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Gunther Bensch[1]

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Abstract

With the 'Sustainable Energy for All' initiative led by the UN and World Bank, the provision of access to modern energy has recently been brought to the top of the international development agenda. However, there is yet little guidance on how to measure modern energy access or its deprivation, energy poverty. This paper discusses five energy poverty measurement approaches and compares their results empirically using a unique household dataset on five sub-Saharan countries. Due to a broad coverage of energy-related issues, this dataset accommodates the data requirements imposed by all metrics. The metrics turn out to perform quite differently in terms of the identification of the energy poor, sensitivities to parameter changes and data requirements. Based on the empirical findings, recommendations are made on essential features of the metrics to support the ambitious goals set out by the 'Sustainable Energy for All' initiative.

JEL Classification: C81, I32, O13

Keywords: Energy poverty measurement; energy access; sub-Sahara Africa

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1. Introduction

"Let's make energy poverty history, that's your challenge." The chief executive of 'Sustainable Energy for All', Kandeh Yumkella, addressed this statement to policy makers assembled at the 2012 Clinton Global Initiative annual meeting to campaign for universal access to modern energy by 2030. The 'Sustainable Energy for All' initiative is currently set up to channel activities for achieving this goal. It is the first initiative to be jointly chaired by the UN Secretary-General and the president of the World Bank Group, underscoring the emphasis placed on energy access. Energy is seen as a critical component, if not prerequisite, for economic development and the alleviation of poverty in terms of such diverse manifestations as deprived health, education, and livelihoods in general (UN-CSD 2001; DfID 2002; FEMA 2006; Guruswamy 2011).

However, beyond a shortfall in empirical evidence on these impact pathways[1], the current challenge for the scientific community is to support operationalizing the universal access goal. A milestone in this endeavour is the multi-tier framework promoted in the recently published Global Tracking Framework (World Bank, ESMAP and International Energy Agency 2013). This multi-tier framework is intended to go beyond binary measures of energy access to capture aspects like the quantity and quality of electricity supplied, the efficiency, safety and convenience of household cookstoves and access to energy services in local enterprises and social infrastructure. This framework is the fruit of lively debates that helped to deepen the understanding of energy access as a complex multidimensional construct. Furthermore, it is widely recognized that energy access is a process that undergoes different phases and levels, conceptually organized into various 'tiers' of access to and use of electricity and modern cooking.

Hence, much effort has been put into capturing the intricacies and complexities of the path that stretches from people's deprivation of their basic energy needs to a state of "vibrant and sustainable social and economic growth" (Bazilian and Pielke 2013: 75) empowered by modern energy access. Without trying to thwart the ambition of globally achieving a truly modern access to energy for everyone, it is debatable whether we do not also need a single, easy-to-understand index of energy poverty. Similar to the international

[1] See the recent literature reviews of Bernard (2010), Estache (2010), Köhlin et al. (2011) and IOB (2013).

poverty line of US$ 1.25, which condenses the challenges behind individual economic development, it seems reasonable to establish a critical threshold for energy poverty. This threshold can be expected not to be just a correlate of the international poverty line, since energy poverty is more than a mere manifestation of deficient income and individual preferences. It is also determined by other factors such as the local availability of energy sources and technologies, cultural dimensions and education. To date, though, there is no clear consensus about the key characteristics of such a metric of energy poverty, which is crucial in effectively identifying the energy-deprived population as well as measures to overcome their deprivation.

This paper analyses five metrics suitable for energy poverty measurement: first, a *minimum energy consumption threshold approach* proposed by Modi et al. (2005) and the UN Secretary-General Advisory Group on Energy and Climate Change (UN-AGECC 2010), second, an *income-invariant energy demand* introduced in Barnes, Khandker and Samad (2011), third, the *Multidimensional Energy Poverty Index* (MEPI) by Nussbaumer, Bazilian and Modi (2012), fourth, the *Correlation Sensitive Energy Poverty Index* (CSEPI) adapted from Rippin (2012) and, fifth, the *Total Energy Access* (TEA) standard presented in Practical Action (2012). In light of the current paucity of secondary data on basic energy use, the metrics are "field-tested" using a rich unique household dataset on five sub-Saharan countries that accommodates the data requirements imposed by all metrics. Except for the MEPI, it is the first time that these metrics are applied to real-world data with the aim of determining energy poverty levels. Energy poverty figures are calculated and compared in order to reveal the degree of sensitivity of the individual metrics as well as the consistency between them. By concentrating on a small sample of countries, critical aspects in the data requirements of the various metrics will be pinpointed for sub-Saharan Africa. At the same time, the set of in total 13 datasets on different energy project evaluations provides a manageable basis to assess how certain electrification and clean cooking interventions affect the incidence of energy poverty. The purpose of this paper is, hence, to identify and expand the most promising avenues for effective energy poverty measurement based on a systematic analysis of the same type of empirical data.

The 13 surveys that delivered the data underlying this study have been conducted in both rural and peri-urban areas in Western and Eastern sub-Saharan Africa: Benin, Burkina Faso, Senegal, Mozambique and Rwanda. The focus on countries south of the Sahara reflects the energy access situation in the region, which can be considered as particularly demanding. As of 2008, 561 million people do not have access to electricity in sub-Saharan Africa, corresponding to as many as 74 percent of the total population. Similarly, only 17 percent of all households (5 percent in rural areas) use electricity, liquid or gaseous fuels as primary fuel to satisfy their cooking needs (UNDP/ WHO 2009). The regional focus furthermore implies a high homogeneity among the analysed countries. While certain energy services, such as space heating, are basically not demanded, the remaining services such as lighting are indispensable for all households. As a consequence, low consumption levels in these energy services are likely to reflect suppressed demand and, hence, to represent symptoms of energy poverty. Finally, the household data also accommodates the new multidimensional measurement approaches that aggregate at the household or even individual level.

The following Section 2 starts out with the recent development in research relevant for energy poverty measurement and presents the selected energy poverty metrics. Section 3 introduces to the data used for the analysis, which follows in Section 4. The discussion in Section 5 concludes this paper.

2. Current approaches towards energy poverty measurement

2.1. The dimension of the challenge or the challenge with dimensions

Research on poverty metrics gained momentum over the past years. An increased notion of poverty as a multidimensional phenomenon coincided with the upcoming availability of datasets that provide the necessary data even for developing countries (Deaton 2010).

Conceptually, this trend owes a great deal to the work of Amartya Sen that laid the foundation for the so-called capability approach. This approach views poverty as a deprivation of capabilities, which are understood as people's real freedoms to achieve so-called functionings they value – either in the form of 'beings' such as being educated or 'doings' such as cooking a warm meal (Sen 1985, 1992). These capabilities are not only components of welfare, but also interact as multidimensional causes of development and deprivation (Sen 1999). In this spirit, the Asian Development Bank applies the capability approach to energy access by defining energy poverty as "the absence of sufficient choice in accessing adequate, affordable, reliable, high-quality, safe and environmentally benign energy services to support economic and human development" (Reddy 2000: 44). The energy services represent functionings in this case. Relevant energy services include energy for lighting, cooking, heating, cooling, information, communication, productive purposes, mobility and in social infrastructure institutions (Sovacool 2012; Practical Action 2013).

Technically, the capability approach allows to be implemented by plural methodologies as it is a flexible and multi-purpose framework rather than a precise theory of well-being and poverty (Sen 1992). A major strand in poverty research employs recently introduced multidimensional poverty measurement approaches that were added to the commonly used unidimensional approaches. The most prominent example is the multidimensional poverty index, which the United Nations Development Programme (UNDP) presents since 2010 in its Human Development Reports.[2] These approaches became necessary as a well-defined unidimensional aggregate variable, such as income in US Dollars, cannot be constructed for poverty dimensions that in general are represented by ordinal data (e.g. access to safe drinking water as a health indicator). Similarly for energy poverty, unidimensional metrics traditionally dominated because energy consumption can be reasonably and easily aggregated, both in monetary and physical terms. Given the various complementary energy services, there are, however, good conceptual reasons to also consider energy poverty as multidimensional. Some of these dimensions can as well only be expressed in terms of ordinal indicators (e.g. usage of improved cooking stoves, ownership of a fridge).

With multidimensional approaches, though, one is always confronted with what is known as the *curse of dimensionality*. This arises when the number of data dimensions becomes so large that their joint analysis and presentation becomes intractable. There are two main approaches to deal with this difficulty: composite indices, which combine information from various dimensions into a single number, and 'dashboard' approaches, which simply report on poverty indicators for each dimension separately.[3] The current debate involves good arguments for and against each of them, both from the normative and

[2] Interestingly, two energy indicators are found within the list of ten non-income dimensions applied by UNDP, namely electricity and cooking fuels, where having no electricity and relying on wood, charcoal, and/or dung for cooking constitutes poverty respectively (UNDP 2010).

[3] Three further 'middle ground' techniques between composite indices and dashboard approaches are presented in Ferreira and Lugo (2013). For the purpose of constructing an intuitive energy poverty measure, these techniques, however, do not seem to be appropriate.

practical point of view.[4] Alternatively, Nussbaumer, Bazilian and Modi (2012) recommend a hybrid approach. Such an approach would include an aggregated set of indicators that are monitored and reported upon individually alongside a composite index. This hybrid approach acknowledges the crude and imperfect nature of composite indices by providing additional, more detailed dashboard information. Bhanot and Jha (2012), for example, enumerate a host of potential dashboard indicator topics ranging from the socio-economic, cultural and political context to the financial and long term feasibility. Still, the hybrid approach does not miss the advantages of a single, easy-to-understand and -interpret composite index that recognizes the correlation between dimensions of wellbeing and enables to easily measure progress over time and to rank countries or regions.

2.2. Selection of energy poverty metrics

The literature proposes a range of candidates. Eight types of metrics can be distinguished that are commonly discussed in the context of energy poverty measurement, four uni- and four multidimensional approaches. A fifth multidimensional metric is borrowed from the general poverty literature (Table 1). Partly, these nine metrics have already been discussed and critically assessed in Pachauri (2011) and Khandker, Barnes and Samad (2012). In order to be selected for the subsequent analysis, the metrics only have to comply with the underlying energy poverty concept in that they identify the people who are deprived of their basic energy needs required for attaining basic living standards. First, this rules out approaches that look at more advanced forms of energy usage. This is the case for the Energy Development Index (EDI) from the International Energy Agency (IEA). By looking at per-capita commercial energy consumption, the share of the commercial sector in total final energy use, and the share of population with access to electricity, the EDI rather measures a country's degree of transition towards a modern energy infrastructure. Second, the emphasis on a basic needs concept entails the use of an absolute energy poverty

[4] One main argument for the dashboard approach by Ravallion (2011) is that the best data on separate dimensions are often found in different data sets. For energy, this is, however, probably less of a problem as energy-related aspects are more likely to be found in single datasets. A second main issue concerns two related features of composite indices: compensability among dimensions, i.e. the possibility of offsetting a disadvantage on some dimension by a sufficiently large advantage on another dimension, and the implicit or explicit use of weights. Critics are, e.g., Ferreira and Lugo (2013) and Bhanot and Jha (2012) and pro arguments can be found in Sen (1997a) and (1997b).

threshold instead of a relative one. As such, the energy poverty status of others and the living conditions in other dimensions but energy are supposed to not affect the energy poverty status of a household.[5] Three further approaches listed in Table 1, which follow a relative concept, are therefore ignored in the subsequent analysis.

Table 1: Selected and non-selected energy poverty metrics

		Dimen-sionality	Reference
ε_1	Minimum energy consumption threshold approach	uni	UN-AGECC (2010)
ε_2	Income-invariant energy demand approach	uni	Barnes, Khandker & Samad (2011)
ε_3	Multidimensional Energy Poverty Index (MEPI)	multi	Nussbaumer, Bazilian & Modi (2012)
ε_4	Correlation Sensitive Energy Poverty Index (CSEPI)	multi	*modification from* Rippin (2012)
ε_5	Total Energy Access (TEA) standard	multi	Practical Action (2012)
NON-SELECTED METRICS			
	Energy budget share-based energy poverty index	uni	Leach (1987); Boardman (1991)
	Borderline income-poor energy consumption approach	uni	Foster, Tre & Wodon (2000)
	Energy Poverty Index (EPI)	multi	Mirza & Szirmai (2010)
	Energy Development Index (EDI)	multi	IEA (2004)

The five metrics are portrayed in the following along the distinction between uni- and multidimensional metrics. This presentation features the calculation formulas and – if applicable – econometric specifications for these metrics, hereafter referred to as ε_1 to ε_5. The concrete variables plugged into these equations will be presented in Section 3. A critical appraisal of the metrics will only follow in the course of the empirical analysis in Section 4.

2.3. Unidimensional energy poverty metrics

Minimum energy consumption threshold approach

The most straightforward way in defining an energy poverty threshold is to normatively determine the set of energy needs that is deemed indispensable and then to calculate the

[5] This is also in line with common practise given that absolute poverty lines are usually applied in developing countries while relative lines tend to dominate in developed countries, with the most well-known one being the fuel poverty line in the United Kingdom (cf. Department of Energy and Climate Change 2012).

respective amount of final energy required. The energy poverty measure for this approach can be written as

$$\varepsilon_1 = \frac{1}{N}\sum_{n=1}^{N} I(y_n < k)$$

where N denotes the size of a population, y_n is the attainment (here energy consumption) of individual n and k is the poverty cut-off. $I()$ is an indicator function equal to 1 if the expression in parenthesis is true and 0 otherwise. Early studies using this approach have been Krugmann and Goldemberg (1983) and Bravo et al. (1983), whose approximations for the poverty cut-off k range from 200 kilogrammes of oil equivalent (kgoe) per capita and year in hot urban areas to 1250 kgoe in cold rural areas.

These authors look at final energy, which refers to primary energy after it has undergone potential conversion and distribution, such as firewood, charcoal and electricity. As however noted by Kemmler and Spreng (2007), useful energy, e.g. in the form of heat and cooling, better measures capability as it determines the extent of the ultimately relevant energy services. Unlike in the case of water and food for instance, for energy, the energy carriers themselves are only means to a multitude of end uses such as space lighting and hot meals (Pachauri 2011). In order to calculate the respective amount of useful energy, one needs to know the efficiencies for each energy carrier and purpose. For example, 2 kg of firewood used for cooking a meal on a three-stone open fire, which have a conversion efficiency of below 15 percent, clearly provides less useful energy than the same amount of firewood used with an improved metal cookstove[6] with an efficiency typically ranging around 25 percent.

Modi et al. (2005) and the UN Secretary-General Advisory Group on Energy and Climate Change (UN-AGECC 2010) propose an alternative, less data-intensive way to approximate useful energy. They require that two poverty cut-offs k have to be exceeded: First, a minimum amount of final energy used in the form of modern fuels (gaseous or liquid fuels or otherwise electricity) and technologies (such as improved biomass cookstoves) for cooking and, second, a minimum amount of electricity for all other services, excluding heating and mobility. More precisely, they define the cut-offs in terms of consumption per year and capita: 40 kgoe for cooking, which is equivalent to 37 litres of liquefied petroleum

[6] See World Bank (2011) for a discussion of different types of improved cookstoves.

gas (LPG) or 105 kg of firewood, as well as 50 kilowatt hours (kWh, equivalent to 4 kgoe) for rural households and 100 kWh for urban households.

Income-invariant energy demand approach

In a set of two publications, Barnes, Khandker and Samad empirically determine an energy poverty threshold based on estimations of final and end-use energy consumption. The threshold is defined as the income decile where energy consumption is significantly different from the consumption in the first decile. Given this construction, the threshold is supposed to represent the point until which energy demand is insensitive to income changes, as households below the point can only consume a bare minimum level of energy according to the authors' interpretation. Defining $\bar{d}$ as the poverty cut-off decile and d_n as the decile the household of individual n belongs to, this second energy poverty measure is defined as follows:

$$\varepsilon_2 = \frac{1}{N}\sum_{n=1}^{N} I(\bar{d} > d_n).$$

The authors apply this method to the household data from the nationally representative Bangladesh Rural Energy Survey of the year 2004 (Barnes, Khandker and Samad 2011) and to the 2005 wave of the India Human Development Survey (IHDS) covering both urban and rural areas (Khandker, Barnes and Samad 2012). Both papers estimate Ordinary Least Squares (OLS) regressions with the following specification to determine the poverty cut-off decile $\bar{d}$:

$$Y_{nj} = \beta_0 + X_{nj}'\beta_1 + \beta_2 C_j + \beta_3 P_j + D_{nj}'\beta_4 + \mu_{nj}. \qquad [1]$$

Energy consumption Y_{nj} of individual n in community j is regressed on a vector of household and community characteristics such as educational attainment or the availability of electricity in the community, X_{nj} and C_j respectively. In the same way as for ε_1, Y_{nj} is measured in terms of kgoe. Additional control variables comprise the vector P_j of local prices of alternative energy sources and a vector D_{nj} of income deciles. μ_{nj} represents the unobserved random error.

2.4. Composite energy poverty indices

Multidimensional Energy Poverty Index

The Multidimensional Energy Poverty Index (MEPI) presented in Nussbaumer, Bazilian and Modi (2012) is an adaptation of the general Multidimensional Poverty Index (MPI), for which a first round of estimates was presented in the 2010 Human Development Report (UNDP 2010). Instead of a single poverty cut-off, the underlying so-called dual cut-off method requires to define thresholds in two steps: dimensional cut-offs z_d for each sub-dimension d, whereas the poverty cut-off k determines in how many sub-dimensions an individual n has to be deprived for being classified as poor (Alkire and Foster 2011). In addition, a weight ω_d is attributed to each sub-dimension. The MEPI can be expressed as follows:

$$\varepsilon_3 = \frac{1}{N}\sum_{n=1}^{N} I(c_n \geq k) \times c_n$$

$$\text{with} \quad c_n = \Sigma_{d=1}^{D}\omega_d I(z_d > y_{nd}) \quad \text{and} \quad \Sigma_{d=1}^{D}\omega_d = 1.$$

Being defined in this way, ε_3 is the product of the incidence of poverty (proportion of people identified as energy poor, also called headcount ratio) and the average intensity of deprivation of the energy poor and can be decomposed by sub-dimension or otherwise by subgroup such as region or ethnicity.[7] According to the authors, attainments y_{nd} for in total six sub-dimensions d are deemed to be relevant, which are all expressed as dummies equalling one if the household has overcome deprivation in that sub-dimension: *modern cooking fuel usage* (this is electricity, LPG, kerosene, natural gas, or biogas), *modern cooking stove usage* (including modern cooking fuel stoves except kerosene stoves as well as stoves equipped with a hood or chimney) and *electricity access*, each with a weight ω_d of 0.2. With a slightly lower weight ω_d of 0.13, the other three indicators *radio or television*, *phone* and *fridge ownership* enter the MEPI. A person is identified as energy poor if the combination of the censored weighted deprivations faced (c_n) exceeds a pre-defined threshold k. While c_n and k

[7] This product has originally been referred to as MPI = H x A, a headcount ratio (H) multiplied by the average deprivation score of the multidimensionally poor (A), see Santos and Alkire (2011). The formula for ε_3 can then be derived as follows: $H \times A = q/N \times (\sum_{n=1}^{N} I(c_n \geq k) \times c_n)/q)$. Here q is the number of people who are multidimensionally poor. Concerning decomposition, with the censored headcount ratio CH_d being defined as $CH_d = \sum_{n=1}^{N} I(c_n \geq k) \times I(z_d > y_{nd})$, ε_3 can easily be reformulated to $\varepsilon_3 = \sum_{d=1}^{D}\omega_d CH_d$ such that the contribution of each sub-dimension to overall energy poverty equals $(\omega_d CH_d/\varepsilon_3)$*100.

may take on values between 0 (no deprivations) and 1 (completely deprived), the authors set their poverty cut-off at $k = 0.3$.

Correlation Sensitive Energy Poverty Index

As a reaction to the original MPI, Rippin (2012) proposed a slightly adapted index that is supposed to overcome several weaknesses of the MPI (see Rippin 2011). While most of the points of criticism have been countered by the creators of the MPI (Oxford Poverty and Human Development Initiative 2012), at least the fundamental discomfort with the arbitrary poverty cut-off remains. Rippin bypasses the need of defining a poverty cut-off k by adding a further axiom to her aggregation model, which is intended to increase the sensitivity of the new metric to inter-personal inequality, the so-called Nondecreasingness under Inequality Increasing Switch. In view of that she calls her new index the Correlation Sensitive Poverty Index (CSPI). In the same way that the MEPI is constructed on the basis of the MPI, a Correlation Sensitive Energy Poverty Index (CSEPI) can be constructed using the structure of the CSPI. In its simplest version, the formula for this fourth energy poverty metric then becomes

$$\varepsilon_4 = \frac{1}{N}\sum_{n=1}^{N} c_n \times c_n$$

with c_n being defined in the same way as for the MEPI. Note that decomposition delivers much higher headcount ratios for the CSEPI than for the MEPI. This has to do with the fact that, in determining the headcount ratio, the CSEPI is far more restrictive: different from the dual cut-off method outlined above, everybody is considered poor who is deprived in any of the six sub-dimensions, hence, following the so-called union identification approach (Atkinson 2003).

Total Energy Access standard

In recent years, the international nongovernmental organization (NGO) Practical Action proficiently contributed to the energy poverty debate. Based on consultations and in cooperation with all relevant actors ranging from the IEA and World Bank over the Global Alliance for Clean Cookstoves to national development cooperation agencies and other NGOs, the Total Energy Access standard (TEA) was presented in the 2012 Poor Peoples Energy Outlook (Practical Action 2012). The TEA is the most demanding metric, since it corresponds to the headcount ratio as defined by the CSEPI. Hence, it considers the intensity of deprivation as irrelevant so that any person deprived in any of the six sub-dimensions enters the metric with a value of 1, representing (complete) energy poverty. For that reason, weighting factors ω_d become superfluous and the energy poverty measure reads as follows:

$$\varepsilon_5 = \frac{1}{N}\sum_{n=1}^{N} I(\,c_n \geq 1)$$

with $c_n = \Sigma_{d=1}^{D} I(z_d > y_{nd})$.

Furthermore, this standard incorporates two extensions that necessitate richer datasets: First, it comprises basically the same household dimensions as the MEPI that are as well expressed as dummies. Yet, it tries harder to capture not only access but also use, e.g. by defining the minimum standard for lighting as 300 lumens (equal to one light bulb) for a minimum of 4 hours per night. A second extension is the incorporation of two further dimensions, energy for enterprises and for community services. This reflects the notion that an individual household's welfare is also influenced by energy services in its livelihood. The operationalization of these issues is still work in progress that keeps up a lively debate (see UN-SE4All 2012). A reasonable preliminary extension of the TEA standard would be to include the energy status of the local health care and milling facilities as these can be considered the most relevant basic energy services for the community service and enterprise dimension, respectively (see also Bates et al. 2009).[8]

3. Empirical approach and data description

The data used for the empirical analysis has been gathered in the five sub-Saharan African countries Benin, Burkina Faso, Senegal, Mozambique and Rwanda – the former three being located in West Africa, the latter two in East Africa. The data has been collected between December 2006 and November 2012 in cooperation with national partner organizations specialized in survey implementation. All surveys took place in the context of impact

[8] Other candidates for the community dimension are schools, telecommunication networks, and street lighting. The preliminary access to energy measurement framework outlined in the latest Poor Peoples Energy Outlook (Practical Action 2013) mentions further potential indicators. These, however, are beyond the scope of a basic energy poverty metric, e.g. the use of cooking fuels at enterprises and community services, the time spent on cooking and whether stoves are regularly cleaned.

evaluations for energy interventions supported or financed by development agencies such as Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) and the Netherlands Ministry of Foreign Affairs. The interventions typically had a regional focus. As can be taken from Table 2, the data stems from 13 surveys conducted in both rural and urban settings, none of which was designed to be nationally representative. The surveys were either baseline surveys for upcoming projects or part of evaluation studies on energy access interventions ranging from improved cookstoves to central grid extension. These latter evaluation study samples comprise both households with access to the new energy technology and comparable households without.

Table 2: Basic survey characteristics[9]

country	survey date	number of households used for analysis	survey setting	probability sampling	energy access intervention
Benin	1-2/2007	329	rural	in part*	central grid
Burkina Faso	11/2010	1006	rural	yes	none *(baseline)*
	2-3/2011	1185	urban	yes	improved cookstoves
	10-11/2012	355	rural	yes	solar photovoltaics
Mozambique	6-7/2008	448	urban	no†	none *(baseline)*
	7/2008	126	rural	yes	none *(baseline)*
	6-7/2011	522	urban	no†	central grid
Rwanda	4-5/2011	1413	rural	yes	none *(baseline)*
	6/2012	524	rural	no‡	biogas
Senegal	9-10/2009	546	urban	yes	improved cookstoves
	10-11/2009	728	rural	yes	solar photovoltaics
	11/2010	216	rural	yes	improved cookstoves
	3/2011	476	rural	yes	none *(baseline)*

Notes: * purposive sampling of electrified households; † purposive sampling of both electrified and non-electrified households (or a follow-up of the latter households after electrification); ‡ purposive sampling of biogas-using households and comparable households without biogas

By virtue of a focus on energy usage in all surveys, the collected data accommodates the data requirements imposed by all metrics outlined in the previous section. Given the heaviness of the data requirements, the complete range of variables needed to construct the different metrics is, however, not available for all households. While imputation methods outlined below have been moderately applied, part of the households had to be discarded

[9] More details on the survey samples, areas and interventions can be taken from Harsdorff and Peters (2010) for Benin, for Burkina Faso: Bensch et al. (2011, 2013), for Senegal: Bensch and Peters (2012, 2013) and Bensch, Peters and Sievert (2013), and for Mozambique: Bensch, Peters and Schraml (2010).

due to missing data. The data set used for the empirical analysis therefore adds up to a total of 7874 household observations with the complete dataset including 9175 households. Most of the 7874 households have only been interviewed once. 720 households have participated in two survey waves, 60 in three surveys. The information has been provided by the knowledgeable respondent in the household who typically is the household head, whereas cooking-related questions have usually been directed to the female responsible for this household chore.

The five metrics described above are computed applying the respective calculation formulas to the household data. The number of household members is accounted for in order to arrive at poverty figures at the individual level. Sampling weights are employed in order to at least compensate for intra-survey oversampling. In a next step, it is scrutinized on the basis of correlation analyses in how far the metrics affect the classification as energy poor. Sensitivity analyses are undertaken with regards to the metrics' parameters and their implicit and explicit assumptions. For this purpose, Spearman and Kendall correlation coefficients are computed to assess the ranking stability of the 34 different regions in the five surveyed countries. Spearman correlation measures the degree to which the ranks of two compared sets of observations increase together, whereas Kendall correlation calculates the difference between the probability that the pair of observations is in the same order and the probability that it is not. Additional survey-specific quantitative and qualitative information helps to appraise the strengths, weaknesses and sensitivities of the individual indices. General quality criteria against which the individual energy poverty measures will be evaluated are set out by Bazilian et al. (2010): statistical rigour, transparency, national input, data availability, simplicity, political attractiveness and usefulness for policy design. Concerning the latter, usefulness for policy design, it is particularly relevant to assess in how far the metrics are sensitive to different types of energy interventions.

The concrete data used for indicator construction is grouped in two sets of variables, one for the uni- and one for the multidimensional approaches. The variables needed for the unidimensional metrics are listed in Table 3. The poverty measure ε_1 simply compares the households' individual attainments with the poverty cut-offs in terms of *final energy consumption* for cooking with modern fuels as well as in the form of electricity used for other purposes, such as lighting. The table also displays *end-use energy consumption*, *energy* *expenditure* and the independent control variables used in either of the two studies that apply ε_2.

Table 3: Variables included in unidimensional analysis

	Applied to ε_1	Applied to ε_2 in BKS 2011[*]	KBS 2012[*]	Total mean
DEPENDENT VARIABLE (= individual attainment y_n)				
Final per capita energy consumption (kgOE/month)	—	yes	—	27.35
— for cooking with modern fuels or improved technologies (kgOE/month)	yes	—	—	9.28
— for other purposes using electricity (kWh/month)	yes	—	—	4.49
End-use per capita energy consumption (kgOE/month)		yes	yes[†]	
— for cooking (kgOE/month)		—	—	5.13
— for lighting (kgOE/month)		—	—	0.002
Per capita energy expenditure (international $/month)		—	yes[†]	7.41
BASIC HOUSEHOLD CHARACTERISTICS				
Age of household head (years)		yes	yes	45.94
Sex of household head (male-1, female-0)		yes	yes	0.88
Highest education among household males (years)		yes	yes	5.80
Highest education among household females (years)		yes	yes	4.81
Log of household agricultural landholding (ares)		yes	yes	n/a
Household non-land assets[‡]		yes	—	0.46
PRICES OF ALTERNATIVE ENERGY SOURCES				
Log price of firewood (international $/kg)		yes	yes	n/a
Log price of kerosene (international $/litre)		yes	yes	n/a
COMMUNITY CHARACTERISTICS				
Community has electricity (0/1)		yes	yes	0.83
Community has primary schools (0/1)		yes	—	0.88
Community has health centres (0/1)		yes	—	0.66
Household income decile indicators		yes	yes	n/a
ADDITIONAL SURVEY-SPECIFIC VARIABLES [§]				
Country		—		n/a
Rural (0/1)		—		0.68
Interview year indicators		—		n/a
Interview conducted in lean season (0/1)		—		0.18
Interview conducted in harvest season (0/1)		—		0.68
Interview conducted in rainy season (0/1)		—		0.25

Notes: n/a = not applicable; * BKS (2011) refers to Barnes, Khandker and Samad (2011) and KBS (2012) to Khandker, Barnes and Samad (2012), respectively; [†] in per household terms; [‡] While BKS (2011) included the monetary value here, I follow the approach of Filmer and Pritchett (2001) and Sahn and Stifel (2003) to construct an asset index, a single index calculated with principal component analysis using information about the ownership of bicycles, motorized vehicles, phones, radios, large animal livestock and the housing conditions (wall and floor material, glass windows). Since the component asset index takes negative values, it is linearly transformed such that it ranges from 0 to 1; [§] Information on the seasonal calendar in the survey regions (lean, harvest, rainy season) have been retrieved from the Famine Early Warning Systems Network (www.fews.net).

In view of the different setting, a few adaptations in the data structure for this second metric are made. First, a couple of control variables from the two categories *prices of alternative energy sources* and *community characteristics* are not included as they are either not applicable to many of the surveyed regions, e.g. the unit price of LPG or wage level in the community, or since they are very uncommon and have therefore not been elicited in many surveys, such as the proportion of community land irrigated. Second, given the cross-country analysis conducted in the present paper, I account for additional survey-specific variables such as the survey year and apply year-specific purchasing power parity (PPP) exchange rates (World Bank's Open Data 2013).[10] Third, I apply different efficiency factors than Barnes, Khandker and Samad for computing end-use energy. Most importantly I abstain from the strong simplification that an efficiency of 100 percent is assumed for any appliance using electricity. Instead I restrict my analysis to the two primary end uses of energy, cooking and lighting, for which plausible efficiency rates are available (see the conversion factor tables in Appendix A). Finally, the dependent variables are only calculated in per capita terms instead of per household terms, since household sizes in the analysed rural regions differ widely and range from 1 to over 50 people.

Table 4 depicts the variables used for calculating the three multidimensional metrics. The table lists the TEA minimum standards and proxy variables for the four different dimensions as defined by Practical Action (2012), namely lighting, cooking and water heating, cooling as well as information and communication. The only difference is that *reliable electricity access in urban households* is included as an additional proxy variable for the lighting indicator.[11] In this manner, I follow the MEPI, which uses *electricity access* as proxy for this dimension, but do so in a more precise way. The only further difference between the TEA and the MEPI is the inclusion of *internet access* in the TEA. This does not have an effect on the metrics, since it does not occur so far that a household has internet access but not a phone or else radio or TV. Even though the changes are minimal, in the following analysis I

[10] A criticism of using PPP exchange rates in poverty analyses is that these conversion factors are weighted averages of prices, where both the prices may not be those faced by the poor and the weights not reflect their consumption patterns. At least for the latter, Deaton and Dupriez (2011), however, show that differences between weights for the poor and aggregate weights do not vary much across countries, leaving the price indices largely unchanged.

[11] It is beyond the scope of this paper to find a common definition for reliability in electricity provision. For the urban areas included in the present analysis, it seems nevertheless clear that electricity provision has been reliable at the time of survey implementation.

refer to these two adapted metrics as TEA+ and MEPI+ in order to distinguish them from the originally proposed ones. The conclusions that can be drawn from the two adapted metrics should anyhow apply to the original versions in the same way.

Table 4: Variables included in multidimensional analysis

Dimension	Minimum standard	Weight* I	Weight* II	(Proxy) variable	Total mean (median)	Deprived if. . .
Lighting	300 lumens (lm) for a minimum of 4 hours per night at household level	0.2	0.173	amount of artificial lighting (lmh) OR reliable electricity access in urban household (0/1)	4835 (600) 0.22	<1200 lmh/ day; no
Cooking and water heating *sufficient fuel usage*	1 kg woodfuel, 0.3 kg charcoal, 0.04 kg LPG or 0.2 l of kerosene or biofuel per person per day, taking less than 30 minutes per household per day to obtain	0.2	0.173	modern main cooking fuel (0/1) (liquid or gas fuel or electricity) OR improved solid fuel cookstove (0/1) and firewood collection time (min)	0.15 0.19 47 (17)	no no >=30 min/ day
household air pollution	Annual mean concentrations of particulate matter (PM2.5) < 10 µg/ m^3 in households, with interim goals of 15 µg/m^3, 25 µg/m^3 and 35 µg/m^3	0.2	0.173	Modern main cooking fuel (0/1) OR improved solid fuel cookstove with chimney or hood (0/1)	*see above* 0.19	no no
Cooling	Households can extend life of perishable products by a minimum of 50% over that allowed by ambient storage	0.133	0.113	fridge ownership (0/1)	0.09	no
Information and communication	People can communicate electronic information from their household	0.133	0.113	phone ownership (0/1) OR internet access (0/1)	0.78 0.01	no no
	People can access electronic media relevant to their lives and livelihoods in their household	0.133	0.113	radio or television ownership (0/1) OR internet access	0.76 *see above*	no no
Enterprises	—	—	0.07	mill in community powered with electricity or renewable or fossil energy (0/1)	0.38	no
Community services	—	—	0.07	health station in community powered with electricity or renewable or fossil energy (0/1)	0.17	no

Note: * The two weights I and II refer to the two variants of the indicator set excluding and including the two dimensions *enterprises* and *community services*, respectively.

The weights (ω^{I}) are those proposed by Nussbaumer, Bazilian and Modi (2012). For the variant of the indicator set including the two dimensions *enterprises* and *community services*, a second weight vector ω^{II} has been defined. It inherits the relative weighing of the first weight vector. The newly proposed CSEPI does not have an own set of indicators. As there are no reasons to apply a different set of indicators to the CSEPI, I apply the same indicators to all three metrics, such that the assessment can be focused on the metrics' different constructions.

In order not to needlessly lose observations, missing data on control variables used to compute ε_2 are imputed. With missing information on the variables of interest for the two unidimensional metrics, the dependent variables listed in Table 3, I proceed as follows: If one of the eight to ten energy type components (e.g. consumption of LPG for cooking) is missing, the component is being imputed. With more than one missing component, I consider the household as missing this indicator. In a similar vein, up to one of the ten variables from Table 4 needed to construct the multidimensional indices ε_3 to ε_5 has been imputed. The general treatment of missing data is outlined in detail in Appendix B.

4. Analysis of energy poverty metric outcomes

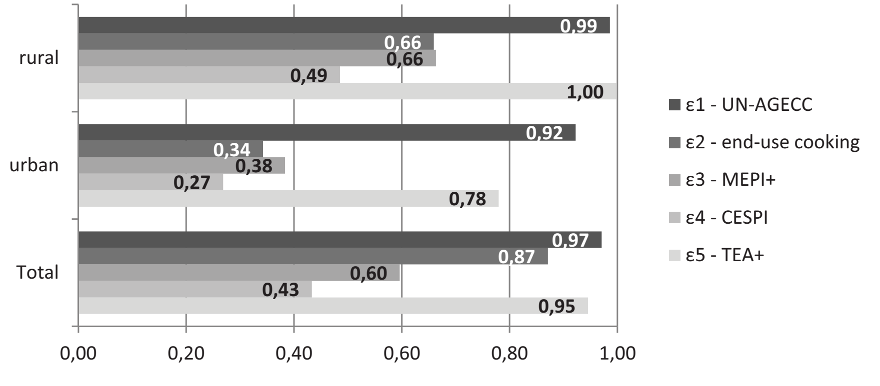
The outcomes for the various energy poverty metrics and surveys are summarized in Table 5. All metrics are bounded between 0 and 1 with 1 implying complete energy poverty. On a first glance, it is striking that for two of the seven presented metrics, the UN-AGECC metric and TEA+, the vast majority of households are considered as energy poor indicated by values close to 1. This outcome is less astonishing for TEA+ given its foundation in the strict energy poverty definition of the union identification approach. The high energy poverty values for the UN-AGECC measure, however, are quite worrying. On the other side, the MEPI+ and CSEPI average out clearly lower at 0.60 and 0.43, respectively (Figure 1). While the two variants of ε_2 on end-use energy for cooking and energy expenditures deliver identical results, the ε_2 variant that looks at final energy consumption (not shown in the table) even classifies all households without exception as energy poor. This has to do with the fact that final energy consumption is largely dominated by firewood usage, which – at least in the surveyed rural areas – is mostly freely available, such that its consumption is relatively inelastic to the income and wealth status of a household. The variant of ε_2 on final energy consumption will not be further considered in the following.

Table 5: Energy poverty metric outcomes, by survey

	Unidimensional metrics				Multidimensional metrics		
	ε_1	ε_2			ε_3	ε_4	ε_5
	UN-AGECC	End-use energy lighting	End-use energy cooking	Energy expen-ditures	MEPI+	CSEPI	TEA+
rural							
Benin 2007	1.00	0.60	0.82	0.82	0.68	0.49	1.00
Burkina Faso 2010	1.00	0.66	0.88	0.88	0.71	0.53	1.00
Burkina Faso 2012	1.00	0.76	0.92	0.92	0.73	0.56	1.00
Mozambique 2008	1.00	0.66	0.87	0.87	0.79	0.65	1.00
Rwanda 2011	1.00	0.67	0.88	0.88	0.81	0.67	1.00
Rwanda 2012	0.81	0.69	0.89	0.89	0.35	0.21	0.98
Senegal 2009	1.00	0.66	0.85	0.85	0.65	0.45	1.00
Senegal 2010	1.00	0.66	0.86	0.86	0.63	0.42	1.00
Senegal 2011	1.00	0.62	0.88	0.88	0.57	0.40	0.99
urban							
Burkina Faso 2011	0.94	0.63	0.86	0.86	0.46	0.32	0.87
Mozambique 2008	0.98	0.65	0.88	0.88	0.70	0.55	0.98
Mozambique 2011	0.97	0.62	0.86	0.86	0.48	0.30	0.95
Senegal 2009	0.83	0.64	0.88	0.88	0.04	0.03	0.44
*adjusted R^2 **	-	0.154	0.152	0.331	-	-	-
observations	7874	7874	6319	7874	7874	7874	7874

Note: * Values on adjusted R^2 are only shown for ε_2 as this is the only metric for which poverty cut-offs have been determined based on OLS regressions (see equation 1 in Section 2.3). In these estimations, robust standard errors are clustered at community level. End-use energy for lighting is the only variable with missing observations, since no information on the usage of lighting devices has been gathered in two urban surveys on improved cooking stove evaluations.

Figure 1: Overall average outcome of the various energy poverty metrics



Comparable data that facilitates appraising the observed energy poverty levels is only available for ε_3, the MEPI. Nussbaumer, Bazilian and Modi (2012) present figures for all five countries considered here based on nationally representative Demographic and Health Survey (DHS) data. Updated figures are available in Nussbaumer et al. (2013). As can be taken from Table 8 in Appendix C, it turns out that most survey areas assessed in this paper score better than the national averages calculated by Nussbaumer and his co-authors. This seems plausible mainly for two reasons. First, for being eligible for energy and particularly electrification interventions, rural communities typically need to have a reasonable level of purchasing power such that households are more likely to afford electricity payments. Second, part of the surveyed households has previously undergone the interventions such that their energy situation has already been improved.

The other metric, for which empirical estimates are available, is ε_2. While Barnes, Khandker and Samad used data from Asia, at least their values on goodness of fit measured in terms of adjusted R-squared can be taken as a quality indicator for the performed estimations. The values presented at the bottom of Table 5 are very similar to those.

4.1. Outcomes for the individual energy poverty metrics

The UN-AGECC metric ε_1 is the energy poverty index that varies least across surveys. The best-performing study and, at the same time, the only rural study whose ε_1 outcome is below 1.00 is the Rwanda biogas study. The particularity of this study is that biogas-using households and comparable households without biogas have been purposively sampled, hence, households that are the better off in their communities. This is important to note, since the 19 percent energy non-poor households found in this study have only been classified as energy non-poor because they disposed of electricity connections. Since ε_1 imposes a double threshold and does not account for biogas lighting, the provision with biodigesters alone cannot lift households out of energy poverty. This also becomes evident when looking closer into the data. For this purpose, Table 9 in Appendix C shows the degree of energy poverty in terms of the two components of ε_1, final energy on modern cooking and final energy used as electricity for other purposes. While for a couple of rural studies the share of households with modern cooking energy levels considered as insufficient falls below 90 percent, only for the Rwanda biogas study there are households with sufficient electricity consumption levels at the same time. The 2010 rural Senegal survey, for example, covers households among whom improved cooking stoves have been randomly disseminated. Here, 62 percent of households are classified as energy poor in the modern cooking component. Since virtually no household consumes sufficient levels of electricity everybody is, however, eventually considered as energy poor by ε_1.

The Rwanda biogas study also reveals the influence of improved cooking stoves on the outcomes for this first metric: Even among the households with sufficient modern cooking energy consumption who own a biodigester and regularly cook with it, 45 percent of the final cooking energy is provided by firewood used with improved cookstoves. This underpins the relevance of a clear and universal definition of which types of stoves can be considered as improved. In the absence of such a clear definition, the present analysis is based on country-specific conventions on which stoves are deemed as improved.

The urban study that performs similarly well in the metric ε_1 is from Senegal. Urban Senegal excels in this comparison with relatively high levels of both electricity consumption and access to clean cooking fuels. This latter aspect can be traced back to the national butanisation programme launched already in the 1970s to foster the usage of LPG through subsidies and promotional campaigns (Schlag and Zuzarte 2008). However, two thirds of households using exclusively the clean cooking fuel LPG are still considered as deprived in cooking energy, since the threshold is set higher than their per capita consumption levels.

Using income deciles as household classifiers, the set of potential poverty cut-offs for ε_2 comprises only eleven discrete energy consumption levels. For this reason it is less of a coincidence that the energy poverty figures are identical for end-use energy for cooking and energy expenditures. Outcomes for ε_2 are, moreover, relatively homogenous across the different surveys, which partly is attributable to the fact that a single poverty cut-off decile has been determined for all surveys. Estimating poverty cut-off deciles for urban and rural areas separately, however, reveals a weakness of this approach: different from the other approaches, the total mean is not a weighted average of urban and rural areas (Figure 1). Instead the energy poverty ratios are in most cases clearly lower for both urban and rural areas, since lower deciles are identified as poverty cut-offs. ε_2 thereby violates the decomposability axiom as part of the axiomatic foundation of ordinal poverty measures, which has been laid out in a series of articles ranging from Chakravarty, Mukherjee and

Ranade (1998) to Alkire and Foster (2011). Note that the remaining metrics satisfy all core axioms of this axiomatic foundation.[12]

A more nuanced picture can be drawn for ε_3, since this metric can be broken down by dimension and into an energy poverty headcount ratio. The respective outcomes are given in Table 9 in Appendix C. Decomposition by dimension allows determining the relative contribution of deprivation in each particular indicator to this composite energy poverty index. It becomes apparent that the two indicators on the *cooking* dimension dominate MEPI+, as their contribution exceeds 50 percent for almost all surveys. At least to some extent, this has to do with the absence of electric cooking. Apart from urban Mozambique, in none of the studies more than two percent of electrified households with electric stoves can be found. The urban households in Mozambique, on the other hand, are a good example which shows that availability does not necessarily imply usage. Since electricity is comparatively expensive there, households often do not use their electric plates as primary cooking stoves.

In contrast, the two indicators on *information and communication* by now effectively add very little to overall energy poverty. A sizable share of households still did not dispose of any of the required appliances in the earlier 2007 and 2008 studies, whereas their number has significantly decreased over time including non-electrified regions. In comparison to its weight ω, the *cooling* dimension contributes disproportionately high to overall energy poverty with around 20 percent. While fridges can typically only be found in central grid covered regions, even in these areas the relative contribution of the indicator is similarly high with its absolute contribution only being slightly lower (see Table 10 in Appendix C).

Coming to the last dimension, the outcomes for *lighting* are more heterogeneous and rather contribute disproportionally low. This is due to two factors: First, most households use the amount of artificial lighting that is deemed sufficient as soon as they are electrified. 84 percent of households with an electricity source (including car batteries and gensets) actually use the electricity for electric lighting and 99 percent among them surpass the 1200 lumen hours per day required by this indicator. Second, the present analysis does not impose a minimum brightness of the lighting source (e.g. 300 lumens as proposed by

[12] Axioms considered as core axioms are symmetry/ anonymity, monotonicity, principle of population/ replication invariance, strong focus, non-triviality, normalization, and decomposability.

Practical Action 2012). It thereby also accounts for fainter low-cost battery-run lamps that have greatly made an entrance in rural African households. Among the five analysed countries, this is particularly true for the two Western African countries Senegal and Burkina Faso. For a final definition of this indicator, it therefore remains to be decided whether a larger number of low-luminosity lamps can compensate for a lack in fewer but more powerful light bulbs. Taking the example of Senegal and Burkina Faso with large households typically living in various huts, this trade-off may break down to the comparison of a few light bulbs illuminating the hut of the household head compared to a variety of battery lamps being available in all huts used for living.

The headcount ratio determined on the basis of MEPI+ can be seen as a light version of ε_5, TEA+. The difference is that the MEPI accepts a certain degree of deprivation, notably up to the poverty cut-off *k* chosen to be 0.3 in this analysis. For this reason there is more variation in the MEPI+ headcount where the urban Senegal study again performs best with an energy poverty headcount of mere 9 percent, whereas according to TEA+ the same sample comprises 44 percent of energy poor people. For the assessed rural areas, TEA+ does not provide any differentiation. Their metric values are confined to 0.98 to 1.00.

Finally, the outcomes for the CSEPI (ε_4) are weighed against its postulated advantages compared to the MEPI. The CSEPI is, first, supposed to be more efficient, since it also makes use of the information on deprivations of households who are considered non-poor in the MEPI. Second, the CSEPI is intended to put more emphasis on the neediest, which becomes evident in the quadratic functional form. For the energy poverty levels found in this study, this can, however, not be observed. The CSEPI outcomes are in all cases lower and their distribution across surveys is skewed in comparison to the MEPI+.

4.2. Consistency between the individual energy poverty metrics

After this assessment metric by metric, a joint analysis of the metrics is performed in the following. The overlap of indices is assessed in a similar way as done by Deutsch and Silber (2005) on multidimensional poverty metrics. Table 6, first, shows in how many of the metrics a household is defined as energy poor. For the multidimensional metrics, the binary headcount is used, which indicates whether a person is multidimensionally poor at all (irrespective of the poverty intensity). Only five metrics are accounted for given that the ε_2

poverty metric outcomes are identical for end-use energy for cooking and energy expenditures and that the headcount for ε_4, the CSEPI, and ε_5, TEA+, is identical. Most households end up being identified as energy poor by all metrics. On average, a household is energy poor according to 4.3 metrics.

Table 6: Number of indices in which households are identified as energy poor

Number of indices	Share of households (in %)	Share of individuals (in %)	Cumulative share of individuals (in %)
0	0.2	0.2	0.2
1	1.4	1.2	1.4
2	3.7	3.2	4.6
3	12.8	15.5	20.1
4	20.9	22.7	42.8
5	61.0	57.2	100.0

Table 7: Correlation between different metrics

	Unidimensional metrics			Multidimensional metrics			Unidimensional metrics			Multi-dimensional metrics	
	ε_1	ε_2 (l)	ε_2 (ex)	ε_3	ε_4	ε_5	ε_1	ε_2 (l)	ε_2 (ex)	ε_3	ε_5
	UN-AGECC	End-use energy lighting	Energy expen-ditures	MEPI+	CSEPI	TEA+	UN-AGECC	End-use energy lighting	Energy expen-ditures	MEPI+	TEA+
ε_1	1						-				
ε_2 (l)	0.02	1					85%	-			
ε_2 (ex)	0.02	0.53	1				64%	75%	-		
ε_3	0.34	0.13	0.10	1			88%	78%	61%	-	
ε_4	0.28	0.16	0.12	0.94	1		-	-	-	-	
ε_5	0.28	0.06	0.04	0.51	0.39	1	94%	83%	64%	92%	-

Note: The left-hand side of the table displays Pearson correlation coefficients and the right-hand side percentages of households defined as energy poor by two indices among households identified as energy poor in any of the two respective indices. Values for ε_2 for cooking are not shown as they are identical to those of ε_2 (ex) given the identical poverty metric outcomes. Percentages cannot be calculated for indicator overlaps with ε_4, since this metric has no headcount.

More specifically, Table 7 shows correlations between metrics. First, by means of Pearson correlation coefficients and, second, in terms of the percentage of households defined as energy poor by two indices among households identified as energy poor in any of the two. Given that in general households are mostly identified as poor, these shares are all relatively high. The correlation coefficients, instead, exhibit a higher variation: correlation among unidimensional metrics as well as between uni- and multidimensional metrics are lower than correlations among multidimensional metrics. The high degree of correlation between MEPI+ and the CSEPI is likely to be driven by the fact that these are the only non-binary indices in that they can also take on values between 0 and 1. At the other extreme, ε_2 is very weakly correlated with all other indices. All in all and having the differences in the metrics' outcomes exposed in Table 5 in mind, a reasonable overlap between the metrics (except for ε_2) could be found.

4.3. Sensitivity analyses

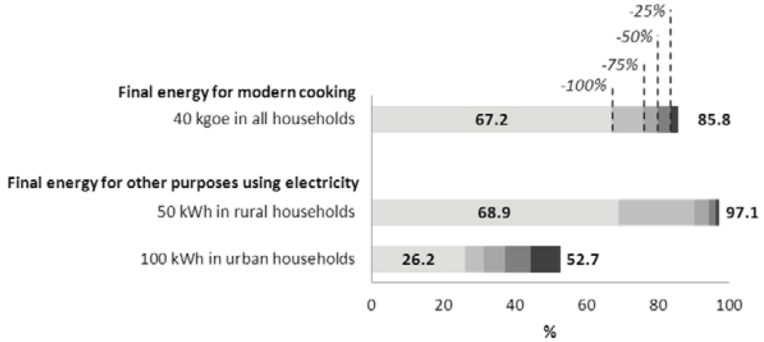
A fundamental question related to the construction of the energy poverty metrics is in how far they are more prone to identify smaller or otherwise larger households as energy poor. For a larger household it may, for example, be easier to acquire electricity-using devices. On the other hand, individual poverty metric outcomes are higher if (energy) poverty is overrepresented among larger households or if the indicators are defined in per capita terms and economies of scale exist in the underlying variable. For example, a household with ten persons may need less than double the amount of cooking fuel for food preparation compared to a household with five persons. Even though the larger household manages to meet its cooking energy needs in the same way, it would be more prone to be classified as energy poor.

To empirically test the sensitivity of the different metrics to this issue, all metrics are as well calculated in per household terms and then compared (not shown). Absolute differences for ε_2 are the highest and the metric is always lower on the individual level, whereas they are quite modest for the other metrics averaging at 0.00 to 0.02. In 9 and 10 of the 13 surveys, the poverty metrics for the two components of ε_1 are higher on the individual level than on the household level supporting the economies of scale hypothesis. For ε_3 and ε_4, they are lower in 11 of the 13 surveys, which hints at the capacity of larger households to easier acquire the appliances included in the multidimensional metrics. ε_5 shows mixed results across the various surveys.

The issue of economies of scale can be accounted for using adult equivalents as a deflator instead of household size, since adult equivalents reflect the consumption needs of household members age- and gender-specifically. While metrics on an adult equivalent basis would generally require collecting far more data, the given dataset makes it possible to check the sensitivity to this matter. For this purpose, the adult equivalence scale proposed by McKay and Greenwell (2007) is applied. The results for ε_2, to which this concept can most reasonably be applied, are identical for all metrics listed in Table 5. In a similar manner, it is tested in how far the ε_2 results differ if households are segmented according to expenditure instead of income deciles.[13] Again no remarkable change occurred.

Another critical point in the concrete implementation of the particular case of ε_2 is the choice of the reference case: the threshold point at which energy consumption is considered to start rising with increases in income is defined where energy consumption is statistically different from the first decile. In this way, an interior threshold point would be identified even if energy would be a normal good and, hence, always rise with income among the whole population. A more convincing approach would therefore be to look at the *marginal* increase in energy consumption along the income distribution. This can be done by iteratively changing the base case decile in the estimations. Results of these estimations are mixed: demand for end-use energy for cooking is inelastic throughout the entire income distribution, for lighting the poverty cut-off is similar to the one determined above. Contrariwise, energy expenditures prove to be very elastic such that only 11 percent of households would be classified as poor according to this measure.

Figure 2: Share of energy poor according to ε_1 components, by different threshold levels



Note: The differently shaded areas indicate the share of the population still considered as energy poor in the respective component of ε_1 when reducing the threshold level by 25, 50, 75 or even 100 percent, respectively.

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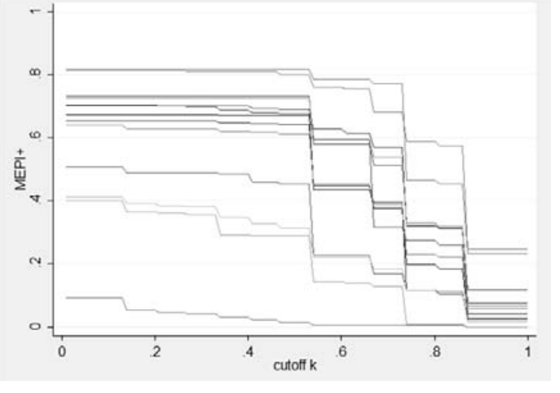
[13] This sensitivity analysis is of interest, since empirical studies have shown that consumption is less volatile and also more accurate than income and, therefore, a better measure of living standards in the absence of multiple seasonal visits (Deaton and Zaidi 2002). Components accounted for are food, telecommunication, housing, schooling and health expenditures.

On the level of the individual metrics, it is furthermore of relevance to see how ε_1 proposed by UN-AGECC would look like if one would modify the threshold levels for its two components, final energy for modern cooking and final energy for other purposes using electricity. The outcomes of a change in the cut-offs by 25, 50 or 75 percent are depicted in Figure 2. It becomes clear that even lowering the bar to zero such that, for example, only household not using any modern cooking fuel would be considered as (cooking) energy poor, would imply that a considerable share of the population remains classified as energy poor.

Figure 3: Robustness of MEPI+ to changes in the cutoff *k*, by survey



Bearing in mind the disputability of MEPI's poverty cut-off k of 0.3, examining the robustness of the metric to changes in k is advised. For this purpose, the ranking stability of the 34 different regions in the five surveyed countries is assessed using Spearman and Kendall correlation coefficients. The ranking turns out to be virtually not affected if setting k to 0.2 or 0.4, indicated by coefficients of between 0.96 and 1.00. The robustness of MEPI+ to changes in the the cutoff k across the whole range from 0 to 1 can best be examined graphically. Figure 3 depicts the outcomes of MEPI+ for all potential values of k (now differentiated by the 13 surveys). The figure exposes that the metric is actually insensitive up to a cut-off value of around 0.5, where a first clear decline can be observed. This is due to many households being at least deprived in the two cooking sub-dimensions and the cooling dimension, which sum up to 0.53. After that, the lines in the figure decreases rather stepwise with the last step being at 0.87. Those households that remain energy poor beyond this point are either deprived in all dimensions or only non-deprived in either the cooling, communication or information dimension.

Finally the inclusion of the community and enterprise dimension addressed in Section 2.4 can be tested for the multidimensional metrics ε_3 to ε_5. Implemented according to the parameters outlined in Table 4 of Section 3, Spearman and Kendall correlation coefficients between 0.75 and 0.90 suggest a somehow larger effect on the metrics. A disapproving feature of the included indicators, however, is that the considered enterprises and social infrastructure institutions, here mills and health stations, are not available in every village. In the present analysis, the households from these villages were considered as deprived in this dimension. Yet, one might argue that availability of these services would better be measured in terms of distance[14], which would again require far more data collection effort. Another frequent issue with mills is that prohibitive pricing may imply that the service – even though available – is not utilized and that poor households rather resort to manual labour instead.

5. Discussion and conclusion

The empirical analysis conducted in the present paper brought to light the diversity in the outcomes of energy poverty metrics currently available in the literature. While all metrics generally identify a high share of people as energy poor in the assessed sub-Saharan countries, the index values of the five analysed metrics differ up to a range from 0.2 to 1.0 for individual surveys. As illustrated in this paper, different implicit and explicit normative judgements inherent in the operationalization of the metrics can be held responsible for these differences. Most fundamentally, this concerns the level of deprivation in capabilities to use energy services that is considered as characterizing energy poverty. The MEPI, for example, allows for a certain degree of deprivation (e.g. a household may be considered energy non-poor even though it neither has a fridge nor a radio or a television set), whereas the Total Energy Access standard applies the most rigorous interpretation. It considers everybody as poor who is deprived in any of the concerned sub-indicators. The threshold levels adopted by the UN Secretary-General Advisory Group on Energy and Climate

[14] In Rwanda, for example, a population is defined as having access to health care if the service can be reached by foot in one and a half hours (National Institute of Statistics et al. 2008).

Change (UN-AGECC) resulted in similarly high levels of energy poverty. Remarkably, even large parts of LPG-using households do not reach minimum levels of cooking fuel consumption according to this metric.

In general, the analysis has underscored that access to electricity, LPG, ICS, and biogas leads to increased usage of energy services. However, it became apparent that the different metrics typically fail to reflect this in their overall classification as energy poor. If at all, effects on the metrics could rather be observed for subcomponents of the metrics, which exist for three of the assessed metrics, namely the UN-AGECC metric, the MEPI and TEA.

The assessment of the household energy consumption data has also drawn attention to the importance of ICS, first, due to the generally overwhelming percentage of the poor who still rely on traditional biomass energy and, second, since the energy poverty metrics legitimately depend crucially on the concept of clean versus traditional cookstoves. The stoves considered as improved in the context of this study have mainly been simple low-cost biomass stoves that are adapted to the needs and habits of the population and locally produced based on metal and/ or clay. While they definitely have an effect on woodfuel demand and may in certain circumstances have sizable impacts on human development (Bensch and Peters 2012, 2013), it is still unclear whether they will be universally accepted as ICS by main actors in the field like the 'Global Alliance for Clean Cookstoves'[15] and, hence, which role they are attributed to in alleviating energy poverty.

The five metrics assessed in this paper are a selection of approaches from the broader field of energy indices, among which only the MEPI has been applied to empirical data before to derive energy poverty levels. The income-invariant energy demand approach proposed by Barnes, Khandker and Samad has shown a couple of drawbacks in the course of the analysis which put into question the suitability of the approach. Not least, the reality in the field suggests that – counter to their assumptions – energy consumption is elastic even among the poorest of the poor. The newly proposed CSEPI does not substantiate its claimed better aptitude for policy guidance than the MEPI in the given context either. Further testing of the index with data from other settings seems recommendable in the

[15] Led by the United Nations Foundation and funded by both public and private partners, among them many bi- and multilateral donors, the objective of the Global Alliance for Clean Cookstoves is to encourage 100 million households to adopt clean cookstoves by 2020. Part of the Alliance's activities is directed towards stove performance testing and classification.

same way as to follow the related ongoing theoretical debate about the MPI, since this may have repercussions on the MEPI. Finally, a common multidimensional indicator set has been proposed in this paper such that the two multidimensional metrics MEPI and TEA can be considered as one metric with the option of context-specifically adapting poverty cut-offs and dimensional weights. To conclude, in terms of index construction the UN-AGECC metric and the MEPI/ TEA performed best in the given setting, not least owing to the additional information provided through their subcomponents. Deciding on the poverty cut-offs (and dimensional weights, if necessary) is ultimately a process that needs further discussions backed by empirical data, which is supposed to reveal the actual implications of these decisions. The same seems to hold for a definite decision on one of the metrics. If the necessary data is available, it seems recommendable for the time being to continue testing and applying the two of them.

The concrete application of the poverty metrics to real-world data revealed that data requirements are high for all metrics. Even having this tailored household energy dataset available, the analysis still had to rely on certain assumptions and conventions, such as energy efficiency factors and improved cooking stove definitions. In addition, even carefully collected data is not immune against measurement error, which can be expected to be particularly pronounced for the consumption of non-market goods as it is the case for collected firewood. In light of the ambitious universal energy access target, the recommendation emanating from this analysis is to restrict a basic energy threshold level to a basket of energy services that can easily and reliably be identified as it is basically the case MEPI/ TEA and to a lesser extent for the UN-AGECC metric.

The one-page TEA questionnaire as sketched in Practical Action (2012) forms an effective basis for eliciting basic energy access. It might be deliberated to which degree modern energy consumption needs to be included more quantitatively in order to account for the data requirements of the originally proposed UN-AGECC metric. In order not to miss relevant new developments, it is further recommended to closely follow the technological transformations and coping strategies that come up in energy poor regions of developing countries. The upcoming low-cost lighting devices mentioned in this paper are only one example among many in the dynamic field of energy provision. With this data at hand, it could be decided on the level of ambition; for example, it seems debatable to reach universal ownership of fridges in the near term, whereas modern cooking can be considered as unanimously indispensable. In this regard, a clear and universal catalogue of which types of stoves can be considered as improved is a necessary complement for any energy access survey.

A basic energy poverty measurement framework resting upon the essential features sketched above is thereby deemed to be readily applicable on large scale. At the same time it could be complemented by more in-depth case study analyses, which may integrate more dimensions and other issues such as the sustainability of energy access. In any case, all decisions on sub-indicator choice and modifications need to be harmonized with the multi-tier framework of the Global Tracking Framework. The objective here is to make the energy poverty metrics an integral part of this indispensable instrument for guiding investment flows in the energy sector to where they are needed and to where they can also make a difference.

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Appendices

Appendix A. Conversion factors

Abbreviations
kg – kilogramme; kgOE – kilogramme oil equivalent; l – litre ; kWh – kilowatt hour ; m^3 – cubic metre; MJ – mega Joule; W – Watt

General Energy Conversion Factors
1 MJ = 0.0238846 kgOE; 1 kWh = 0.086 kgOE (see http://www.iea.org/stats/unit.asp)

Conversion Factors for Common Woodfuel Units

Woodfuel	Conversion		Countries	Source
Firewood	kg per chariot	375	Burkina Faso, Senegal	APEX (2007)
	kg per ster (1 m^3)	350	Rwanda	HP (2007)
	kg per bundle	20	Benin, Burkina Faso, Rwanda, Senegal	HP (2007), Me (2008)
	kg per bundle	5	Mozambique	GRNB (2007)
Charcoal	kg per sack	60	Benin, Burkina Faso, Mozambique, Rwanda	GOBD (2009)
	kg per tomato can	0.8	Burkina Faso	Eh (2006)

Conversion Factors used in the Calculation of Final and End-use Energy:

Final energy consumption of energy carrier *e* in kgOE/month =

monthly consumption of *e* in units **[survey data]** x energy content of *e* in kgOE **[2]** per unit **[1]**

End-use energy consumption for cooking of energy carrier *e* in kgOE/month =

monthly consumption of *e* for cooking in units **[survey data]** x energy content of *e* in kgOE per unit **[2] + [1]** x conversion efficiency for cooking with *e* in % **[3]**

End-use energy consumption for lighting with lighting device *d* using energy carrier *e* in kgOE/month =

monthly lighting consumption with lighting device *d* in hours	x	energy content of *e* used with lighting device *d* in kgOE per unit	x	amount of *e* in units used with lighting device *d* each hour	x	Overall luminous efficiency in %
[survey data]		**[4] + [2] + [1]**		**[5]**		**[7]**

or alternatively, for batteries and candles:

monthly consumption of *e* for lighting in units	x	energy content of *e* in kgOE per unit	x	Overall luminous efficiency in %
[survey data]		**[2] + [1]**		**[7]**

Energy Content of Different Carriers and Typical Efficiencies at Final Consumption Stage of Cooking

Energy carrier [*e*]		**Unit** [1]	**Energy content** (kgOE per unit) [2]	**Conversion efficiency for cooking** (%) [3]	**Source of [2] and [3]**
Liquefied petroleum gas (LPG)		kg	1.086749	60	O'SB (2007)
Kerosene	(pressure)	l*	0.842171	55	"
	(wick)			35	"
Biogas	(60% methane)	m^3	0.544569	60	"
Charcoal	(efficient)	kg	0.716538	30	"
	(traditional)			20	"
Firewood	(efficient)	kg	0.382154	25	"
	(traditional)			15	"
Crop residue		kg	0.322442	12	"
Electricity		kWh	0.085985	75	BKH (2004)
Petrol fuel used with genset		l	0.128140	-	HURS (2012)
Car battery		battery charge	0.085985	-	†
Chinese D cell battery		battery	0.000172	-	ĀBK (2010)
Candle		candle	0	-	ĀBK (2010)

Notes: * with 1 l of kerosene corresponding to 820 g (Barnes, Khandker and Samad 2010); † it is assumed that one battery charge can be converted to 1 kwh of electricity given a 12V car battery with an energy capacity of around 80 Ah; assumed moisture content: 15% for firewood and 5% for crop residues.

Typical Efficiencies of Different Lighting Devices at Final Consumption Stage of Lighting

Lighting device [*d*]	Energy carrier used with lighting device [4]	Amount of energy carrier used with lighting device each hour [5]	Overall luminous efficacy (lm/W) [6]	Overall luminous efficiency (%)† [7]	Source of [6] and [5]
Paraffin candle	candle	—	0.2	0.03	O'SB (2007)
Kerosene wick	kerosene	0.01 l	0.1	0.01	" ; Mi (2003)
Kerosene hurricane	kerosene	0.02 l	0.16	0.02	" ; Mi (2003)
Incandescent (40 W)	electricity	0.040 kWh	10.75	1.57	"
Florescent (20 W)	electricity	0.020 kWh	60	8.78	"
Compact florescent lamp (9 W)	electricity	0.009 kWh	41	6.00	"
Battery-driven lamp*	battery	—	8	1.17	‡
Rechargeable lamp	electricity	0.012 kWh	8	1.17	"
Gas lamp	LPG	0.03 kg	1.5	0.22	SDB (2005)
Biogas lamp	biogas	0.15 m^3	0.7	0.10	" ; Sa (1988)

Notes: * Including fixed torches, which are battery-driven torches that are installed permanently at walls inside the houses; † The overall luminous efficiency can be calculated by dividing the overall luminous efficacy of a lighting device by the overall luminous efficacy of ideal monochromatic green light at 555 nm, which is 683.002 lm/W (Ives 1910; Wyszecki and Stiles 2000). ‡ The luminous efficacy of flashlight bulbs can be said to vary over the approximate range of 8 to 22 lm/W, the wattage of rechargeable lamps is assumed to be 12W; Values for paraffin candles are also applied to oil lamps.

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Appendix B. Treatment of missing data

In principle, the following five imputation methods have been applied depending on the method's plausibility in light of the type of missing information:

1 - conditional mean or median (e.g. conditional on region, survey, households with kerosene lamps)

2 - regression-based (Ordinary Least Squares (OLS) and probit), control variables used comprise the country, rural setting (0/1), interview year indicators, number of adults and children in the household, household size in terms of adult equivalents, sex of household head (0/1), migrant in household (0/1), walls of stone or brick (0/1), windows fitted with glass (0/1), cement flooring (0/1), ownership of bicycles, motor vehicles, large animals and a bank account (each 0/1), head of household is a farmer, occupied in public service or in a private enterprise (each 0/1)

3 - derived from other (imputed) variables, e.g. for the age of the household head, the survey-specific age difference within couples and the age of the wife have been used

4 - derived from imputations of the individual components of the variable

5 - additional non-response variable generated – following a standard approach (e.g., Morris 2006, Augurzky et al. 2012) missing values are replaced by the reference case and an additional dummy variable indicating missing values is included

Imputations of control variables in the unidimensional analysis

	Number of missings	Imputation method
BASIC HOUSEHOLD CHARACTERISTICS		
Age of household head (years)	457	3-2-1-5
Sex of household head (male-1, female-0)	37	2-1
Highest education among household males (years)	329	2
Highest education among household females (years)	329	2
Log of household agricultural landholding (ares)	360	2-1
Asset index	398	4*
PRICES OF ALTERNATIVE ENERGY SOURCES		
Log price of firewood (international $/kg)	2	1
Log price of kerosene (international $/litre)	105	1
COMMUNITY CHARACTERISTICS		
Community has electricity (0/1)	524	1-5
Community has primary schools (0/1)	477	1-5
Community has health centres (0/1)	524	1-5
Household income decile indicators	2212	4*
Household expenditure decile indicators	1324	4*

Note: * For the *household income decile*, the components comprise (i) earned income, (ii) revenues from (non-transformed and transformed) agricultural products, (iii) revenues from livestock products or services, (iv) expenditure on agriculture and (v) received remittances (all imputed by means of OLS); *household expenditure* is composed of expenditure on (i) food, (ii) telecommunication, (iii) housing, (iv) schooling and (v) health; the components of the *asset index* are ownership of (i) a bicycle, (ii) a motorized vehicle, (iii) a phone, (iv) a radio, (v) large animal livestock and (vi - viii) the housing conditions (wall and floor material, glass windows).

Imputations of variables of interest in the unidimensional analysis

The *variables of interest* in the unidimensional analysis are all compiled of between 8 and 10 components (see below). In case, one of these component variables is missing, it is replaced by an imputed variable. The applied imputation approaches are the same as outlined above. If more than one component is missing the household is considered as missing this indicator.

	Candles	**agricultural residues**	**firewood**		**charcoal**	**kerosene**	**biogas**	**LPG**
			collected	**bought**				
Energy expenditure	▪	—	—	▪	▪	▪	—	▪
Final energy	▪	▪	▪	▪	▪	▪	▪	▪
Number of missings	181	0	1428	30	67	46	233	16
End-use energy (cooking)	—	▪	▪	▪	▪	▪	▪	▪
Number of missings	—	0	1428	30	971	0	0*	16
End-use energy (lighting)	▪	—	—	—	—	▲ (tin lamp) ▲ (hurricane l.)	▲	▲
Number of missings	181	—	—	—	—	1575; 1583	25	1552
Imputation method	1	—	3-2	2-1	1	1	3	1

	dry cell batteries	**electricity**	**generator fuel**	**recharging of car battery used as electricity sources**	**TOTAL number of components**
Energy expenditure	▪	•	•	•	9
Final energy	▪	▪	—	—	10
Number of missings	72	38	2	28	
End-use energy (cooking)	—	▪	—	—	8
Number of missings	—	99	—	—	
End-use energy (lighting)	▪	▲▲▲▲ (rechargeable, incandescent, florescent and compact florescent lamp)			10
Number of missings	152	1560 - 1632			
Imputation method	2	4 - ▲: 1	1-3		

Notes: relevant information: ▪ = consumption of energy carrier; • = expenditure on that type of energy; ▲ = lighting consumption with lamps using the energy carrier; * Biogas consumption for cooking has been inferred based on the number of times households cook per week and a factor of 0.227 m^3 per capita and day (Otim, Okaka and Kayima 2011).

Imputations of dimensional indicators in the multidimensional analysis

The multidimensional metrics are composed of six subindicators. In case, one of the component variables needed to create these subindicators is missing, it is replaced by an imputed variable. The applied imputation approaches are the same as outlined above. If more than one component is missing the household is considered as missing this indicator. For the variant that includes the dimensions *enterprises* and *community services*, it is abstained from performing additional imputations on the two respective subindicators.

Dimension	(Proxy) variable	Number of missings	Imputation method
Lighting	threshold amount of artificial lighting	1731	4
	reliable electricity access in urban household	0	—
Cooking and water heating	modern main cooking fuel	1	3
	improved solid fuel cookstove	0	—
	improved solid fuel cookstove with chimney or hood	0	—
	firewood collection time	1155	2
Cooling	fridge ownership	1	2
Information and communication	phone ownership	28	2
	internet access	—	—
	radio or television ownership	7	4

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Appendix C. Complementary results tables

Table 8: Comparison of MEPI outcomes with those determined by Nussbaumer and co-authors based on DHS data

country	own collected data			DHS data	
	survey setting	year of survey	MEPI+/ ε_3	year of DHS	MEPI
Benin	rural	2007	0.68	2006	0.83
Burkina Faso	rural	2010	0.71	2003	0.87
	urban	2011	0.46		
	rural	2012	0.73	2010	0.64
Mozambique	rural	2008	0.79	2003	0.87
	urban	2008	0.70		
	urban	2011	0.48	2009	0.82
Rwanda	rural	2011	0.81	2007/8	0.88
	rural	2012	0.35	2010	0.79
Senegal	rural	2009	0.65	2005	0.53
	urban	2009	0.04		
	rural	2010	0.63	2010/11	0.47
	rural	2011	0.57		

Note: The figures determined on the basis of the DHS data come from Nussbaumer, Bazilian and Modi (2012) for the years before 2009 and from Nussbaumer et al. (2013) for the years 2009 and beyond. The newer figures are, however, not perfectly comparable, since the methodology has been slightly adapted. Nussbaumer et al. (2013) also make use of a variable in the DHS datasets indicating the location of cooking. It seems that households cooking with traditional fuels outdoors are not anymore counted as deprived in the household air sub-dimension. I do not follow this modification, since it is not yet clear in the literature, in how far exposure to harmful smoke effectively differs between indoor and outdoor cooking.

Table 9: Decomposition of energy poverty metrics ε_1 and ε_3

	ε_1 components: Final energy for… cooking with modern fuels or improved technologies	ε_1 components: Final energy for… other purposes using electricity	Relative contributions of ε_3 dimensions: Lighting	Cooking: *amount of fuel*	Cooking: *household air*	Cooling	Information and communication: *phone*	Information and communication: *radio/TV*	ε_3: Energy poverty headcount ratio
rural									
Benin 2007	1.00	0.90	0.09	0.28	0.28	0.19	0.14	0.01	0.97
Burkina Faso 2010	1.00	1.00	0.15	0.28	0.28	0.19	0.05	0.05	1.00
Burkina Faso 2012	1.00	1.00	0.19	0.27	0.27	0.18	0.02	0.07	1.00
Mozambique 2008	0.86	0.97	0.20	0.22	0.25	0.17	0.11	0.05	0.99
Rwanda 2011	0.45	1.00	0.24	0.23	0.25	0.16	0.07	0.05	1.00
Rwanda 2012	0.30	0.75	0.19	0.18	0.37	0.25	0.00	0.01	0.67
Senegal 2009	0.99	0.99	0.12	0.30	0.30	0.20	0.02	0.05	1.00
Senegal 2010	0.62	1.00	0.14	0.30	0.31	0.20	0.02	0.02	0.99
Senegal 2011	1.00	0.99	0.14	0.29	0.29	0.20	0.02	0.07	0.86
Total rural	0.85	0.97	0.16	0.27	0.29	0.19	0.05	0.05	0.95
urban									
Burkina Faso 2011	0.92	0.56	0.15	0.29	0.30	0.18	0.01	0.06	0.72
Mozambique 2008	0.97	0.82	0.21	0.26	0.26	0.17	0.03	0.07	0.94
Mozambique 2011	0.92	0.71	0.07	0.33	0.33	0.20	0.02	0.05	0.81
Senegal 2009	0.80	0.21	0.10	0.24	0.37	0.22	0.00	0.06	0.09
Total urban	0.89	0.53	0.15	0.29	0.30	0.19	0.02	0.06	0.60

Table 10: Absolute contributions of ε_3 dimensions to overall energy poverty outcome

	Absolute contributions of ε_3 dimensions					
	Lighting	Cooking		Cooling	Information and communication	
		amount of fuel	*household air*		*phone*	*radio/TV*
rural						
Benin 2007	0.06	0.19	0.19	0.13	0.10	0.00
Burkina Faso 2010	0.11	0.20	0.20	0.13	0.04	0.03
Burkina Faso 2012	0.14	0.20	0.20	0.13	0.01	0.05
Mozambique 2008	0.16	0.17	0.20	0.13	0.09	0.04
Rwanda 2011	0.19	0.19	0.20	0.13	0.06	0.04
Rwanda 2012	0.07	0.06	0.13	0.09	0.00	0.00
Senegal 2009	0.08	0.20	0.20	0.13	0.01	0.03
Senegal 2010	0.09	0.19	0.20	0.13	0.01	0.01
Senegal 2011	0.08	0.17	0.17	0.11	0.01	0.04
urban						
Burkina Faso 2011	0.07	0.13	0.14	0.08	0.01	0.03
Mozambique 2008	0.15	0.18	0.18	0.12	0.02	0.05
Mozambique 2011	0.03	0.16	0.16	0.10	0.01	0.02
Senegal 2009	0.00	0.01	0.01	0.01	0.00	0.00

Note: While relative contributions of the various indicators sum up to 100 percent, their absolute contributions sum up to the outcome of ε_3, which, for example, equals 0.68 for the Benin 2007 survey (Table 5).