



# Consolidating and improving the assets indicator in the global Multidimensional Poverty Index

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## ABSTRACT

This article traces a methodological path for constructing a statistically and normatively validated assets indicator, that in turn can be used within an internationally comparable measure of multidimensional poverty. The article validates a revision to the assets indicator of the global Multidimensional Poverty Index (global MPI) that makes the best possible use of existing data. Our normative focus is shaped by Amartya Sen's capability approach, framing assets in relation to human activities. But surprisingly few asset items were available for 75 countries and 3.5 billion people, the standard set for indicator revisions, so the paper notes the lack of comparable data, as well as the lack of data on the quality, quantity or gendered ownership of assets. Drawing on empirical antecedents and complemented by normative reasoning, this article uses tetrachoric exploratory factor analysis, multiple correspondence analysis, classical test theory, item response theory and a non-parametric Mokken scale procedure to identify a set of items that proxy asset deprivations. Measures were trialled across 26 purposefully-selected countries. The final counting-based assets index includes nine statistically validated items (adding computer and animal cart to the original global MPI assets indicator). It has higher reliability than other options, and is arguably the most rigorous feasible indicator to compare asset deprivations that can be constructed from existing global MPI data sources. The methodological approach outlined here could be used to design and validate assets indicators within national, regional, or bespoke multidimensional poverty measures elsewhere.

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## 1. Introduction

In recent years, multidimensional poverty measures have become accepted as complements to monetary poverty measures because they show the joint distribution of direct deprivations a person or household experiences. For example, the Atkinson Commission of the World Bank advocated monitoring global poverty using monetary and non-monetary measures, including a multi-dimensional indicator, while the Third United Nations Decade for the Eradication of Poverty uses global monetary and multidimensional poverty indices to track trends (UN 2018, World Bank, 2017). Sustainable Development Goals Indicator 1.2.2 reports countries' national multidimensional poverty metrics. In Europe, the At-Risk-Of-Poverty and Social Exclusion measure includes Material Deprivation and Quasi-joblessness in addition to the monetary At-Risk-Of-Poverty indicator (Atkinson, 2019). The dimensions and indicators of official national multidimensional

poverty indices (MPIs) in developing countries vary, yet nearly all include dimensions related to health, education, and living standards. In living standards, to date 21 developing countries include some indicator of asset ownership in their official multidimensional poverty statistic,<sup>1</sup> as does the global MPI, the Arab MPI, and a previous Latin American MPI (UNDP & OPHI, 2021; UNESCUA, UNICEF & OPHI, 2017; ECLAC, 2015).

It is difficult to specify how asset indices should be designed and justified. One challenge is to create an asset index that can meaningfully compare different households, given that relevant assets in urban areas vary greatly from those in remote rural areas, and vary across households with different characteristics in terms of education, employment, and household size. A second challenge is statistical – what tests are appropriate to use in designing asset indices, and how are they to be interpreted? The third is data: an asset indicator used within a multidimensional poverty index will almost certainly be data constrained. So how can existing data be

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<sup>1</sup> Afghanistan, Angola, Bhutan, Ghana, Honduras, India, Malawi, Malaysia, Morocco, Mozambique, Nepal, Nigeria, Pakistan, State of Palestine, Philippines, Rwanda, Sierra Leone, South Africa, Sri Lanka, Thailand and Vietnam (MPPN, 2021).

explored to create the most parsimonious yet reliable and informative index possible – and what criteria should be used to assess when an indicator is strong enough to validate and when it is too weak and should be dismissed?

This article outlines how these research questions were critically explored in relation to the assets indicator of the global Multidimensional Poverty Index (global MPI).<sup>2</sup> The global MPI was designed in 2010 as an international measure of acute poverty covering over 100 developing countries (Alkire & Santos, 2014), and revised in 2018 (Alkire et al., 2018). First published in the 20th Anniversary 2010 Human Development Report, it complements traditional monetary poverty measures by capturing which of ten internationally recognised deprivations each person faces at the same time with respect to education, health, and living standards. The global MPI seeks to provide the most comparable measure possible for cross-country investigations and provide relevant information for policies that reduce poverty by confronting the interlinked deprivations poor people face.

The original assets indicator in the global MPI (MPI-O) was jointly designed by the Oxford Poverty and Human Development Initiative (OPHI) and the United Nations Development Programme's Human Development Report Office (UNDP HDRO). In 2014 UNDP HDRO developed an experimental assets indicator (MPI-E). Empirically, the MPI-O and MPI-E results matched closely (Alkire & Jahan, 2018). Yet adjudicating between or going beyond these required a thorough exploration of the wider literature and methodologies, which this paper undertakes.

A further objective is to clarify the methodology by which data-constrained asset indicators might be designed for use in regional or national MPIs. National MPIs, many of which take their inspiration from the global MPI, are adopted as official permanent poverty statistics, usually alongside and complementing national monetary poverty statistics (World Bank, 2018).

This paper outlines the interplay between statistical test results, normative reasoning, and trial measures that justify this revision of the assets indicator of the global MPI. After considering alternative methodologies of asset indicator construction, we chose an analytical approach similar to that adopted in the revised 13-item material deprivation indicator in the European Union (Guio et al., 2012, 2016, 2017), but with some differences, such as applying a Mokken scale procedure.

After a concise overview of the considerable literature on asset index construction, the paper sets out the methodology and results of a systematic review of over 100 Demographic and Health Surveys (DHS), Multiple Indicators Cluster Surveys (MICS) and selected national surveys, from which the global MPI is constructed, to identify potentially new household assets. It then presents the results of statistical assessments of the MPI-E assets indicator, and potential alternatives to the MPI-O and MPI-E. The discussion draws on normative reasoning and interpretation of the statistical tests to empirically evaluate a range of trial asset indices. The following sections present the revised assets indicator which was incorporated into the revised global MPI (Alkire & Jahan, 2018; Alkire & Kanagaratnam, 2020), and some concluding remarks.

## 2. Asset index construction

Asset indices are difficult to design – conceptually and empirically. The term assets can cover a wide range of tangible and non-tangible productive and durable goods. Their measurement

accuracy varies: durable goods are considered easier to measure than productive assets (Chowa et al., 2010). Asset indices have been used to triangulate or stand in for monetary poverty measurements based on household consumption expenditures (Ngo & Christiaensen, 2018; Wittenberg & Leibbrandt, 2017) – especially when income or expenditure data are missing (Sahn & Stifel, 2000), have substantial measurement errors, or do not reflect permanent income (Ferguson et al., 2003; Filmer & Pritchett, 2001; Maitra, 2016).

Asset indices typically aggregate a set of assets using, or partially justified by, methods such as a counting approach, principal component analysis (PCA), factor analysis, and/or multiple correspondence analysis (MCA) – although some authors also utilise anchored regression analysis,<sup>3</sup> or so-called 'asset scores' that simply count the number of (weighted) items, where weights are assumed to be equal to the inverse of the proportion of households who own that item (Morris et al., 2000; see also Cappellari & Jenkins, 2007 for a related application of a 'sum score' to a deprivation scale construction). While the literature is large and interdisciplinary, this section reviews some quantitative methods that have been used to justify existing asset indices.

The asset index included in the global MPI in 2010 (the MPI-O) was a counting-based measure that assigned a household a deprived status in assets if it did not own more than one of a radio, television, telephone, bicycle, motorbike or refrigerator, and if it did not own a car or truck. It had an indirect relationship with the DHS Wealth Index (Alkire & Santos, 2010).

It is worth noting that sub-indices are often not advised within a MPI because they obscure information that is potentially relevant to policy. For example, if a health subindex is created such that a child is deprived in health either if they lack immunisation or did not have an assisted birth, and the subindex rates each child as deprived or non-deprived, policy actors who wish to address the health deprivation do not know whether to focus on immunisation or maternal health. However, for assets, an index is justified because the aim is only to have a critical mass of assets, rather than particular assets, and its diversity will make it relevant across ages, rural/urban areas, occupations, and personalities. This means that statistical and data reduction exercises that are not appropriate for assessing multidimensional poverty measures overall, nor for assessing most indicators within them, are appropriate for the asset indicator. For this reason, we find the justification of the material deprivation index in the European Union (see Section 2.1), to be interesting in this very distinctive but similar context.

Reasoned justification is required. An exploratory index (MPI-E) introduced in 2014 by UNDP HDRO included, in addition to the assets in the MPI-O: motorboat, animal cart, land, cattle/cow/bull, horse/donkey/mule, goat, sheep, and chicken. The items 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 information asset, but did not have at least one mobility asset (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 cow or horse, or two goats or sheep, or 10 chickens) (HDRO, 2016). If a household lacked all three information items, it was deprived in assets regardless of how many mobility and livelihood items it owned. The MPI-E was proposed because: a) the number of items included in the MPI-O was criticised as being too few (seven, compared to eleven in the MPI-E); b) the MPI-O did not include the productive assets of

<sup>2</sup> This paper draws on Vollmer and Alkire (2018, 2020), which more comprehensively present all the results of tests conducted in the identification of the revised assets indicator.

<sup>3</sup> Other authors utilised regression techniques using additional expenditure or price data (Stifel & Christiaensen, 2007; Ngo, 2018; Ngo & Christiaensen, 2018), but such data are unavailable in the DHS and MICS.

rural poor people, such as land and livestock (Kovacevic, 2015); and c) the threshold for being non-deprived in the MPI-O was *not* conditioned on the possession of communication assets. The MPI-O required ownership of *any* two small assets or a car/truck for a household to be non-deprived, whereas the MPI-E required two items from two categories, one of which was information. It was not immediately apparent how these two alternatives, or others, should be rigorously compared and reasonably assessed.

Considering the improvements in many of the DHS, MICS and national surveys in recent years, and building on previous insights, this paper sets out a more general framework for constructing and assessing asset indicators. The remainder of this section briefly reviews the literature and sets out the main methodologies we apply: tetrachoric exploratory factor analysis (EFA), MCA, classical test theory (CTT), item response theory (IRT) and a non-parametric Mokken scale procedure (MSP).

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 to assess household wealth in India. Utilising DHS data and applying PCA to 21 asset variables spanning consumer durables, dwelling characteristics, 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 therefore are unsuitable for constructing a robust linear index (Filmer & Pritchett, 2001, pp. 116 and 128). The authors retained the first principal component and assigned all individuals in each household a standardised index score derived from normalised asset variables. This score was then used to categorise the sample into quintiles. As highlighted in Alkire et al. (2015), Filmer and Pritchett’s approach has been applied widely, including in studies of poverty and inequality such as Lelli (2001), McKenzie (2005), Nguefack-Tsague et al. (2011), Sahn and Stifel (2000), and Roche (2008).

Drawing on Filmer and Pritchett (2001), Sahn and Stifel (2000) and Asselin (2002), Booyesen et al. (2008) used an asset index to compare poverty over time and across seven African countries. They utilised MCA instead of PCA or factor analysis to identify variables because it is better suited for discrete and categorical data and imposes fewer constraints on the data. MCA was deployed to construct an indicator matrix that depicted each household’s asset 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 were similarly phrased). This resulted in an 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, flooring, and water source. MCA has subsequently been widely used in other studies, such as Asselin and Anh (2008), Deutsch et al. (2012), Batana and Duclos (2010), and Ballon and Duclos (2016).

In contrast, Giesbert and Schindler (2012) utilised non-parametric, parametric, and semi-parametric estimation techniques to construct comprehensive and liquidatable asset indices in an empirical application of Carter and Barrett’s (2006) asset-based poverty traps theory in rural Mozambique. Using 2002 and 2005 panel waves of the *Trabalho de Inquérito Agrícola* household surveys and drawing on Adato et al. (2006), the indices were constructed based on a livelihood regression, using a household fixed-effects panel model with a second-order polynomial expansion of continuous assets and interaction effects between basic assets. 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. Two indices were designed by predicting the fitted values from the estimated

regression coefficients: a comprehensive index of 30 assets (mostly productive assets such as land and livestock, and durable household assets), and a liquidatable asset index of 12 potentially sellable assets. Findings indicated that the respective indices explain 24% and 5% of the (within) variation of the livelihood measure. The main advantage of this method is that the results are intuitive and easily interpreted. By scaling the asset index in poverty line units, a score above one identifies households with an income above the poverty line (Giesbert & Schindler, 2012, pp. 1597–1600).

Similarly, the Comparable Wealth Index (CWI) utilised regression techniques to compare wealth across countries and time. By adjusting the original DHS Wealth Index, which drew on PCA 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. The CWI used a sequenced statistical approach where the 2002 DHS survey from Vietnam was chosen as a baseline survey, and eight anchoring points were identified. Between five and eight regression points across the 172 DHS surveys 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 (Rutstein & Staveteig, 2014).<sup>4</sup> The method is sophisticated but, as highlighted by Chakraborty et al. (2016), cannot be used to derive absolute wealth comparisons because the CWI is benchmarked against the Vietnamese DHS 2002 and hence remains a relative measure of wealth.

Each of the applied statistical methods has strengths and weaknesses based on their underlying assumptions and details of how they are implemented, as well as whether they treat data as cardinal or ordinal. These affect how they could be used to construct or validate an assets indicator in the global MPI. For example, while EFA makes no assumptions regarding the relationships among the observed indicators and the latent factors, confirmatory factor analysis (CFA) attempts to confirm measurement theory and assumes multivariate normality (Alkire et al., 2015). Similarly, as Townend et al. (2015) highlight, while PCA has become popular to construct 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, researchers also make many technical decisions that drive the results, including, for example, what kind of normality to assume, or 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 allows variables to retain unique variance that is unexplained by the latent variable, such as in factor analysis (Grace-Martin, 2017). However, the biggest challenge is that these statistical approaches reflect relationships within a given dataset (or a set of collapsed datasets), producing weights *relative* to that dataset without normative justifications. This implies that the weights could change with every update, which would impede robust cross-country and intertemporal analyses in the future (Alkire et al., 2015). A direct uptake of component scores, asset scores, or similar statistical weights that rely on the eigen decomposition of the corresponding dataset(s) for the revised assets indicator would severely limit the global MPI, as it aims to measure and compare an underlying concept of *absolute poverty*, globally and over time (Alkire & Santos, 2014).

<sup>4</sup> See also Brown et al. (2019) for a similar approach.

Statistical data reduction and latent trait techniques in asset index design are therefore important to obtain an empirical understanding of the interrelations between items and the dimensional structure of the data (Klasen, 2000),<sup>5</sup> but not as a strict selection criterion. When applied to the global MPI assets indicator, the results of these statistical methods are interpreted normatively, tested empirically in trial measures, and considered in selecting the final counting-based measure with normative weights, which provide consistency over time.

## 2.1. Methodology

In selecting the methodologies used to assess indicators for potential inclusion in an asset index, we draw on a body of related work, including Guio et al. (2012, 2016, 2017) who utilised a theory-based analytical framework to justify the counting-based material deprivation indicator in the European Union. Guio et al. deployed EFA, MCA, CTT (via Cronbach's Alpha), 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 EU member states.<sup>6</sup> Our approach differs in that the asset items were not based on perceptual data, nor did we assume that preferences were homogenous within countries. We also draw upon our previous methodology to validate the structure of a relative autonomy indicator in Bangladesh (Vaz et al., 2013; 2018), which extended these techniques to include others such as the MSP, an additional analysis of reliability using non-parametric IRT.

As our approach uses these statistical data reduction techniques primarily as exploratory and analytical tools, we align with Steinert et al. (2018), who cautioned against the assumption that a 'one-size-fits-all' measurement model based on structural equation modelling (SEM), often used in the design of composite poverty indices, yields valid results.<sup>7</sup> Our analytical approach – in line with Guio et al. (2012, 2016, 2017) and Vaz et al. (2013, 2018) – focuses on understanding the construct, internal, and face validity of the assets indicators tested in this paper, as well as their reliability, to assess the options in empirical trials, and inform the normatively chosen consolidated assets indicator that draws on Amartya Sen's capability approach, framing assets in relation to human activities (Sen, 1999). Decisions are taken in light of data challenges inherent to designing an

assets indicator that is informative within a multidimensional poverty index that measures *acute poverty* across over 100 countries.

Data-driven techniques dominated the identification and revision of the EU material deprivation variables for the whole EU population. CFA and related *confirmatory* multivariate statistical procedures were largely not applied, in part due to data limitations. Similarly, while the DHS surveys, for example, include "easy-to-collect data on a household's ownership of selected assets" (DHS, 2018), their thematic focus is population, health, and nutrition. Data on prices of assets, their quality and age, the quantity of each item owned per household, or on preferences, accessibility and affordability of items, are lacking (Dotter & Klasen, 2014, p. 20; see also Harttgen et al. who noticed the lack of age and depreciation of assets recording in DHS surveys that renders them poor predictors of asset services (2013, p. 541), which is arguably required to design a measurement model to be tested in a CFA). The binary nature of ownership, measured at the household level, has also been found to limit the cross-geographical validity of composite poverty indices derived from SEM, even in ethnically homogenous populations (Steinert et al., 2018, p. 65).

Another reason we did not focus on CFA was empirical. We ran a Doornik-Hansen test for multivariate normality that rejected the null hypothesis of multivariate normality on the 11-item schedule of the MPI-E in Pakistan and Haiti, two examples of countries with a large and small sample size ( $\chi^2(22) = 5.82e + 07$ ,  $p < .0001$ ;  $\chi^2(22) = 9.29e + 07$ ,  $p < .0001$ ), as well as on a 7-item alternative assets schedule (Alternative 2 in Section 4.2.2) on a larger pool of 26 countries ( $\chi^2(14) = 6.28e + 07$ ,  $p < .0001$ ). While multivariate normality is not an assumption of EFA, it is of CFA, and this was not supported. Therefore, CFA was not used in this paper, nor were associated goodness-of-fit indices and statistics. Instead, we used IRT as it is the appropriate generalised SEM model for binary data. As more and better data on quality, functionality, affordability, and depreciation over time of items becomes available, CFA modelling could be further explored, including to also assess convergent and discriminant validity commonly used, for example, to test whether the assets index would be unidimensional or multidimensional. Instead, the revision utilised three statistical approaches based on different properties to understand the dimensional structure of the data: EFA (based on correlations), MCA (based on entropy), and the MSP, which is a non-parametric IRT.

Finally, given that the asset index in the global MPI is based on data sources that are not purposefully designed to create such an index, a data- rather than theory-driven research approach seemed more appropriate for this study. As these techniques explore the statistical commonalities between data, a word of caution is apt: data commonalities may be higher in purposefully designed data, such as in data collected in the thematic module on material deprivation in the EU Statistics on Income and Living Conditions (EU-SILC), than in results obtained when such methods are applied to ad-hoc or non-purposefully collected data.

With that background, the methodology of this paper is as follows. Having identified the purpose and the datasets, we established a minimum threshold for data availability of 75 countries and 3.5 billion people (outlined in Section 3). In addition to data availability, we required potential indicators to be recognised as 'assets of the poor' (or 'poor people's assets') in participatory literature such as the seminal *Voices of the Poor* volumes (Narayan et al., 1999; Narayan & Petch, 2002). Potential assets could have multiple purposes, such as contributing to people's wellbeing and economic activity, and acting as insurance against economic shocks (OPHI, 2018).

<sup>5</sup> Klasen, who applied PCA to design a composite measure of deprivation in South Africa, also cautioned: "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).

<sup>6</sup> The identified 'optimal' material deprivation indicator in the European Union consisted of 13 equally weighted items covering basic and social necessities, such as food, clothes, shoes, internet access, and leisure activities (Guio et al., 2016). The original 2009 material deprivation indicator consisted of nine items, which was perceived as too few (Guio et al., 2017) and faced similar criticisms as the MPI-O. In contrast to the global MPI assets indicator, 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 50 possible items tested (Guio et al., 2012), several 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, none of the tested items could be considered a productive or capital asset.

<sup>7</sup> Steinert et al. applied multiple-group comparisons in SEM in KwaZulu-Natal, South Africa, and were unable to identify acceptable fits to test the cross-geographical validity of the composite poverty index. The authors' main conclusion is that "previous rankings and comparisons of household poverty levels across South Africa (or even across KwaZulu-Natal) could thus be less reliable than thought" (2018, p. 64) and therefore called for further refinements "to identify whether these indices can serve as an adequate measurement tool for identifying the poorest and most deprived households, both within and across countries" (2018, p. 64–65).

We tested a set of preliminary asset indicators – the MPI-E and four alternatives to the MPI-E and the MPI-O – for their dimensional structure and reliability (internal consistency of a scale of items) via tetrachoric EFA, MCA, CTT, IRT,<sup>8</sup> and a MSP. Results are presented for a set of 26 countries that cover almost 3 billion people (Table 1). Key test results are disaggregated by urban and rural populations. The results from these statistical tests are discussed, which then informed 24 trial measures in total, using a counting structure with different vectors of asset items. The trials utilised basic descriptive characteristics of alternative indices such as the percentage of the population who are classified as deprived in assets, the uncensored headcount ratio (Alkire et al., 2015). These trial measures systematically added or subtracted assets one at a time, to test the empirical consequences of including new items to those included in the MPI-O, or excluding or substituting existing items from it. This approach provided extensive insights that advanced our aim to consolidate, and possibly improve, an existing indicator that has been used in the global MPI since 2010, rather than to design a completely new indicator. A similar approach was applied by Alkire and Kanagaratnam (2020), illustrating the iterative interplay of normative and technical considerations underlying adjustments in four original indicators of the global MPI – child mortality, nutrition, years of schooling, and housing – which involved considering the joint distribution of alternative indicators across 20 trial measures. Such a procedure has therefore started to become common practice in the measurement of multidimensional poverty.

The 26 countries were purposefully selected, and include large population countries, with DHS datasets from 2012–16, and at least two countries from five of the six regions that the global MPI covers. The countries range from low-income to lower-middle-income status (according to the World Bank Atlas Method). We acknowledge the potential limitation of this approach, namely that the internal validity and reliability of the study findings presented here were used to calibrate the revised assets indicator of the global MPI, which covers over 100 countries (hence, external validity was assumed from the internal validity of 26 countries). This was a pragmatic decision<sup>9</sup> and can be examined further.<sup>10</sup>

The analytical advantages of this approach are considerable, as it became feasible to revise the asset indicator in the light of statistical tests, as well as to clarify the differences between, and

distinctive value-added, of the previous asset indicators (MPI-E and MPI-O).<sup>11</sup>

### 3. Data

#### (a) Data availability of potential new asset items

We conducted a systematic review of 100 DHS, MICS, and selected national surveys, covering 5.6 billion people in total (based on 2015 population estimates), to identify potential new asset items based on available variables (OPHI, 2018).<sup>12</sup> The review identified nearly 30 potential new items that were grouped into 11 categories (Table 2). Table 2 presents the number of countries for which data on each item were available and the corresponding population covered. At the review stage, we used a generous definition of asset ownership, and included consumer durables and productive assets such as farm animals owned, consumption of goods such as iodized salt; demerit goods such as tobacco; and 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 many were used in Ferguson et al. (2003).

As shown in Alkire and Santos (2014), data on assets used in the MPI-O were available in all DHS and MICS (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 were only available in 15 countries, 91 countries had data on livestock. Yet only 84 countries (covering 2.1 billion people) had data on the number of chickens or poultry owned, while nine countries (covering 1.6 billion people) of the 91 countries that had data on agricultural land ownership lacked data on land size.

We set a benchmark of 75 countries and a population coverage of 3.5 billion as a critical mass for the potential inclusion of items (Alkire & Jahan, 2018). This criterion ruled out many potential items including small physical assets such as tables and beds, all electrical assets except for computers, as well as waste management. Items that did not meet the two criteria (or only one) were retained for the analysis either if they featured in the MPI-E (such as motorboat, or farm animals), or if strong conceptual reasons existed to do so, such as a relationship to the SDG targets or another.<sup>13</sup>

#### (b) Treatment of missing values and data

Following Tabachnick and Fidell (2007, in Yong and Pearce, 2013), missing values were dropped from the EFA, MCA, and CTT to prevent overestimation (unless otherwise stated). The IRT was utilised with and without the listwise option that handles missing values through listwise deletion. In the trial measure analysis, we report asset estimates as a lower-bound estimate of assets deprivation. Hence, if values on any of the items in the schedule were missing it was assumed that the household did not own the asset.

<sup>8</sup> 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 in social sciences (see Nunally, 1978, cited in Guio et al., 2016). The main weakness is that the statistic assumes equal variance (' $\tau$ -equivalence') among variables (Guio et al., 2017). 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. Further, we performed the  $H$  coefficient (Bentler, 2007) to analyse the maximal reliability of the tested scales in the EFAs, which overcomes the assumption of ' $\tau$ -equivalence' as it accounts for the different standardised factor loadings of the retained items and their contributions to the scale scores (McNeish, 2017, pp. 19–20). However, the measure has its own assumptions that make it less useful for this study (see Savalei & Reise, 2018; Sideridis et al., 2018; Morera & Stokes, 2016). Reliability is estimated using an assumed *optimally weighted* composite from the standardised factor loadings and technically requires a polychoric correlation matrix – in contrast to the tetrachoric EFA used in this paper. The measure is more common in structural equation modelling (particularly CFA) where items are (or are assumed to be) continuous measurements, and where items that load weakly on factors are retained. The tetrachoric EFA in this paper excludes factor loadings below 0.5, and tests individual items instead though IRT. We thus present coefficient  $H$ , but only for reasons of completeness, and only with the retained items.

<sup>9</sup> Pooling data for the large number of countries used in the global MPI (over 105) proved challenging, and certain important tests or graphs, such as the MCA dimension projection plots, were not possible to construct. Hence, the decision was taken to analyse a set of 26 purposefully selected countries.

<sup>10</sup> Alkire et al.'s methodological note (2018) presents each missing item in the assets indicator for the 105 countries, and Alkire et al. (2022) shows that aggregate results and the ranking of countries remained similar under both the revised and original global MPI.

<sup>11</sup> Statistically, the MPI-O was compared via Spearman correlation coefficients with the DHS Wealth Index (Alkire & Santos, 2010). While the global MPI was presented as a robust measure of acute poverty in 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 & Santos, 2014, p. 268). The MPI-E was first presented by Kovacevic and Calderon in 2014 as a follow-on from two HDRO-organised conferences in 2012 and 2013 based on theoretical delineations (Kovacevic & Calderon, 2014; Kovacevic, 2015).

<sup>12</sup> The surveys were implemented between 2006 (Azerbaijan) and 2016–17 (Nigeria). Note that at this review stage, all surveys were scrutinised for data availability. If a variable carried 100% missing values, it was discarded.

<sup>13</sup> For example, internet access formed part of the 13-item revised material deprivation indicator in the European Union (Guio et al., 2016).

**Table 1**

The 26 countries used in the 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 <sup>1</sup>	2015	207,653
Cambodia	East Asia and the Pacific	DHS	2014	15,762
Colombia	Latin America and the Caribbean	DHS	2015–16	48,653
Côte d'Ivoire	Sub-Saharan Africa	DHS	2011–12	23,696
Democratic Republic of the Congo (DRC)	Sub-Saharan Africa	DHS	2013–14	78,736
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
United Republic of Tanzania	Sub-Saharan Africa	DHS	2015–16	55,572
Uganda	Sub-Saharan Africa	DHS	2016	41,488
Zimbabwe	Sub-Saharan Africa	DHS	2015	16,150
				<b>2,994,072</b>

<sup>1</sup>Pesquisa Nacional por Amostra de Domicílios.

If the household lacked data for *all* items, the entire assets indicator was set as missing and subsequently dropped from the analysis (consistent with Alkire & Santos, 2014).

#### (c) Treatment of land and livestock variables

All potential new variables included in the statistical analysis and the trial measures are binary. However, land and livestock are dichotomous variables which are coded according to some discrete deprivation threshold. A household was considered non-deprived in land if it owned any land or more than 0.3 ha, 0.6 ha, 1 ha, 3 ha, 6 ha, or 10 ha of land (unknown land size or missing values on land size, were treated as deprived, in accordance with the coding of missing values on items in the MPI-O). For livestock, households were considered non-deprived if they fulfilled the MPI-E criteria or owned equivalent to 1 or 1.5 livestock units.<sup>14</sup>

## 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). Factor analysis is a model of the measurement of a latent variable which is appropriate for an asset indicator (though not for multidimensional poverty

<sup>14</sup> Comparing livestock in the absence of price data is challenging. An 'exchange ratio' was developed to describe livestock numbers across species and to produce a single figure for the total 'amount' of livestock owned (Njuki et al., 2011; Dida, 2017). Different species of different average sizes were converted into tropical livestock units (TLU). For global comparisons, the concept of a livestock unit is preferred and study results are based on Table 1 of Chionda 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 (FAO, 2011). The concept of a livestock unit is imperfect for 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 globally.

indices more generally). It 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 & Osborne, 2005).<sup>15</sup> Following Guio et al. (2012) and Vaz et al. (2013), 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 (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 the scree plot in Fig. 1).

Eight asset items were retained using a 0.5 primary factor loading and a 0.3 cross-loading threshold (Table 3). Factor loadings for all items were high (above 0.7), except for animal cart and land, which scored below 0.6. The factor loadings of the first two factors explained most of the observed variance (89.6%). The model meets the minimum standards for the acceptable Average Variance Extracted (AVE) of  $> 0.5$ , yet it is below the minimum validity threshold for a good construct ( $> 0.7$ ).<sup>16</sup> The items explain an error

<sup>15</sup> A factor should consist of at least three variables; rotated factors with two variables should be highly correlated with each other ( $r > 0.70$ ) to be considered a factor (Tabachnick & Fidell, 2007, in Yong and Pearce, 2013, p. 80). If the unique variance is above 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, in StataCorp 2013; Dekkers, 2008).

<sup>16</sup> AVE measures how much variance is captured by a construct versus the level that is caused by measurement error. Composite Reliability assesses the internal consistency in a scale similar to Cronbach's Alpha. The minimum threshold for a good Composite Reliability is  $> 0.7$ , but as the coefficient depends on the number of items, a value of  $> 0.8$  is considered suitable for narrowly defined scales with five to eight items. Both measures are commonly used in SEM and CFA to assess the convergent validity of a model, but also provide useful information in EFA (where 'proportion of variance explained' is usually used instead of AVE), that is when such statistical methods are used to assess if the model confidently measures the assumed underlying latent (Alarcón & Sánchez, 2015; Netemeyer et al., 2003).

**Table 2**

Availability of household-level data on 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	51	4,065,077
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	81	4,881,674
		Sewing machine	25	2,041,114
		Fan/electric fan	35	2,343,743
		Air conditioner	51	3,910,776
		Water heater	16	527,542
		Washing machine	54	4,125,874
		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)	91	5,191,266
		Land size	82	3,551,006
		Livestock (any)	91	5,132,547
		Number of cows/cattle/buffalo	84	2,514,439
		Number of horses/ donkeys/mules	80	2,141,453
		Number of goats	81	1,987,506
		Number of sheep	79	1,858,885
		Number of chickens/poultry	84	2,110,914
		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
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 a day	71	4,525,145
		Men smoke more than four cigarettes a 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, age 15–49	39	3,761,155
		Men, age 15–59	34	3,593,859
11	Household waste management	Disposal of household waste	19	2,043,989

of 32.8% for Factor 1 and 47.3% for all retained items. The model fit for sampling adequacy can be considered adequate, but is mediocre, 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 (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 MPI-E factor labels of information, mobility, and livelihood, and resulted in, at best, moderately internally consistent factor scales (Cronbach's Alpha for the first factor: 0.63; for all retained items, 0.44; the Composite Reliability meets the acceptable standard of 0.7 for the first factor and all retained items, but not for the second factor).

We also performed the EFA of the MPI-E disaggregated by rural and urban populations of the 26 countries (Table 4 and Table 5). In contrast to the rural results, the urban results produce a Heywood case (due to the negative uniqueness of motorbike); Factors 2 and 3 of the urban population are a replica of Factors 1 and 2 on the

total population, while on the results for the rural population land is not retained.

Overall, the EFA did not provide sufficient support for the three-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.

#### 4.1.2. Multiple correspondence analysis

MCA can be viewed as a generalisation of PCA to ordered categorical and binary data, and is based on entropy (Guio et al., 2012). Since MCA is a descriptive statistical approach to model a latent concept, rather than a latent variable, MCA compels all included variables in the model to contribute to the latent concept. In contrast, EFA variables retain unique variance that is unexplained by the latent variable. MCA in conjunction with the results from EFA therefore helps to further explore the dimensional structure of the data. In particular, MCA allows analysis of the *individual contributions* of each item ownership or lack thereof to the variance found in the dimensions, and provides a visual demonstration of

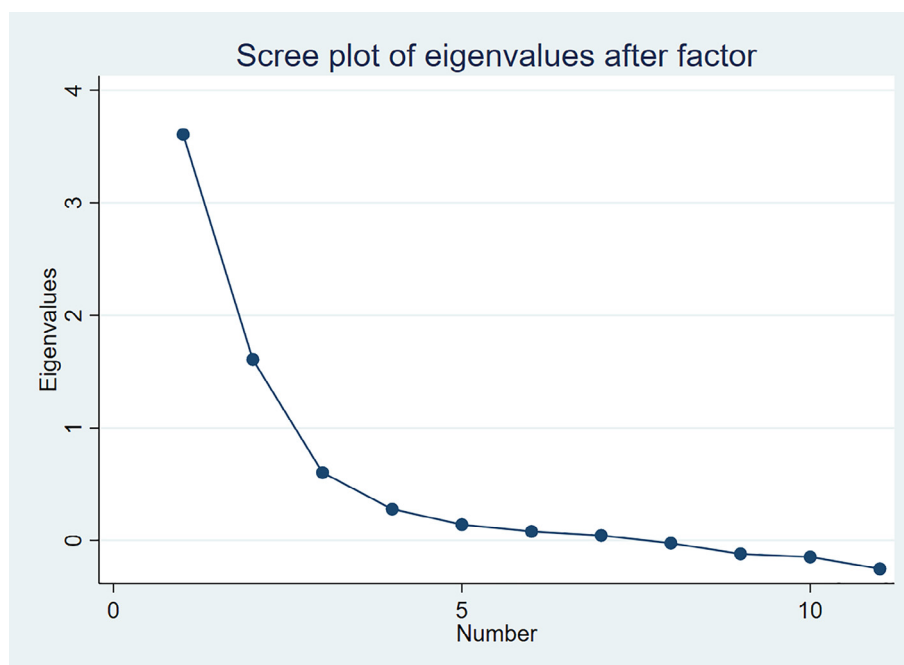


Fig. 1. MPI-E, scree plot of eigenvalues, set of 26 countries.

Table 3

MPI-E, exploratory factor analysis, set of 26 countries.

Pooled				
	Factor 1	Factor 2	Factor 3	Number of observations
Proportion of variance explained	62%	27.6%	10.4%	1,470,046
Rotated factor loadings(1)				
Variable	Factor 1	Factor 2	Factor 3	Uniqueness
Information: Telephone	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
	Factor 1	Factor 2	Factor 3	All items
Items retained	4	3	1	8
Cronbach's Alpha	0.63	0.36	.	0.44
Average Variance Extracted	0.672	0.416	.	0.562
Composite Reliability	0.891	0.672	.	0.909
Coefficient-H	0.903	0.741	.	0.931
Kaiser-Meyer-Olkin	.	.	.	0.65

Note: (1) Blanks represent loading below 0.5; oblique rotation; iterated principal factor extraction method.<sup>17</sup>

how ownership of the 11 items in the MPI-E are clustered and projected.

First, we specified an MCA of the Burt matrix for the data and used principal normalisation to scale the coordinates by the principal inertias to analyse the column categories (StataCorp, 2013). We

found that two dimensions explain 82.94% of the total inertia (i.e., variance, Abdi & Valentin, 2007), of which the first dimension explains 75.05% (the third dimension only explains 0.10% of the inertia).<sup>18</sup>

Fig. 2 plots the origin axes of the two dimensions, which helps to show data associations. We used the overlay option to obtain a combined graph of the biplot graphs for the 11 variables. The plot reveals the clustering of variables due to the relative position of their Euclidean values on a two-dimensional plot (Dijkstra et al.,

<sup>17</sup> As outlined in Vollmer and Alkire (2018, pp. 16–19 and 56–59), this trend was also observed when tested at the individual country level (for Democratic Republic of the Congo, Ethiopia, Haiti, Kenya, Nigeria, and Pakistan). Test results were similar when the same analysis was performed for different land and livestock variables configurations, using minimum land size cut-offs (either 0.3ha or 3ha) and a one livestock unit cut-off.

<sup>18</sup> Number of observations: 1,470,046.

**Table 4**

MPI-E, exploratory factor analysis, set of 26 countries, rural population.

<b>Pooled</b>				
	<b>Factor 1</b>	<b>Factor 2</b>	<b>Factor 3</b>	<b>Number of observations</b>
Proportion of variance explained	63%	26.7%	10.3%	919,745
Rotated factor loadings(1)				
<b>Variable</b>	<b>Factor 1</b>	<b>Factor 2</b>	<b>Factor 3</b>	<b>Uniqueness</b>
Information: Telephone	0.6081			0.3421
Information: Television	0.7350			0.1485
Information: Radio				0.8511
Mobility: Bicycle				0.7559
Mobility: Motorbike		0.7304		0.3136
Mobility: Motorboat				0.8800
Mobility: Car	0.6891			0.5071
Mobility: Animal cart				0.5758
Livelihood: Refrigerator	1.0067			0.0574
Livelihood: Land				0.8201
Livelihood: Livestock			0.7597	0.4562
	<b>Factor 1</b>	<b>Factor 2</b>	<b>Factor 3</b>	<b>All items</b>
<b>Items retained</b>	4	1	1	6
Cronbach's Alpha	0.5763	.	.	0.5098
Average Variance Extracted	0.600	.	.	0.585
Composite Reliability	0.852	.	.	0.892
Coefficient-H	1.014	.	.	1.014
Kaiser-Meyer-Olkin	.	.	.	0.6367

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

**Table 5**

MPI-E, exploratory factor analysis, set of 26 countries, urban population.

<b>Pooled</b>				
	<b>Factor 1</b>	<b>Factor 2</b>	<b>Factor 3</b>	<b>Number of observations</b>
Proportion of variance explained	63.2%	22.8%	14%	550,301
Rotated factor loadings(1)				
<b>Variable</b>	<b>Factor 1</b>	<b>Factor 2</b>	<b>Factor 3</b>	<b>Uniqueness</b>
Information: Telephone		0.7154		0.4634
Information: Television		0.8923		0.1751
Information: Radio				0.9220
Mobility: Bicycle				0.8905
Mobility: Motorbike	2.6847			–6.2070
Mobility: Motorboat				0.9124
Mobility: Car		0.7222		0.4549
Mobility: Animal cart			0.5968	0.6343
Livelihood: Refrigerator		0.8784		0.2185
Livelihood: Land			0.6186	0.5917
Livelihood: Livestock			0.8386	0.2858
	<b>Factor 1</b>	<b>Factor 2</b>	<b>Factor 3</b>	<b>All items</b>
<b>Items retained</b>	1	4	3	8
Cronbach's Alpha	.	0.5687	0.3839	0.4373
Average Variance Extracted	.	0.651	.	1.407
Composite Reliability	.	0.880	.	1.054
Coefficient-H	.	0.904	.	0.922
Kaiser-Meyer-Olkin	.	.	.	0.6179

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

2016). Data points farthest away from the origin (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 emerges where 'yes' and 'no' responses to questions on item ownership are clustered together. 'No' responses to nine items are clustered more strongly and are most distant from the origin along the horizontal axis, with telephone and television the farthest away from the origin. This corresponds with the relatively high contribution of these items to the inertia of Dimension

1 (see [Appendix 1](#), which presents the statistics for column categories in principal normalisation, and [Fig. 3](#), where a projection plot of the column coordinates after MCA also 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 [Fig. 2](#), Dimension 1 contrasts these category values. Land, livestock, and animal cart ownership, however, are the farthest away from the origin of Dimension 2 ([Fig. 2](#), circled). [Appendix 1](#) also shows that ownership of these three items are the greatest contributors to Dimension 2, and in [Fig. 3](#) land, livestock, and animal cart are the only variables that show a different

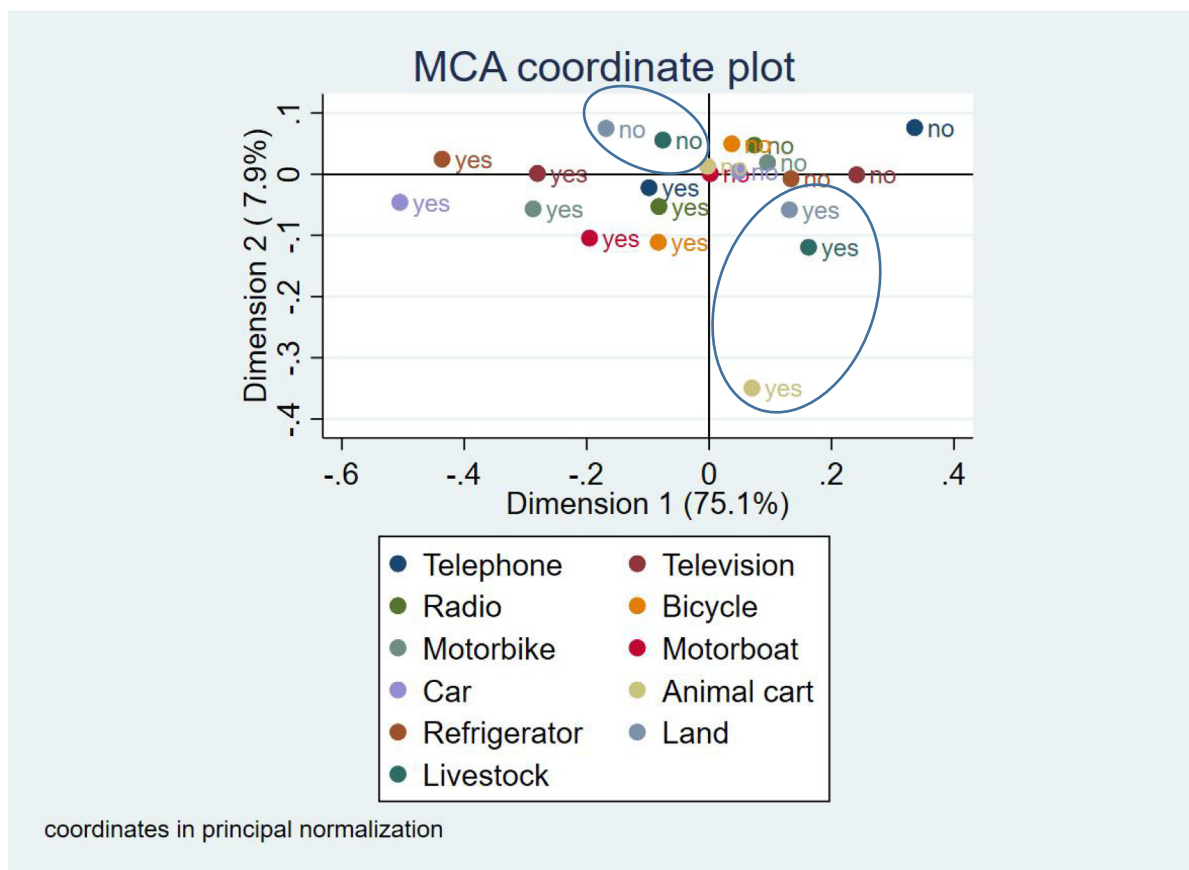


Fig. 2. MPI-E, MCA coordinate plot, set of 26 countries.

ordering in the *first dimension* in their projection (ownership is displayed before non-ownership).

That the responses on the ownership of land, livestock, and, to a lesser degree, animal cart, are clustered and ordered somewhat differently from the other items (Fig. 2 and Fig. 3), highlights their potential incompatibility with the other variables. This can be interpreted as confirmation of the EFA results (Table 3), where the three items were retained on the less powerful second factor.

For the rural and urban populations, 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 (see coordinate plots in Fig. 4 and Fig. 5). While the projection plot of the column coordinates after MCA for the urban population confirmed the results for the total population (Fig. 6), the rural population results showed that the ordering of animal cart in the first dimension is displayed in line with the other eight items (non-ownership is displayed before ownership; Fig. 7). This highlights that animal cart ownership is a distinctly rural item.

From the analysis of the pooled data for 26 countries with reasonable sample sizes, disaggregated by rural and urban populations, and using the 11-item schedule of the MPI-E, we identified two dimensions (at best) in the data. 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. The MCA shows that the first dimension explains 75.05% of the overall 82.94% inertia, suggesting that the available assets should be grouped in one dimension only or, at least, that insufficient reason exists to do otherwise. However, further tests are required to provide more evidence on this.

## 4.2. Statistical validation of alternatives to MPI-E and MPI-O

### 4.2.1. Exploratory factor analysis

The review of over 100 surveys found 30 potential new asset items, and we identified three additional variables that meet at least one of our data availability criteria (75 countries, at least 3.5 billion people): internet access, computer possession, and bank account. Based on the preceding analysis, we excluded land and livestock variables on conceptual and empirical grounds: both items were clustered and ordered differently from the other items in the MCA coordinate and dimension projection plot; and land demonstrated the highest uniqueness of the eight retained items of the EFA on the MPI-E and was not retained on any factor in the rural population due to its high uniqueness. We also excluded the motorboat variable, for two reasons: first, it did not meet the data availability criteria (data were only available in 68 countries covering 2.1 billion people); second, the variable carried 70.8% missing values in the set of 26 countries. Excluding the motorboat variable allowed the number of observations to be substantially increased to 3.3 million. Instead of these three variables, we included the three additional variables and performed EFA on the set of 26 countries for these 11 items, as well as for the rural and urban populations, calling this 'Alternative 1'. Note that test results still explore the dimensional structure of the data and do not act as a definite (de-)selection criterion. The trial measures will continue to work with all items that are (and may be), temporarily excluded in these statistical tests.

Based on the EFA with oblique rotation, a two-factor solution underlying asset deprivation emerged for the 26 countries (following the Kaiser criterion; Fig. 8).

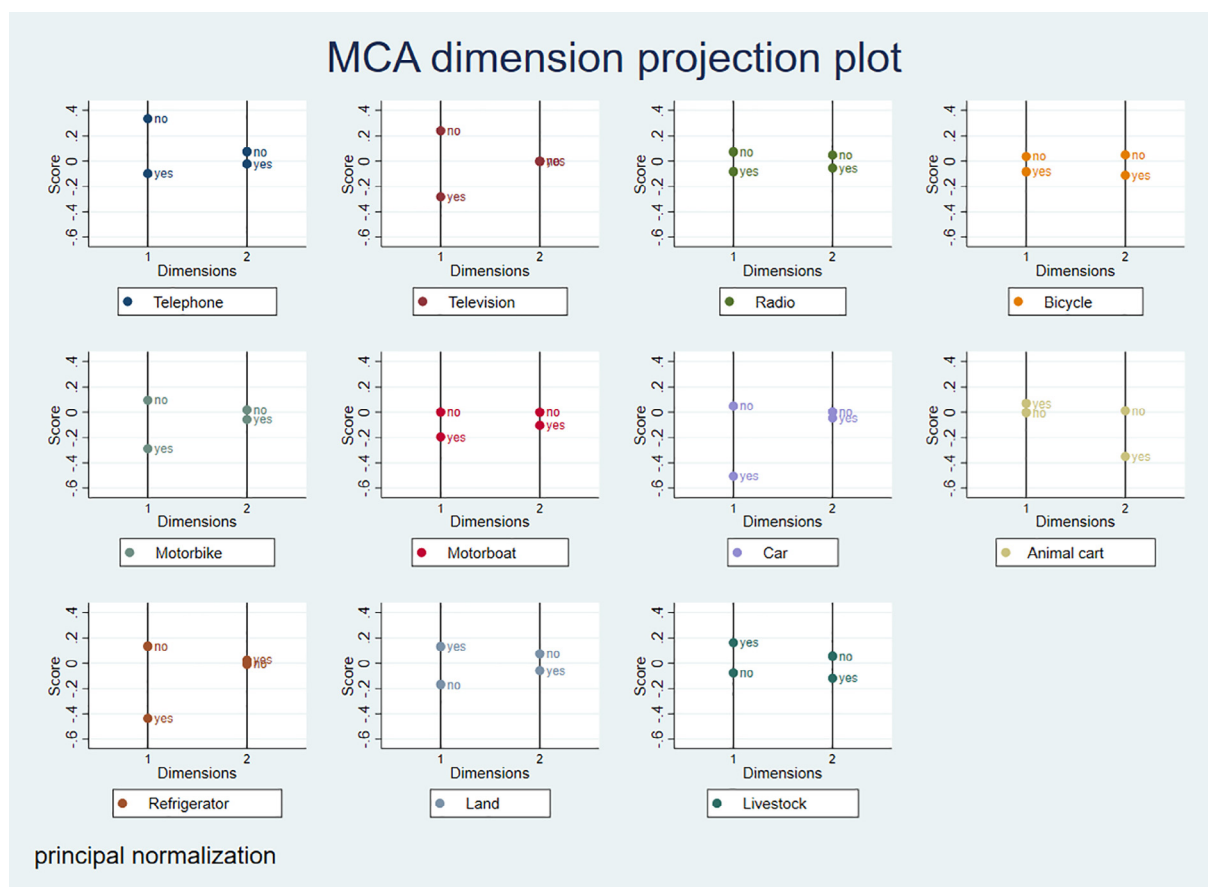


Fig. 3. MPI-E, MCA dimension projection plot, set of 26 countries.

Using a 0.5 primary factor loading and a 0.3 cross-loading threshold, six items were retained in the first factor, which explained 82.2% of the variance (Table 6). The factor meets the standard for an acceptable AVE. Radio, bicycle, and animal cart show high uniqueness. Cronbach's Alpha of the first factor is 0.74, above the minimum threshold for satisfactory internal consistency, while the alpha of all retained items was also above 0.7 (including bank account, the only item that scored a sufficiently strong factor loading on the second factor). The Composite Reliability for the first factor and all retained items meet the acceptable standard of 0.7. Motorbike was not retained with a primary factor loading of above 0.5; neither does it show high uniqueness. Overall, the model fit for sampling adequacy was strong (or 'meritorious', with a KMO test measure of 0.84) and better than the three-factor solution used in the MPI-E.<sup>19</sup>

#### 4.2.2. Classical test theory

Based on the EFA test results (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. This alternative contains all items from the first factor of Alternative 1 (it excludes bank account, as its inclusion lowered the Cronbach's Alpha from 0.7445 to 0.7365). It includes motorbike, an item not retained

on the first factor of Alternative 1. The resulting Cronbach's Alpha is almost as strong as that of Factor 1, but with the added advantage of, with motorbike, having another item included which features in both the MPI-O and the MPI-E.

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.

Appendix 2 provides an overview of the Cronbach's Alphas across various asset versions in our sample, including for the MPI-O and the MPI-E. None of the options showcased a high reliability by Cronbach's Alpha, considered to be 0.8 and above (see Guio et al., 2012, p. 229). The highest Cronbach's Alpha was for Alternative 2 (0.74). The items are consumer durables, except for internet access, which is an intangible asset. The Cronbach's Alpha of Alternative 2 is higher than that of the MPI-E in all 26 countries, and the MPI-O in 24 countries. This combination excludes radio and bicycle. As radios and bicycles are potential assets of poor people (Narayan et al., 1999, Narayan & Petsch, 2002), we included these in Alternative 4, in addition to animal cart, but exclude internet, which was included in Alternative 3 (which added bicycle but not radio to Alternative 2). We utilised Cramer's V, which measures the association between two nominal variables, to assess the potential redundancy of computer and internet. Cramer's V ranges from zero to one, where one indicates a strong association. We found a correlation of 0.62 between computer and internet for the set of 26 countries.<sup>20</sup> Instead of merging both items, we

<sup>19</sup> As shown in Vollmer and Alkire (2018, pp. 27–28), disaggregated for 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 Cronbach's Alpha for the urban population, while for the rural population the Cronbach Alpha was slightly lower (0.67).

<sup>20</sup> Cramer's V ranged from 0.46 in Peru to 0.87 in Armenia.

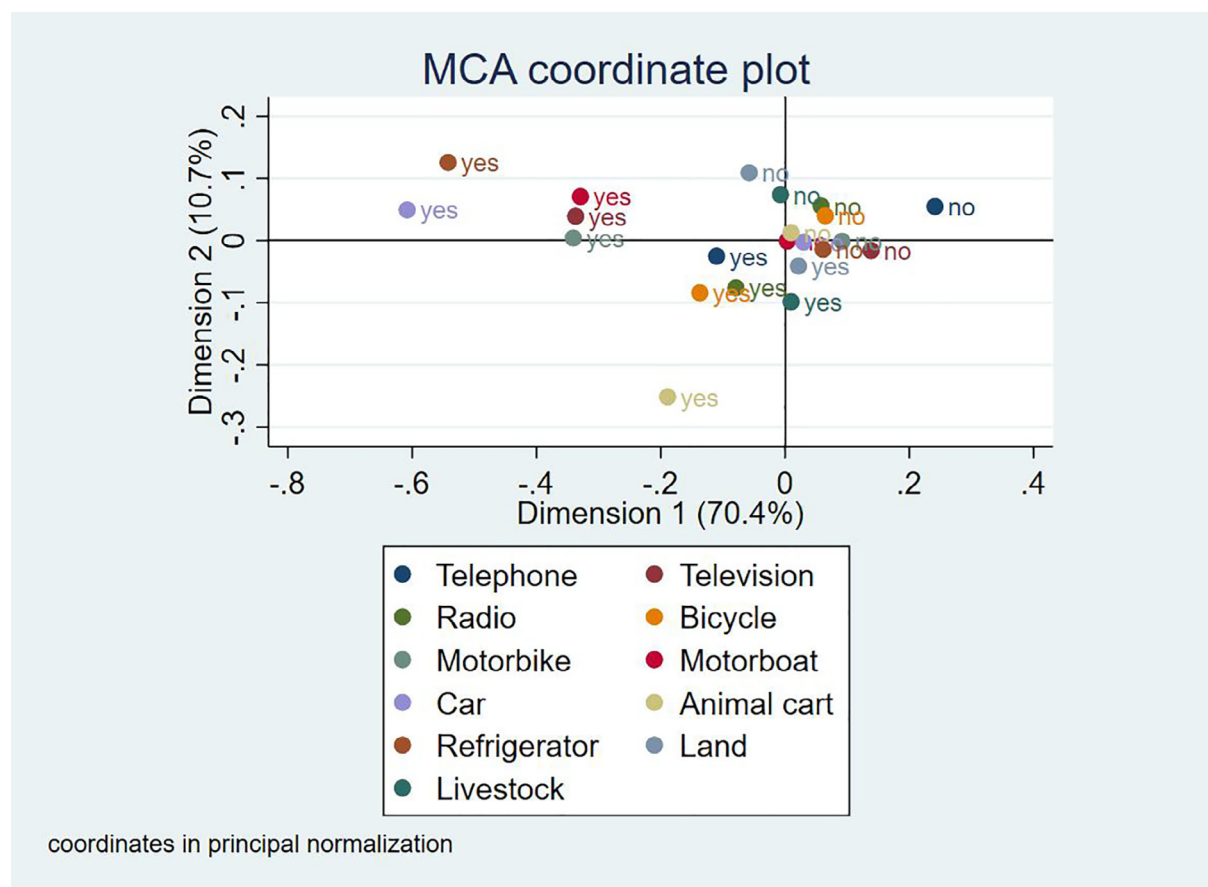


Fig. 4. MPI-E, MCA dimension projection plot, set of 26 countries, rural population.

excluded internet from Alternative 4, as data on the internet variable are only available in 51 countries, and because it is a conceptually distinct item from the otherwise tangible consumer durables.

#### 4.2.3. Item response theory (IRT)

CTT provides information on the reliability of a scale. We used IRT, which offers additional information on the reliability of each individual item in the scale, to further explore the reliability of the alternative asset indices. IRT indicates 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) is a function of both the level of the latent trait and the item's properties (StataCorp, 2017). Thus, IRT provides information on the difficulty of obtaining that item and is therefore potentially useful in assessing the extent to which the final assets indicator encompasses items that range from low to high in terms of difficulty (called 'severity' by Guio et al., 2016). It also offers details 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). Conceptually, IRT is related to the most common *order of acquisition of durable goods approach*, first introduced by Paroush (1965; 1973; see also Deutsch & Silber, 2008), and is therefore more often applied in recent literature on the construction of assets schedules (Deutsch et al., 2020).

In Vollmer and Alkire (2018, pp. 30–37), we applied IRT to two of the alternatives above: Alternative 2, as it showed the highest internal consistency of Alternatives 2–4 as measured by Cronbach's Alpha; and Alternative 4, the most comprehensive, as it includes

radio, bicycle, and animal cart, but excludes internet. Here, we present the results for Alternative 4.

**4.2.3.1. IRT on Alternative 4, set of 26 countries.** We specified a one-parameter logistic model (1pl; Table 7), which estimates the prevalence ('difficulty') of ownership of each of the nine items in Alternative 4. The estimate of the item discrimination parameter shared by all items is 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 found that a telephone is the easiest item to obtain, with a coefficient of  $-2.07$ , while an animal cart is the most difficult, 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 other items. It is easier because household members only need an ability level greater than  $-2.07$  to be expected to succeed in obtaining this item. In contrast, for a car and an animal cart one would need an ability level of  $2.17$  and  $2.89$ , respectively.

Given the markedly low discrimination parameter, we checked the item fit between a 1pl and 2pl model, one which allows for a separate discrimination parameter, by performing a likelihood-ratio test. The result is a near-zero significance level ( $\chi^2(8) = 2438758.60$ ;  $p = 0.0000$ ), favouring a 2pl model. This is confirmed by the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), which are both lower with a 2pl model, favouring the latter (see Kline (2011); 1pl: AIC:  $4.33e + 07$ ; 2pl: AIC:  $4.08e + 07$ ; 1pl BIC:  $4.33e + 07$ ; 2pl: BIC:  $4.08e + 07$ ) (see Appendix 3 for the 2pl model results).

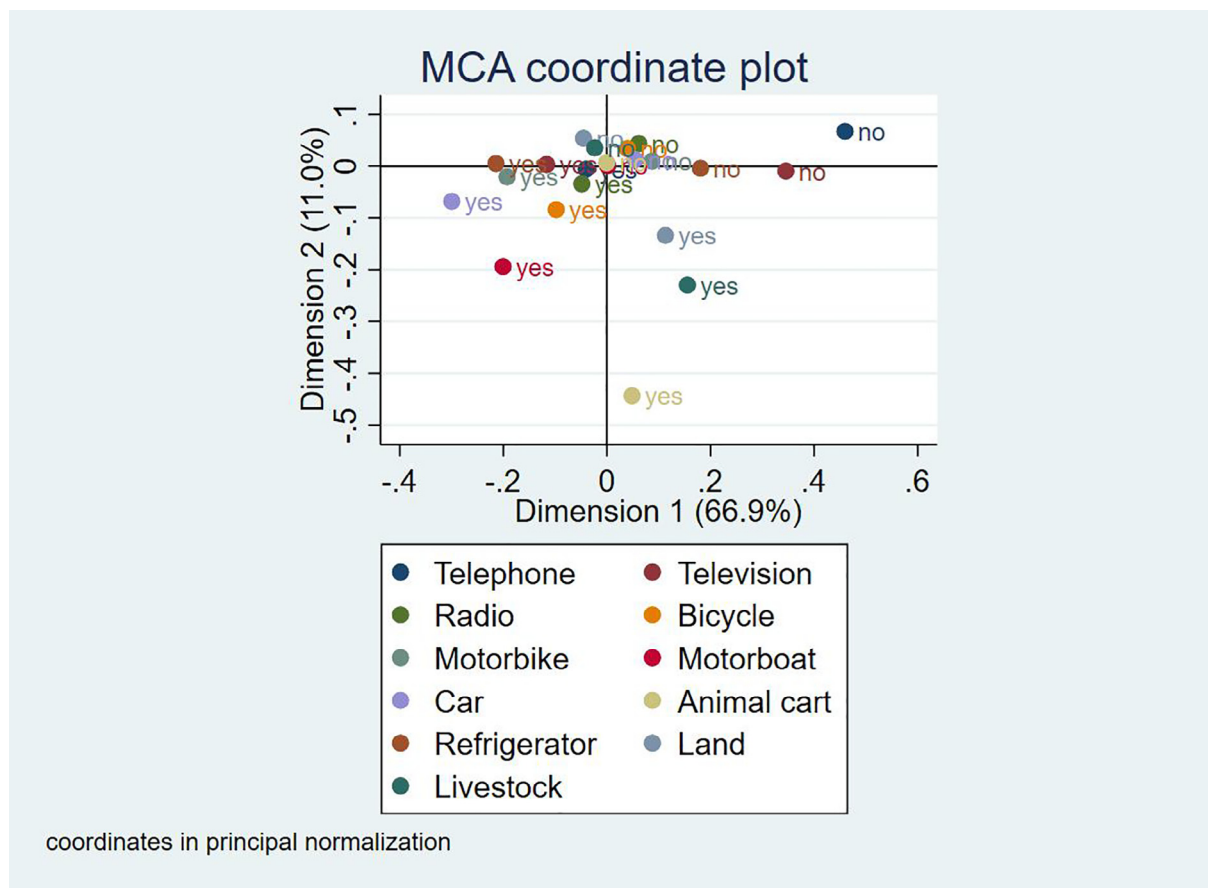


Fig. 5. MPI-E, MCA dimension projection plot, set of 26 countries, urban population.

We visualised 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 2pl model. Guio et al. (2012, 2016, 2017) interpret ICCs 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; material deprivation in their case), and as a measure of severity of material deprivation, the likelihood that the person/household will 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., a severity of between 0 and +3 standard deviations), are interpreted by Guio et al. as a 'good' index of material deprivation.

Since 0 is coded as not having that item (therefore, deprived) and 1 as having the item (non-deprived), the interpretation in our analysis is that 0 and +3 indicates that fewer than half of the population own the item, because the items are expensive, are only for specific uses, are not in demand or are not widely available. Items with >3 standard deviations are only owned by a minority, rendering them statistically less reliable. In other words, a severity of between 0 and +3 standard deviations highlights degrees of reasonable difficulty of owning an item (the *severity of non-deprivation* in item ownership). 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.

Since ICCs based on a 1pl model plot the difficulty but not the discrimination of each item, we present the ICCs based on a 2pl model here. Fig. 9 depicts the discriminating ability of the item

on the y-axis, where a more upright curve depicts higher correlations with the latent trait, in our case material wealth. It shows 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 (2.01 vs. 1.57) (Appendix 3), car's discrimination is greater than that of radio (2.3 vs. 0.5). Telephone and television have a negative difficulty; while discriminating, they are the easiest items to obtain and conform less well to the ideal pattern of depicting the severity of non-deprivation.

Finally, bicycle and animal cart do not have a vertical S-shape; therefore, around their respective difficult value they discriminate less well between households of similar levels of the latent trait.<sup>21</sup> By excluding these two items from the list and redoing the Cronbach's Alpha, the scales show greater reliability in all 26 countries, except Colombia (Appendix 2). For the pooled data, Cronbach's Alpha increased to 0.68, up from 0.61 for Alternative 4.

#### 4.2.4. Mokken scale procedure

As a final test of the dimensional structure and reliability of the potential alternative scales for the revised global MPI, we performed an MSP, which is a non-parametric IRT based on

<sup>21</sup> We also conducted the analysis with the listwise option, which handles missing values through listwise deletion, where observations with any missing items are dropped from the analysis (StataCorp, 2017). 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 switched positions in the ascending order of difficulty; second, in the 2pl model, radios joined bicycles and animal carts as items that do not depict the vertical S-shape curve of the other items.

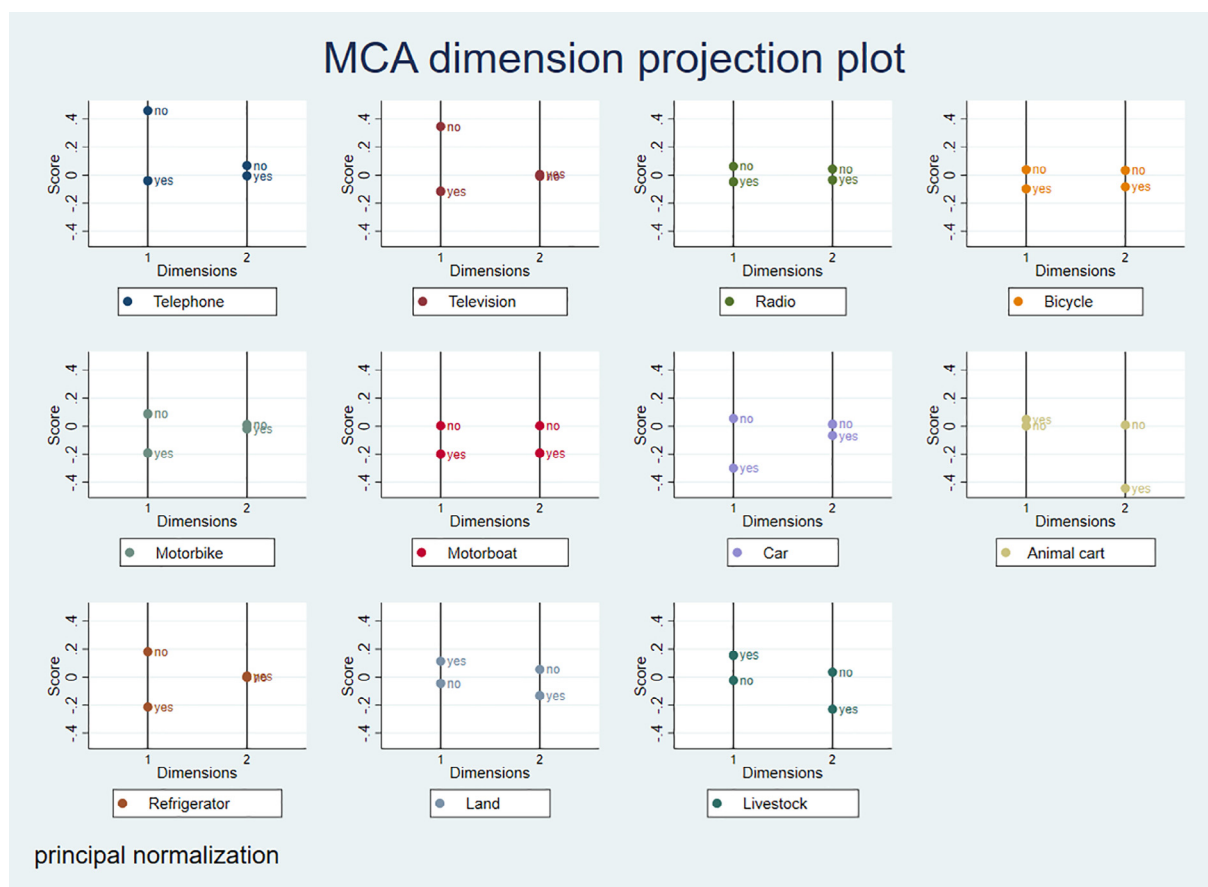


Fig. 6. MPI-E, MCA dimension projection plot, set of 26 countries, urban population.

“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 was only performed for a smaller set of six countries,<sup>22</sup> given that the procedure is extremely slow for very large datasets (van der Ark et al., 2013). The aim was to test if the items that are supposed to measure asset deprivation are grouped in only one, or more, Mokken scales.

First, we tested Alternative 3, which comprises eight items. The MSP identifies one scale that does, however, exclude bicycle (an item characterised by high uniqueness in all EFAs). All the remaining items score a Loevinger’s  $H$  coefficient above 0.5, a strong item fit for a scale.

For Alternative 4, which comprises nine items, the MSP identifies two scales. The first 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 a Loevinger’s  $H > 0.3$ .

As a final check, we also tested the 11 MPI-E items. The MSP identifies two scales. The first 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. The second consists of land, animal cart, and livestock, yet all items have medium-scale quality ( $0.4 \leq H < 0.5$ ). We conclude, therefore, that the MSP rejects the

MPI-E measurement model of 11 items grouped in three dimensions.

## 5. Discussion

### (a) Lessons learned from statistical results

The statistical results 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, and applying statistical methods that were suitable for the data and their underlying distribution, we found insufficient reasons to assume that potential asset items should be grouped into more than *one dimension* of assets deprivation. Any other categorisation than having all assets grouped in one category of assets ownership found insufficient support from the applied statistical tests (i.e., to group items into information, mobility, or livelihood categories, like the MPI-E, or to distinguish items based on their utility – e.g., between durables and productive assets, or tangibility – e.g., tangible and intangible assets). From a normative standpoint, most items are cross-cutting in nature; for example, any mobility item (such as a motorboat) can be a livelihood item, and almost any information item (such as telephones or computers) can be a livelihood item. Thus, placing asset items into one counting-based indicator of assets deprivation without defined sub-categories seems to be appropriate from a statistical *and* conceptual point of view.
2. Land and livestock are tangible productive assets of rural poor people, flagged as pivotal in the seminal *Voices of the Poor* series.

<sup>22</sup> Democratic Republic of the Congo, Ethiopia, Haiti, India, Nigeria, and Pakistan. Number of observations: 3,022,474.

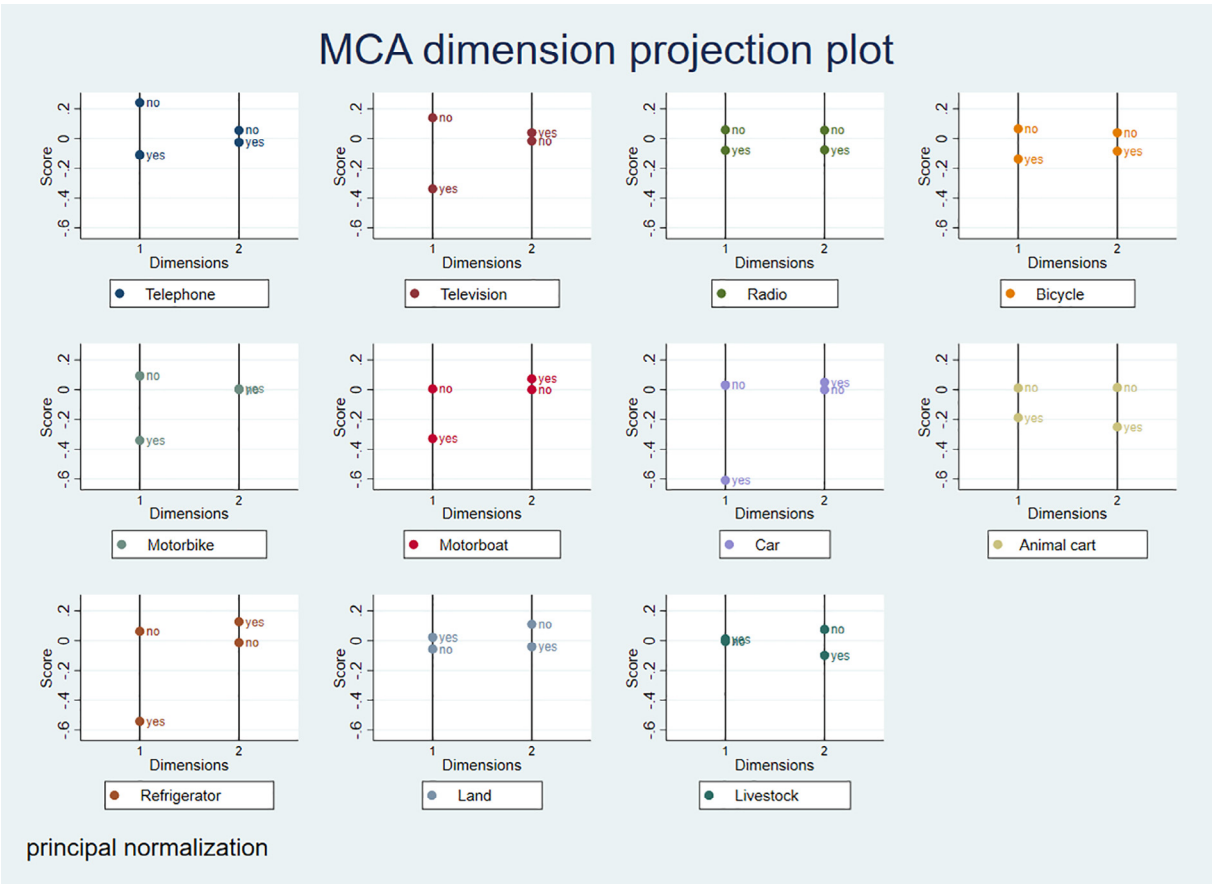


Fig. 7. MPI-E, MCA dimension projection plot, set of 26 countries, rural population.

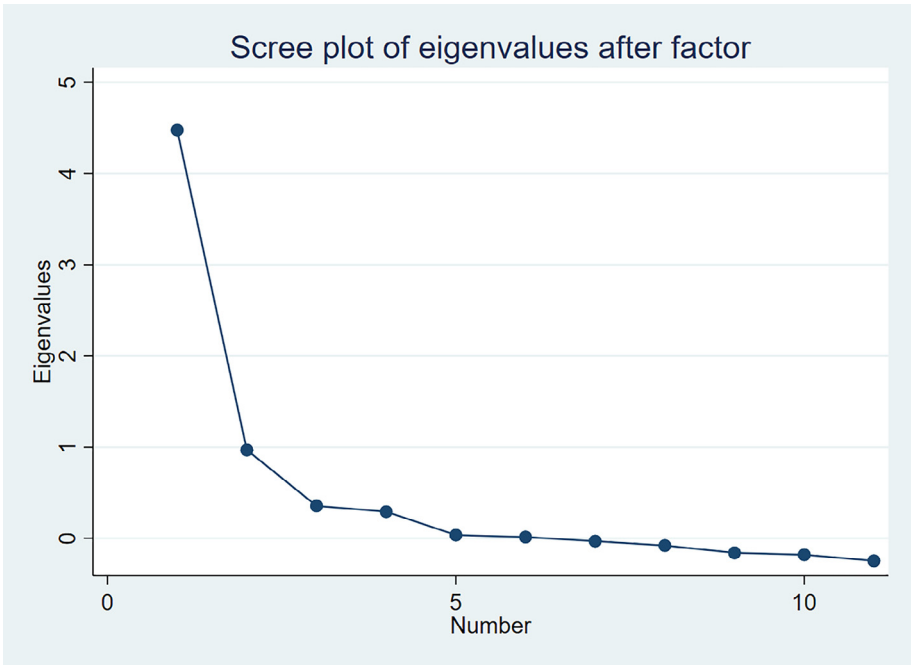


Fig. 8. Alternative 1, scree plot of eigenvalues, set of 26 countries.

**Table 6**  
Alternative 1 – EFA, set of 26 countries.

<b>Pooled</b>			
	<b>Factor 1</b>	<b>Factor 2</b>	<b>Number of observations</b>
Proportion of variance explained	82.2%	17.8%	3,251,694
Rotated factor loadings(1)			
<b>Variable</b>	<b>Factor 1</b>	<b>Factor 2</b>	<b>Uniqueness</b>
Telephone	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
	<b>Factor 1</b>	<b>Factor 2</b>	<b>All items</b>
<b>Items retained</b>	6	1	7
Cronbach's Alpha	0.7445	.	0.7365
Average Variance Extracted	0.599	.	0.581
Composite Reliability	0.897	.	0.905
Coefficient-H	0.922	.	0.927
Kaiser-Meyer-Olkin	.	.	0.8395

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

However, the lack of statistical support for their inclusion and serious data constraints meant their inclusion could not be justified. These plus additional conceptual concerns, detailed in Vollmer and Alkire (2018) and Alkire and Jahan (2018), and elaborated below, need to be addressed to identify valid and reliable cut-offs for these crucial assets. If included in the future, greater data on other productive assets of urban poor people is also needed. Urban populations have diverse livelihoods and productive assets are often rented rather than owned (and if owned, they tend to be associated with the household head's employment, such as equipment for small businesses (Banks, 2016)). While *housing* is undoubtedly one of the most important physical productive assets of urban poor people (and is therefore 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 urban poor people (Baharoglu & Kessides, 2002; Moser, 1998; Narayan et al., 1999). As this is also true for rural poor people (Ellis, 2000), we call for more research into this, and greater availability of data on tangible and non-tangible productive assets in DHS, MICS, and national surveys.

3. There is weaker statistical support for radios, bicycles, and animal carts to be included in the assets indicator. However, as these are assets that poor people are more likely to own, they provide an example of how purely statistical exercises may create an asset index that deviates from its fundamental aim.
4. The statistical tests indicate that a computer was a salient item to own and seems to strengthen the resulting assets indicator, so it was included in the indicator. This seems to be even more relevant in the wake of the COVID-19 pandemic.

#### (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, 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 & Jayne, 2014). Winters et al.'s (2009) meta-regression analysis covering 15 developing countries identified that greater land access is linked to increased agricultural production. Land is regarded as a stock renewable resource that fulfils various functions for human use, foremost the production of food, fibre, and fuel (FAO & UNEP, 1999).

The importance of land as a key productive asset of poor people is undisputed. However, the statistical test results highlight the distinct character of this crucial productive asset compared to other items such as consumer durables (e.g., telephone, television, or refrigerator). The results also highlight that data constraints, outlined below, will need to be addressed in order to construct an internationally comparable indicator on minimum land ownership.

First, data on farm productions and inputs under various farming systems, such as the value of food production per hectare or the ratio of irrigated land, are missing in most DHS, MICS, and national surveys.<sup>23</sup> Average farm sizes vary substantially at the regional and global levels (FAO, 2018): the hectare-weighted median in farm size ranged from 0.7 ha in Malawi to 4.57 ha in Niger in sub-Saharan Africa; from 0.94 ha in Guatemala to 9.2 ha in Nicaragua in Latin America and the Caribbean. Small average farm sizes characterise Europe and Central Asia, for example, 0.32 ha in Tajikistan, and this is a similar pattern in Asia (ranging from 0.54 ha in Bangladesh to 1.31 ha in Cambodia). It was not possible to set a globally comparative minimum land size cut-off that would also provide any meaningful results regarding the quality of land or any welfare benefits obtained from smallholder activities. Setting land size cut-offs is therefore only meaningful at best at the regional level.

Second, missing values were assumed to be signs of deprivation in the MPI-O assets indicator and only dropped if the household lacked data on all items in the scale. This was of negligible concern for the original seven items included in the MPI-O, as missing values were minimal (below 1% in our set of 26 countries, see Appendix 4). However, the relatively low percentage of missing values in land ownership (below 1% where data were available in our set of countries), compared to the very high percentage of missing values in land size (up to 69.7% in Angola or 68.9% in India; Appendix 4), means that this assumption is incorrect.<sup>24</sup> Missing values on farm animals were also considerable in several countries, including Bangladesh, Colombia, India, and the Philippines (see Appendix 4). Thus, even if a minimum land size cut-off was identified (and used in subsequent trial measures) or farm animals were counted as livestock units, one had to code missing values as either deprived or non-deprived, which would have led to biased estimates.

Third, data heaping in self-reported land size was also seen (Vollmer & 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 5 ha (12 acres), and then flattened. Precisely where the data heaps occur differs between countries, which poses a severe risk of setting a global comparative cut-off for a minimum land size that misses data heaps in some countries. This would blur the interpretation of results, and mean that comparability between countries is lost.

The quantity of land size (either 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 using a minimum livestock unit cut-off as this concept is not linked to the price and consump-

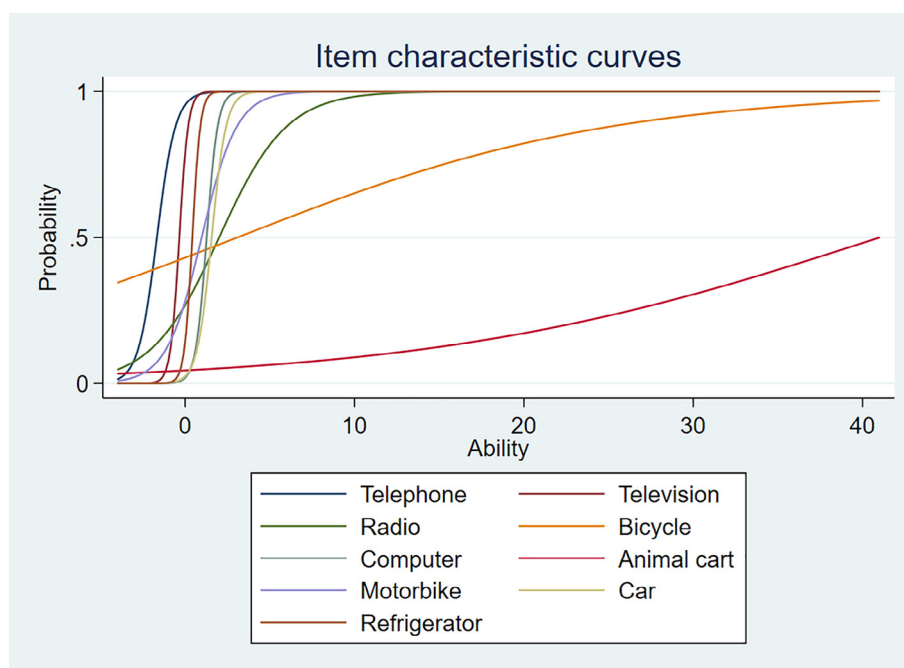
<sup>23</sup> As are sale prices of farm animals (or the quantity of farm animals sold and/or consumed).

<sup>24</sup> 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).

**Table 7**

1pl model for Alternative 4, set of 26 countries.

Pooled						
One-parameter logistic model Log likelihood = −21635773					Number of observations 5,264,508	
Variable	Coefficient	Standard Error	z	p	95% CI	
Discrimination	1.228921	0.0007482	1642.55	***	1.227454	1.230387
Difficulty						
Telephone	−2.068108	0.0015893	−1301.29	***	−2.071223	−2.064993
Television	−0.5280328	0.0009737	−542.30	***	−0.5299412	−0.5261244
Bicycle	0.2326839	0.0009579	242.90	***	0.2308064	0.2345615
Refrigerator	0.6540087	0.0009904	660.35	***	0.6520676	0.6559499
Motorbike	0.8301822	0.0010339	802.97	***	0.8281558	0.8322085
Radio	0.9983687	0.0010845	920.57	***	0.9962431	1.000494
Computer	1.884981	0.001533	1229.61	***	1.881977	1.887986
Car	2.170364	0.0016625	1305.48	***	2.167106	2.173622
Animal cart	2.887494	0.0024385	1184.11	***	2.882714	2.892273

**Fig. 9.** Item characteristics curves, 2pl model, Alternative 4.

tion data of farm animals. Minimum data requirements for a meaningful indicator of land that is relevant to policymakers should portray the ratio of cultivated and irrigated land per person among the agricultural population in any given farming system, while data on the quality and use of farm animals would better link livestock to the concept of human poverty and welfare.

### (c) Trial analysis

As a final step to identify the revised assets indicator, we calculated 24 trial indicators of asset deprivations. Table 8 presents the different versions, which were grouped into seven categories, using the MPI-O as basis. This follows the global MPI practice first established in Alkire and Santos (2010), who calculated between four and eight trial measures for up to 108 countries for the global MPI in 2010 (see also Alkire & Kanagaratnam, 2020; UNDP & OPHI, 2019). The objective was to empirically analyse items that stood out during the statistical tests, such as radio, bicycle, animal cart, land, livestock, and bank account. We also assessed how the car variable would behave if treated not as a veto, but as any other

item in an equally weighted list of items. Comprehensive tests results are available in the [supplementary materials](#), together with summary statistics about the percentage of ownership of items in each country. We focus the discussion here on a subset of interesting observations.

First, certain items, such as a radio or a bicycle, are widely owned in some countries, but not in others. For example, while more than half of the population in Kenya and Haiti owned a radio, less than 10% of the population did in Bangladesh, India, or Armenia. Fewer than 3% of people owned bicycles in Ethiopia, whereas nearly half the population did in Tanzania. Consequently, excluding a radio from the 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 2 and 1). 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 8**

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<sup>1</sup>**

12. MPI-O plus computer, animal cart, motorboat, min. land size 3 ha
13. MPI-O plus computer, animal cart, motorboat, min. land size 6 ha
14. MPI-O plus computer, animal cart, motorboat, min. land size 10 ha
15. MPI-O plus computer, animal cart, motorboat, any land size
16. MPI-O plus computer, animal cart, min. land size 6 ha, 1.5 livestock units

**Three new items (bank, overcrowding, livestock)**

17. MPI-O plus computer, animal cart, min. land size 6 ha, 1 livestock unit, bank account, overcrowding (3 persons/room)
18. MPI-O plus computer, animal cart, min. land size 10 ha, 1.5 livestock units, bank account, overcrowding (3 persons/room)
19. MPI-O plus computer, animal cart, min. land size 6 ha, 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 10 ha, 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

<sup>1</sup>The analysis also comprised computations for lower end cut-offs of land ownership, at 0.3 ha, 0.6 ha, and 1 ha.

While the assumption seems justified that, in Armenia for instance, the greater prevalence of a computer (78%) and access to internet (77%), so-called high-end possessions and amenities (Rutstein & Staveteig, 2014), may have replaced a radio as a popular item to access information, no such assumption can be made in Kenya, where data on computer and internet were missing (Appendix 4). 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 seemed to reduce the analytical 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, or where these items are still not widely owned. The same is true for bicycles, which in most of the countries do not yet seem to have been substituted by higher-end possessions such as motorbikes (motorbike ownership was lower than for bicycles in 19 out of the 26 countries). In contrast, adding a computer to the MPI-O assets list resulted in little change in the uncensored headcount ratio (a reduction of approximately 0.05 percentage points between trial version 4 and 1). This is due to low levels of computer ownership as an higher-end item in our sample (less than 20%).

In other words, although radios and bicycles stood out as items that did not fit as well into the identified one dimension of asset deprivation, normative reasons led to the decision not to substitute these items, but to keep both included in the revised assets indicator.

A second 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 an item that discriminates between households of similar ability levels in the latent trait – in our case, material wealth. Empirically, we found that using a car not as a veto, but the same 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). Households that own a car also own at least two of the smaller MPI-O items (telephone, television, radio, bicycle, refrigerator, or motorbike). From a conceptual and communications point of view, it seems logical to continue assigning a car the veto role in the revised indicator to highlight the exceptional status of this higher-end item.

Third, we found that an animal cart, another difficult item to obtain in the IRT analysis, is a rather *localised item*. The percentage of households who owned an animal cart was the second-lowest of the 17 items that were eventually placed into the kitchen sink<sup>25</sup> analysis of trial version 24 (only a motorboat was owned less frequently). Senegal and Zimbabwe stood out as countries where animal carts were more prevalent: approximately one-third of the population owned them. Unsurprisingly, adding animal cart and motorboat to the MPI-O (trial version 8) resulted in rather moderate changes in the uncensored headcount ratio (decreases of 5.4% and 5% in Senegal and Zimbabwe, but of a maximum of 2% in the other countries).

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

<sup>25</sup> In this measure (named after kitchen sink regression, that utilises a long list of independent variables), we assembled all the MPI-E items plus computer, internet, bank account, sewing machine, air conditioner, and washing machine. Sewing machine did not meet either of our two data availability criteria (75 countries, at least 3.5 billion people), and air conditioner and washing machine only met the population criteria. However, they were used 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).

It is important to highlight that an animal cart is distinctly a rural item, as shown by the MCA projection plot for the rural population. While the assets indicator of the global MPI aims to be 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).<sup>26</sup>

Fourth, using different land sizes changed, as expected, the uncensored headcount ratios considerably with, for example, up to six and seven percentage point decreases with a 3 ha cut-off in Côte d'Ivoire and Tanzania. African countries such as the Democratic Republic of the Congo and Ethiopia were particularly affected by such decreases and fluctuations remained pronounced in some countries even when very generous cut-off points were used (e.g., 10 ha, with up to six percentage points difference in Tanzania to a 3 ha cut-off). Fluctuations increased even further when lower cut-offs were used, such as 0.3 ha and 1 ha (with, for example, 27 and 18 percentage point decreases, respectively, in Ethiopia). The fluctuations highlight different patterns of land ownership in different countries, as touched on in discussion point b.

Fifth, the kitchen sink 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 45% in Ethiopia. The kitchen sink approach of identifying those deprived in assets is distinct from the IRT analysis identifying the 'severity of non-deprivation'. Whereas the latter aims at identifying the non-deprived population in assets by including items that are hard to obtain such as refrigerators, cars, or motorbikes, the kitchen sink approach assembles as many items as possible. Consequently, if a household has none or only one of a long list of possible items, it is likely that the household is deprived in assets.

Both approaches are prone to overestimations. 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 assembles only items with inflection points on the ICCs between 0 and +3 standard deviations, exclusively 'hard to obtain' items. The kitchen sink approach increases the certainty about the population who suffer asset deprivations but overestimates 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 Ethiopia, the reductions are substantial, and 45% of those previously deprived in assets became non-deprived. Also, and importantly for the global MPI, the comparability of this assets indicator 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.

The remaining items, bank account and overcrowding, faced additional challenges. While ownership of a bank account relates well to such concepts as 'liquid assets' (Haveman & Wolff, 2004), a lack of data on the liquid savings that households hold may mean that having a bank account results in a false positive. Overcrowding or lacking "sufficient living area", as described by UN-HABITAT, relates well to SDG Target 11.1 and the Human Right to Adequate Housing (Article 25), and is often used in asset indices (e.g., Filmer & Pritchett, 2001; Angulo et al., 2016; Gallo & 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, room sizes vary

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, these uncertainties led to the decision to not include these, and to propose trial version 23 as the recommended assets indicator. The indicator is identical to Alternative 4, 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 was moderate. Senegal and Zimbabwe showed the greatest reductions – approximately 5% – driven by the greater prevalence of animal carts in the two countries.

## 6. Concluding remarks

This paper has shown how diverse methodologies can be applied to extensive trial measures and interpreted within a normative framework to create a parsimonious yet justifiable asset index for use within a multidimensional poverty measure, one that takes data limitations into account. This interplay between options, criteria, and the purpose of the asset indicator was used to rule out certain asset index structures for the global MPI; for example, insufficient reasons were found to structure the assets indicator using sub-dimensions. The revision sought to include land and livestock variables, but tests showed the sensitivity of results to these indicators, and data scrutiny observed comparability issues that did not, unfortunately, fulfil the criteria. The final proposed asset indicator comprises a statistically validated expansion of the number of items in the scale (from seven in the MPI-O to nine), and an increased reliability. To give one example, the Cronbach's Alpha coefficient of the new indicator was higher than the MPI-E in 25 of 26 countries in our empirical analysis (except for Egypt), and higher in 21 countries than the MPI-O.<sup>27</sup>

Thus, the *consolidated* indicator measures assets deprivation within a multidimensional poverty measurement framework, at the global level, more accurately than the alternatives considered.

A larger takeaway of this consolidation process on the design of asset indices and related composite poverty indices is the transparency about the decision-making process, in light of available data and measurement theory on multidimensional poverty. Others, who may have important additional insights, can easily engage in this conversation. We hope that the proposed method to combine statistical methods with a meaningful data inventory, trial measure analyses, and transparent normative considerations will help future applications to follow a similar path and overcome what Steinert et al. (2018) warned of, a 'one-size-fits-all' measurement approach to such indices.

<sup>27</sup> Except for Indonesia, Kenya, Cambodia, Myanmar, and the Philippines (Appendix 2). However, these countries lack data on computer (Appendix 4), except for Myanmar, which explains the lower reliability of the new indicator in these countries. A similar improvement was found in Guio et al. (2016, p. 229) when the nine-item material deprivation indicator for the whole EU population was increased to 13 (from 0.69 to 0.85). Still, it should be noted that in none of the 26 countries did the coefficient surpass the satisfactory threshold of 0.7, thus remaining acceptable at best. This can be explained by the structure of the data, based on DHS, MICS, and national surveys that still lack, in contrast to the EU-SILC, a thematic module on assets that would allow identifying greater communalities and reliabilities in the data (by introducing, for example, questions on preferences). While our analysis identified an asset indicator (Alternative 2) that surpassed the 0.7 threshold, by omitting radio and bicycle and including computer and internet, this indicator had conceptual weaknesses. While the scale can be considered satisfactory, it still varied across the 26 countries (it was below 0.7 in 19 countries, and in seven of these below 0.6), and almost inclusively assembled tangible household durables that require electricity. This option would have increased the existing perceived urban bias of the assets indicator and would have excluded important assets of poor people.

<sup>26</sup> For a debate on whether the MPI-O assets indicator has an urban bias, see Dotter and Klasen (2014).

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 MPI-O list of items must also be seen in the light of the many decisions that were taken in the process, 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 are limited? 3) Should 'assets' be renamed, for instance, to 'material deprivation' or another 'factor label' to describe the revised index (given that the term 'assets' is very broad and may create certain expectations, particularly with respect to productive assets)? 4) Should statistical weights replace the normative weights of counting-based asset indices? 5) Should conceptually strict approaches to assets deprivation be adopted to identify relevant assets, thus moving to more conceptual approaches such as that introduced by Paroush on 'sequences of acquisition'? 6) Should a car be treated like any other item, even though it is often a higher price item? In this paper we discussed the empirical and normative logic underlying the choices on these topics.

Naturally, this paper raises many research questions that cannot immediately be addressed. First, we used asset data from household surveys; it is essential to bring this interplay of quantitative techniques together with further participatory and qualitative analyses of the assets of poor people. Second, it is crucial to compare this asset index with trial indices constructed using non-traditional data, such as from participatory wealth ranking exercises, to explore and triangulate findings. Third, it would be useful to analyse the relationship between this asset index and the DHS Wealth Index, or monetary household-level aggregates (in datasets that include these), refreshing the longstanding literature exploring assets as a proxy for permanent income, for example. Fourth, it is essential for this methodologically engaged discussion of asset indicators to be applied next to datasets that cover the quality, quantity, age, gendered ownership, and other features of assets, to explore how to use the additional information and observe to what extent a basic indicator proxies or does not proxy more nuanced alternatives. This can help to inform future asset questionnaire design. Fifth, data from multiple time periods (especially longitudinal data) make it possible to explore determinants of change in the asset indicator, and how these match or differ from determinants of household consumption more generally –

or to redo natural experiments or randomised control trials (RCTs), but focusing on assets instead of a monetary aggregate (for example, on the long-term effect of cash transfers on asset holdings, and how and why these vary). We hope that this paper sparks further discussion of the most rigorous asset indicators that should be incorporated into multidimensional poverty indices.

#### *CRedit authorship contribution statement*

**Frank Vollmer:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Sabina Alkire:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing.

#### **Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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**Appendix 1. MPI-E: MCA statistics for column categories in principal normalisation, set of 26 countries**

Pooled									
Categories	Overall			Dimension 1			Dimension 2		
	Mass	Quality	% inert	Coord	Sqcorr	Contribution	Coord	Sqcorr	Contribution
Telephone									
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 four 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
Democratic Republic of the 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

(continued on next page)

**Appendix 2** (continued)

	MPI-O	MPI-E	Alternative 2	Alternative 3	Alternative 4	Alternative 4 minus bicycle and animal cart
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 Log likelihood = −20416394						Number of observations 5,264,508
Variable	Coefficient	Standard Error	z	p	95% CI	
Telephone						
Discrimination	1.820406	0.0031982	569.20	***	1.814137	1.826674
Difficulty	−1.662328	0.0017425	−954.01	***	−1.665743	−1.658913
Television						
Discrimination	3.846589	0.007247	530.79	***	3.832385	3.860792
Difficulty	−0.3390132	0.0006471	−523.92	***	−0.3402815	−0.337745
Radio						
Discrimination	0.5003772	0.0012086	414.01	***	0.4980083	0.5027461
Difficulty	2.01035	0.004819	417.17	***	2.000905	2.019795
Bicycle						
Discrimination	0.0904803	0.0010816	83.66	***	0.0883604	0.0926001
Difficulty	3.090521	0.0390546	79.13	***	3.013976	3.167067
Computer						
Discrimination	3.090935	0.0060115	514.17	***	3.079153	3.102718
Difficulty	1.275574	0.0010543	1209.93	***	1.273508	1.27764
Animal cart						
Discrimination	0.0747796	0.0026552	28.16	***	0.0695754	0.0799838
Difficulty	41.01983	1.458176	28.13	***	38.16186	43.87781
Motorbike						
Discrimination	0.9594936	0.0014354	668.44	***	0.9566802	0.9623069
Difficulty	0.9803006	0.001565	626.40	***	0.9772333	0.983368
Car						
Discrimination	2.345628	0.0040348	581.35	***	2.33772	2.353536
Difficulty	1.571117	0.0013896	1130.61	***	1.568394	1.573841
Refrigerator						
Discrimination	4.257918	0.0089206	477.31	***	4.240434	4.275402
Difficulty	0.4290063	0.0006268	684.46	***	0.4277779	0.4302348

**Appendix 4. Missing values 26 items (in percentage), 26 countries**

	Armenia	Angola	Bangladesh	Brazil	Democratic Republic of the 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

## Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.worlddev.2022.105997>.

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