Energy Economics 101 (2021) 105445

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

Energy poverty in Uganda: Evidence from a multidimensional approach

Vincent Fred Ssennono [a], Joseph M. Ntayi [b], Faisal Buyinza [c], Francis Wasswa [c], Sylvia Manjeri Aarakit [d,*], Chris Ndatira Mukiza [a]

[a] *Uganda Bureau of Statistics, Kampala, Uganda*
[b] *Faculty of Economics, Energy and Management Science Makerere University Business School, Kampala, Uganda*
[c] *School of Economics, Makerere University, Kampala, Uganda*
[d] *Department of Entrepreneurship, Makerere University Business School, Kampala, Uganda,*

ARTICLE INFO

Keywords:
Multidimensional energy poverty
Inequality
Intensity
Incidence
Uganda

ABSTRACT

Energy poverty measurement has taken various approaches with the most preferred being Multidimensional in nature. This paper augments the multidimensional energy poverty measurement to estimate a national multidimensional energy poverty index for Uganda. It applies the M-Gamma method on data from the 2018 National Electrification Survey (NES) which captures various aspects of energy poverty. Results show that, 66% of Ugandans are multidimensionally energy poor, 33% are severely energy poor and the average deprivation score is 51%. The multidimensional energy poverty index for Uganda (MEPI-U) is estimated at 0.33. Implying that, the proportion of the population that is multidimensionally energy poor is deprived in five or more indicators at the same time. This paper's computed MEPI-U suggests that, exclusion of context specific indicators over estimates multidimensional energy poverty. Further, results show that energy poverty does not follow a uniform distribution, the M-Gamma approach reveals high inequality distribution by residence, gender and regional location. Policies that seek to alleviate the energy deficit in Uganda should be multidimensional, comprehensive and should take into account energy poverty differences across subgroups. Affirmative action interventions targeting the rural areas should continue to be prioritised.

1. Introduction

Energy is crucial for socio-economic and sustainable development (Action, 2018; IEA, 2019). In particular, energy provides essential capabilities that enable people to meet their basic needs and live satisfactorily (Churchill et al., 2020; Birol, 2007). However, the inability to obtain essential energy services for a decent and healthy life are manifests of energy poverty by individuals (Day et al., 2016). Energy poverty has been conceptualised as a "situation of inability to realise the essential capabilities due to insufficient choice in accessing affordable, reliable, adequate, quality and safe energy services in a reasonable manner" (ibid). Sen (1976) argues that poverty should be considered as the absence of opportunities and choices for living a basic human life. This implies that while many people are considered non-energy poor because they are "electrified", they may be deprived of an adequate supply of electrical and other forms of modern energy services for both consumptive and productive use (Peters and Sievert, 2016; Lozano and Taboada, 2020). Thus, energy-related deprivations pose adverse effects on wellbeing of people (Churchill and Smyth, 2021; Llorca et al., 2020; Thomson et al., 2017).

From this perspective, this paper's rationale stems from two influential positions: First, the need to broaden measurement indicators and their operationalisation to capture context-specific aspects of multidimensional energy poverty. Existing studies (Nathan and Hari, 2020; Pelz et al., 2018; Thomson et al., 2017; Bensch, 2013) argue that multidimensional energy poverty measurement indicators are not only complicated but also muddled and remain inconsistent. Second, and more importantly, inequality or distributional factors have received limited attention in multidimensional energy poverty measurement, yet they have a strong bearing on energy poverty assessment. For instance, Nussbaumer et al. (2012) developed a composite metric (Multidimensional Energy Poverty Index -MEPI) using multidimensional approach to poverty (Alkire et al., 2011). Critical to note, the metric is good for interntaional comparison and has been widely used to assess energy poverty in Sub-Saharan Africa (Ashagidigbi et al., 2020; Alem and Demeke, 2020; Crentsil et al., 2019; Adusah-Poku and Takeuchi, 2019;

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* Corresponding author: Department of Entrepreneurship, Makerere University Business School, Kampala, Uganda.
E-mail addresses: vincent.ssennono@ubos.org (V.F. Ssennono), saarakit@mubs.ac.ug (S.M. Aarakit).

https://doi.org/10.1016/j.eneco.2021.105445
Received 13 September 2020; Received in revised form 5 June 2021; Accepted 29 June 2021

Tait, 2017).

However, the metric approach has some limitations. First, it is limited in what it conveys as the indicators used are lamped and inclined towards the binary approach of operationalisation- scores are based on whether households have access to electricity or not (Culver, 2017; Lozano and Taboada, 2020; Tait, 2017). Second, the approach captures “few” indicators and ignores several crucial indicators (Lozano and Taboada, 2020; Thomson et al., 2017; Bensch, 2013). Exclusion of crucial indicators may over or underestimate energy poverty (Pachauri and Rao, 2020). Third, the focus is mainly on energy poverty “incidence” and “intensity” ignoring severity and inequality among the energy poor. However, available evidence shows that energy poverty, just like poverty is not equally distributed across subgroups (Aristondo and Onaindia, 2018; Klasen and Lahoti, 2020; Pandey et al., 2020).

In Uganda, evidence on energy poverty is scanty. For instance, Nussbaumer et al. (2012) attempt to measure and quantify multidimensional energy poverty for Uganda, however, this was done at a global level and used fewer indicators given limitations in the dataset they used. Others such as Munro and Bartlett (2019), Miller and Ulfstjerne (2020) and Kay et al. (2021) looked at only one dimension- energy access while Nabukalu and Gieré (2021) measured only cooking solution dimension. Aspects of electricity service and appliance dimension have been ignored beyond administrative data. However, no study to our knowledge has measured and quantified energy poverty in a multidimensional way for three dimensions in Uganda.

It is in this regard that this paper is novel for Uganda as it attempts to fill the gap and contributes to literature in three ways. First, the paper proposes a multidimensional energy poverty index for Uganda (MEPI-U). Second, it extends the existing multidimensional energy poverty approach (Nussbaumer et al., 2012) to include more measurement indicators from World Bank’s Multi-tier framework (Bhatia and Angelou, 2015) and further augment it with inequality component[1]using M-gamma method (Alkire and Foster, 2019). The inequality component is estimated by calculating the (a) social exclusion scores, (b) inequality scores and (c) estimating the distribution of deprivation among the energy-poor using the deprivation scores (ibid). Introducing inequality component into energy poverty measurement and assessment provides a richer understanding of energy poverty distribution across sub-groups, and or any other population characteristics (Klasen and Lahoti, 2020; Pandey et al., 2020). Lastly, Uganda provides a good case study in this regard, not only because the country lacks a national metric but also Uganda’s energy situation is similar to many other countries in Sub-Saharan Africa (IEA World Energy Outlook, 2019) hence, the findings can be applicable to many other countries.

The rest of the paper is organised as follows: Section 2 puts into context energy poverty in Uganda, Section 3 discusses the theoretical underpinnings and analytical framework on who is defined as energy poor this paper while Section 4 details the Multidimensional Poverty Index (MPI) methodology as articulated by Alkire and Foster and adopted for energy poverty and furthers highlights the M-Gamma approach to inequality. Further, the section highlights data and sources employed. Section 5 then presents the results, analysis and discussion and section 6 provides the conclusions and policy recommendations.

2. Context

Uganda has made remarkable progress in reducing income poverty from 56% in 1992 to 21.4 in 2017 and maintained economic growth of about 6% per annum (UBOS- Uganda Bureau of Statistics, 2018). Further, the Uganda national Vision 2040 prioritises access to clean, affordable and reliable energy services for all (Ministry of Energy and Mineral Development, 2019). This commitment has been further reaffirmed in the third National Development Plan (NDP III) [National Planning Authority-NPA, 2020] and revised draft 2019 National Energy Policy (Ministry of Energy and Mineral Development, 2019). The Government has also strengthened institutional and policy frameworks and increasingly promoted use of modern energy services and technologies (Energy Africa -Uganda, 2018).

However, the energy situation has not substantially improved. Access to electricity is currently 28%, with total installed generation capacity at 1182 MW and peak electricity demand of approximately 650 MW (Ministry of Energy and Mineral Development, 2019). To put this into context, electricity access in Uganda (28%) is much lower than Kenya (75%) and almost less than half the Sub-Saharan African (SSA) average (42%). Even within the country, access rates vary significantly with a high concentration in urban and peri-urban areas while the rural areas do not exceed 10% (Blimpo et al., 2020). The per capita electricity consumption is also one of the lowest in the world, estimated at 215 kWh per capita compared to Kenya, with 355 kWh per capita, SSA’s average of 552 kWh per capita and the World’s average of 2975 kWh per capita. In addition, the quality of electricity is one of the poorest in the region (Meyer et al., 2018). Households and firms spend several hours a day (4 h on average) without electricity service and in instances when electricity is available, blackouts are prevalent, with more than 30% reporting never having electricity despite being connected to the grid (Blimpo and Cosgrove-Davies, 2019a, 2019b). The power tariff rate has been hiking continuously making Uganda’s power the most expensive in the East African region and second in the world after Sweden. On average Uganda’s domestic tariff is 20 cents USD/kWh (ERA|Electricity Regulatory Authority, 2020) while Kenya’s is 12 cents USD/kWh. Ironically, people in Uganda spend approximately 22% of their average yearly income on energy, which is five times the amount the average Ugandan household earns. In fact, Uganda was recently ranked 168th out of 190 in terms of accessing electricity service for business a position lower than the counter parts in EAC for example Rwanda (59th), Kenya (70) and Tanzania (85th) (World Bank, 2019) which interestingly Uganda exports electricity too.

Furthermore, cooking energy is of concern because without sufficient means to cook food, people often adopt negative coping mechanisms, including skipping meals, under cooking food, adding life threatening chemicals (such as Paracetamol) to fasten cooking and sell/barter food for cooking fuel (Miller and Ulfstjerne, 2020) while others tend to rely on suboptimal fuels with high Greenhouse gas (GHG) emissions. Currently, over 90% of households rely on biomass (i.e. firewood in rural areas and charcoal in urban areas) for cooking (Bamwesigye et al., 2020). Consequentially, deforestation is widespread and the forest cover is reducing at annual rate of 2.4% (UBOS- Uganda Bereau of Statistics, 2020) hence fuel wood is increasingly scarce and expensive. At the same time, rural women and children spend more time −2h to7 hours- collecting firewood and carry 15kgs – 20kgs on average daily, yet this time could be spent on child care, education, socializing or income generating activities. Further still, the WHO reports show that, about 20% of women and young children in Uganda die prematurely each year as a result of breathing fumes from indoor biomass stoves, a clear indication of energy poverty.

In conclusion, Uganda is energy poor in various aspects given the relatively poor performance in energy access, utilisation (cooking) and service and appliance provision. It is also key to note that energy poverty has serious fatal implications on human health. However, what is yet to be established is the share of Ugandans that are poor in all these issues related to energy access and usage.

3. Literature review and analytical framework

3.1. Theoretical and empirical literature review

Theoretically, energy poverty as a concept has extensive definitions in the literature but no single internationally accepted definition yet. For

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[1] Inequality refers to the distribution of the energy poor across sub-groups (Aristondo and Onaindia, 2018)

example, Day et al. (2016) defines energy poverty as a "situation of inability to realise the essential capabilities as a result of insufficient access to affordable, reliable, available, quality and safe energy services in a reasonable manner". While Sen (1992) argues using the capability theory of human development that poverty is a state of deprivation of various capabilities. This can take the form of lack of people's real freedoms to achieve functions they value either in the form of 'beings' (such as being educated, being in good health) or 'doings' (such as cooking, lighting). The underlying assumption is that individuals have different preferences and desires. If everyone is provided with the same set of capabilities, they have the freedom to achieve the same level of well-being. Accordingly, the energy dimension of poverty also known as energy poverty is conceptualised as a capability deprivation (Sen, 1976), which implies lack of capability to attain essential and valued purposes. The theory provides a useful framework for understanding complexities associated with energy poverty assessment. Technically, the capability framework is flexible and multi-purpose and allows for different methodologies. At the heart of the capability approach is an appreciation of the diversity of human needs and desires, and more general set of outcomes that capabilities might give rise to (Middlemiss et al., 2019; Day et al., 2016).

Therefore, this paper anchoring on Sen's capability theory focuses on the "doings" component to estimate a multidimensional Energy Poverty Index for Uganda (MEPI-U). Simply put, energy poverty is conceptualised as a multidimensional deprivation in which the energy-poor cannot realise essential capabilities in either one or more dimensions (e.g. cooking solution, electricity access or energy services and appliances) due to different reasons (Day et al., 2016; Teschner et al., 2020).

Empirical evidence on MEPI reveals that there have been numerous approaches that have been applied to quantify and assess energy poverty. Rademaekers et al. (2016), Thomson et al. (2017), Pelz et al. (2018) and Bensch (2013) classify energy poverty measurement approaches into unidimensional and multidimensional approaches. The unidimensional approach such as expenditure-based (Boardman, 1991) provides a single/aggregate level value based on one specific dimension. The unidimensional measures are objective and straightforward to interpret. However, they capture a narrow picture of the energy poverty challenge. Hence, the approach is unsuitable for assessing complex aspects of energy poverty (Nussbaumer et al., 2012; and Thomson et al., 2017).

The multidimensional approach was developed as a more comprehensive approach to energy poverty measurement (Nussbaumer et al., 2012). The approach calculates composite indices (both individual and aggregate level indices at the same time), easy to interpret and supports cross-country comparison. The multidimensional approach has been extensively used to assess energy poverty in SSA (ul-Ann and Mirza, 2020). For example, Adusah-Poku and Takeuchi (2019) used the framework to evaluate household energy poverty incidence in terms of cooking and lighting based on Ghana Living Standards Surveys. They found high incidence of multidimensional energy poverty in the country. Similarly, Crentsil et al. (2019) found that, the incidence and intensity of multidimensional energy poverty between, 2008 and 2014 remained high in Ghana, and that deprivations on access to modern cooking fuels and indoor air pollution were the largest contributors to MEPI. Tait (2017) adopted the same approach and developed metrics that are both multidimensional and contextually responsive to supporting better policymaking on energy access for the poor people in South Africa. Their findings suggest that context influences both how an indicator is conceptualised and the choice of methods to operationalise it. Meaning that context-specific indicators are essential in quantifying energy poverty. Ashagidigbi et al. (2020) used the approach to estimate household energy poverty and its drivers in Nigeria. Results show high incidence of energy poverty in the country and mainly due to reliance on sub-optimal cooking solutions. Similarly, consumption of large amounts of charcoal led to high incidence of MEPI in Ethiopia (Alem and Demeke, 2020).

Despite its wide use, some scholars (e.g Lozano and Taboada, 2020; Pachauri and Rao, 2020; −ul-Ann and Mirza, 2020; Tait, 2017) point out that the multidimensional approach is limited in what it captures. The drawback of the MEPI lies in two aspects, (i) the approach does not capture inequality and its distribution aspects among the energy poor. (ii) exclusion of some context specific indicators which are important in capturing multiple energy-driven deprivations. This paper attempts to address these limitations and fill these gaps.

Evidence shows that electricity improves health outcomes, household time allocation, lighting, ease of doing domestic chores and consequently increasing children's reading time, information access and low fertility rates (Churchill and Smyth, 2021; Llorca et al., 2020). However, electricity availability was related to students' absenteeism in India (Ahmad et al., 2014). Empirical evidence further shows that poor quality of electricity in terms of power outages, fluctuations, and low voltage increase the probability of a household being income poor (Pepino et al., 2020). In Kenya for instance, about 22% of the households that had electricity reported lack of electricity service for about half of the time in a day suggesting electricity service is quite unreliable (Bajo-Buenestado, 2020).

Numerous studies have demonstrated that exposure to household air pollution is a significant cause of increased respiratory symptoms, respiratory infections, and chronic obstructive pulmonary akin (Rajper et al., 2020; Pratiti et al., 2020; Zhang et al., 2019; Faisal et al., 2020). Cooking using solid biomass fuel and cookstove without a chimney lowers Children's IQ and deprives them of a good education (Brabhukumr et al., 2020). Relatedly, available studies on productive use of electricity in Uganda reveal limited use of electrical appliances for productive activities in most communities than other countries in East Africa (Peters and Sievert, 2016). Blimpo et al. (2020) argue that Uganda's poor electricity infrastructure increases electricity transmission costs. This makes the per unit of energy one of the most expensive in the East African Region.

3.2. Multidimensional approach versus other approaches

Scholarly debate on energy poverty measurement examines three main approaches, that is: unidimensional/expenditure-based, consensual and multidimensional approaches (Bensch, 2013; Rademaekers et al., 2016; Thomson et al., 2017; Pelz, et al., 2018). Nonetheless, the debate is centred around the appropriateness of objective, subjective or a combination of both objective and subjective measures in assessing energy poverty. Some scholars argue in favour of using both objective and subjective measures of energy poverty (Hills, 2012; Biermann, 2016; Robinson et al., 2018; Thomson et al., 2017; Churchill and Smyth, 2021). While some are in favour objective measures (Boardman, 1991; Healy and Clinch, 2004; Bouzarovski and Petrova, 2015; Day et al., 2016; Thomson et al., 2017) and others have argued in favour of self-reported/purely subjective measures (Gordon et al., 2000). The next subsections highlight some of the pros and cons of these approaches and justify the choice of the multidimensional approach to energy poverty measurement. A summary of these approaches is presented in Annex 1.

3.2.1. Unidimensional/expenditure-based approach

This defines domestic energy deprivation based on the level of expenditure on energy by households against absolute or relative thresholds. The approach explores the ratio of household income to energy expenditure. A household can be considered energy poor if the expenditure is too high above a certain threshold or too low below a certain threshold. The acceptable threshold remains an area of contention though. For example, the 10% and twice-national median thresholds developed by Boardman is an absolute measure where by a household is qualified to be energy poor if they spend more than a fixed 10% per cent of their income on energy (Boardman, 1991). By comparison, energy costs under a relative threshold are typically calculated on a median cost to income ratio. The use of the median value is preferable to the mean value as fuel expenditure is asymmetrically distributed (Herrero, 2017).

This approach has been used widely by different countries in European Union. The most used approach is the UK's 10% threshold (Boardman, 2010; Day et al., 2016; Hills, 2012; Thomson et al., 2017; Churchill et al., 2020). Among the main reasons for the popularity of the expenditure approach are its perceived objectivity and the quantifiable nature of the approach. However, one of the limitations is that, the approach is extremely sensitive to methodology decisions of which may result in different rates of incidence that are likely to either underestimate or over-estimate energy poverty (Churchill et al., 2020; Herrero, 2017). In addition, the definition of income/threshold and whether to use actual or estimated required energy expenditure and whether to restrict energy poverty to a specific income group creates a lot of disparities (Thomson et al., 2017).

3.2.2. Consensual approach

Due to the weaknesses of the unidimensional/expenditure-based approach, assessment of energy poverty using surveys was developed by Mack and Lansley (1985) and later improved by Gordon and others based on relative poverty approach (Gordon et al., 2000). The approach defines energy poverty as perceived material deprivation felt by households that are unable to keep their homes warm (Churchill et al., 2020; Thomson et al., 2017). This approach captures three self-reported indicators i.e. the ability to warm or heat homes, ability to pay utility bills on time and living in a damp and rot free home to be proxies of energy poverty prevalence (Bouzarovski et al., 2014).

The approach allows for capturing of wider elements of household energy poverty such as household experiences and their perceived impacts of being energy poor. Households freely express their perceived experiences about energy poverty, for instance in situations where desired expenditure on energy is much higher than actual expenditure (Churchill et al., 2020). The approach is less cumbersome to implement and takes into account contextual differences (Thomson et al., 2017). However, one of the main weakness is the subjective nature of the indicators used to capture energy poverty. These indicators are not only unreliable but also susceptible to error of exclusion due to cultural sensitivity of energy poverty. For instance, households may not identify themselves as energy poor even when they may be characterised as energy poor under objective measures or if households feel ashamed to admit their inability to adequately heat their homes (Churchill et al., 2020). While others may be considered non-poor due to their consumption preferences other than lacking resources (Rademaekers et al., 2016).

3.2.3. Multidimensional approach

This conceptualizes energy poverty as energy deprivation following the idea of multidimensional poverty index (Alkire and Foster, 2011). For example, the Alkire-Foster approach identifies 'the multi dimensionally poor' in two steps using two thresholds or 'cutoffs'; one is indicator-specific and another relates to the number of indicators. Thus, a deprivation value is attached to a household/person relative to weighted sum of other deprivations. The multidimensional energy poverty approach is widely used for quantifying energy poverty especially in developing countries (ul-Ann and Mirza, 2020).

Among the strengths of this approach is the ability to provide both composite and aggregate level indicator which supports international comparison and easy analysis (Nussbaumer et al., 2012). The approach also allows for combination of both objective and subjective indicators classing them into dimensions (Churchill et al., 2020). In addition, the approach is flexible and comprehensive; suitable for capturing multifacet nature of energy poverty in the population (Day et al., 2016). The limitation however lies on lack of agreed upon indicators, deprivation scores and cut-offs (Pelz, et al., 2018; Sokołowski et al., 2020). That notwithstanding, a number of approaches have been advanced in literature to calculate deprivation scores/weights and cut-off points.

Therefore, the paper adopts the multidimensional approach to energy poverty measurement but captures additional context specific indicators (both objective and subjective) and further calculates the multidimensional energy poverty index (MEPI) for Uganda. The paper also extends the existing approach to estimate energy poverty severity, inequality and its distribution across sub-groups in the population (Abeje et al., 2020; Seth and Santos, 2018; Klasen and Lahoti, 2020), which is novel in application.

3.2.4. M-gamma inequality approach

Efforts to capture the component of inequality in energy poverty assessment are limited (Abeje et al., 2020; Seth and Santos, 2018). As earlier argued, existing multidimensional energy poverty indices have focused on the incidence and intensity of energy poverty from a household perspective. Analysis based on a household perspective assumes that energy services are distributed/enjoyed equally, or according to individual needs. However, the assumption of equal distribution is inconsistent with the theoretical literature on intra-household bargaining, which has shown that well-being outcomes depend on the bargaining power within the household where equal distribution is almost impossible (Quisumbing and Maluccio, 2000; Aronsson et al., 2001). Klasen and Lahoti (2020) affirm that household-based assessments of multidimensional poverty are biased in capturing India individuals' inequality. Accordingly, a number of scholars have noted sub-group differences in multidimensional energy poverty in Sub-Saharan Africa (Crentsil et al., 2019; Ashagidigbi et al., 2020). This paper recognises the importance of identifying the poorest among the energy poor- an indicator that is very lean in energy poverty literature. Sen (1976) proposed the idea and Alkire and Foster (2019) used it to measure inequality among the income-poor using the M-Gamma Class in income poverty. The paper adopts Alkire and Foster (2019) approach by incorporating the three "I"s of the multidimensional poverty—incidence, intensity, and inequality-to understand inequality among the energy-poor people in Uganda. Another unique contribution, this paper considers measures of social exclusion (ibid).

3.3. Analytical framework

To better understand "who" is multidimensional energy poor (MEP) or "not", the paper follows the broad deprivation definition as provided in Alkire-Foster methodology. The paper maps and identifies who is *energy poor* in this study context following a sequential approach as illustrated in Fig. 1. The flow diagram shows three different dimensions for identifying the energy poor—in terms of Electricity access, cooking solution and end-use technology used (access to community services). The person is considered energy poor if deprived in at least four of the thirteen indicators. Table 1 under section 4.3 shows detailed explanation of the deprivation cut-off used to estimate energy poverty in Uganda.

4. Data and methods

4.1. Data and sources

The paper utilises the National Electrification Survey (NES) carried out between May and September 2018. The NES is a nationally representative cross-section survey of 5491 households with 28,606 persons conducted by Uganda Bureau of Statistics (UBOS). It allows a disaggregated analysis at sub-national levels (such as regions, rural/urban) and social groupings (such as gender, lifecycle, typologies of households). The NES follows a multi-topic approach with information collected at individual, household, institutional establishments and community levels. Specifically, the survey captures information on households and the community, regarding electricity indicators, cooking and cooking solutions, and household expenditure (fuel and electrical appliances, affordability and willing to pay for energy services).

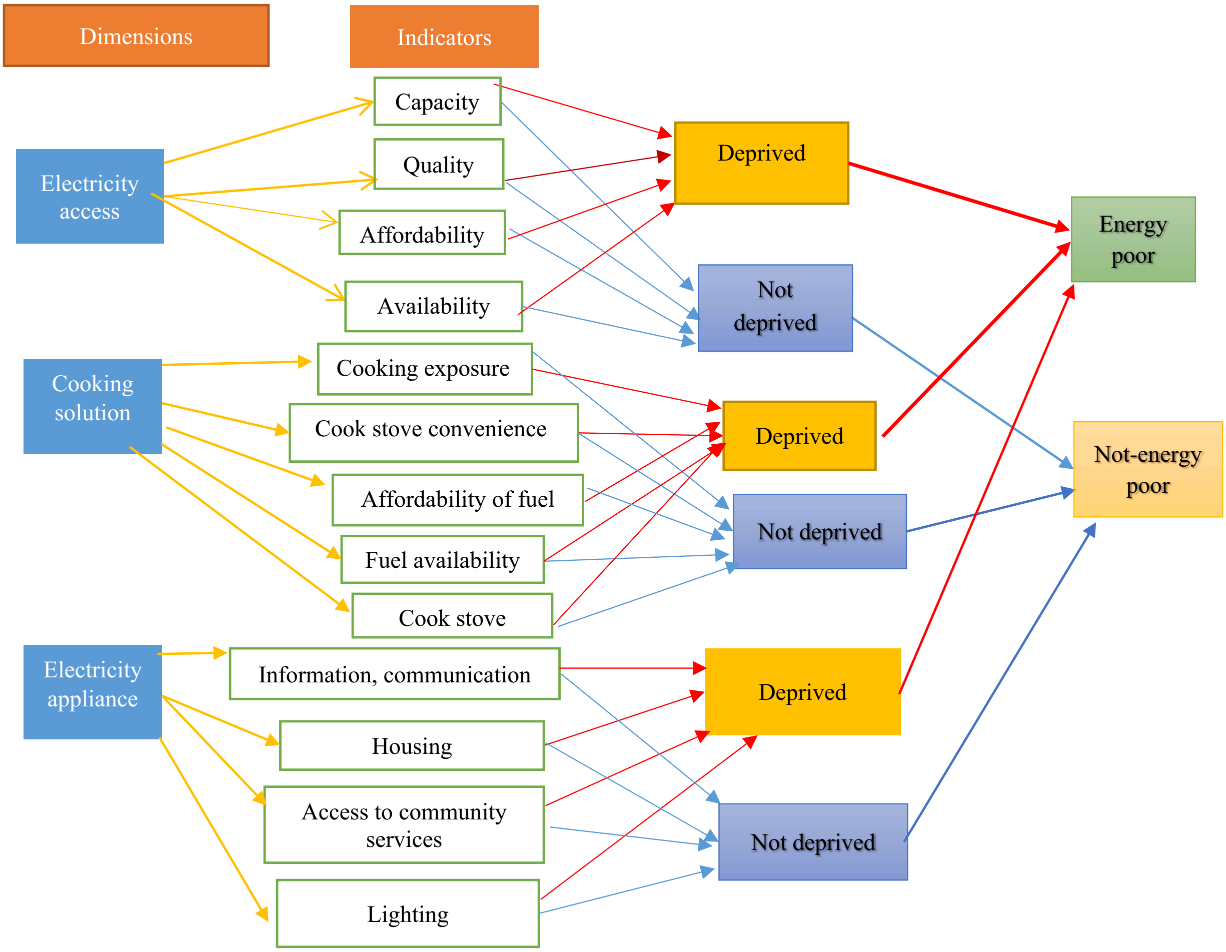

Fig. 1. Mapping the multidimensional energy poor.
Source: Authors' own compilation, 2021.

This NES is unique in the sense that it was designed to specifically capture all energy-specific indicators, unlike other national surveys. Previous studies such as Nussbaumer et al. (2012); Crentsil et al. (2019) and Ashagidigbi et al. (2020) have used the Uganda Demographic Health Survey (UDHS) or the Uganda National Population Survey (UNPS), which are rather limited in energy indicators questions. This paper uses the NES because it provides richer information regarding electricity access, usage, cost, affordability, reliability, capacity, cooking technology, cooking fuels, time for cooking and time for collecting firewood, outages.

On electricity indicators, the NES has household's information on the source of electricity used (grid, min-grid, generator, or solar), electricity access (capacity of electricity to power appliances, electricity availability, service interruption (reliability) and voltage fluctuations), affordability (ability to purchase the minimum amount of electricity), and health and Safety electricity service. In addition, information on outages, electricity consumed (kWh), and monthly expenditure on electricity is provided. The NES captures questions on the incidence of falling sick; the need to travel to health facilities at night; and the reasons for not travelling to a health facility if any. For cooking solutions, household information on cooking stoves used (i.e. type, location in the dwelling, open space, separate kitchen, chimney or hood), fuel used, duration of fuel use (exposure), size of the cooking space, the amount spent on fuel, as well as injury/harm/damage from fuel, was collected.

Finally, the survey also contains information on household demographics, characteristics, and ownership of electricity consuming gadgets like smartphones, phone chargers, Televisions, Electric iron. Gender-disaggregated and time-use questions about common household chores like collecting firewood, preparing cooking stoves, and cooking are also included. The data allows disaggregation and detailed analysis at household head sex, income levels, urban vs rural, and at a sub-national level (Central, East, North and West).

4.2. Methods

4.2.1. Construction of the multidimensional energy poverty index

The Alkire-Foster (AF) Multidimensional Poverty approach is widely favoured in global energy poverty assessment. It allows for the inclusion of large of indicators (Alkire et al., 2020), whose analysis can be disaggregated to various subgroups and any other characteristics of the population. Using the AF approach and as articulated in Alkire et al. (2020), this paper constructs a MEPI-U as illustrated in Fig. 3 below.

Using Fig. 2, the following steps are used to construct the MEPI-U:

Step 1: Use thirteen weighted indicators in three dimensions—Electricity Energy supply (Energy access), Cooking solution, and Electricity service and appliance. Given that no weighting approach is faultless (JEC, 2008), the paper follows Alkire et al. (2020) where a nested uniform weighting scheme is used—dimensions have equal weight. Within each dimension, each indicator has equal weight (Fig. 2). Precisely, each person is assigned a deprivation score according to individual deprivations in each of the thirteen indicators.

Step 2: For each equally weighted dimension, the maximum deprivation score is 100%, implying that each dimension's maximum deprivation score is 1/3 (33.3%) (Fig. 2). Electricity energy supply (energy access), and electricity service and appliance dimensions have four indicators each, such that each indicator is weighted as 1/12 [1/3*1/4].

Table 1
Dimensions, indicators, and cut-offs and reference

Dimensions	Indicator	Variable	Deprivation cut-off (energy poor if) (1/0)	Reference
Electricity Energy supply (energy access)	Capacity	Power capacity ratings	Household has Power capacity ratings of less than 500 kWh per day or uses a solar lantern or has no access to electricity	Bensch (2013); UNDP (2010), Bekele et al. (2015a, 2015b); Nussbaumer et al. (2012); Crentsil et al., 2019 Ashagidigbi et al. (2020); Manjeri et al. (2021); Groh et al. (2016); Bhatia and Angelou (2015), Thomson et al. (2017)
	Availability	Availability of power	Household has power for less than 4 h during the day or less than one in the evening	Culver (2017); Thomson et al. (2017); Dang and La (2019); Lozano and Taboada (2020), Bajo-Buenestado (2020); Pepino et al. (2020)
	Quality	Quality of power	Household experiences low voltage of electricity damage appliances or uses a solar system that cannot power large devices or households, such as candles, dry cell batteries, kerosene lamps, etc. due to lack of access.	Chakravorty et al. (2014); Bhatia and Angelou (2015), IRENA (2019); Pepino et al. (2020); Meles (2020)
	Affordability	Affordability of power	Household spends >5% of total income on energy, or household can't afford to pay a connection fee, and even if they are waived, they can't afford the electricity bills	Boardman, 1991; Sharma et al. (2019); Yip et al., (2020); Tait (2017); Okushima (2017); Bouzarovski et al. (2017); Churchill and Smyth (2020)
Cooking solution	Cooking exposure	Cooking exposure	If it uses a three-stone/open-fire stove or using an unimproved cooking stove with traditional fuels in a poorly ventilated area.	Bensch (2013); UNDP (2010); Bhatia and Angelou (2015)
	Convenience of cooking stove	Cook stove Convenience	If fuel acquisition and preparation time is 7 h or more per week	Kowsari and Zerriffi (2011)
	Safety of primary cooking stove	Cook stove safety	The household is deprived of severe/fatal accidents in the last 12 months due to cooking stones or fuels.	Kowsari and Zerriffi (2011); Kimemia and Van Niekerk (2017)
	Affordability	Expenditure on cooking fuel	Expenditure on cooking fuel is more than 5% of the total household income or cannot afford ICS	Bensch (2013); Fankhauser and Tepic (2007); Mudombi, et al. (2018)
	Fuel availability	Availability of cooking fuel	cooking fuel is available less than 80% of the year	Bhatia and Angelou (2015); Vigolo et al. (2018)
Electricity service and appliance	Lighting	Lighting appliance ownership	Household neither has Incandescent Light Bulb, Fluorescent Tube Compact Fluorescent, Light (CFL) Bulb, LED Light Bulb nor Torch/ flashlight/ lantern	Bhatia and Angelou (2015); UNDP (2010); Bekele et al. (2015a, 2015b); Nussbaumer et al. (2012); Thomson et al. (2017), Abbas et al. (2020)
	Information, communication, and entertainment	Information, communication, and entertainment appliance ownership	Household neither has radio, mobile phone, phone charger, TV nor VCD/DVD	Bensch (2013); UNDP (2010); Bekele et al. (2015a, 2015b); Nussbaumer et al. (2012); Crentsil et al. (2019); Ashagidigbi et al. (2020)
	Housing	Roofing Type	If Household members live in a dwelling with grass thatched roof	Okushima (2017)
	Access to community services	Existence of at least one enterprise powered with electricity in the community	Has no Milk collection centre, Grain/saw/oil mill, Mobile phone charging/repairing service Restaurant/tea nor coffee shop in the community-powered with electricity	Bensch (2013); Bhatia and Angelou (2015); Lozano and Taboada, 2020; Munro and Bartlett (2019); Abbas et al. (2020)

Source: Authors own construct based on literature, 2021

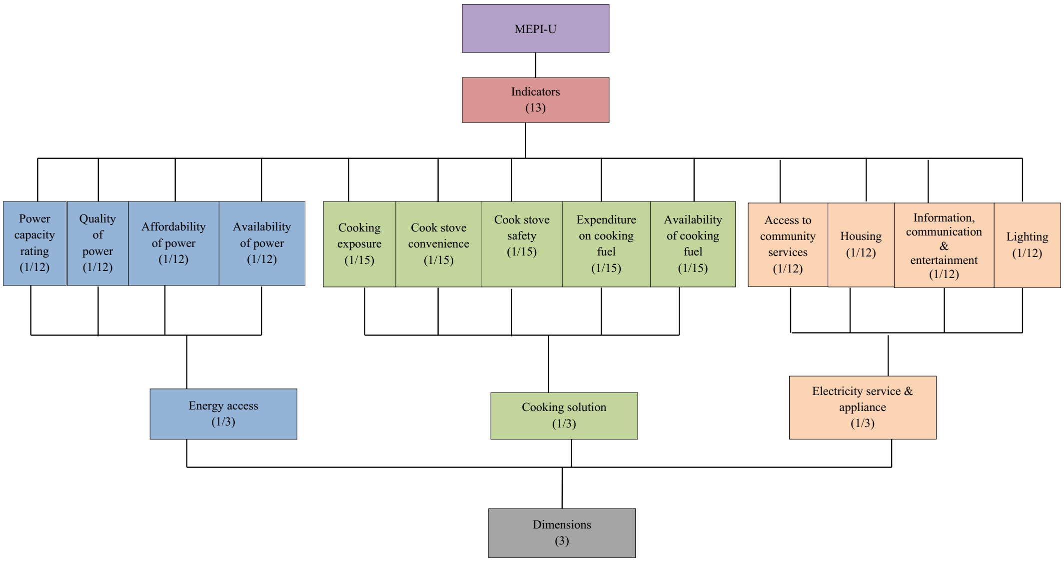

Fig. 2. Composition of multidimensional energy poverty index for Uganda.
Source: Authors own construction, 2021.

The Cooking solution dimension has 5 indicators, so each indicator is weighted as 1/15 [1/3*1/5]. As noted in the Uganda daft National energy policy, 2019 and the NDP III, all the three dimensions are equally important for the country.

Step 3: Lastly, to identify the MEP people (as illustrated in Fig. 1), each indicator's deprivation scores are summed to obtain the household deprivation score. A cut-off of 30% is used to distinguish between poor and non-poor people. This cut-off has been widely used in the application of the MEPI (Nussbaumer et al., 2012; Tembo et al., 2020; Lozano and Taboada, 2020). Other scholars like Munyanyi and Awaworyi Churchill (2020) used 30% cut-off as an alternative cut-off. If the deprivation score is 30% or higher for at household (and everyone in it), then it is considered multidimensionally energy poor. People with a deprivation score of 50% or higher are considered to be *severely multidimensionally energy poor*

4.2.2. Estimating the MEPI

In estimating the Multidimensional Energy Poverty (MEP) properties that is, incidence (Headcount-H), intensity (A) and the index (M0), the following equations were used.

(a) Incidence/headcount ratio (H): is the proportion of multidimensionally energy-poor people in the population. It takes the following form:

$$H = \frac{q}{n} \tag{1}$$

where q is the number of people who are multidimensionally energy-poor and n is the total population.

(b) Intensity of poverty (A): this reflects the weighted component indicators' average proportion in which multidimensional energy-poor people are deprived. For multidimensional energy-poor people only (those with deprivation scores greater than or equal to 30%), the deprivation scores are summed and divided by the total number of multidimensionally energy-poor people. That is;

$$A = \frac{\sum_{i=1}^{q} s_i}{q} \tag{2}$$

where s_i is the deprivation score that the i^{th}a multidimensionally energy-poor person experiences. The deprivation score s_i of the i^{th} multidimensionally poor person can be expressed as the sum of the weights associated with each indicator j where ($j = 1, 2, \ldots, 13$) in which person i is deprived, $s_i = c_{i1} + c_{i2} + \ldots + c_{i13}$.

(c) The Index (M_0): This is the product of multidimensional poverty incidence/headcount ratio (H) and the intensity of poverty (A). That is:

$$M_0 = H^*A \tag{3}$$

where, M_0 is the MEPI for Uganda.

Thus, the contribution of dimension d to multidimensional energy poverty can be expressed as:

$$contrib_d = \frac{\sum_{j \in d} \sum_{1}^{q} c_{ij}}{n} \Big/ M_0 \tag{4}$$

where d is electricity energy supply (energy access), cooking solution or electricity service and appliance. Commonly, the M_0 can also be expressed as the weighted sum of the censored headcount rates h_j of each indicator j. The censored headcount rate of indicator j refers to the proportion of people who are multidimensionally energy poor and deprived in this indicator and it takes the following form:

$$M_0 = \sum_{j=1}^{13} c_j h_j \tag{5}$$

where c_j is the weight associated with indicator j (either 1/12 or 1/15), and the weights sum to 1

While both the incidence (H) and intensity (A) measures provide relevant information on the level of multidimensional energy poverty, M_0shows the development/changes in energy intensity and incidence.

4.2.3. Inequality among energy poor using M-gamma method

In addition to measuring M_0, this paper extends the AF methodology and uses M-gamma[2] method to calculate inequality among energy poor people. Efforts to capture the component of inequality in energy poverty assessment are limited (Abeje et al., 2020; Seth and Santos, 2018). Existing MEP indices have focused on the incidence (H) and intensity (A) of energy poverty from a household perspective. Here, analysis based assumes that energy services are distributed/enjoyed equally, or according to individual needs. However, the assumption of equal distribution is inconsistent with the theoretical literature on intra-household bargaining. This has arguably shown that well-being outcomes depend on the bargaining power within the household where equal distribution is almost impossible (Quisumbing and Maluccio, 2000; Aronsson et al., 2001). Klasen and Lahoti (2020) further concretise the argument that household-based assessments of multidimensional energy poverty are biased in capturing inequality among individuals. Implying that, energy poverty does not necessarily follow the same pattern as assumed (Barnes et al., 2011). This paper recognises the importance of identifying the poorest among the energy poor-an indicator that is very lean in energy poverty literature. Sen (1976) proposed the idea, and Alkire and Foster (2019) used it to measure inequality among the income-poor using the M-gamma Class.

Generally, the M-gamma family of measures is defined by $M_0^\gamma = \mu(c^\gamma(k)$, for $\gamma \geq 0$. Where if;

$\gamma = 0$, $M_0^0 = H$ is the headcount ratio that measures the incidence of multidimensional poverty

$\gamma = 1$, $M_0^1 = M_0$ is the adjusted headcount ratio that includes the breadth of deprivation.

$\gamma = 2$, M_0^2, the squared count measure, emphasises the severity of deprivation by squaring each person's deprivation score and measures social exclusion.

4.3. Justification of dimensions and indicators

The choice of dimensions and indicators included in quantifying MEPI-U was guided by empirical literature, data, and policy considerations as articulated in Step 3-subsection 4.2.1. The choice of the dimensions, indicators, deprivation, and weights used to measure each, as well as the deprivation cut-offs is further justified in Table 1. Nonetheless, the paper details in the next subsections the use of each dimension plus its indicator in literature.

4.3.1. Electricity energy supply (access to electricity)

The United Nations Development Programme (UNDP) recognises electricity access as one dimension of energy poverty (Alkire and Jahan, 2018). Various scholars such as Nussbaumer et al. (2012); Tait (2017); (Sadath and Acharya, 2017); Adusah-Poku and Takeuchi (2019); Alem and Demeke (2020); and Ashagidigbi et al. (2020) have adopted the dimension in quantifying energy poverty at the household level using a binary approach. The binary measure of electricity access, which determines if a household has access to an electricity source or not, is too crude as several key attributes are unaccounted for (Lozano and Taboada, 2020). Factors such as capacity, availability, reliability, affordability, and access quality are relevant in gauging how sustainable these electrification efforts are. Electrical energy poverty goes beyond the absence of electricity access. In this regard, electricity access dimension in this paper has four variables: capacity, availability, quality, and affordability.

However, legality, reliability, and health and safety indicators were

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[2] More details about the general-gamma methodology can be found in Alkire and Foster (2019).

not considered in comprising the access to electricity dimension due to data limitation. For example, identifying illegally connected people to the electricity grid is not easy, while Uganda's payment mechanism is not well streamlined, making formality indicator challenging to measure. The reliability indicator was excluded because it is not easy to estimate how often power goes off in different parts of Uganda. Health and Safety indicator was excluded due to a few households that experienced severe or fatal accidents related to energy use.

4.3.2. *Cooking dimension*

Sustainable Development Goal (SDG) 7 aims to end energy poverty globally by 2030, with target 7.2 focusing on cooking fuels and technology (United Nations, 2015). Similarly, Uganda's government stipulates cooking solutions as a priority to ending energy poverty (NPA, 2020). Strategically, the draft 2019 National Energy Policy (MEMD, 2019) provides a broad framework to regulate different fuels' access and use for various sectors. Various scholars noted cooking as one of the priority areas in ending energy poverty. In this regard, the MEPI-U encapsulates cooking solution as a dimension. This dimension covers cooking methods (fuels and technology) and the consequences of using polluting and inefficient cooking solutions. In this paper, the cooking solution dimension has five indicators: cooking exposure, the safety of the primary cookstove, convenience[3], affordability, and fuel availability (Bouzarovski and Petrova, 2015).

4.3.3. *Electricity service and appliance*

The third National Development Plan for Uganda (NDP III) states that in order to transform the country into a middle-income economy, electricity services should support both consumptive and productive uses (NPA, 2020). In this paper, electricity service and appliance dimension are intended to capture the end-user services (Nussbaumer et al., 2012). The electricity appliances that use electricity services include mobile phones, television, or radio are considered key in accessing health, education information, among others (Culver, 2017). Electricity services and appliances encourage communities to engage in productive uses of electricity, improving their energy consumption and economic activities, which enhances their ability to pay for the tariff. However, deprivation in any of the four indicators described in MEPI-U discourages the individuals in engaging in productive uses (Lozano and Taboada, 2020; Munro and Bartlett, 2019).

4.4. *Unit of analysis*

Klasen (2007) argued that it is not possible to identify the ultimate beneficiary and determine with any certainty how much these indicators benefit one individual as opposed to another in the households. As a result, this paper hypothesis that indicators are true public goods (non-rival and non-excludable) accessible equally to everyone within the household (Klasen and Lahoti, 2016; Vijaya et al., 2014). In order to quantify the number of energy poor people in Uganda, this paper considers individuals as the unit of analysis. The paper acknowledges intra-household differences in the dimension of the cooking solution where mostly women and girl are affected, but the paper does not consider gender energy poverty inequality.

5. Results and discussion

This section provides the results, analysis and discussion. These are reported for incidence (uncensored and censored head count ratio) by dimension and geo-demographic characteristics for individual indicators In addition, findings for MEP in terms of incidence, intensity and the index are discussed together with those inequality using the M-gamma method.

5.1. *Incidence of aggregate deprivation*

5.1.1. *Uncensored headcount*

Table 2 shows the deprivation rates for each indicator by broad dimension- which is the proportion of people who are deprived, regardless of whether they are multidimensionally energy poor or not (Alkire et al., 2015). Results in Column (1) show that, majority of Ugandans are deprived in quality (64%) and capacity (57%) while fewer Ugandans are deprived in affordability indicator under the electricity access dimension. Results in Column (2) reveal that, under the cooking dimension-cooking exposure has the highest deprivation rate (78%). While results in Column (3) indicate that, people are more deprived in access to community services (62%) and lighting (35%) under electrical appliances and services dimension.

A similar trend is observed across geo-spatial characteristics, with the northern followed by the eastern regions being deprived in specific indicators that mimic the national level trends by dimension. However, these results do not say much about the intensity of energy poverty or deprivations' joint distribution. Overall, the implication is that suffering from one deprivation is not equivalent to suffering from multiple deprivations at the same time.

5.1.2. *Censored headcount*

Table 3 presents results for censored headcount ratio—the proportion of the population that is multidimensionally energy-poor and deprived in specific indicators at the same time (Alkire et al., 2015). Like in the uncensored headcount ratio, a similar trend is observed in the censored headcount ratio. Results indicate that, within the population of the multidimensional energy-poor, high deprivation is observed in the quality (58%) and capacity (54%) of electricity supply under electricity access dimension (Column1), cooking exposure (30%) under cooking dimension (Column 2) and access to community services (39.5%) as well as lighting (32%) under electricity service and appliances (Column 3). Majority of the energy poor in Eastern and Northern Uganda were deprived in lighting (46%) and roofing type respectively. Suggesting that, they lack essential appliances to access modern energy service.

5.2. *Extent of multidimensional energy poverty*

Table 4 shows results for multidimensional energy poverty for Uganda. Specifically, we report results on incidence, intensity, the index (MEPI-U) and severity of energy poverty. Column (1) reports results for incidence (also called multidimensional headcount ratio) (*H*) which is the proportion of multidimensionally energy-poor people in the population. Results show that, approximately 66% of Ugandans are multidimensionally energy-poor. Disaggregation by geo-spatial characteristics reveals that, the incidence of energy poverty in rural areas (75%) is nearly twice that of urban areas (40%) and highest in Northern Uganda (89%). Further decomposition by demographic characteristics shows that, the incidence of energy poverty is higher among female headed households (70%); widows/widowers (76%) and households with more than five members (68%). In addition, incidence of energy poverty is high among the people in the lowest wealth quintile (93%) and those employed in agriculture (78%). Implying that, majority of people counted as multidimensionally energy-poor live in rural areas and these are mostly vulnerable groups (women, widows/widowers, children etc). These people are materially poor and often work in agricultural sector (See UNHS report, UBOS, 2018).

As complementary results to incidence of energy poverty, Column (4) shows severity of energy poverty, this, refers to the proportion of the poorest among the energy-poor people. Results show that, approximately 33% of those considered energy poor are severely energy-poor. Severity of energy poverty among the rural poor (40%) is nearly three times that of urban poor (14%) and severity is high among people in

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[3] Improved cook stove (IC) mitigates emissions and improves short term health, fuel cost, availability and service quality

Table 2
Deprivation by indicators at the national and residence

	Col. (1)				Col. (2)					Col. (3)			
	Electricity Access				Cooking solution					Electricity services and appliances			
	Capacity	Availability	Quality	Affordability	Cooking exposure	Convenience of cooking stove	Safety of primary cooking stove	Affordability	Fuel availability	Lighting	Information, communication and entertainment	Roofing type	Access to community services
Uganda	**56.5**	**49.6**	**64.3**	**34.8**	**77.8**	**18.0**	**7.7**	**18.4**	**18.3**	**35.2**	**30.9**	**21.8**	**62.4**
Area of residence													
Rural	25.9	21.9	39.2	18.1	70.2	17.1	5.1	22.8	16.5	24.7	16.4	6.6	76.1
Urban	67.6	59.7	73.4	40.9	80.6	18.4	8.6	16.8	18.9	39.0	36.2	27.3	57.4
Region													
Central	32.5	27.0	43.1	17.3	68.1	15.9	4.5	22.6	13.0	29.3	14.5	1.6	58.6
Eastern	70.9	60.4	70.1	40.2	84.2	15.8	6.9	23.0	15.6	49.3	42.8	20.8	49.7
Northern	83.3	78.0	85.3	51.9	75.3	27.8	17.1	15.1	28.6	36.2	46.0	74.0	63.3
Western	47.9	41.9	65.4	35.2	83.7	15.2	4.8	12.0	18.8	27.0	25.7	5.4	77.7

Source: Authors' computations based on the NES (2018) MEMD (2020)

Table 3
Censored headcounts ratios at the national level and by residence

	Col. (1)				Col. (2)					Col. (3)			
	Electricity Access				Cooking solution					Electricity services & appliances			
	Capacity	Availability	Quality	Affordability	Cooking exposure	Convenience of cooking stove	Safety of primary cooking stove	Affordability	Fuel availability	Lighting	Information, communication & entertainment	Roofing type	Access to community services
Uganda	54	49.3	57.7	31.3	30.2	7.8	2	10.7	8.4	32.1	30.3	21.3	39.5
Area of residence													
Rural	59.3	59.3	67.9	37.1	61.6	14.6	8	14.5	16.7	37	35.5	27	42.4
Urban	21.5	24.4	21.5	29.6	15.3	33.3	8.5	2.5	11	11.8	18.6	15.8	5.5
Region													
Central	30.2	26.6	34.9	12.9	30.2	7.8	2	10.7	8.4	21.8	13.8	1.2	19.7
Eastern	67.3	60.2	66.8	36.6	70.7	13.6	6.1	20.2	13.7	46.4	41.8	20.6	40
Northern	81.6	77.7	83.7	51.3	70.4	25.1	16.5	14.6	27.1	35.6	46	72.2	57.3
Western	45.7	41.4	53.7	30.6	51.1	8.9	4.4	9.6	15.8	26.4	24.9	5.3	46.6

Source: Authors computations based on the NES (2018).

Table 4
Incidence, intensity, and index, $k = 30\%$

	Col. (1)	Col. (2)	Col. (3)	Col. (4)	Col. (5)
	Incidence/ Headcount Ratio (%)	Intensity (%)	Index	Severe of energy Poverty (%)	Population Share (%)
	(H)	(A)	(M_0)		
Uganda	**65.6**	**50.5**	**0.331**	**32.7**	**100.0**
Area of residence					
Rural	75.0	51.5	0.386	39.5	73.4
Urban	39.5	45.5	0.180	14.0	26.6
Region					
Central	39.6	43.8	0.174	10.7	28.0
Eastern	75.6	50.2	0.380	38.8	25.7
Northern	89.4	57.4	0.513	65.7	19.7
Western	58.4	47.9	0.280	25.5	26.7
Sex of household head					
Male	64.2	50.1	0.321	31.0	76.1
Female	70.0	51.8	0.363	38.1	23.9
Marital Status					
Married monogamy	63.8	49.8	0.318	30.1	66.4
Married polygamy	66.2	51.1	0.338	33.6	14.0
Divorced/ separated	69.4	51.5	0.358	41.1	6.5
Widow/ widower	75.9	53.1	0.403	42.8	11.1
Never married	50.3	51.5	0.259	28.4	2.0
Household size					
1 person	63.1	51.0	0.322	29.8	2
2–4 persons	58.0	51.0	0.296	30.2	26
5+ persons	68.4	50.4	0.345	33.7	72
Wealth quintile					
Lowest 20%	93.1	56.3	0.524	64.6	14.3
Second	85.9	52.1	0.448	48.3	19.1
Middle	71.6	49.7	0.356	35.3	19.7
Fourth	59.2	48.4	0.286	24.2	22.3
Highest 20%	34.8	43.3	0.151	7.6	24.6
Sector of employment of HH head					
Agriculture	78.2	52.1	0.407	43.1	62.9
Manufacturing	62.3	45.0	0.280	20.0	4.1
Construction	51.3	44.4	0.228	12.4	4.2
Trade	42.2	45.5	0.192	13.4	10.2
Services other trade	43.3	47.1	0.204	17.3	18.6

Source: Authors' computations based on the NES (2018)

Northern Uganda (66%) than Central Uganda (11%). Disaggregation by demographic characteristics shows that, energy poverty is more severe among female headed households (38%), widows/widowers (43%) and in households of at least five members (34%). Results also indicate that, energy poverty is more severe among people in the lowest wealth quintile (66%) than those in the highest wealth quintile (8%), and among those employed in agriculture (43%).

Column (2) highlights findings for intensity (A) which is the average deprivation score among the energy poor. Using the cut-off of 30%, the intensity of energy poverty in Uganda is estimated at 51%. Results show that, intensity of energy poverty is high in rural areas (52%) and in Northern Uganda (57%). Disaggregation by demographic characteristics reveals that, intensity of energy poverty is relatively higher among female-headed households (52%) and widows or widowers (53%). Although there are no significant differences by household size, intensity of energy poverty is higher among people in the lowest wealth quintile (56%) those employed in Agriculture (52%).

Column (3) shows findings for multidimensional energy-poverty index (M_0) which refers to the proportion of the population who on average are deprived in one or more dimensions. The index as derived in eq. 3 is the product of two intuitive partial indices (the H and A of energy poverty). Results reveal that, the multidimensional energy poverty index for Uganda (M_0) is approximately 0.33.

The findings suggest that, at 30% cut off, the multidimensional energy poverty index for Uganda (M_0) stands at 0.33. The index is close to that of other African countries (Crentsil et al., 2019; Adusah-Poku and Takeuchi, 2019; Ashagidigbi et al., 2020). About, 27.5 million people (66%) are multidimensionally energy poor and the average deprivation score is estimated at 51%, while 13.9 million people (33%) are severely energy poor. It is critical to note that a multidimensionally energy-poor person is on average, deprived in more than one full dimension (energy access, cooking solution or energy services and appliances). Meaning that, they experience multiple deprivations (in more than five indictors) at the same time. For instance, a person may be deprived off in terms of quality, capacity, availability, affordability of electricity service, lighting and cooking exposure at the same time. This is typical of Uganda where the majority of the populace fall under tier 1 [4]in terms of access to electricity and cooking solution indicators and world considered them to have no access at all (Bhatia and Angelou, 2015). This finding is in line with earlier studies in Uganda (Blimpo et al., 2020; Blimpo et al., 2018) and similar findings are reported in other countries (Sadath and Acharya, 2017).

Disaggregation of $M_0$by geo-spatial characteristics reveals that, MEP is more of a rural phenomenon with those living in Northern Uganda worst hit. Multidimensional energy-poverty in rural areas (0.386) is nearly three times that of urban areas (0.180) and relatively higher in Northern Uganda (0.513) compared to Central Uganda (0.174). The plausible explanation is that, majority of people in Uganda reside in rural areas and these people rely on sub-optimal fuels and technologies to meet their basic household energy needs (UBOS, 2020). Secondly, rural areas face acute shortage energy infrastructures hence experience multiple deprivations (Blimpo et al., 2020; Tsimpo and Wodon, 2014). Similarly, Northern Uganda experienced a political turmoil for over 20 years which affected development in that area (Samarakoon et al., 2021).

The findings further suggest disparities by demographic characteristics. Energy poverty in Uganda has a "female" face, deep-rooted among those in the lowest wealth quintile and those employed in agriculture (Table 4-column (3)). That is, MEP is high among the widows/widowers (0.403); in female headed households (0.363) and among people living in households with more than five members (0.345). In addition, MEP is high among people in the lowest wealth quintile (0.524) and those employed in agriculture (0.407). Women and girls for instance, are explicitly tasked with domestic chores like collecting firewood and cooking using fuel wood in poorly built, congested, and unventilated houses. Literally they are exposed to indoor air pollution, which adversely affects their health (Lozano and Taboada, 2020; Llorca et al., 2020; Zhang, 2019). Other scholars report similar findings in other countries in Sub-Saharan Africa (Abeje et al., 2020; Aristondo and Onaindia, 2018; Tembo et al., 2020). The trend for the MEPI-U is similar to its properties (incidence and intensity).

5.3. *Contribution of individual indicators to multidimensional energy poverty index*

To understand what matters more in energy poverty index assessment, Fig. 3 shows the contribution of each indicator to the overall Multidimensional Energy Poverty Index (MEPI-U). Results show that,

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[4] Have no access to electricity or have it for less 4 h a day. For detailed explanation refer to Bhatia, M., and Angelou, N. (2015). *Beyond connections: energy access redefined.*

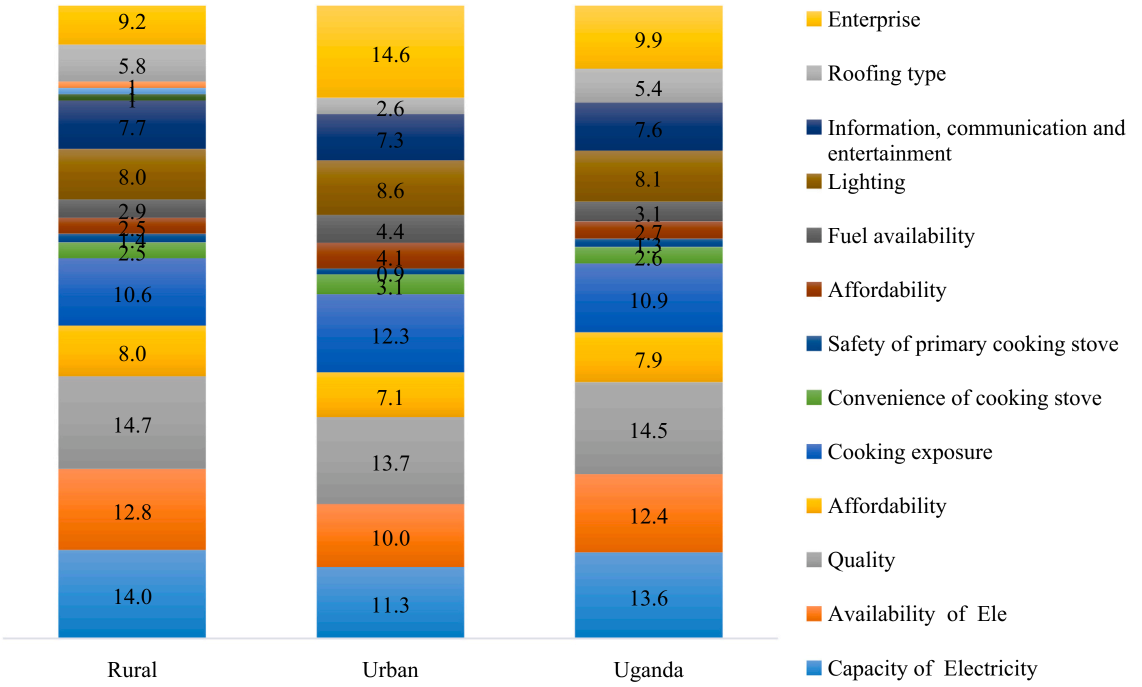

Fig. 3. Percentage contributions of indicators to the MEPI-U, by rural and urban areas.
Source: Author's own computations based on the NES (2018) MEMD (2020).

overall, the highest contribution arises from quality of electricity supply (14.5%), followed by capacity (13.6%), availability of electricity service (12.4%), and cooking exposure (10.9%). Although a similar trend is observed for rural residence, there is a notable difference for urban residence where access to community services (14.6%) is the biggest contributor followed by quality of electricity supply (13.7%) and cooking exposure (12.3). These results suggest that MEP is more associated with quality, capacity and availability of electricity supply, all indicators that partly comprise the access to electricity dimension. This finding is in line with other studies (Manjeri et al., 2021; Blimpo et al., 2020). In urban areas, poor quality and limited capacity of electricity supply deprives people in productive uses (Okoboi and Mawejje, 2016; Peters and Sievert, 2016). Similarly, quality of electricity supply in terms of unreliability of electricity service was reported as a major source of energy poverty in Kenya (Bajo-Buenestado, 2020) and Vietnam (Dang and La, 2019). Further still, cooking exposure is a big challenge for both rural and urban. The plausible explanation is that, most people in Uganda rely on biomass for cooking.

Table 5
M-gamma measures, intensities, and inequalities for Uganda by region.

	$M_0^0 = H$	$M_0^1 = M_0$	M_0^2[a]	A	A'	V	V_P[b]
Uganda	**65.6**	**33.1**	**17.90**	**50.5**	**27.3**	**0.069**	**0.023**
Area of residence							
Rural	75.0	38.6	21.15	51.5	28.2	0.062	0.024
Urban	39.5	18.0	8.84	45.5	22.4	0.056	0.010
Region							
Central	39.6	17.4	8.09	43.8	20.4	0.051	0.009
Eastern	75.6	38.0	21.27	50.2	26.8	0.069	0.026
Northern	89.4	51.3	31.61	57.4	34.6	0.053	0.027
Western	58.4	28.0	14.71	47.9	24.4	0.069	0.019

Source: Authors own computations based on the NES (2018).

[a] M_0^2 corresponds to a measure of social exclusion Alkire and Foster (2019).

[b] Vp is the variance applied to the distribution of deprivation scores among the poor

5.4. *Depth of inequality among the energy-poor people*

Table 5 shows results for inequality among the energy-poor using M-Gamma Class approach (Alkire and Foster (2019). The paper estimated the social exclusion rates (M_0^2), inequality (v) and distribution of deprivation scores (V_P). Results reveal that, in Uganda approximately 18% of the multidimensionally energy-poor people are socially excluded. The energy poverty inequality score is estimated at 0.069 while the distribution of deprivation score among the energy-poor is very low (0.023). Implying that, people who experience severe energy poverty also face high social exclusion rates. Further disaggregation, reveals that, whereas social exclusion and inequality rates are high for people living in rural areas and in Northern Uganda than their urban counterparts, the distribution of deprivation scores indicate that inequality is relatively high among the urban energy poor (0.010). The energy-poor, living in Central region, command the highest rates of inequality distribution. These findings suggest that, the distribution of energy poverty is not homogeneous across the population. Probably, most people in Uganda are experience energy poverty differently even when they live in the same household or geographical location (Munro and Bartlett, 2019). The finding is line with studies in other countries (Klasen and Lahoti, 2020; Barnes et al., 2011).

In general, this paper's findings are consistent with literature on intra-household bargaining that argues that welfare outcomes depend on the bargaining power within the household where equal distribution is almost impossible (Quisumbing and Maluccio, 2000; Aronsson et al., 2001).

5.5. *Testing for statistical difference between MEPI-U and MEPI*

Table 4 reports comparison results between the new metric (MEPI-U) and the existing MEPI (Nussbaumer et al., 2012). Such comparison is crucial in ascertaining whether the exclusion of "important" variables in quantifying MEP leads to over or underestimation of energy poverty. It should be noted that, the MEPI-U is estimated based on thirteen indicators while the MEPI was based on six indicators[5]. However, both used the same deprivation cut off (30%) and equal weighting procedure. First, we compute the MEPI-U (A1) which is then compared with the MEPI (A2). Second, we test the statistical difference between the two indices to arrive at a conclusion. Results presented in Table 6 reveal statistically significant differences in the intensity and overall index of energy poverty. The intensity of energy poverty for the current paper (A1) is estimated at 51% while for Nussbaumer et al. (2012) (A2) stood at 66%. Similarly, the aggregate level index for MEPI-U ($M0_1$) is lower at 0.33 compared to MEPI's ($M0_2$) at approximately 0.44. Decomposing analysis by geo-spatial characteristics reveals a similar trend. The results suggest that, exclusion of some essential indicators/variables overestimates MEP (Pachauri and Rao, 2020; Tait, 2017).

Therefore, further decomposition of indicators (vital premise in this analysis) provides a better picture of MEP than use of lamped indicators. Further, decomposition captures deprivations within the population with electricity access which the lamped indicators ignore. In SSA and Uganda in particular, people with access to electricity still experience deprivations concerning quality, capacity, and electricity availability. Households with access to electricity experience about 14 h of power interruption in a week (UBOS, 2020). Further, the approach (MEPI-U) considered the current situation where numerous interventions relating to SDG 7 which are being implemented, notably, the rural electrification programs and improved cookstoves (ICS). Low levels of intensity of energy poverty could be a result of using improved cookstoves (with better efficiency levels) that ultimately reduce air pollution (Action, 2018).

Table 6
Multidimensional energy poverty metrics

Multidimensional Headcount Ratio(H)				TTEST
Region				
Central	40%	0.045	41%	0.054
Eastern	79%	0.023	80%	0.023
Northern	91%	0.014	85%	0.028**
Western	60%	0.020	64%	0.024
Overall	66%	0.018	66%	0.018
Intensity of energy Poverty(A)				
Region				
Central	44%	0.008	68%	0.009***
Eastern	50%	0.010	73%	0.009***
Northern	57%	0.008	75%	0.013***
Western	48%	0.007	70%	0.010***
Overall	0.51	0.006	0.66	0.008***
Multidimensional Poverty Index (Mo)				
	MEPI-U ($M0_1$)	**SE**	**MEPI ($M0_2$)**	**SE**
Region				
Central	0.174	0.019	0.251	0.037*
Eastern	0.399	0.012	0.539	0.020***
Northern	0.524	0.011	0.620	0.025***
Western	0.289	0.011	0.396	0.015***
Overall	0.331	0.009	0.438	0.014***

Notes: *** statistically significant at 0.01: ** statistically significant at 0.05: * statistically significant at 0.1
Source: Authors own computations based on the NES (2018)

5.6. Robustness checks

As guided by Oxford Poverty and Humana Development Initiative (OPHI), there are 3 levels of sensitivity analysis. In particular, the MEPI as guided by OPHI technics was tested for its sensitivity to changes in parameters such as the energy poverty cut-off and dominance checks for sub-national indices.

a) Annex Fig. A1 (a, b and c) confirms that level, incidence, and intensity of multidimensional poverty (MEPI, H, and A) for various levels of the poverty cut-off k follows the expected pattern. For instance, when k = 20% MPI is 0.37; incidence is 80%, indicating that a large majority of the population is deprived in at least one of the weighted dimensions; and intensity is 45%, meaning that those 80% are, on average, deprived in close to half the dimensions. When k is larger than 70% (2 or more dimensions), energy poverty drastically reduces to 3%, implying that a few people are deprived in more than three quarters of the weighted dimensions. The Figures suggest that there are no sharp discontinuities in MEPI and H around the chosen k-value of 30%.
b) Dominance checks of sub-national MEPIs for various levels of the poverty cut-off k. Since the lines do not intersect between k-values of 10% to 70%, it means that the MEPI is robust to changes in the poverty cut-off from 10% to about 70%. This implies that the same broad diagnosis of energy poverty level by sub-national pertains, so does the ranking between the sub-national in Annex-Fig. A2.
c) The Spearman and Kendall rank correlation coefficients between the sub-national s' rankings using the selected energy poverty cut-off, 30%, and the ranking for alternative energy poverty cut-offs around 30%. It can be seen that the Spearman coefficient is equal to 1 for k = 20% and k = 60%. The Kendall coefficient is 1 for values between k = 20% and k = 60%, implying that around 100% of the comparisons are concordant in each case. When the rank correlation coefficients Spearman and Kendall were calculated for different combinations of weights (each dimension taking the weight of 30% and the other three 25% each), the analysis revealed that for the five structures the Spearman coefficient and the Kendal Tau-b coefficient is 100% of the comparisons are concordant in each case Annex-Table A2, establishing the robustness of the MEPI to a range of plausible weights from 20% to 60% per dimension.

d) The percentage of robust pairwise combinations by sub-national showed that 100% of the pairwise sub-regions comparisons are robust to changes in the dimensions' weights from 20% to 60% per dimension. In the case of variations in the poverty cut/off, 100% of the pairwise sub-national comparisons are robust to changes in k from 20% to 60% Annex-Table A3, showing that the structure of the Uganda nationals MEPI is robust to changes on the values of k and weights.

6. Conclusion

This paper uses a comprehensive energy microeconomic data from the Uganda National Electrification Survey (NES), 2018 conducted by the Uganda Bureau of Statistics to estimate a multi-dimensional energy poverty index for Uganda (MEPI-U). The dataset is nationally representative with 5491 households and 28,606 persons with the ability to disaggregate analysis at sub regional levels and social groupings. In addition, the paper first quantifies the incidence/headcount ratio, and intensity of energy poverty then extends the MEPI-U to estimate the extent of energy poverty inequality using the M-gamma methodology, a novel area in Uganda's energy poverty literature. The paper also statistically establishes the limitations in calculating energy poverty when few indicators are included in estimations.

To estimate the MEPI-U, 13 indicators aggregated into 3 broad dimensions (energy access, cooking solution and energy service and

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[5] (a)Modern cooking fuel, (b) Indoor pollution, (c) Electricity access (d) Household appliance (e) ownership Entertainment/education appliance and (f) ownership Telecommunication means.

appliance) are utilised. Results reveal that energy poverty is widespread in Uganda. First, with regard to incidence of aggregate deprivation for the censored headcount ratio, high deprivation among the multidimensionally energy-poor persons was observed in quality-58% and capacity-54% of electricity supply both indicators of the electricity access dimension with cooking exposure coming in 3rd. Second and more revealing is on the index, results show that the multidimensional energy poverty index for Uganda (MEPI-U) is estimated at 0.33. Simply put, the proportion of the population that is multidimensionally energy poor (incidence) is 66% (about 27.5 million people) with the average deprivation score (intensity) of 51% while those in severe energy poverty are 33%. This means that, the multidimensionally energy poor in Uganda are deprived in at least one full dimension or they experience multiple deprivations (deprived in more than five indicators) at the same time, while a half of the multidimensionally energy-poor are in severe energy poverty. Third and more specific, multidimensional energy poverty is more of a rural phenomenon with those living in Northern Uganda worst hit. That is, multidimensional energy poverty in rural areas (0.386) is nearly three times that of urban areas (0.180) and relatively higher in Northern Uganda (0.513) compared to Central Uganda (0.174). The findings further reveal that energy poverty in Uganda has a "female" face, deep-rooted among those in the lowest wealth quintile and those employed in agriculture. Fourth, on the issue of inequality, energy poverty is unequally distributed across subgroups with the M-Gamma approach showing high inequality distribution by residence and regional location. Lastly, a comparison between (Nussbaumer et al., 2012)'s MEPI (used 6 indicators) to this paper's computed MEPI-U (used 13 indicators) as opposed to 6 indicators used by Nussbaumer and others) showed that the MEPI-U was 0.33 while MEPI was 0.438 which was statistically significant. This led to the conclusion that energy poverty is high but not as high as when computed with more indicators. Implying that the exclusion of important indicators overestimates energy poverty for Uganda.

From a policy perspective, the results show how heterogeneities in datasets and measurements provide different indices. That is few indicators overestimate the extent of multidimensional energy poverty while more disaggregated indicators lean towards giving a true picture on ground. This demonstrates the need to invest in good comprehensive datasets for better evidence-based planning. In addition, given that the dimension contributing most to energy poverty is that of electricity access, with indicators of quality, capacity and availability of electricity supply being the key drivers of energy poverty in that dimension, government programmes and interventions aimed to addresses these three issues should be prioritised and be universal. Rural programmes plus interventions that target female headed/widower/widow households should be designed and emphasised. This will in the long run reduce energy poverty tremendously and sustainably.

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.

Acknowledgement

We extend our appreciation to Dr. Madina Guloba (Economic Policy and Research Centre-Makerere University) and Prof Muyiwa S. Adaramola (Norwegian University of life sciences-Norway) for editing and proof reading the paper.

Appendix A

Table A1: Approaches, metric/measures and indicators for energy poverty

Approach		Type of Measure	Description	Strength	Weakness
Unidimensional e.g. the energy expenditure-income approach	Boardman (1991); Healy and Clinch (2004); Thomson et al. (2017); (Churchill and Smyth, 2020)Awaworyi Churchill and Smyth, (2020)	Objective Captures energy poverty using the proportion of income that households spend on energy or fuel.	Measure energy poverty objectively using the level of expenditure on energy against absolute or relative thresholds. And aggregates energy poverty to a single indicator The approach argues that energy poor households tend to spend relatively higher shares of their income on energy. Further suggesting minimum thresholds of for instance 10% beyond which a household is considered energy poor	Captures affordability and or Adequacy of energy services for those with low income. Besides high share of income spent on energy, this indicator captures the condition of after energy costs as income being too low. Useful in distinguishing energy poverty from generalized poverty -poverty due to energy costs. Generally, the indicator is simple, easy to communicate and measures an absolute value of energy poverty regardless of changes in the population. It has been widely used by researchers Capture severity by use of different thresholds	Captures mainly quantifiable aspects of energy poverty. Hence, more suited for developed countries where household expenditure on energy is easily quantified & traceable It is highly arbitrary thus can easily underestimate or overestimate energy poverty. Sensitive to energy price rises Ignores subjective indicators
onsensual	Gordon et al. (2000)	Subjective Employs self-reporting of energy poverty.	Uses many indicators; Perception based-self-reported indicators i.e. the ability to warm or heat homes, ability to pay utility bills on time and living in a damp and rot free home to be proxies of energy poverty	Captures non-quantifiable aspects of energy poverty They provide useful insight on perceived energy poverty than quantitative metrics. They can complement other indicators.	Respondents may give biased opinions hence highly subjective in nature and may be difficult to interpret. Can easily underestimate energy poverty.
Multidimensional e.g. Multidimensional Energy Poverty Index (	Nussbaumer et al. (2012, 2013)	Both objective and subjective. Analyse energy poverty based on multiple dimensions of deprivation.	Composite indices Capture both dimension specific metrics and single aggregate index.	They provide standard internationally comparable and easy to interpret indicators Capture both objective and subjective aspects of energy.	Lacks harmonization on number of dimensions, weighting procedure and indicator cut-off points. Can easily under or over-estimate energy poverty.

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Approach	Type of Measure	Description	Strength	Weakness
			Useful in African context where household energy costs are not easily traceable.	Requires complex datasets which may not be readily available

Source: Summarized from (Churchill and Smyth, 2020)Churchill and Smyth, (2020); Pelz et al. (2018); Thomson et al. (2017) and Bensch (2013).

A.1. Results for robustness checks

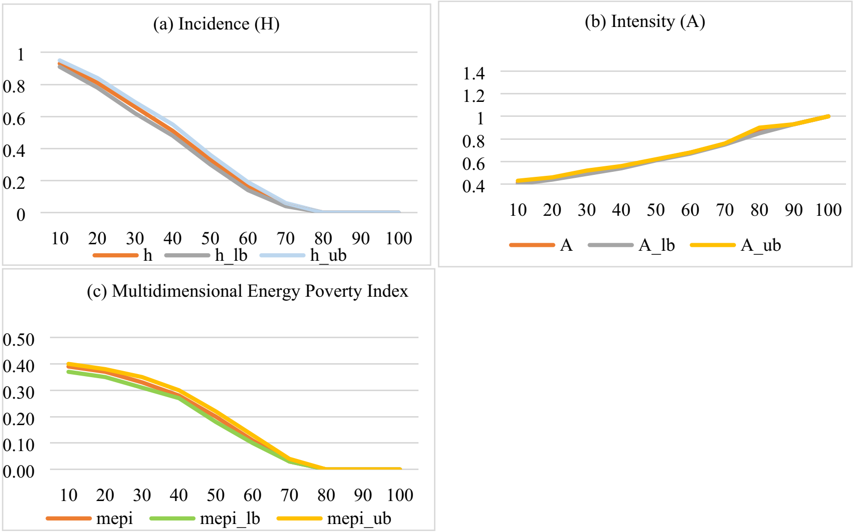

Fig. A1: Incidence of Multidimensional, intensity and MEPI for different values of the energy poverty cut-off, *k*.

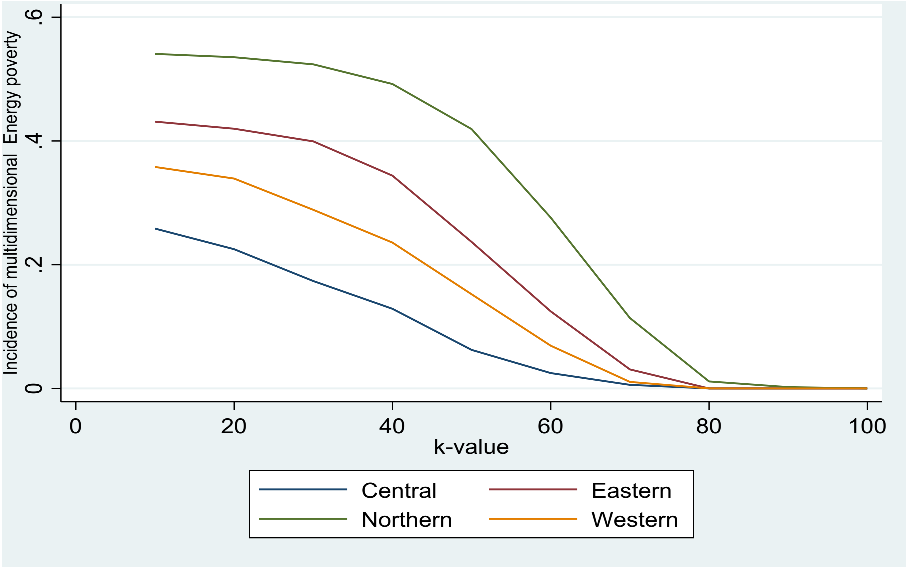

Fig. A2: Dominance of regional MEPI for different values of energy poverty cut-off, k.

Table A2: Correlation among sub-national (regional) Ranks for Different Poverty Cut-offs

		k = 30
k = 20	Spearman	1.00
	Kendall Tau-b	1.00
k = 30	Spearman	1.00
	Kendall Tau-b	1.00
k = 40	Spearman	1.00

(*continued on next page*)

(*continued*)

		$k = 30$
	Kendall Tau-b	1.00
k = 50	Spearman	1.00
	Kendall Tau-b	1.00
k = 60	Spearman	1.00
	Kendall Tau-b	1.00

Source: Author's own computations based on the NES (2018)

Table A3: Correlation among sub –national's(regional) Ranks for Different Weight Structures, 2017

			MEPI Weight 1	MEPI Weights 2	MEPI Weights 3	MEPI Weights 4
MEPI Weight 1	Equal weights: 33% each dimension.		1			
MEPI Weights 2	50% Electricity Energy supply (energy access	Spearman	1	1		
	25% Cooking solution	Kendall	1			
	25% Electricity service and appliance					
MEPI Weights 3	50% Electricity Energy supply (energy access	Spearman	1	1	1	
	25% Cooking solution	Kendall	1	1		
	25% Electricity service and appliance.					
MEPI Weights 4	50% Electricity Energy supply (energy access	Spearman	1	1	1	1
	25% Cooking solution	Kendall	1	1	1	
	25% Electricity service and appliance					

Source: Author's own computations based on the NES (2018).

Table A4: Breakdown of M_O^1 and M_O^2

		Censored Headcount Ratio	Dimensional Breakdown	Censored Intensity	Censored Adjusted Headcount	Shapley Breakdown	Relative Contribution	Relative Contribution	Percentage Point Diff.
Indicator	w_j	H_j	w_jH_j	A_j	M_{OJ}^1	$w_jM_{Oj}^1$	w_jH_j/M_0^1	$w_jM_{Oj}^1/M_0^2$	Δ
Capacity	0.08	54.04	4.50	53.65	28.99	2.42	13.59	13.51	0.08
Availability	0.08	49.25	4.10	54.81	27.00	2.25	12.39	12.58	−0.20
Quality	0.08	57.74	4.81	52.42	30.27	2.52	14.52	14.11	0.41
Affordability	0.08	31.29	2.61	56.50	17.68	1.47	7.87	8.24	−0.37
Cooking exposure	0.07	54.11	3.61	50.78	27.47	1.83	10.89	10.24	0.64
Convenience of cooking stove	0.07	12.97	0.86	52.13	6.76	0.45	2.61	2.52	0.09
Safety of primary cooking stove	0.07	6.56	0.44	58.31	3.82	0.25	1.32	1.43	−0.11
Affordability	0.07	13.59	0.91	53.46	7.26	0.48	2.73	2.71	0.03
Fuel availability	0.07	15.43	1.03	53.49	8.25	0.55	3.10	3.08	0.03
Lighting	0.08	32.08	2.67	54.81	17.58	1.47	8.07	8.20	−0.13
Information, communication and entertainment	0.08	30.28	2.52	57.62	17.45	1.45	7.62	8.13	−0.52
Roofing type	0.08	21.30	1.77	59.01	12.57	1.05	5.36	5.86	−0.50
Access to community services	0.08	39.50	3.29	51.01	20.15	1.68	9.93	9.39	0.54
			33.1	27.28		17.88	100.0	100.0	0.0

Source: Authors own computations based on the NES (2018)

Appendix B. Supplementary data

Supplementary material

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