et al. (2003).

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 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 (covering 3.7 billion people) have data on the number of chickens or poultry owned, while nine countries (covering 1.6 billion people) 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

[12] The surveys were implemented in a time span from 2006 (Azerbaijan) to 2016–17 (Nigeria).

Jahan, 2018). Many potential asset items were ruled out including small physical assets such as tables and beds, and the entire group of electrical assets except for computer. Items that met only one of the two benchmarks of data availability were retained if strong conceptual reasons existed to do so, such as relation to the SDG targets or another. For example, internet access formed part of the 13-item revised material deprivation indicator in the European Union (Guio et al., 2016, p. 219).

(b) Treatment of Missing Values and Missing Data

Following Tabachnick and Fidell (2007, in Yong and Pearce, 2013, p.81), missing values were dropped from the EFA, MCA and CTT to prevent overestimation (unless otherwise stated), and the IRT was utilised with and without the listwise option that handles missing values through listwise deletion. In the trial measure analysis, where 24 potential asset specifications were compared utilising the structure of the MPI-O with different vectors of asset items, we report asset estimates as a lower-bound estimate of assets deprivation. Hence, if values on any of the items in the indicator were missing it was assumed that the household did not own the asset, and the entire assets indicator was set to missing and subsequently dropped from the analysis if the household lacked data for *all* items (this is consistent with Alkire and Santos, 2014, p.256).

(c) Treatment of Land and Livestock Variables

All potential new variables included in the statistical analysis and the trial measures are binary. Land and livestock are dichotomous variables, however, which are coded according to some deprivation threshold. A household was considered non-deprived in land if it owned any land or more than 0.3ha, 0.6ha, 1ha, 3ha, 6ha or 10ha (where unknown land size (or missing values on land size) was treated as deprived, in accordance with the coding of missing values on selected asset items in the MPI-O as outlined above).[13] In livestock, households were considered non-deprived if it fulfilled the MPI-E criteria or owned a livestock equivalent to 1 or 1.5 livestock units.[14]

[13] Note that land size is self-reported in the DHS and MICS surveys and that the data was *not* corrected for data heaping.

[14] 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

Table 2. Availability of Household-Level Asset Items in 100 DHS, MICS and National Surveys

Household-level indicators				
Focal area		**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

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; but it was chosen 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.

		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

4. Results

4.1 Statistical Validation of MPI-E

4.1.1 Exploratory factor analysis

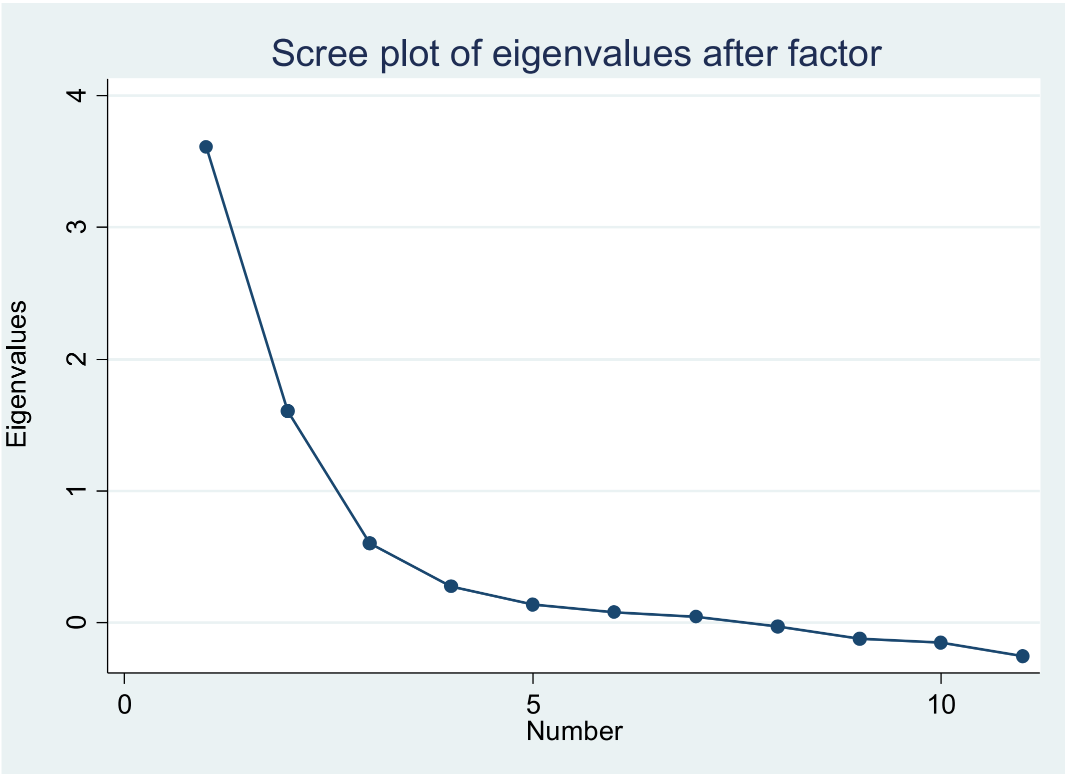
First, we performed tetrachoric EFA for binary variables to see whether the assumed three-factor solution of the MPI-E emerged (information, mobility and livelihood). FA is a model of the measurement of a latent variable. This model assumes that there are *m* underlying factors whereby each observed variable is a linear function of these factors (common variance) together with a residual variate (unique variance) (Costello and Osborne, 2005).[15] Following Guio et al. (2012,

[15] 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).

p.16) and Vaz et al. (2013, pp.6–8), factor loadings were rotated 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 set 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 Figure 1).

Figure 1. MPI-E: Scree Plot of Eigenvalues, Set 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). Overall, the EFA did not support the dimensional structure of the MPI-E and also highlighted the distinctiveness of the land and livestock variables. To explore this further, we also conducted MCA.

Table 3. MPI-E: Exploratory Factor Analysis, Set of 26 Countries

Pooled				
	Factor1	**Factor2**	**Factor3**	**Number of observations**
Proportion of variance explained	62%	27.6%	10.4%	1,470,046
Rotated Factor Loadings(1)				
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

Note (1): (1) Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.[16]

[16] As outlined in Vollmer and Alkire (2018, pp.16-19; pp.56-59), this trend was observed when tested at individual country level as well (for DR Congo, Ethiopia, Haiti, Kenya, Nigeria and Pakistan), and when the data was disaggregated for the rural and urban populations in our set of 26 countries. Also, test results were similar when the same analysis was performed for different configurations of the land and livestock variables, where various minimum land size cutoffs (using either 0.3ha or 3ha) and a one livestock unit cutoff were used (Vollmer and Alkire, 2018, p.17; p.19; pp.60-66). The first factor was composed throughout of telephone, television, car and refrigerator. Land was not retained in any scenario with a primary factor loading of above 0.5, but instead depicted a high unique variance throughout. By using livestock units throughout all scenarios, we found that this variable was retained in the second or third factor as either the only item, or as one of only of two items. The second and third factors explained approx. 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, moving forward the alternatives to the MPI-E were not further pursued.

4.1.2 Multiple correspondence analysis

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

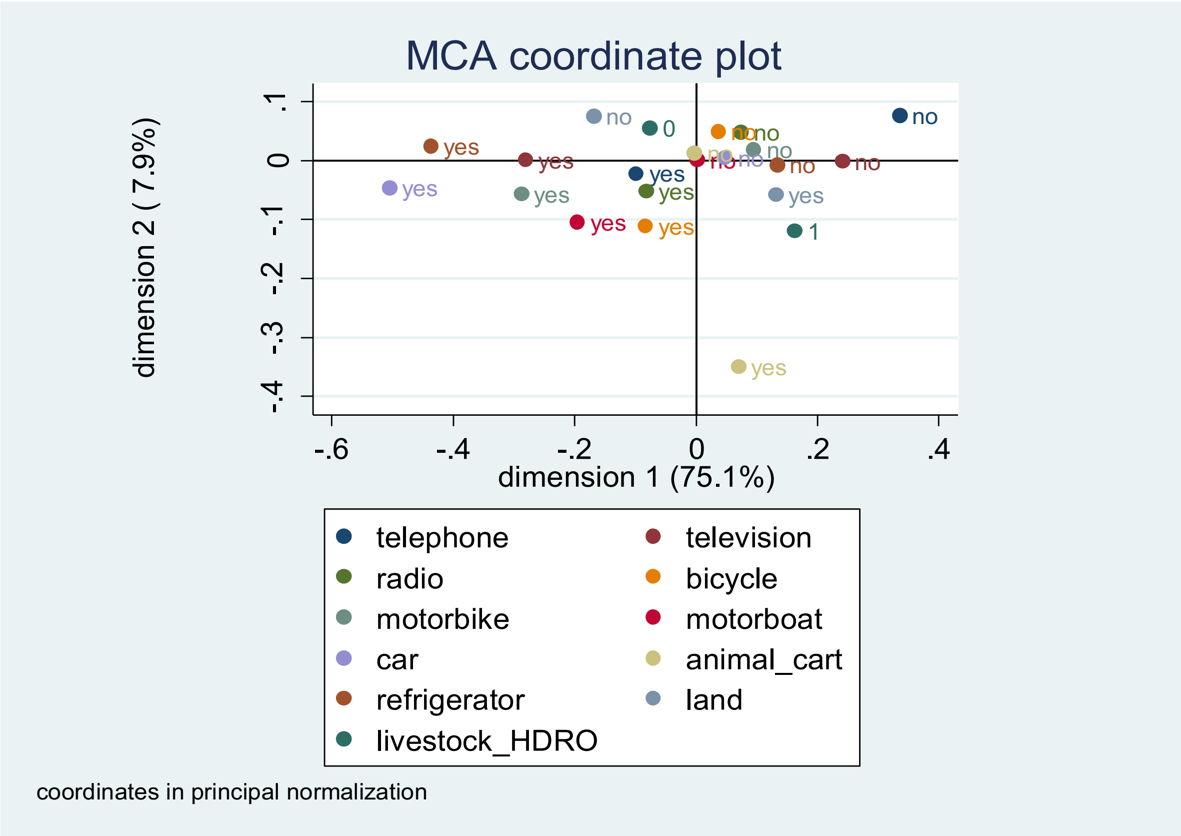
Figure 2 plots the origin axes of the two dimensions, which helps to see data associations. We opted to use the overlay option to obtain a combined figure of the biplot figures for the 11 variables. The plot reveals the clustering of variables due to the relative position of their Euclidean values on a two-dimensional plot (Dijkstra et al., 2016, p.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, respectively, 'yes' and 'no response' to the questions of 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 1, which presents the statistics for column categories in principal normalization, and in Figure 3, where a 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 in Figure 2, 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 1, as well, where the ownership of those

[17] Number of observations: 1,470,046.

three items are the greatest contributors to dimension 2[18], and Figure 3, where 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).

Figure 2. MPI-E: MCA Coordinate Plot, Set of 26 Countries



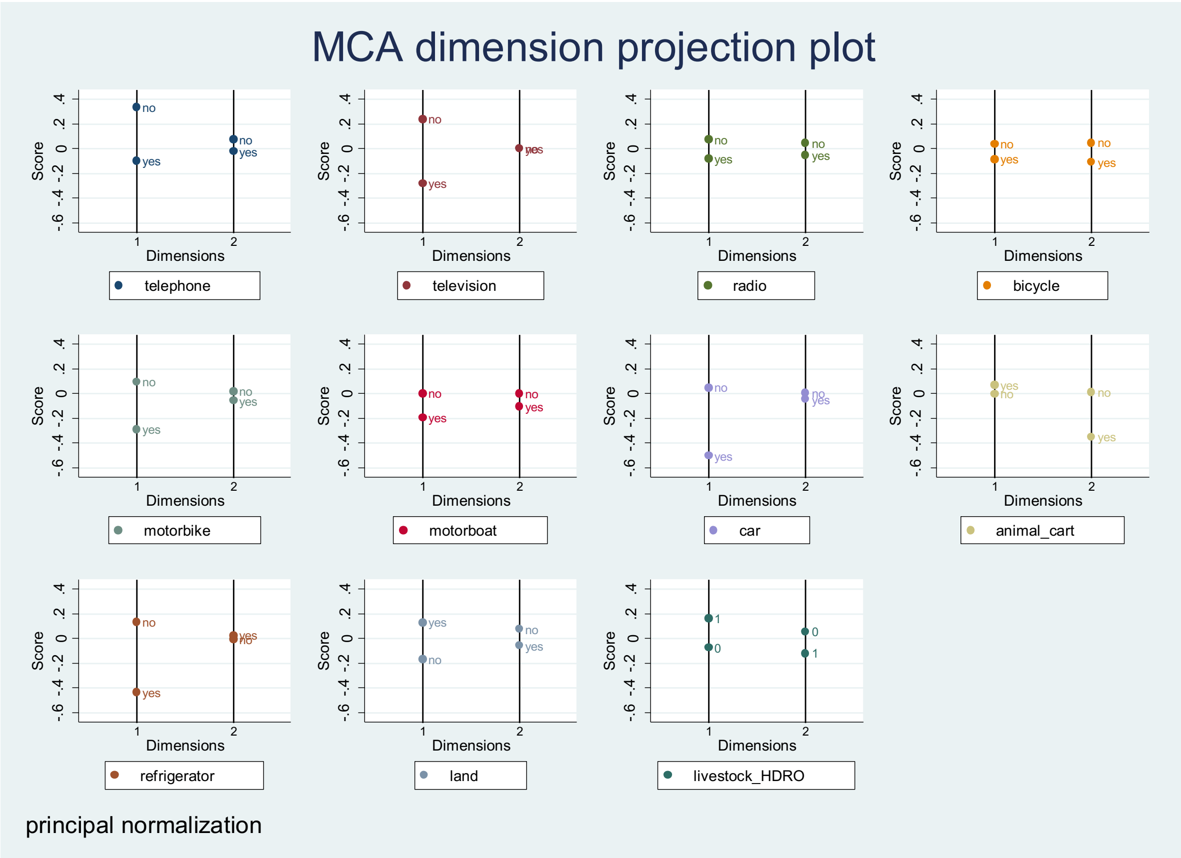
Therefore, given that responses to the ownership of land, livestock and, to a lesser degree, animal cart, are clustered and ordered somewhat differently from the other items as shown in Figure 2 and Figure 3, their potential incompatibility with the other variables is certainly highlighted and may be 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.

As shown in Vollmer and Alkire (2018, pp.22-25; pp.68-69), for the rural and urban population we found a similar two-dimensional pattern, where the first dimension explains 70.4% and 66.9% of the total inertia of 81.1% and 78.3% respectively. The respective MCA coordinate plots confirmed the identified pattern in Figure 2 by which land and livestock are clustered differently

[18] Ownership of a bicycle also contributes quite strongly to the inertia of dimension 2. Land and livestock contribute more strongly to the inertia of dimension 2 than to the inertia of dimension 1, which they share with radio, bicycle, motorbike, motorboat and animal cart. Ownership of livestock and the lack of land ownership are the strongest contributors to the inertia of dimension 2 overall.

to the other items (with a slightly less pronounced trend in rural areas). While the projection plot of the column coordinates after MCA for the urban population showed a confirmation of the results obtained for the total population, the results for the rural population showed that the ordering of animal cart in the first dimension in its projection is arrayed in line with the other eight items (non-ownership is arrayed before ownership). This highlights that animal cart must be considered a distinct rural item.

Figure 3. MPI-E: MCA Dimension Projection Plot, Set of 26 Countries



To conclude, 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 in using the 11-item schedule of the MPI-E, and neither dimension includes only the information indicators, or all the remaining indicators. This is a divergence from the measurement model proposed by the MPI-E. 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.

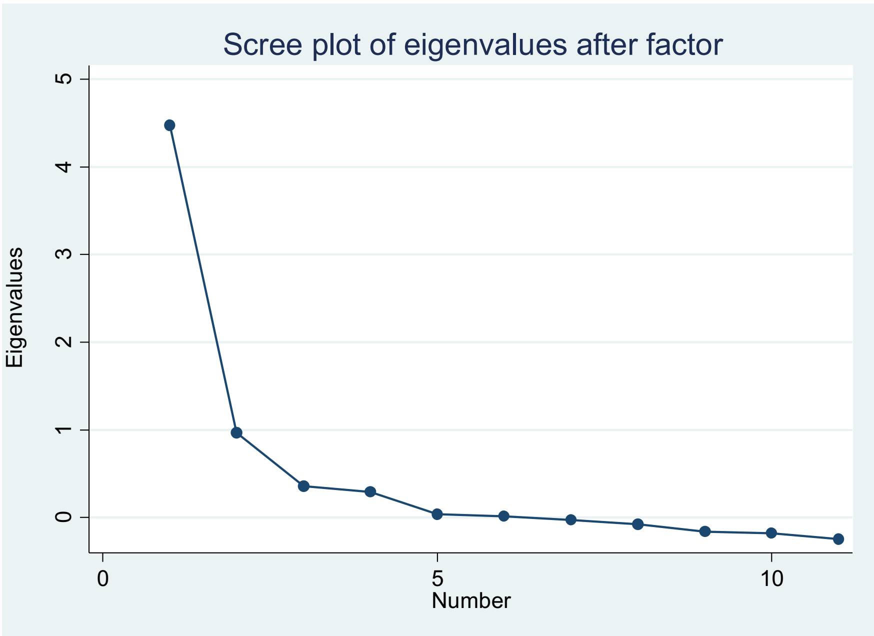
As the MCA coordinate plot in Figure 2 and the statistics for column categories in principal normalization in Appendix 1 demonstrate, there seems to be a fundamental difference between *not* having a television or a telephone, the strongest contributors to the inertia of dimension 1 of the "no" responses, and *not* having land, the strongest contributor to the inertia of dimension 2 of the "no" responses. Thus, while there is enough reason to assume that populations would not want *not* to have a television, a telephone or similar household durables and amenities, regardless of whether they are in an urban or rural area, a lack of land ownership in particular, and by extension a lack of livestock ownership, may be interpreted as a succinct livelihood choice. This choice is more pronounced in urban areas, but also accounts for rural areas.

4.2 Statistical Validation of Alternatives to MPI-E and MPI-O

4.2.1 Exploratory factor analysis

The systematic review of over 100 DHS, MICS and national surveys presented in section 3 found 30 potential new household-specific asset items, and we identified three asset variables that meet at least one of our data availability 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 these three additional variables. We performed an EFA on the set of 26 countries for these 11 items, as well as for the rural and urban population, calling this 'Alternative 1'.[19]

Figure 4. Alternative 1: Scree Plot of Eigenvalues, Set of 26 Countries



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

For the set 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 Figure 4).

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 4). 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 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-E.

Table 4. Alternative 1: EFA, Set of 26 Countries

Pooled			
	Factor1	**Factor2**	**Number of observations**
Proportion of variance explained	82.2%	17.8%	3,251,694
Rotated Factor Loadings(1)			
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

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

As shown in Vollmer and Alkire (2018, pp.27-28), disaggregated for the rural and urban populations in our set of 26 countries, we found that the same seven items were retained and the first factor showed satisfactory internal consistencies of above 0.7 as measured by Cronbach's Alpha for the urban population, while for the rural population the Cronbach Alpha was with 0.67 slightly lower.

4.2.2 Classical test theory

Based on the test results obtained through EFA in section 4.2.1, we computed the Cronbach's Alpha for three additional Alternatives:

1. **Alternative 2.** Telephone, television, computer, internet, motorbike, car and refrigerator: 0.742,
2. **Alternative 3.** Telephone, television, computer, internet, bicycle, motorbike, car and refrigerator: 0.703,
3. **Alternative 4.** Telephone, television, radio, bicycle, motorbike, car, animal cart, refrigerator and computer: 0.613.

For a complete overview of the Cronbach Alphas across various asset versions in our set of 26 countries, including for the MPI-O and the MPI-E, see Appendix 2. Of the possible Alternatives, we find the highest Cronbach's Alpha for Alternative 2 (alpha 0.74). The items are mostly consumer durables, with the exception of internet access, which is an intangible asset. The Cronbach's Alpha of this alternative is higher than the Cronbach's Alpha of the MPI-E in all 26 countries, and higher in 24 countries than the MPI-O. Note that this combination excludes radio and bicycle. As radio and bicycle are potential assets of the poor (Narayan et al., 1999; Narayan and Petsch, 2002), we include them in Alternative 4, in addition to animal cart, but exclude internet. We utilised Cramer's *V*, which measures the association between two nominal variables, to assess the potential redundancy of computer and internet. Cramers *V* ranges from zero to one, where one indicates a strong association. We find a correlation of 0.62 between computer and internet for the set of 26 countries.[20] Instead of merging both items, we exclude internet, 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.

4.2.3 Item response theory

Classical test theory provides information on the reliability of a scale. We further explored the reliability of the Alternative asset indices with IRT, which provides additional information on the

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

reliability of each individual item in the scale. IRT provides information on how a person's response to a questionnaire item, in our case the ownership of assets, relates to some potential unobserved latent trait, such as the amount of material wealth, where the probability of "success" (e.g. owning an asset 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 difficulty to obtain that item and is thus potentially useful in assessing the extent to which the final assets indicator encompasses items that range from low to high in terms of difficulty to obtain that item (this is called 'severity' in Guio et al., 2016, p.226; p.231). It also provides information on the discrimination of an item, where a large discrimination parameter denotes higher correlations with the latent trait, in our case material wealth (StataCorp, 2017, p.3)[21].

In Vollmer and Alkire (2018, pp.30-37), we applied IRT to two of the Alternatives presented in section 4.2.2. Alternative 2 was tested as it showed the highest internal consistency of Alternatives 2-4 as measured by Cronbach's Alpha, while Alternative 4 was the most encompassing alternative that includes radio, bicycle and animal cart, but excludes internet. Here, we present the results of Alternative 4 as it is the most comprehensive.

4.2.3.1 IRT on Alternative 4 for a set of 26 countries

We specify a one-parameter logistic model (1pl - see Table 5), a model that estimates the prevalence ('difficulty') of ownership of each of the nine items of Alternative 4. The estimate of the item discrimination parameter shared by all items is estimated as 1.22. This suggests that the items are only moderately discriminating, that is, in the vicinity of a given 'difficulty' estimate, any two households with distinct characteristics would have similar predicted probabilities of responding that they possess an item. Based on the 1pl model, we find that a telephone 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). In other words, the probability of having 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 -2.07 to be expected to succeed obtaining this item, while for a car and an animal cart one would need an ability level of 2.17 and 2.89.

Given the rather low discrimination parameter we checked item fit between a 1pl and 2pl model, one which allows for a separate discrimination parameter, by performing a likelihood-ratio test.

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[21] The discrimination parameter provides information 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" (StataCorp, 2017, p.3).

The test result is near a zero significance level ($\chi 2$(8)=2438758.60; p=0.0000), which favours a 2pl model. Results are presented in Appendix 3.

Table 5. 1pl Model for Alternative 4, Set of 26 Countries

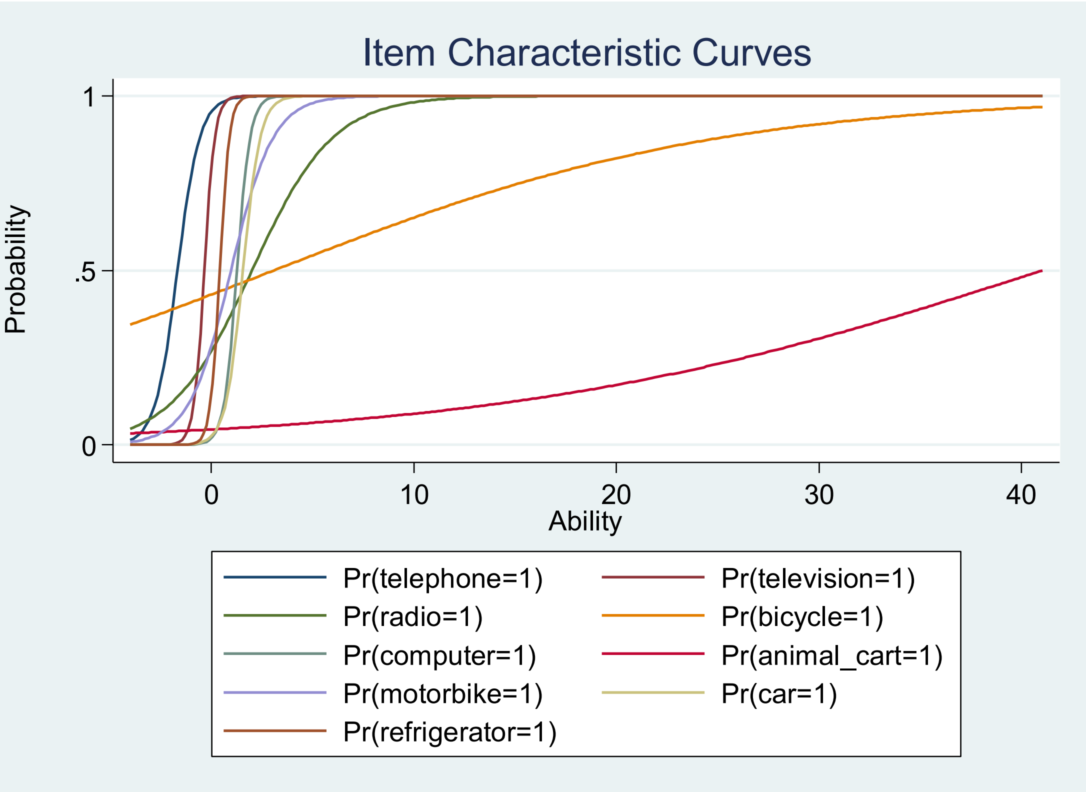
Pooled						
One-parameter logistic model						**Number of observations**
Log likelihood = -21635773						5,264,508
Variable	**Coefficient**	**Standard Error**	*z*	*p*	**95% CI**	
Discrimination	1.228921	.0007482	1642.55	***	1.227454	1.230387
Difficulty						
Phone	-2.068108	.0015893	-1301.29	***	-2.071223	-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

We visualize the relationship between items and being deprived in Alternative 4 – between the items and the latent trait – by plotting the item characteristic curves (ICCs) for the 1pl and 2pl model. Guio et al. (2012; 2016; 2017) interpret the ICC as a measure of discrimination between the deprived and non-deprived in material deprivation (the more upright/vertical a curve the more the item discriminates between the deprived and non-deprived in the latent trait, that is material deprivation in their case) and as a measure of 'severity' of material deprivation, the likelihood that the person/household will lack/not be able to afford 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.

For 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 less than half of the population own the item, because the items are expensive, are for special use only, are not in demand or not widely available. In other words, a severity of between 0 and +3 standard deviations highlight the different degree of difficulty of owning an item (the *severity of non-deprivation* in item ownership one might say)). 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. The 'severity of the non-deprivation' approach potentially increases the certainty about the non-deprived population in assets, particularly if the asset schedule assembled only items with inflection points on the ICC between 0 and +3 standard deviations, thus exclusively 'hard to obtain' items that discriminate between the deprived and non-deprived in assets, but may overestimate the uncensored headcount ratio in assets deprivation as to be further debated in the discussion section c which presents the trial measure results.

Since ICCs based on a 1pl model plots the difficulty but not the discrimination of each item, we present the ICC based on a 2pl model here (see Figure 5)[22]. By looking at Figure 5, which depicts on the y-axis the discriminating ability of the item where a more upright curve depicts higher

Figure 5. Item Characteristics Curve, 2pl model, Alternative 4



correlations with the latent trait, in our case material wealth, 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 and hence conform to the ideal pattern of depicting the *severity of non-deprivation*. While radio depicts a greater severity/difficulty than car

[22] As can be seen in Appendix 4 for the 1pl model, the probabilities represent the expected scores for each item along the latent trait continuum and shows that the probability of possessing a phone is higher than the probability of possessing all other items, with a car and animal cart being the most complicated to possess.

(2.01 vs. 1.57), the discrimination of the car is greater than of radio (2.3 vs. 0.5). Telephone and television depict a negative difficulty; in other words, whilst discriminating, telephone and television are the easiest items to obtain and hence conform less well to the ideal pattern of depicting the severity of non-deprivation.

Finally, bicycle and animal cart do not show 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[23]. 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 2, last column). For the pooled data, the alpha increased to 0.68, from 0.61 of Alternative 4. However, given that this paper was part of an exploratory exercise, and that the statistical results would require normative interpretation, we decided not to exclude the items at this stage.

4.2.4 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 set of six countries only[24], 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 Alternative 3 as identified in section 4.2.2, which is composed of eight items and has a Cronbach Alpha of 0.7 for the set of 26 countries (telephone, television, computer, internet, bicycle, motorbike, car and refrigerator). 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.

Next, we tested Alternative 4 as identified in section 4.2.2, which is composed of nine items and has a Cronbach Alpha of 0.61 for the set of 26 countries (telephone, television, radio, bicycle,

[23] 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 4,178,032. 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.

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

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 $H>0.3$.[25]

5. Discussion

(a) Lessons Learned from Statistical Results

In sum, the statistical results presented in section 4 indicate four major lessons:

1. Given the available data across a set of 26 purposefully selected countries with a reasonable sample size and a wide global population coverage, we find reasons to argue that the potential asset items 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-E, 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). 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 statistical and 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 data constraints and conceptual concerns, as outlined in detail in Vollmer and Alkire (2018, pp.39-44), Alkire and Jahan (2018, p.5; p.14) and further debated in discussion point b below, will need to be addressed further in order to identify valid and reliable cutoffs for these crucial assets. If included in the future, greater data availability on productive assets of the urban poor are 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

[25] As a final check, we also tested the 11 items of the MPI-E. 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-E measurement model of 11 items grouped in three dimensions.

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. However, these are assets poor persons would obtain as a priority, so further exploration is required.
4. A computer is a salient item in terms of statistical tests and seems to strengthen the resulting assets indicator so should be considered further.

(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,[26] 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).[27] 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,[28] which showed a positive correlation in eight of 15 countries (2009, p.1435; p.1446).[29] Land is regarded as a stock renewable resource that fulfils various functions, foremost the production of food, fibre, fuel or other biotic materials for human use (FAO and UNEP, 1999, p.8).

[26] 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".

[27] 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.

[28] 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 studies' 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).

[29] 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).

The importance of land as a key productive asset is not in doubt. However, the statistical test results presented in section 4 highlighted the somewhat distinct character of this crucial productive asset in comparison to other consumer durables such as telephone, television or refrigerator. In addition, data constraints[30] will need to be addressed further in order to construct an internationally comparable indicator on minimum land ownership.

Firstly, data on farm productions and inputs under various farming systems[31], such as the value of food production per hectare or the ratio of irrigated land, are missing in most DHS, MICS and national surveys, as are sale prices of farm animals (or the quantity of farm animals sold and/or consumed). As land fertility and average farm sizes vary quite dramatically at the regional and global level (FAO 2018) - the hectare-weighted median in farm size varies strongly both at the regional and global level, where it ranged from 0.7ha in Malawi to 4.57ha in Niger in Sub-Saharan Africa, from 0.94ha in Guatemala to 9.2ha in Nicaragua in Latin America and the Caribbean, while 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) - it was eventually impossible to set a globally comparative minimum land size cutoff that would also hold any meaning as to the quality of land or any welfare benefits obtained from smallholder activities. Setting land size cutoffs is meaningful at best at the regional scale.

Secondly, and as outlined in section 3, missing values were assumed to be signs of deprivation in the assets indicator of the MPI-O and only dropped if the household lacked data on all items in the scale. For the original eight items included in the MPI-O, this was of negligible concern, as most missing values were minimal (in our set of 26 countries below 1% for example). When considering land, the relatively low percentage of missing values in land ownership (below 1%

[30] 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).

[31] 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 (Dixon et al., 2001, p.29).

where data on the variable were available in our set of countries) versus the very high percentage of missing values in land size (up to 69.7% in Angola or 68.9% in India, see appendix 5) disallows this assumption. Thus even if a minimum land size cutoff was identified (and used in the subsequent trial measures) or farm animals were counted in 'livestock units', one had to code missing values, as either deprived or non-deprived that would have led to biased estimates[32]. Missing data on livestock was also considerable in many countries, including Bangladesh, Colombia, India and the Philippines, as shown in appendix 5.

Thirdly, data heaping in self-reported land size was also identified in the set of 26 countries (see Vollmer and Alkire, 2018, p. 41). Data heaps are caused by "the natural inclination of respondents to round off numbers" (Carletto et al., 2016, p.6) and occurred, in most of the 26 countries, up until 5ha (12 acres), and flattened afterwards.[33] In many cases data heaps occurred at round numbers, but as Guatemala in particular demonstrates, exceptions exist, where additional data heaps occurred at 6.2ha (4%), 7.8ha (2.9%) and 37 or more hectares (5.3%). Where exactly the data heaps occur is different in any given country which poses a severe danger of setting a global cutoff for a minimum land size that misses data heaps in any given country. This would blur the interpretation of results, and the comparability between countries is lost. Given the absence of internal and external rules for latent data heaping mechanisms at the global scale for self-reported land sizes and appropriate imputation techniques in the field of multidimensional poverty measurement (Alkire et al., 2015, p.228), this posed serious problems to accurately identify those deprived in minimum land size.

In conclusion, the quantity of land size (be it any land size as used in the MPI-E or potentially a minimum land size) as an indicator of land deprivation was ruled out as conceptually too restrictive and marred by measurement error, as was the usage of a minimum livestock unit cutoff as this concept is not linked to price and consumption data of farm animals. Minimum data requirements for a meaningful indicator of land that is relevant to policy makers should understand the ratio of

[32] 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 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).

[33] 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%).

cultivated and irrigated land per person among the agricultural population in any given farming system, while better price and consumption data on farm animals would link livestock better to the concept of human poverty and welfare.

(c) Trial Analysis

As a final step, we calculated 24 trial indicators of asset deprivations for our 26 countries. Table 6 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 design process for the global MPI in 2010. The objective was to empirically explore and further analyse certain items that stood out during the statistical tests conducted in section 4. 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 in meetings between March and August 2018. Comprehensive tests results are available in the supplementary materials, together with summary statistics about the percentage of ownership of items in each country. We deliberately excluded using Alternatives 2 and 3 from section 4.2.2, but operated with Alternative 4 (which in Table 6 is trial measure 23). Instead of discussing all test results in this paper, we focus on several observations that shaped the final revised assets indicator of the global MPI that will be presented at the end of this section.

First, certain items, such as a radio or a bicycle, are owned widely in some of the countries, 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 uncensored headcount ratio of assets in Kenya and Haiti, respectively (compared to the MPI-O, trial version 1), whereas the uncensored 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 6. 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[34]

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

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

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

Rutstein and Staveteig, 2014, p.1), may have 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 5). 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 to reduce the discriminatory power *if* such an exclusion causes a greater uncensored 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 uncensored headcount ratio (a reduction of approximately 0.5 percentage 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 4, normative 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 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 Alternative 4 in the IRT analysis presented in section 4.2.3.1, is a rather *localised item*. The percentage of people who owned 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 more prevalent: 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 uncensored 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 Vollmer and Alkire (2018, p.25) and discussed in this paper in section 4.1.2. While the assets indicator aims at being salient for both urban and rural populations, including this localised item seemed just given that the uncensored headcount ratio in assets in rural areas of the MPI-O has been considerably higher than in urban areas, which has been perceived as an urban bias contributing to the emergence of the MPI-E (Kovacevic (2015); 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 uncensored 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),[35] 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 make visible different patterns of land ownership in different countries of our pool.[36]

Fifth, the 'kitchen sink'[37] analysis produced reductions in the uncensored headcount ratio throughout, ranging from small changes to the MPI-O in Brazil (-0.02%) to decreases of up to

[35] 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 uncensored headcount in some countries, of up to 22% in Ethiopia for example.

[36] 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 smallholders' data portrait of the FAO (FAO, 2018). 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 uncensored 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.

[37] In this measure (which we called 'Kitchen Sink', derived from Kitchen Sink regression that utilises a long list of independent variables) we assembled all items of the MPI-E plus computer, internet, bank account, sewing machine, air conditioner and washing machine. Hence, for this special analysis we also used with sewing machine a household item that did not meet any of our two data availability criteria (75 countries, at least 3.5 billion people), whereas air conditioner and washing machine only met the population criteria. They were used however as these items are important physical assets that regularly feature in asset index constructions, such as found in Filmer and Pritchett (2001) or Ferguson, et al. (2003).

45% in Ethiopia. The 'kitchen sink' approach of identifying those who are deprived in assets is distinct from identifying the 'severity of non-deprivation' which underpinned the IRT analysis presented in section 4.2.3. Whereas the latter aims at identifying the non-deprived in assets by including items that are hard to obtain such as refrigerators, cars or motorbikes[38], the kitchen sink logic assembles as many items as possible. Consequently, if a household has none or only one item out of a long list of possible items, it is very likely that the household is indeed deprived in assets.

Both of these 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 uncensored headcount ratio, particularly *if* the asset schedule assembled only items with inflection points on the ICC between 0 and +3 standard deviations, thus exclusively 'hard to obtain' items. The 'kitchen sink' approach increases the certainty about the population who suffer deprivations in assets but may overestimate the non-deprived population as the scale includes items that are owned by many and can thus be assumed to be affordable, widely available or in strong demand. As shown by the Ethiopian case, the reductions are substantial indeed, and 45% of those previously deprived in assets became non-deprived. Also, and rather importantly for the global MPI, the comparability of this assets index across countries is weaker and less transparent because not all surveys have identically defined components, and country differences may reflect incomparability in the underlying data. For these reasons, 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 in a false positive. Overcrowding or lacking '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

[38] 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 is also increased 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 3, where it is highlighted that data for tables and chairs were only available in 31 and 37 countries respectively covering less than 3.5 billion people).

standards of living indices (e.g. Filmer and Pritchett, 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, the size of the rooms varies extensively, and that "there is no basis in 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 Alternative 4 as presented in section 4.2.2, 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 set 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.

6. Concluding Remarks

This paper demonstrates how the revision of the asset indicator of the updated global Multidimensional Poverty Index 2018 resulted in an improved measure of assets deprivation at the global level. Based on a conversation between statistical test results, normative reasoning and extensive trial measures of possible asset indices, the revised indicator maintained one dimension of assets deprivation and 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 revision sought to consolidate and improve the asset indicator of the global MPI by a statistically validated expansion of the number of items (from previously seven to nine following the revision), and an increased reliability of the items in the scale compared to the previous asset indicators (MPI-O and MPI-E). Of the 26 countries in our empirical analysis, the Cronbach's Alpha coefficient of the new indicator (which is akin to Alternative 4 when items are equally weighted) was higher than for the MPI-E in 25 countries (except for Egypt) and for the MPI-O in 21 countries, except for Indonesia, Kenya, Cambodia, Myanmar and the Philippines (see appendix 2). These countries lack data on computer however (see appendix 5), except for Myanmar, which explains the lower reliability of the new indicator in these countries. While our analysis identified an asset indicator that surpassed the 0.7 threshold for satisfactory internal reliability as measured by Cronbach's Alpha by omitting radio and bicycle and including computer and internet (Alternative 2), we found that this statistically strongest indicator had conceptual weaknesses. It is vital not to permit statistical tests to drive indicator selection without normative reasoning. For example, this indicator would have increased an already perceived urban bias of the assets indicator. Thus, we conclude that the *consolidated* indicator measures assets deprivation at the global level more accurately than the MPI-O and MPI-E, as well as the Alternative 2, for the well over 5 billion people that live in the 105 countries that the revised global MPI covers.[39]

[39] By embedding the analysis in the large literature on asset index construction in welfare economics, the decision to add computer and animal cart to the list of items of the MPI-O must be seen considering 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' to describe the revised assets index (given that the term 'assets' is very broad and may create 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-E? 5) Should conceptually strict approaches to assets 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? 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 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 pending data improvements as voiced in this paper, as well as in Dotter and Klasen (2014, p.20), Alkire and Jahan (2018), Alkire (2014) and Alkire et al. (2015, p.228).

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Appendices

Appendix 1. MPI-E: MCA Statistics for Column Categories in Principal Normalization, Set of 26 Countries

Pooled									
	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

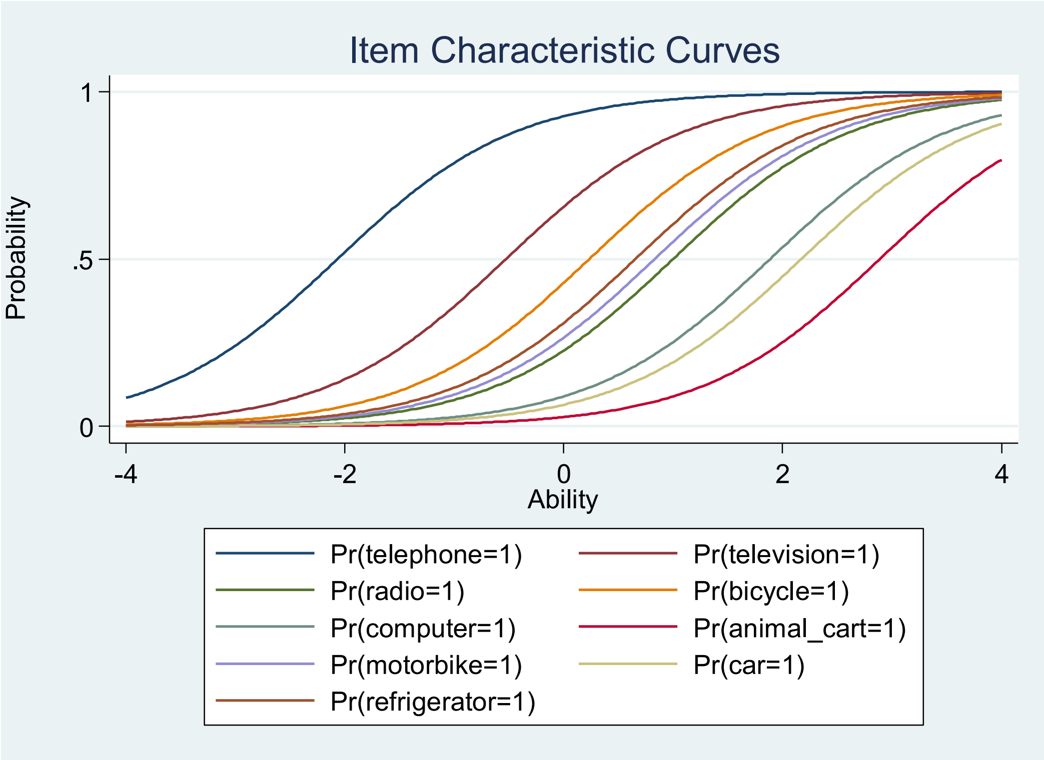
Appendix 2. Cronbach's Alpha for MPI-O, MPI-E and 4 Alternatives, Set of 26 Countries

	MPI-O	**MPI-E**	**Alternative 2**	**Alternative 3**	**Alternative 4**	**Alternative 4 minus bicycle and animal cart**
Pooled	0.583	0.4776	0.742	0.7034	0.6129	0.6779
Armenia	0.2356	0.2973	0.513	0.4982	0.3087	0.3172
Angola	0.6896	0.4964	0.7627	0.7365	0.6972	0.7531
Bangladesh	0.4523	0.4667	0.5727	0.5333	0.5155	0.54
Brazil	0.3685	0.3685	0.5753	0.5753	0.4577	0.4577
DR Congo	0.6256	0.4759	0.6982	0.6372	0.638	0.7105
Côte d'Ivoire	0.511	0.4444	0.6346	0.5586	0.5273	0.6195
Colombia	0.5625	0.5625	0.6703	0.6781	0.6238	0.6073
Egypt	0.2954	0.3795	0.382	0.3601	0.3471	0.3982
Ethiopia	0.6398	0.4028	0.6636	0.6753	0.6651	0.6814
Guatemala	0.6611	0.5167	0.7434	0.7291	0.6659	0.7126
Haiti	0.6338	0.4333	0.691	0.6767	0.6302	0.6829
India	0.5534	0.4905	0.7251	0.6757	0.5795	0.6567
Indonesia	0.6811	0.4935	0.6829	0.6821	0.6306	0.6702
Kenya	0.5833	0.5035	0.5158	0.5207	0.5538	0.5755
Cambodia	0.5675	0.4429	0.5739	0.5464	0.5039	0.5802
Myanmar	0.6306	0.5107	0.6674	0.671	0.6111	0.638
Malawi	0.6589	0.5629	0.6673	0.6523	0.6702	0.6922
Nepal	0.5475	0.4173	0.6423	0.6369	0.5835	0.6125
Peru	0.5431	0.2748	0.7003	0.6733	0.5799	0.6295
Philippines	0.6543	0.5463	0.6332	0.6267	0.602	0.6575
Pakistan	0.5921	0.4628	0.7428	0.7138	0.5962	0.6711
Senegal	0.487	0.4112	0.64	0.5976	0.4979	0.6073
Tajikistan	0.3994	0.3466	0.4831	0.4928	0.4085	0.4154
Tanzania	0.6248	0.5098	0.675	0.6318	0.6373	0.6901
Uganda	0.5752	0.4948	0.6601	0.6024	0.6087	0.6679
Zimbabwe	0.5358	0.458	0.6615	0.605	0.5679	0.6361

Appendix 3. 2pl Model for Alternative 4, Set of 26 Countries

Pooled						
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

Appendix 4. Item Characteristics Curve, 1pl model, Alternative 4



Appendix 5. 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