# Towards accessibility or affordability? Multidimensional energy poverty across the South African urban-rural divide

Yuxiang Ye<sup>a,\*</sup>, Steven F Koch<sup>b</sup>

 <sup>a</sup>School of Economics and Finance, University of the Witwatersrand, Johannesburg, South Africa
 <sup>b</sup>Department of Economics, University of Pretoria, Pretoria, South Africa

# Abstract

This study combines energy affordability and accessibility into a multidimensional energy poverty measure, which we stratify by rural and urban locale. Accessibility considers a number of binary indicators related to the type of energy used for a series of household activities, while affordabilit is determined by the ratio of household required energy expenditure to total expenditure. We employ an equivalence scale approach to estimate household energy requirements using publicly available household expenditure survey data. Our results suggest extensive urban-rural disparities across our multidimensional indicators - 37% of rural households are affordability deprived, which is nearly double urban affordability deprivation; the ruralurban differences are at least double, when it comes to clean cooking, lighting, space heating, water heating and multidimensional headcount poverty. After splitting the households by degrees of energy poverty, it is found that the extreme energy-poor are more likely to be income-poor. However, urban extreme energy-poor is driven by affordability deprivation, while more than half of the rural extreme energy-poor are deprived in both affordability and accessibility.

Keywords: Energy poverty, Access, Affordability, Household basic needs

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<sup>\*</sup>Corresponding author.

*Email addresses:* yuxiang.ye@wits.ac.za (Yuxiang Ye), steve.koch@up.ac.za (Steven F Koch)

# 1. Introduction

The United Nation's Sustainable Development Goal (SDG) 7 aims to ensure access to affordable, reliable, sustainable and modern energy for all by 2030 [1].<sup>1</sup> Previous electrification efforts brought access to 1.1 billion people worldwide between 2010 and 2019, while the share of the global population with access to electricity grew to 90% in 2019 [2]. Despite this success, onethird of the world's population still lacks access to clean fuels and technologies, especially for cooking, while polluting fuels and inefficient technologies used for cooking have negative impacts on the environment, economic development, and most notably, on the health of women and children [3]. Furthermore, modern energy, in an era of increasing energy prices in developing countries [4], creates a financial burden, especially for poorer households [5]. Such burdens may force households to limit their energy consumption to purchase other goods or limit other goods to purchase energy [6]. Households without access and/or which are unable to afford their energy needs for cooking, space heating, water heating and lighting are referred to as energy-poor [7, 8, 9]. Such households could be poor in access, affordability or both, which we refer to as multidimensional energy poverty.

We construct a multidimensional measure of energy poverty accounting for both energy accessibility and affordability. Previous multidimensional energy poverty studies mostly focus on access to modern energy services

<sup>&</sup>lt;sup>1</sup>Although modern energy sources are assumed to be reliable, South Africa, the focus of this study, has faced scheduled rolling blackouts - referred to as *load shedding* since 2008.

[10, 11, 12]. Nussbaumer et al. [10] develop a different multidimensional energy poverty index (MEPI) with binary access indicators. This MEPI has been widely applied in the literature [11, 12]. The World Bank's multitier framework (MTF) also focuses on access [13]. However, its complexity may pose difficulties for global tracking purposes [14], due to an intensive data requirement, as well as its sensitivity to decisions in its design [15].

Whether a household can afford to use the (modern) energy services it needs should not be ignored, however [16, 17, 18]. The literature has often defined affordability based on a 10% indicator or via a residual income approach [19]. Thus, a household is recognized to be energy-poor in terms of affordability if it *needs to spend* more than 10% of its income on energy [9, 16]. To incorporate affordability, studies typically consider costs to accessing the grid [18, 20] or use actual energy expenditure [18, 21], because required energy is not observable. However, actual household energy expenditure may lead to an underestimate of the deprivation associated with energy affordability [18, 22]. Therefore, we use an estimate of household required energy expenditure underpinned by equivalence scales derived from income and expenditure surveys [7, 23]. The method is motivated by household heterogeneities in *needs* and data availability, especially in developing countries. Thus, it differs from engineering methods that model energy demand via detailed domestic energy usage, appliances or building characteristics information. Intuitively, Ye and Koch [7] and Ye et al. [23] argue that households are different in a range of dimensions, so will have different energy needs,

which should be accounted for in the analysis. The method itself is completely general; it can be adjusted for local circumstances and data. It can also incorporate other types of data, such as temperature, engineering, building and appliance efficiency information [24], if that information is accessible.

The residual income approach is also underpinned by required energy consumption [25], although household disposable income net required energy expenditure is the residual. Essentially, modern energy services are not the only basic need and households should be able to purchase goods and services beyond energy. The residual methods focus on the amount left to purchase goods and services beyond energy; examples include the after fuel costs poverty (AFCP) indicator [26] and the low income high costs (LIHC) indicator [27]. One concern with the AFCP is that it identifies income-poor households whose situation is worsened by high energy expenditure. Nearly all low-income households could be classified as energy-poor via AFCP, regardless of their energy requirements. Hence, it may not offer a clear separation between income poverty and energy poverty [28]. With the LIHC indicator, the default is that non-poor households, with respect to income, cannot be energy poor. It does not capture vulnerable households who were pushed into income poverty due to their expenses on energy consumption [28]. For these reasons, we adopt energy share threshold approach, rather than the residual approach. Originally, the 10% threshold arose from the observation that it was twice the median energy expenditure share of income in 1988 in the United Kingdom (UK) [29].

Ours is not the first attempt to examine multidimensional poverty capturing both affordability and accessibility, nor is it the first to consider a developing country. In their analysis of India, Pachauri et al. [17] include energy access and the quantity of energy consumed, underscored by household power requirements calculated from engineering estimates. Winkler et al. [18] compare three countries - Brazil, South Africa and Bangladesh - using actual energy expenditure as a share of disposable income to capture affordability. Zhang et al. [21] use the same affordability measure as Winkler et al. [18] in their analysis of energy poverty in China.

Our developing country context is South Africa, a middle-income developing country with extensive inequality. It achieved 85% electrification in 2020, with rural electrification slightly lower (75%) [30]. Although the high electrification rate allows electricity to be the main source of energy for domestic use, the rapid rise in electricity prices raises affordability concerns, especially for low income households in urban and rural areas [7, 31, 32, 33, 34]. Relevant local literature has focused on access measures [11, 35, 36, 37] or a comparison of multidimensional access measures to single dimension affordability measures [38]. Tait [39] is the only local multidimensional paper we could find considering both accessibility and affordability, although affordability is determined by actual, rather than *required* energy expenditure. To this end, our research further extends the limited local literature which tends to be one-dimensional [7, 32, 33, 40], and contributes to the understanding of multidimensional measures of energy poverty through its determination of the affordability of *required* energy expenditure.

We follow Alkire and Foster (AF) [41] to combine the multiple dimensions; there are two – accessibility and affordability. We use data from a recent household budget survey, the South African Living Conditions Survey (LCS) 2014/2015 [42]. Given the variables in the data, accessibility is referred to as access to clean fuels for cooking, lighting, space heating and water heating, while energy affordability is determined by the ratio of household required energy consumption to household expenditure. Further, we split our analysis by urban/rural locale, partly because of the disparity in access by location [43], as well as differences in electrification already outlined [30]. As implied by these differences, our results suggest extensive urban-rural disparities in both affordability and accessibility, and, therefore, in multidimensional poverty. In particular, urban households are less deprived in both dimensions, regardless of the weights we apply to the various components of the measure.

# 2. Data and methodology

### 2.1. South Africa descriptive data

The data is sourced from a recent household expenditure survey in South Africa, the Living Conditions Survey (LCS) 2014/2015 [42]. The survey captured information from 23380 households across the country, including detailed information on household income and consumption expenditure, electricity access, energy usage patterns, and a number of household-level

characteristics. One important reason we use the LCS survey data is that the results from the analysis can be compared to Ye and Koch [7].

Before conducting the empirical analysis, we tidied the data, removing households whose energy expenditure cannot be separately determined; some households have consolidated water and electricity bills, for others rent includes electricity, and some do not purchase any form of energy. Further, we limited the data to households with no more than seven adults and no more than five children, primarily because larger households are quite rare in the data. We also drop observations with missing information related to domestic appliances (refrigerator, freezer, cellphone, TV, radio, satellite TV and geyser), the main energy source for cooking, lighting, water heating, space heating, and living space (estimated area of the dwelling). In the end, 17162 observations remain for the empirical analysis.

In order to check the representativeness of the retained sample, we further compare the mean of selected variables with dropped samples in Table A.1. The table shows only a few differences in some variables. **Recall that we dropped households who have consolidated water and electricity bills (1088 out of 23380) and some that do not purchase any form** of energy (1185 out of 23380). For the former, we are not able to separate their electricity expenditure from the consolidated bill; and for the latter, it is not possible to figure out why they spent nothing on household energy use. Therefore, the reported energy **expenditure values for these households (**1088 + 1185 = 2273**) could**  be far away from their actual energy expenditure. For this reason, we add an additional panel at the bottom of Table A1 to present the conditional mean of household energy expenditure which is conditional on energy expenditure greater than zero, with a sample size of 3945 (= 6218 - 1088 - 1185). As can be seen, the conditional mean energy expenditure for this dropped subgroup (i.e. 3945 households who reported positive energy expenditure values in the data) is ZAR323.55 per month which is closer to the mean for the retained sample than previous value.

Further, renters account for 56% of the dropped sample compared to 13% of the retained, which also relates to the relatively higher proportion of single adult (34%) and no child (53%) households, as well as the larger proportion living in an urban formal settlement (63%). There are also fewer FBE recipients (6%) in the dropped data. Here, FBE refer to free basic electricity – a policy to allocate 50 kWh electricity per month to poor households for free [5]. It is reasonable that renters are more likely to be single or two-adult households without children, especially those in apartment complexes, and they are more likely to live in cities. It is also less likely that an indigent household will be in a position to sign a rental agreement, and, therefore, FBE is understandably lower within the dropped sample. In addition, the difference in the space variables is due to the fact that the space information

for renters was not captured as fully as it was for the rest of the households.<sup>2</sup> Within the dropped sample 23% of households stay in a medium to larger size home (no less than 60  $m^2$ ), not including renters. Thus, although there is some evidence of selection in our sample choices, it does not appear to be extensive, and, therefore, should not influence the generality of our conclusions.

We further split households by urban and rural setting. In the survey, household have been categorised across four geography types – urban formal, urban informal, traditional area, and rural formal, following the national census of 2001. The definition of the geography types mainly uses levels of population density, economic activities and infrastructure similar to international definitions of urbanisation [45]. To be consistent with the international literature on urban/rural classification, we reclassify urban formal and informal as urban, while rural households come from the rural formal and traditional area initial classifications [46].

Regarding the expenditure variables, household consumption expenditure rather than income has been used in this study, because many households in developing countries may not be formally employed and could have inconsistent sources of income [47]. In addition, home production is quite common,

 $<sup>^{2}</sup>$ In the survey, the living space information for renters is recorded as "not applicable" which indicates a household either not living in a permanent structure or in one with multiple households in one permanent structure [44], which is consistent with a typical apartment complex.

hence, consumption expenditure instead of income is considered to be more representative. We also inflated/deflated all reported expenditures to the midpoint of the survey year using consumer price index (CPI), due to the fact that the LCS 2014/2015 was conducted over the period of a year. The data from the survey have been collected in a number of files, including a person file, a household file, a household assets file and an expenditure and income file. For the analysis, we use haven [48], tidyverse [49], knitr [50], lubridate [51] and xtable [52], which are packages for R [53], to organize the data for the analysis, prepare the data in tables and write the paper in a completely repeatable manner [54]. Code for the preparation of the data, figures, tables and all empirical modelling is available from the authors, upon request.

#### 2.2. Constructing the multidimensional measure

We follow the Alkire-Foster (AF) method [41] to construct our multidimensional energy poverty index (MEPI). To accommodate the mixed energy usage patterns in the South African domestic sector, we use four binary access indicators, as shown in Table 1, including: clean sources of energy for cooking, lighting, space heating and water heating.<sup>3</sup> In terms of energy affordability, if the ratio of household required energy expenditure to total expenditure is greater than 10%, a household is considered to be deprived in

<sup>&</sup>lt;sup>3</sup>Clean fuels refer to electricity, liquefied petroleum gas (LPG), natural gas, biogas, solar, and alcohol fuel stoves according to the 2014 World Health Organization (WHO) guidelines for indoor air pollution from household fuel combustion [2].

this dimension. We discuss the estimation of required energy consumption and selection of the threshold, below.

Dimension (weight)	Indicator (weight)	Deprived if
Access (0.5)	Clean fuels for cooking (0.15) Clean fuels for lighting (0.15) Clean fuels for space heating (0.1) Clean fuels for water heating (0.1)	Household primarily used any fuel besides electricity, gas, or solar energy.
Affordability (0.5)	The ratio of household required en- ergy expenditure to total expendi- ture (0.5)	The ratio is greater than 10%.

Table 1: Dimensions of multidimensional measure.

Within the AF methodology, weights can be evenly or unevenly distributed, depending on the relative importance of each indicator, i.e., higher weights indicating greater importance [55]. With this principle in mind, we first weight accessibility and affordability equally as in other developing country studies of energy poverty, e.g. [21]. More importantly, they are two of the few components of SDG 7, which are of equal importance to achieve the goals. Next is to weight the binary indicators within the accessibility dimension.

As shown in Table 1, higher relative weights are assigned to cooking (0.15) and lighting (0.15), while space heating and water heating are given lower weights (0.1), since higher weights are normally assigned to indicators with greater importance. Access to clean fuels and technologies for cooking is viewed as a major priority among the SDG 7 targets [2, 56]. However, the

recent research [57] argues that slow progress in expanding clean cooking access is hindering progress on several socio-economic goals globally, for example, health, gender, equity, climate and so on. In terms of clean lighting, it has been viewed as a fundamental human need irrespective of household characteristics [11], and lack of access to clean lighting might be detrimental to women's health [58] as well as the education of children and adults [59]. As Nathan and Hari [60] suggest, clean cooking and lighting are still major concerns in many developing countries. Therefore we put more emphasise on these two indicators in our weighting strategy in order to highlight the significance of making clean cooking and lighting accessible and affordable to all.

With respect to the lower weights on space and water heating, on the one side, the mild South African weather limits the need for space heating because people could keep warm with more clothes and/or warm blankets instead of heating the space using some form of heat energy [11], while piped water is a luxury in many areas in the country which constrains the ability to use geysers (electric water heaters). On the other side, adopting clean energy sources and technologies for space and water heating could benefit households in terms of health, indoor air pollution and some other aspects. For these reasons, the indicators are included but weighted lower in our analysis.

Households are identified to be energy poor if they exceed a pre-defined threshold, or poverty cut-off k. Specifically, a household i is energy poor if its weighted deprivation count  $c_i$  exceeds the threshold.<sup>4</sup> We propose two energy poverty cut-offs, as suggested in Alkire et al. [61]. More specifically, a household is energy poor if it is deprived in at least one fifth of the weighted indicators ( $k \ge 0.2$ ). Energy poor households are further divided into two subgroups:

- Moderate energy-poor: a household is moderately energy poor if it is deprived in 20%-50% of the weighted indicators, 0.5 > k ≥ 0.2.
- Extreme energy-poor: a household is extremely energy poor if it is deprived in at least half of the weighted indicators,  $k \ge 0.5$ .

The household measures are aggregated into a headcount ratio, which is simply the proportion of households that are energy poor. This headcount ratio H = q/n, where q is the number of multidimensionally energy poor households and n is the total number of households, is the incidence of multidimensional energy poverty. According to the AF method, the MEPI is the product of the headcount ratio (H) and the average intensity (A) of deprivation of the energy poor [62], which is approximately the average number of dimensions for which households are energy poor.<sup>5</sup>

<sup>&</sup>lt;sup>4</sup>Mathematically,  $c_i = \sum_{j=1}^d w_j I_{ij}$ , where  $w_j$  is the assigned weight for indicator j, with  $w_j > 0$  and  $\sum_{j=1}^d w_j = 1$  for all j = 1, ..., d. Further,  $I_{ij} = 1$  if household i is deprived in indicator j, otherwise it equals 0.

<sup>&</sup>lt;sup>5</sup>Mathematically, the intensity of multidimensional energy poverty is computed as  $A = \sum_{i=1}^{n} c_i(k)/q$ , where  $c_i(k) = 0$  when  $c_i \leq k$ , and  $c_i(k) = c_i$  when  $c_i > k$ . Therefore we have  $MEPI = H \times A = \sum_{i=1}^{n} c_i(k)/n$ .

### 2.3. Defining energy affordability

As noted earlier, one of the dimensions of our analysis is energy affordability, which is defined by the required energy poverty ratio (EPR), the ratio of required energy expenditure to household expenditure [16],

$$EPR = \frac{Required \ energy \ expenditure \ (i.e., \ required \ usage \times price)}{Total \ expenditure}.$$
 (1)

A household is deprived on energy affordability if EPR > 10%. Unfortunately, household energy requirements are not generally known. Therefore, we estimate unobservable household required energy expenditure following Ye et al. [23]. They derive required energy expenditure by rescaling a reference household's energy expenditure, where the scale factor is household specific, and is indirectly determined from a semiparametric model of household energy expenditure shares.

As discussed in [23], reference energy is based on a *reasonable* living standard in South Africa, where the reference household for the analysis is a single (adult) person living in their own moderately-sized property (between 30 and 59  $m^2$ ) located in a formal urban area. The model controls for a range of additional variables that might affect either energy expenditure (shares), such as the time of year or relate to standards of living. In that regard, spring and fall, which represent times of comfortable temperatures, serve as the reference. Furthermore, having a refrigerator or freezer, cooking with clean energy sources, being able to communicate with a cellphone and able to access entertainment through at least a television (TV), radio or satellite TV are used as references of a reasonable standard of living. We do not include geysers in our reference group, because a connection to piped water for a dwelling is often a luxury, while hot water may not be provided through individual geysers, either in homes without them or in apartment buildings. Relatedly, our reference households are assumed not to need free basic electricity (FBE).

Although access to clean fuels for cooking, lighting and heating could also relate to reasonable standards of living [7, 23], we do not specify these features here, because they are separately accounted for in the accessibility dimension of our multidimensional measure. Specifically, we zero-out the variables *no clean cooking* and *geyser* for the semiparametric regression (Table A.2) in calculating the energy equivalence scale, such that our estimated required energy expenditure does not cross into the accessibility dimension. As shown in Table A.2, a number of variables related to household energy consumption are included in the regression, in order to capture the differences of energy expenditure across households.

In our sample, average monthly household energy expenditure differences between geyser owners (ZAR 656.25) and non-geyser owners (ZAR 217.72) are quite large, indicating that geysers are an important driver of household energy consumption. Thus we control for *geysers* in the regression, for calculating the household specific equivalence scale. However, only a small proportion of households (19%) own geysers (see Table A.1), suggesting geysers are not a prevalent appliance among South African households. Further, clean water heating is one of the indicators within our accessibility dimension, which could capture the ownership of geyser in a household as well. Therefore, we switch off the *geyser* variable when calculating required energy consumption; thus, we avoid double counting of the water heating indicator in our multidimensional measure. In terms of clean cooking, due to the fact that more than 80% of households have access to clean cooking, requiring clean cooking for all might be plausible, when calculating household required energy. But, as mentioned above, we do not want to have this indicator counted twice in the final energy poverty estimates, so we exclude this variable in equivalence scale calculation.<sup>6</sup>

#### 3. Results

#### 3.1. Energy usage patterns for South African households

We first briefly summarise household energy expenditure by urban and rural areas in Table 2. The table shows that, on average, total household expenditure in urban areas is more than double their rural counterparts.

<sup>&</sup>lt;sup>6</sup>Moreover, our results suggest limited impact of excluding these two variables on required energy and poverty estimation. For instance, excluding *geyser* only will slightly decrease the estimated required energy consumption and thus reduce the final energy poverty rate (MEPI = 12.15%). While including both the variables *no clean cooking* and *geyser* will increase the required energy estimates a little bit and therefore increase the MEPI rate as well (MEPI = 12.78%). All the results are available from the authors, upon request.

Table 2: Descriptive statistics.

Variable	Urban	Rural	Total
Monthly total household expenditure (unit: ZAR)	9862.16	4260.16	7466.24
Monthly energy expenditure (unit: ZAR)	380.12	193.56	300.33
Energy share	0.06	0.07	0.07
Energy share $> 10\%$	0.17	0.20	0.18
Monthly electricity expenditure (unit: ZAR)	362.79	171.83	281.12
Monthly gas expenditure (unit: ZAR)	5.53	4.15	4.94
Monthly liquid expenditure (unit: ZAR)	7.14	8.56	7.75
Monthly solid expenditure (unit: ZAR)	4.67	9.03	6.53
Monthly paraffin expenditure (unit: ZAR)	6.27	7.78	6.92
Monthly wood expenditure (unit: ZAR)	0.91	3.64	2.08
Electrification rate	0.94	0.92	0.93
Observations	9822	7340	17162

Electrification rate: the proportion of households connected to the national grid. Energy share is calculated as the ratio of household energy expenditure to total expenditure. Expenses of residential energy sources includes: 1) Electricity: conventional metering, prepaid, or free basic electricity; 2) Gas: refilling gas and gas in cylinders; 3) Liquid fuels: paraffin, petrol and diesel for household use (not transport use); 4) Solid fuels: bought firewood, charcoal, candles, coal, bought dung, crop waste, and other household fuel. In addition, the market values of free basic electricity and fetched firewood and dung are also recorded in the data. In our analysis, total energy expenditure includes expenditure or market values from all of these energy sources.

Further, electricity expenditure accounts for a large proportion of total energy expenditure for both urban and rural groups, implying that electricity is the main energy source for domestic daily use.<sup>7</sup> Such high rates make sense,

<sup>&</sup>lt;sup>7</sup>In South Africa, some municipalities send estimated electricity bills to the conventional metering customers and then the meters will be read once every few months, which means these households' electricity expenditure may not be calculated based on their actual meter reading. Unfortunately we are not able to identify which ones received the estimated bill and which ones did not. However, 83.7% (19572 out of 23380) of sample households are using prepaid meters in the LCS data, while the number is 91.6% for our selected observations (15718 out of 17162), which reduces concerns over electricity consumption measurement error.

	Clean sou	irce	Traditional/dirty source					
	Electricity	Gas	Paraffin	Wood	Coal	Animal dung	Candle	None
Urban $(N = 982)$	22)							
Cooking	91.20	3.70	3.30	1.20	0.50	0.00	_	0.00
Lighting	96.50	0.00	1.10	_	—	—	2.30	—
Space heating	54.30	2.50	11.10	5.00	2.00	0.10	_	24.80
Water heating	93.90	0.90	3.10	1.40	0.50	0.10	_	0.00
Rural ( $N = 734$	.0)							
Cooking	64.40	2.10	2.50	30.20	0.30	0.40	_	0.00
Lighting	93.00	0.00	1.00	_	_	_	6.00	_
Space heating	28.20	0.50	4.90	32.80	1.30	0.40	_	31.80
Water heating	66.10	1.10	2.20	29.80	0.30	0.50	_	0.00
Total ( $N = 171$	62)							
Cooking	79.70	3.00	3.00	13.60	0.40	0.20	_	0.00
Lighting	95.00	0.00	1.10	_	_	_	3.90	_
Space heating	43.10	1.60	8.40	16.90	1.70	0.20	_	27.80
Water heating	82.00	1.00	2.70	13.60	0.40	0.30	_	0.00

Table 3: Main source of energy for cooking, lighting, space heating and water heating (% of households).

1) Electricity: including electricity from the national grid, generator or solar energy. 2) "--" represents "not applicable".

given the electrification rate in the country; in total, 93% of households have been connected to the national grid.<sup>8</sup> Households spend approximately 7% of their budget on energy consumption, with a (sample) median energy share of 5.15%. When determining deprivation due to energy affordability, we use 10% in our threshold, because it is about twice the median energy share. We check the sensitivity of this selection in our analysis.

<sup>&</sup>lt;sup>8</sup>The electrification rate in the LCS data is higher than that of the country, currently; the national electrification rate is about 85.3% in total with an urban/rural split of 88.1% and 80.2% according to World Bank [30].

Despite the high electrification rate and high expenses on electricity, our results in Table 3 suggest that South African households use various energy sources for cooking, lighting, space heating and water heating. In total, roughly 80% of the households primarily use electricity for cooking and water heating and almost all households (95%) light their homes with electricity. Due to the mild weather in the country, less than half of South African households mainly use electricity for space heating purposes and about 28% do not heat their homes with any energy source. In addition, the usage of dirty sources of energy, like paraffin (also known as kerosene) and wood, is prevalent. More than 13% of the households use firewood for cooking and heating, while 8% use paraffin for space heating.

The disparities in energy use are clearer after splitting the sample by location. About 30% of rural households primarily use firewood for cooking, space heating and water heating, partly because people may be able to fetch their firewood from local forest areas. Although paraffin has been recognised as a polluting fuel and is not recommended for household use [63], more than 11% of urban households choose it for space heating. Paraffin is still widely distributed in South Africa; it can be purchased at supermarkets and gas/petrol stations and, more importantly, it is cheaper than electricity. We do see that the proportion of households primarily using electricity for water heating is higher than that for cooking across both urban and rural groups, which is consistent with literature suggesting that water heating, rather than space heating, is the largest end-use of electricity in the residential sector in South Africa [64].

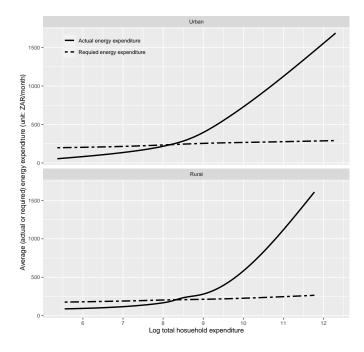


Figure 1: Actual and required energy expenditure by income and settlement type.

#### 3.2. Estimates of energy affordability deprivation

Before presenting the energy affordability results, we briefly summarise the estimates of household required energy expenditure and the required energy poverty ratio. Since our required energy expenditure is underpinned by the reference group, we present the descriptive statistics of the reference group and estimated required energy expenditure in Table A.3. In addition, we present the semiparametric regression results in Table A.2. Figure 1 presents a smooth plot of actual and required energy expenditure by household income and settlement type. On average, both actual and required

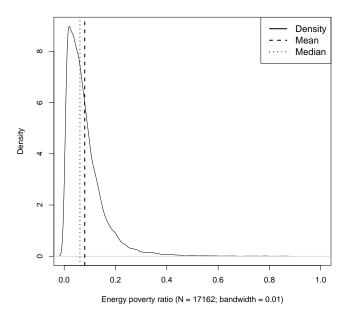


Figure 2: Kernel density of energy poverty ratio

energy expenditure increase with total expenditure across urban and rural areas, although actual energy expenditure increases much faster than the required expenditure. Moreover, mid- to high-income groups spend much more than they need, while lower income households require more energy than they consume, indicating that their energy needs have not been satisfied. Mean required energy expenditure for urban households (ZAR 244.63) is higher than that for rural (ZAR 201.99), and both are lower than mean actual monthly energy expenditure (ZAR 300.33) in the full sample (see Table 2).

The kernel density plot of the required energy poverty ratio in Figure 2 shows that the mean and median ratios are 0.08 and 0.06 respectively, which

are close to mean (0.07) and median (0.05) energy expenditure shares (the share of total household expenditure devoted to energy consumption). Hence, our selection of 10% as the energy affordability threshold is not unreasonable.

In total, we obtain 27 per cent as the proportion of deprived households (Table 4). Roughly one fifth of urban households and 37% of rural households suffer energy affordability deprivation. In other words, these households *need* to spend more than 10 per cent of their income to satisfy their energy requirements. Further, our estimates for urban, rural and the full sample are greater than those underpinned by actual energy expenditure (see *Energy share* > 10% in Table 2). As described in [7] and [23], estimated required energy expenditure arises from a weighting process, which maps a reasonable standard of living from a reference household to all other households, and those weights are determined by the household and its characteristics. To this end, estimates underpinned by required energy, rather than actual, can better reflect the energy affordability situation across heterogeneous households.

#### 3.3. Multidimensional energy poverty estimates

The results of our multidimensional energy poverty estimates together with the deprivation indicators are summarised in Table 4. More than onethird of the households are identified as multi-dimensionally energy poor (the incidence of energy poverty); on average, the energy poor are deprived in about 55% of the weighted indicators (the intensity). Accordingly, one-

	Urban	Rural	Total
Deprivation of energy affordability	20.31	36.72	27.33
Deprivation of clean cooking	5.07	33.49	17.22
Deprivation of clean lighting	3.42	6.96	4.94
Deprivation of clean space heating	18.19	39.41	27.27
Deprivation of clean water heating	5.14	32.78	16.96
Multidimensional headcount ratio $(H)$	22.86	55.98	37.02
Average intensity $(A)$	54.94	54.54	54.68
$MEPI = H \times A$	12.56	30.53	20.24

Table 4: Energy poverty estimates (% of households).

fifth of South African households are energy poor in multiple dimensions after adjusting the headcount ratio to account for the intensity of the deprivation suffered (MEPI). As expected and as shown in the table, not all the households are deprived in all the indicators.

The results are also decomposed by location, where we see that the incidence of energy poverty in rural areas is more than double that for urban areas. With respect to accessibility indicators, rural deprivation rates for clean cooking, space and water heating are all more than 30%, while urban rates are closer to 20%. The urban-rural disparity in terms of clean fuels for cooking and heating is a major concern for achieving the SDGs, because that disparity has been rising in Sub-Saharan Africa (but declining in most other regions of the world) [2]. Although we are not able to provide a time-varying figure, our results reveal evident disparity between urban and rural areas in access to clean energy for household daily use. It is evident that additional research is needed to see if there have been improvements, or not, in the regional dimension of energy poverty over the last number of years.

When comparing our estimates with previous results, the incidence of energy poverty is lower than the single dimensional measure underpinned by the Foster-Greer-Thorbecke (FGT) approach applied to the same data [7]. This difference arises from the fact that the headcount ratio of their FGT measure only considers satisfaction of household energy requirements, without incorporating the accessibility of modern energy services, which we find to be better in at least some indicators. Our MEPI is similar to multidimensional results reported in Mbewe [38], who used different South African data from the same year. However, our estimated affordability deprivation rate is much higher than in Mbewe [38], because we use required energy consumption, rather than actual consumption, for the affordability measure.

	Energy	Energy non-poor	
	Moderate energy-poor	Extreme energy-poor	
Urban $(N = 9822)$			
Income poor	1.02	15.20	16.41
Income non-poor	0.91	5.73	60.73
Rural $(N = 7340)$			
Income poor	11.69	32.47	18.92
Income non-poor	5.26	6.57	25.10
Total $(N = 17162)$	)		
Income poor	5.58	22.58	17.49
Income non-poor	2.77	6.09	45.49

Table 5: Headcount ratio of energy poor and income poor (% of households).

	Energy poor		Energy non-poor
	Moderate	Extreme	-
Monthly household expenditure (unit: ZAR)	4435.77	1521.60	10574.71
Monthly energy expenditure (unit: ZAR)	179.28	138.53	390.05
Energy share	0.05	0.10	0.05
Energy share $> 10\%$	0.09	0.40	0.09
Number of adults	3.19	2.20	2.79
Number of kids	2.01	0.98	1.20

Table 6: Statistics of household characteristics for energy poor and non-poor.

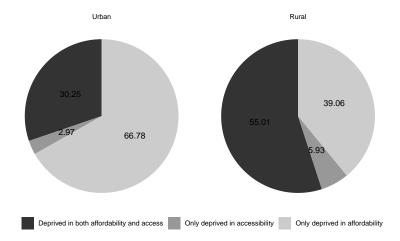


Figure 3: Distribution of the extreme energy-poor households (% of households).

### 3.4. Energy-poor and income-poor

Based on our energy poverty estimates, we are able to answer a common question related to energy poverty: are energy poor households also income poor? Table 5 shows the headcount ratio across the energy-poor and incomepoor groups. In our analysis, a household is defined to be income-poor, if its per capita expenditure is not greater than South Africa's upper-bound poverty line for April 2015 - ZAR 992 per person per month [65]. Not surprisingly, there is overlap across the two groups; however, income poverty and energy poverty are not identical problems. Dividing the group by the degree of energy poverty, we see that most of the energy-poor are extremely energy-poor in both urban and rural areas.

Thus, extreme energy-poor households are more likely to also be incomepoor, because the households that are identified as both the income-poor and extremely energy-poor groups dominate across the urban, rural and full sample. Indeed, the average monthly total expenditure of the extreme energy-poor is the lowest among the energy-poor and non-poor groups (Table 6). 40% of extreme energy-poor households spend more than 10% of their expenditure on energy consumption, further indicating their poor economic situation. Given the bond between energy and income poverty, our results are a reminder that the energy-poor do not have to be income-poor, although extreme poverty tends to incorporate all facets of poverty, income and energy. Thus, eliminating extreme energy poverty is likely to require an extensive improvement of the economic situation in these households. When dividing the extreme energy-poor in terms of accessibility and affordability (Figure 3), two-thirds of the urban extreme energy-poor are deprived only in affordability, meaning that these households primarily used clean fuels for daily purposes, although they need to spend more than 10% of their income to meet those requirements. In rural areas, more than half of the extreme energy-poor are deprived in both accessibility and affordability. The urban-rural disparity in these dimensions of energy poverty implies the need for location differentiated energy access and affordability policies. For example, for urban residents, more policy focus could be placed on the impact of energy pricing, as well as the improvement of energy efficiency in buildings and appliances. In rural settings, more attention should be placed on the provision (and possible subsidization) of clean and cheaper energy/technology substitutes, such as solar-based micro-grids.

Table 7: Energy poverty estimates with equal weights for the indicators (% of households).

	Urban	Rural	Total
Multidimensional headcount ratio $(H)$	34.70	66.35	48.23
Average intensity $(A)$	30.05	45.02	38.86
$MEPI = H \times A$	10.43	29.87	18.74

#### 3.5. Sensitivity analysis

As is well known for the AF method, the weights, the cut-offs and the threshold for affordability deprivation can influence the outcome; hence, we

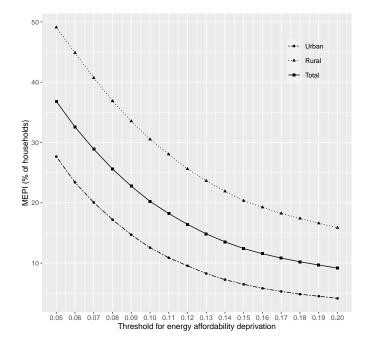


Figure 4: MEPI and the threshold for energy affordability deprivation.

conduct a series of tests to describe how the multidimensional estimates will change with some of the key parameters.

First, we plot the relationship between MEPI and the threshold for energy affordability in Figure 4, considering a threshold in the range of 0.05 to 0.2. As shown in the figure, the higher the threshold, the lower the deprivation rate, and vice versa. Second, we assign equal weights to the indicators in constructing the multidimensional measure. When doing so – see Table 7 – we find an increased headcount ratio than before (see Table 4). However, there is not much change to the MEPI, because the intensities decrease after assigning equal weights, even though the headcounts rise.

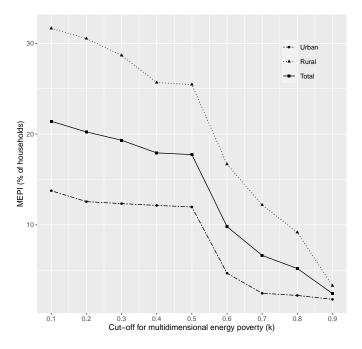


Figure 5: MEPI and the cut-off k.

Finally, we examine how the MEPI changes with the cut-off k. In general the MEPI decreases with the the cut-off, as shown in Figure 5. Specifically, the MEPI values jump discontinuously at k = 0.5 across all the groups, which supports our selection of 0.5 as the cut-off for extreme energy poverty. The figure also shows consistency in the ranking between urban and rural groups. In summary, the results indicate that changes in the weights of the indicators and cut-off (threshold) do not lead to large changes in the MEPI, when limiting the parameters to reasonable ranges around those chosen for the analysis. Thus, the MEPI is robust to the key parameters used in the multidimensional index construction.

# 4. Conclusions

Based on the Alkire-Foster method, we construct a multidimensional energy poverty measure that incorporates both accessibility and affordability. We use household basic energy needs, rather than actual energy use, in the affordability dimension. Therefore, our multidimensional energy poverty index is underpinned by household required energy consumption – following fairly recent literature [7, 23]. Our results offer an update to local literature, as well as another way to examine the affordability dimension of multidimensional poverty. Our results are underpinned by the 2014/2015 South Africa Living Conditions Survey data, which allows for the most up to date measure of multidimensional energy poverty and is used in the previously noted literature.

The main results of this study are summarised as follows: 1) Electricity is the main source of energy for household daily use, as is expected, given the high electrification rate in the country; however, about 30% of rural South African households still primarily use firewood for daily cooking and heating, while 11% of urban households prefer paraffin for space heating. 2) With respect to affordability, it is not surprising that the proportion of rural households deprived in affordability (37%) is almost double that for urban households (20%). Since our estimation is underpinned by household basic needs, the results suggest that these deprived households *need* to spend more than 10% of their income on energy consumption. 3) More than one-third of South African households are identified as multi-dimensionally energy poor and the final multidimensional index is about 20%. Further, our results suggest extensive urban-rural disparities across the indicators included in our multidimensional measure. 4) We also offer some insight with respect to the relationship between income and energy poverty, finding some overlap between the two groups, although energy poverty and income poverty are not the same. When dividing by the degree of energy poverty, the extreme energy-poor are more likely to be income-poor, while their deprivations in accessibility and affordability dimensions are different. For instance, most of the urban extreme energy-poor only have an affordability issue, while more than half of the rural extreme energy-poor are deprived in both affordability and accessibility.

Due to data limitations, we are not able to include energy prices or actual household electricity usage (in kWh) in estimating required energy consumption. Instead, we use energy expenditure, which is the multiple of the price and usage. Given significant tariff increases, since 2015, as well as multiple epochs of scheduled load-shedding in the country, it is expected that at least some features of electricity consumption will have changed. Thus, an update with more recent data, when it becomes available, may be needed, at least to allow for comparison with estimates from previous data. Further, the selection in our sample choices might slightly affect the generality of our conclusions; therefore, a energy consumption focused survey may be necessary in the country to capture more accurate data on household energy usage and expenditure and relevant consumption

#### behaviour.

### Declaration of competing interest

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

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# Appendix A. Additional Tables

	Retained sample $(N = 17162)$		Dropped s	ample $(N$	= 6218)
	Mean	Standard deviation	Sample size	Mean	Standard deviation
Monthly total household expenditure (unit: ZAR)	7466.24	11638.54	6218	7305.15	10941.11
Monthly energy expendi- ture (unit: ZAR)	300.33	351.13	6218	221.95	304.71
Energy share	0.07	0.06	6218	0.05	0.07
Number of $adults = 1$	0.22	0.41	6218	0.34	0.47
Number of $adults = 2$	0.32	0.47	6218	0.33	0.47
Number of $adults = 3$	0.22	0.41	6218	0.14	0.35
Number of $adults = 4$	0.14	0.34	6218	0.08	0.27
Number of $adults = 5$	0.07	0.25	6218	0.04	0.20
Number of $adults = 6$	0.03	0.17	6218	0.02	0.14
Number of $adults = 7$	0.01	0.11	6218	0.01	0.10
Number of children $= 0$	0.42	0.49	6218	0.53	0.50
Number of children $= 1$	0.22	0.42	6218	0.18	0.39
Number of children $= 2$	0.19	0.39	6218	0.13	0.34
Number of children $= 3$	0.10	0.30	6218	0.06	0.23
Number of children $= 4$	0.05	0.21	6218	0.03	0.17
Number of children $= 5$	0.02	0.14	6218	0.01	0.12
Urban formal	0.50	0.50	6218	0.63	0.48
Urban informal	0.07	0.25	6218	0.07	0.26
Traditional area	0.40	0.49	6218	0.23	0.42
Rural	0.43	0.49	6218	0.06	0.23
Clean cooking	0.83	0.38	6187	0.83	0.38
Fridge	0.80	0.40	5874	0.65	0.48
Cellphone	0.92	0.27	6125	0.91	0.29
Entertainment	0.88	0.32	5910	0.80	0.40
Geyser	0.19	0.39	6021	0.16	0.37
Summer	0.36	0.48	6218	0.36	0.48
Winter	0.25	0.43	6218	0.25	0.44
Very small space	0.10	0.30	5784	0.05	0.23
Small space	0.25	0.44	5784	0.10	0.29
Medium space	0.34	0.48	5784	0.14	0.35
Large space	0.14	0.35	5784	0.07	0.25
Very large space	0.04	0.19	5784	0.02	0.16
Renter	0.13	0.33	6162	0.56	0.50
FBE	0.14	0.35	6218	0.06	0.23
Conditional on energy exp Monthly energy expendi-	enditure > 300.33	$ \xrightarrow{42}_{351.13} $	3945	323.55	303.90
ture (unit: ZAR)	000.00	001.10	0340	020.00	000.00

Table A.1: Summary statistics of retained and dropped samples.

*Note:* This table shows the mean of selected variables for both the retained and dropped samples in the LCS 2014/2015 data. Within the dropped samples (6218), the number of observations for each variable could vary due to missing information related to that variable.

Variable	Scaling coefficient	Standard error
Log of total household expenditure <sup>1</sup>	1.0000***	(0.0000)
Number of $adults = 2$	-0.0094***	(0.0007)
Number of $adults = 3$	-0.1027***	(0.0013)
Number of $adults = 4$	-0.1384***	(0.0014)
Number of $adults = 5$	-0.1527***	(0.0011)
Number of $adults = 6$	-0.1114***	(0.0019)
Number of $adults = 7$	-0.0110**	(0.0040)
Number of children $= 1$	-0.0108***	(0.0008)
Number of children $= 2$	$0.0034^{***}$	(0.0010)
Number of children $= 3$	$0.0625^{***}$	(0.0012)
Number of children $= 4$	$0.0586^{***}$	(0.0016)
Number of children $= 5$	$0.0572^{***}$	(0.0018)
Urban informal	$0.1310^{***}$	(0.0011)
Traditional area	0.2090***	(0.0007)
Rural	$0.0061^{***}$	(0.0017)
No clean cooking	$0.3204^{***}$	(0.0008)
No fridge	$0.0996^{***}$	(0.0008)
No cellphone	-0.0360***	(0.0011)
$No \ entertainment$	$0.0279^{***}$	(0.0009)
Geyser	$-0.4172^{***}$	(0.0009)
Summer	-0.0101***	(0.0011)
Winter	-0.0489***	(0.0012)
Very small space	$0.0335^{***}$	(0.0010)
Medium space	-0.0545***	(0.0011)
Large space	-0.0911***	(0.0010)
Very large space	-0.1790***	(0.0017)
Renter	-0.0371***	(0.0013)
FBE	0.1853***	(0.0018)

Table A.2: Semiparametric index model parameter estimates (N = 17162).

Significance levels: \*  $p \leq 0.05$ , \*\*  $p \leq 0.01$ , \*\*\*  $p \leq 0.005$ . Additional note: <sup>1</sup> - For identification, this parameter estimate is set to unity.

Table A.3: Descriptive statistics of reference group and semiparametric results.

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Panel A: Reference group (N =	= 44)					
Monthly total household expenditure (unit: ZAR)	709.09	1543.51	2109.58	3517.62	4312.04	16192.75
Monthly energy expenditure (unit: ZAR)	89.92	99.74	179.84	196.58	231.10	802.40
Energy budget share	0.01	0.05	0.07	0.08	0.11	0.25
Panel B: Estimated energy equ	ivalence	scale and	required en	nergy exper	nditure (N	= 17162)
Energy equivalence scale	0.56	0.86	0.97	0.98	1.09	1.51
Required energy expenditure (unit: ZAR/month)	129.84	199.19	223.88	226.40	252.30	349.32