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SOMMAIRE

Elicitation of the Determinants of Energy Poverty in Cote d'Ivoire

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Abstract

The aim of this paper is twofold. It provides a comparison of the main approaches used to compute energy poverty indices and investigates the determinants of energy poverty. The two main approaches for computing energy poverty index are compared and the best performing is used. Using the data from the Living Standard Measurement Survey of 2015, the estimates highlight that 74.89 percent of the population suffer from energy poverty. The deprivation score is 0.1578 higher for households that are poor in comparison to those who are not economically poor, and 37.71 percent of this difference is due to differences in characteristics between poor and non-poor. The analysis reveals that education is negatively correlated with energy poverty and that above 53, age is positively associated with energy poverty. Regional as well as urban-rural differences play an important role in energy poverty. These results call for removing accessibility constraints by reinforcing energy supply especially for elderly and accounting for household's head characteristics while designing policy to alleviate energy poverty.

Keywords: energy poverty, multidimensional index, Côte d'Ivoire

JEL codes: I3, Q4

1. Introduction

Universal access to affordable, reliable, sustainable, and modern energy is considered as a priority for the United Nations for the period 2015–2030. This seventh Sustainable Development Goal (SDG) is one of the main challenges for Africa, particularly Sub-Saharan Africa. The sub-Saharan region of Africa (SSA) faces a chronic energy deficit as about 600 million people do not have access to electricity (Sy et al., 2019). Those who are connected do not necessarily have access to reliable and affordable electricity. Furthermore, in 2019, around 900 million people lacked access to clean cooking facilities (Africa Energy Outlook, 2019). The statistics from World Energy Outlook (2018) indicate that the SSA region has the greatest concentrated levels of energy poverty.

The concept of energy poverty in developing countries refers to the problem of inadequate access to modern types of energy such as electricity and Liquefied Petroleum Gas (LPG). Energy poverty is defined as "the absence of sufficient choice in accessing adequate, affordable, reliable, high-quality, safe, and environmentally friendly energy services to support economic and human development" (Reddy, 2000).

The development of tools to measure and monitor the evolution of energy poverty is widely discussed in the literature. The most popular method for measuring energy poverty in developing countries remains the multidimensional energy poverty index (MEPI). This approach for measuring energy poverty has several advantages including the property of monotonicity as well as the property of additive decomposability by population subgroup and by dimension. However, the assignment of weights while calculating the MEPI is somewhat controversial and based on the arbitrary and value-driven process.

Furthermore, as it stands, the calculation of the MEPI requires detailed information on the energy end-use technologies at household level that might often not be available according to the country analysed.

In Côte d'Ivoire, according to the statistics of the National Authority for Regulation in Electricity Sector (in French, Autorité Nationale de Régulation du secteur de l'Electricité en Côte d'Ivoire, ANARE-CI), 82 percent of the localities are covered by the electricity grid in 2022. However, these localities represent 95 percent of the whole population. In addition, only 67 percent of households had access to electricity at the same period. Furthermore, according to the National Statistics Office, in 2021 only 38 percent of the households use LPG as the main source of energy for cooking. This situation contrasts with all the programs implemented to make energy accessible and affordable to households and thus, reduce energy poverty. These programs include subventions of LPG for domestic use since 1993, subventions for households to make the connexion fees affordable, as well as the national rural electrification program.

In terms of electrification and access to electricity, the government has assiduously implemented two flagship initiatives, the National Rural Electrification Program (Programme National Electrification Rurale, PRONER) and the Electricity for all Programme (Programme Électricité Pour Tous, PEPT). The promotion of LPG use by the government started in 1993. The objective of this butanization policy was to improve households' access to modern cooking services. It also aimed at gradually replacing firewood and charcoal with LPG. Although these initiatives have yielded some results, much remains to be done to improve households' wellbeing. Why does the energy poverty have not declined consequently? What are the factors driving the energy poverty?

The paper aims at analysing the determinants of the energy poverty in Côte d'Ivoire. For this purpose, two energy poverty indices are computed, and their performances have been compared.

Based on the best performing energy poverty index, a probit model with endogenous binary covariate is estimated using the data from the LSMS-2015 of Côte d'Ivoire to analyse the determinants of the energy poverty. The estimates show that the energy poverty rate is 74.89 percent and that they are significant differences across regions and between urban and rural areas. As determinant, it has been found that being poor increases by 0.1305 point the probability of energy poverty. Furthermore, the education level of the household's head, female household's head, head of household living in couple and the household size are negatively associated with energy poverty while. A U-shaped relationship has been found between the age of household's head and energy poverty. This paper contributes to the literature by providing a guidance for the choice of a methodology for constructing energy poverty index based on a comparison between two approaches commonly used. Furthermore, this paper provides an analysis that disentangles the role of income poverty in energy poverty. By this way, the estimates for the determinants of the energy poverty are not biased by endogeneity or omission issues.

The rest of the paper is organized as follows. Section 2 reviews the literature on energy poverty measurement and its determinants. Section 3 describes the empirical strategies and the data, while Section 4 presents the results. Section 5 concludes and provides the policy recommendations.

2. Literature review

The use of deprivation analysis to capture poverty has been popularized in line with the Sen's theory of capability. This theory focuses on the level of quality-of-life individuals are able to achieve according to the real freedom they have. Indeed, energy poverty defined as the lack of access to modern type of energy, can be linked to their resource's endowments and to the opportunities they face for achieving good life experience. The analysis of energy poverty and how to alleviate it widely depend on the environment in which energy good are provided since energy poverty is a multidimensional phenomenon. Then, household could be deprived for some dimensions, i.e., use unsafe energy due to the lack of market for the safe energy that can limit their capacity to access it.

There is a wide literature on the measurement of energy poverty since it is a multidimensional phenomenon. In fact, energy use covers energy for lighting and cooking (Foster et al. 2000), for transportation (Mirza and Szirmai, 2010), as well as for services use (Nussbaumer et al., 2012), including communication, entertainment, education. Furthermore, the energy used by a household has multiple sources usually classified in modern versus pollutant sources and including electricity, solar home systems (Diallo and Moussa, 2020), LPG, and primary energy sources among others. Thus, measuring energy poverty implies dealing with the access and use of energy (quantity consumed) or the capability to use energy service or both.

Table 1 summarise the literature on the construction of energy poverty indices per region, including sub-Saharan Africa, India, and other countries of the World. Several approaches have been developed for measuring energy poverty at household level as well as at region or state level. These approaches can be grouped into two categories: (i) approaches based on energy consumption, and (ii) approaches based on deprivation.

The approaches based on the energy consumption level can be implemented where data are collected on household's energy consumption from various sources and for various uses. These approaches use the conceptual framework for the computation of income poverty, especially consumption expenditures-based poverty. They consist in aggregating the household's energy consumption and to defining a threshold that is computed as the basic energy needs. Thus, energy poverty occurs if the energy consumption level for a household that does not meet the basic needs.

Foster et al. (2000) apply this approach to Guatemala's data and use a Foster, Greer, and Thorbecke type index to analyse the incidence, intensity and severity of the energy poverty. In their paper, energy for lighting and cooking has been considered. However, their application does not account for the variation in energy needs according to several aspects of welfare as well as the efficiency in energy use. To overcome these limitations, Pachauri (2002) compute a basic needs level that varies according to the power requirement of energy services and adjust the energy consumption for economy of scale at household level. Khandker et al. (2012) compute an end-use energy consumption that is the energy consumption adjusted for appliances, technologies, and mode of use. In the same vein, Ramji et al. (2012) define the level of basic needs according to the income level arguing that the basic needs vary across income groups. In addition to the energy shortfall, Mirza and Szirmai (2010) include an index for energy inconvenience in the measure of energy poverty.

Several examples of computation of the threshold (basic energy needs) have been done in the literature. Bravo et al. (1979) measured energy poverty in terms of physical energy amount and identified 27.4 kilograms of oil equivalent (kgoe) per household per month as the minimum amount. Goldemberg (1990) defined 32.1 kgoe per household per month as the minimum amount, while Modi et al. (2005) computed 50 kgoe per household per month for cooking and lighting as energy poverty line. Foster et al. (2000) estimated a minimum level of energy for rural and urban households. They estimated the minimum amount for rural households to comprise two bulbs, five hours service for radio use while for urban areas with additional appliances such as television and refrigerator use, the minimum energy level is estimated to be 50 kgoe. All these works used the minimum amount of energy for estimation of energy poverty line in terms of physical amount without considering economic aspects.

The second set of approaches build on deprivation instead of energy consumption level. These approaches have been widely used since the seminal work by Nussbaumer et al., (2012) due to their low data requirement, their simplicity of implementation and analysis. These approaches do not need data on energy consumption level per household. They use the framework of the multidimensional poverty index (MPI) developed by the Oxford Poverty and Human Development Initiative (OPHI). They consist in aggregating deprivation indicators for various energy services. The discussions on these approaches are on the weighting set.

The weights are usually set based on a budget allocation approach. It consists in fixing the set of weights “arbitrary” based on the importance of each indicator according to the researcher’s view. One approach is to set the same weight per dimension and within each dimension, the weights per indicator are the same. This approach has been used in the seminal work by Nussbaumer et al. (2012) and in recent developments by Acharya and Sadath (2019) and Sadath and Acharya (2017). Another approach consists in setting different weights per dimension as well as per indicator within each dimension to account for the difference of effects of each indicator on energy poverty (Adusah-Poku and Takeuchi, 2019; Crentsil et al., 2019; Mendoza et al., 2019; Ogwumike and Ozughalu, 2015; Ozughalu and Ogwumike, 2018). The weights can be set according to a more scientific approach (Gupta et al. 2020). In such a framework, a principal component analysis (PCA) is used to compute the weight. This approach is used to contextualise the weighting set.

Although it exists a large literature on energy poverty, this literature mainly focuses on the methodology to construct an energy poverty index and to establish a diagnostic of the state of energy poverty. Very few papers investigate the determinant of the energy poverty, and especially in sub-Saharan Africa context. Edoumiekumo et al. (2013) and Ogwumike and Ozughalu, (2015) investigate respectively the determinants of energy poverty, extreme energy poverty, and both energy poverty and extreme energy poverty in the Nigerian context.

Both energy poverty and extreme energy poverty vary across region and between urban and rural areas (Ren et al., 2024; Rizal et al., 2024; Qurat-ul-Ann and Mirza, 2021).

Household's head education level is negatively associated with both energy poverty and extreme energy poverty while the opposite effect is observed for age and gender (being female) of the household's head. However, household's size is negatively associated with extreme energy poverty (Manasi and Mukhopadhyay, 2024) and positively associated to energy poverty while Edoumiekumo et al. (2013) find no significant effect of household's size.

Other determinants of energy poverty include remittance received (Qurat-ul-Ann and Mirza, 2021) or income in general (Ren et al., 2024), house ownership and house condition (Qurat-ul-Ann and Mirza, 2021), household head's health condition and employment status (Manasi and Mukhopadhyay, 2024; Rizal et al., 2024).

Table 1: Summary of the literature

Study	Area and Period of Analysis	Methodology	Definition of Energy Poverty/Indicators Used
For sub-Saharan African countries			
Ogwumike and Ozughalu, (2015)	Nigeria, Nigeria living standard measurement survey, 2014	MEPI is constructed as well as the incidence of energy poverty. The determinants of energy poverty are analysed.	Three (3) indicators are used: Access to modern energy source for cooking, indoor air pollution (causing indoor pollution), access to mains electricity and/or electricity from generator
Olang et al. (2018)	Kenya, data collected from 204 households in Kisumu City.	MEPI is constructed as well as the incidence of energy poverty.	Use of same indicators as Nussbaumer et al. (2012)
Ozughalu and Ogwumike (2018)	Nigeria, Harmonized Nigerian Living Standard Measurement Survey, 2010.	MEPI is constructed as well as the incidence of energy poverty. The determinants of extreme energy poverty are analysed.	Six (6) indicators of deprivation in basic energy services are used : Access to modern energy source for cooking, indoor air pollution (causing indoor pollution), access to mains electricity and/or electricity from generator, ownership of appliances (fridge/refrigerator), Ownership of entertainment/education appliance (radio/television), Having means of communication (mobile phone or a land line phone)
Adusah-Poku and Takeuchi (2019)	Ghana, Ghana Living Standards Surveys Rounds 5 and 6.	MEPI is constructed as well as the incidence and the intensity of energy poverty.	Use of same indicators as Nussbaumer et al. (2012)

Study	Area and Period of Analysis	Methodology	Definition of Energy Poverty/Indicators Used
Crentsil et al. (2019)	Ghana, repeated cross-sectional data between 2008 and 2014.	MEPI is constructed as well as the incidence and the intensity of energy poverty.	Use of same indicators as Nussbaumer et al. (2012). The indoor air pollution is captured by cooking with biomass fuel in an enclosed area.
Bekele et al., (2015)	Ethiopia, using a cross sectional primary dataset of 466 households in 2012-13 in Addis Ababa.	MEPI is constructed as well as the incidence and the intensity of energy poverty.	Five (5) indicators are used: fuel used for cooking, indoor air pollution (by type of stove used for cooking), access to electricity, ownership of any energy appliance for cooking, baking, heating, washing, entertainment, education, etc. and use of these energy appliances.
Nussbaumer et al. (2012)	African countries with Demographic Health Survey data available between 1997 and 2009.	MEPI is constructed as well as the incidence and the intensity of energy poverty.	Six (6) indicators are used: modern cooking fuel, indoor air pollution, electricity access, household appliance ownership such as refrigerator, entertainment appliance ownership like TV or radio and telecommunication means like mobile phone.
Edoumiekumo et al. (2013)	South of Nigeria using the Nigerian Living Standard Measurement Survey 2010.	MEPI is constructed as well as the incidence of energy poverty The determinants of energy poverty are analysed.	Three (3) indicators are used: access to modern cooking fuel, indoor pollution, and access to electricity.

Table 1: Summary of the literature (continued)

Study	Area and Period of Analysis	Methodology	Definition of Energy Poverty/Indicators Used
India			
Gupta et al. (2020)	India, National Sample Survey Organisation (NSSO) 2011	Household Energy Poverty Index (HEPI) is constructed using a principal component analysis (PCA)	Combines indicators of deprivation (in radio, TV, PC, fan, cooler, washing machine, phone, safe cooking fuel, and lighting), of use (per capita LPG consumption, per capita electricity consumption), of affordability (household's monthly expenditure per capita), and accessibility conditions (elevation, and living in forest area).
Pachauri, 2002)	India, Indian household survey data for 1983–2000.	A regression method for comparing the basic energy needs per household in different segment with the real use.	Energy poverty is when the household does not consume a quantity of energy that meets its basic needs after controlling for Economic variables (total household expenditure, equipment available), Demographic variables (Rural/urban location and household size), Dwelling attributes (covered area of dwelling, dwelling type, and construction type)
Khandker et al. (2009)	India, India Human Development Survey, 2005	Headcount energy poverty measure. End-use energy below an energy poverty line. Comparison between energy poverty and income poverty.	The energy poverty line is the level of energy consumption required to sustain welfare. End-use energy is the total amount of energy used adjusted for the efficiency of the appliance, technology, and mode of use.

Study	Area and Period of Analysis	Methodology	Definition of Energy Poverty/Indicators Used
Ramji et al. (2012)	India, using the 55th, 61st and 66th round of the National Sample Survey Organisation.	Comparing energy consumption per source to a poverty line.	Energy consumption that does not meet basic pattern after controlling for income level. Energy consumption includes firewood, electricity, kerosene, and LPG.
Jain et al., (2015)	India, Access to Clean Cooking Energy and Electricity – Survey of States (ACCESS), 2015	State level energy poverty index constructed as an average of access rate to energy for various tiers. One index for electricity and another for cooking energy.	Consider electricity access and cooking energy access from various tiers. Tiers are constructed based on six dimensions: capacity, duration, reliability, quality, affordability, and legality for electricity and on five dimensions: health and safety, availability, quality, affordability, and convenience for cooking energy.
Sadath and Acharya, (2017)	India, using Human Development Survey (2011–12)	MEPI is constructed as well as the incidence and the intensity of energy poverty.	Three (3) dimensions used with a total of height (8) indicators: access to electricity, access to LPG, type of stove, use of firewood, dung, crop residue, kerosene, charcoal or coal for cooking or lighting purposes.
Acharya and Sadath, (2019)	India, using Human Development Survey (2004–05 and 2011-12)	MEPI is constructed as well as the incidence and the intensity of energy poverty. Comparison of MEPI over time to assess improvements.	Use of the same indicators as previous study Sadath and Acharya (2017).

Table 1: Summary of the literature (continued)

Study	Area and Period of Analysis	Methodology	Definition of Energy Poverty/Indicators Used
Nayan Yadava and Sinha (2019)	India, 29 Forest Fringe villages of Madhya Pradesh, survey conducted with 325 respondents,	Energy Access Index (EAI) following a budget allocation method for weighting.	Ten (10) indicators are used: access to electricity, mechanical power, means of transport, household fuel, frequency of buying or selling fuel per week, distance travelled for fuel collection, household members' involvement in fuel collection, time spent in fuel collection per week, impact on health of women due to fuel collection, involvement of children in the same.
Others countries around the world			
Foster et al. (2000)	Gautemala; uses Encuesta Nacional de Ingresos y Gastos Familiares 1998/99	Foster, Greer, and Thorbecke type index	If energy consumption (for lighting and cooking) does not meet basic energy needs, then the household is poor. Various sources are considered: batteries, candles, electricity, fuelwood, kerosene, and butane gas are considered for the study.

Study	Area and Period of Analysis	Methodology	Definition of Energy Poverty/Indicators Used
Mirza and Szirmai, (2010)	Pakistan, Energy Poverty Survey 2008-09	Composite index constructed as a simple average of standardized (using min/max approach) selected indicators. Energy shortfall index Energy poverty index	Seven (7) indicators are used to construct an energy inconvenience index: frequency of buying and collecting a source of energy, distance travelled from household, means of transport used, household member's involvement in energy acquisition, time spent on energy collection per week, household health, children's involvement in energy collection. Energy shortfall index computed as the gap between energy use and basic energy requirement. Energy poverty index is computed as a simple average of energy inconvenience excess and energy shortfall; a negative value indicates energy poverty.
Mendoza et al. (2019)	Philippines, 17 regions and 81 provinces, data from 2011 to 2016	MEPI is constructed as well as the incidence and the intensity of energy poverty.	Seven (7) indicators of energy deprivation are considered including those used by Nussbaumer et al. (2012) and indicator for deprivation in space cooling appliances and ownership of personal computer.

Source: Authors compilation based on the literature reviewed for this study.

3. Empirical strategies

The aim of this paper is twofold: (i) to estimate the energy poverty index according to the most used approaches in the literature and to provide empirical comparison of these approaches, and (ii) to investigate the determinants of the energy poverty in Côte d'Ivoire.

2.1. Construction of the energy poverty indices

The two approaches compared herein are (i) the multidimensional energy poverty index (MEPI) and (ii) the energy poverty index based on principal component analysis (PEPI). Both the MEPI and PEPI use the same indicators of deprivation, only the weights for each indicator are different. Thus, even if the values of these indexes will differ, they are expected to be correlated.

Let $D_k, k = 1,..,K$ denotes the deprivation indicator (binary outcome taking the value 1 if household is deprived for the k^th^ indicator. The energy poverty index is given by:

$$EP_i = \sum_{k=1}^{K} \omega_k D_{ik} \quad (1)$$

Where ω_k denotes the weight for the k^{th} indicator and D_{ik} the deprivation status for household i for the k^{th} indicator. Finally, EP_i can be both MEPI and PEPI.

The MEPI introduced by Nussbaumer et al. (2012) builds on the methodology of the multiple poverty index developed by the Oxford Poverty and Human Development (OPHI). This approach consists in setting a fixed set of weights to each indicator of deprivation for computing a deprivation score. The set of weights can be symmetrical (Acharya and Sadath, 2019; Sadath and Acharya, 2017) per dimension or asymmetrical (Adusah-Poku and Takeuchi, 2019; Crentsil et al., 2019; Mendoza et al., 2019; Ogwumike and Ozughalu, 2015; Ozughalu and Ogwumike, 2018). Setting the weights symmetrical implies that all the dimensions are considered having the same importance. Contrarily, setting the weights asymmetrical allows to put emphasis on some dimensions that has a larger contribution to energy poverty.

The PEPI approach uses a principal component analysis (PCA) on the indicators of deprivation. PCA has been widely used for index construction in the literature (Nardo et al., 2005), including for constructing an household energy poverty index (Gupta et al., 2020). It consists in a spectral analysis of the correlation matrix. Let $u = (\alpha_1, \dots, \alpha_K)$ denotes the eigenvector associated to the higher eigenvalue of the correlation matrix, and p_k denotes the deprivation rate for the kth indicator. Thus, the weight of the indicator k is given by:

$$\omega_k = \frac{\frac{\alpha_k}{\sqrt{p_k(1-p_k)}}}{\sum_{j=1}^{K} \frac{\alpha_j}{\sqrt{p_j(1-p_j)}}} \quad (2)$$

Using PCA for constructing index allows to set the weights more scientifically (Gupta et al., 2020). However, this approach suffers for some limitations. The weight for each indicator depends on the deprivation rate for this dimension and how the indicator is correlated with the other indicators. The higher the deprivation rate for an indicator, the higher the weight for this indicator; and the lower an indicator correlates with the others, the lower the weight for this indicator. This is an important limitation for comparison purposes in both spatial and temporal schemes: the computed PEPI for two different periods are not comparable and the same applies for the computed PEPI for two different areas. Using the PEPI approach helps contextualizing the weighting set by allowing the weights to reflect the local importance of each indicator since the deprivation rates and the correlations between indicators are specifics to countries and periods.

2.2. Analysis of the determinants of energy poverty

While higher standards of living – measured in this paper by a level of consumption expenditure above the national threshold – can lead to an increased usage of modern energy goods, increased usage of modern energy goods can also contribute to a higher level of income and standard of living. A household's income, ceteris paribus, would depend on the health of its members (healthy members being more productive than the unhealthy members), and the health of its members would clearly be influenced by the extent to which it has access to non-hazardous modern energy goods (Behm et al., 1980; Benzeval et al., 2000; Deaton, 1999). Ill health may also, of course, deplete family savings or lead to family indebtedness through illness related expenditure. Thus, monetary poverty is endogenous while estimating the determinants of energy poverty. Furthermore, the literature highlights a bidirectional relationship between energy poverty and monetary poverty (Saxena and Bhattacharya, 2018). Therefore, to investigate the determinants of the energy poverty, a probit model with endogenous binary covariate is used. This model is estimated using a full information maximum likelihood approach that is unbiased and asymptotically efficient. As for robustness check, an instrumental variables probit model is estimated. The latter is a limited information approach that provides unbiased estimations but not asymptotically efficient. We also provide estimation from a standard probit model that is likely to be biased when there is an endogenous explanatory variable. Furthermore, we conduct an exogeneity test to ascertain our approach.

To ascertain this idea, we analyse the linkage between energy poverty and monetary poverty by conducting a balanced group test. Then, differences in deprivation score and energy poverty rate between poor and non-poor have been further investigated using an Oaxaca-Blinder decomposition method to identify the part of the difference in deprivation score due to characteristics differences between the two groups.

Since our outcome is binary, we used the Oaxaca-Blinder decomposition models for binary outcomes proposed by Yun (2004) and Fairlie (2005).

For the analysis of the determinants of energy poverty, removing the simultaneity bias requires instruments for consumption expenditure – exogenous variables that are correlated with consumption expenditure but are not otherwise associated with energy goods usage. In this paper, the ownership of a car is seen to satisfy the requirements for use as instrumental variables. This variable is correlated with consumption expenditure but is not directly associated with the use of electricity or LPG access. The use of cars is generally associated with higher income and hence income poverty (Besley and Burgess, 2000). Car ownership is associated with participating in more activities and increased employment opportunity, and consequently it results in an increase in household income (Klein, 2024).r However, there are no strong reasons to believe that electricity or LPG usage lead to higher ownership of cars. Ownership of cars is therefore used as instruments for income poverty, and consistent estimation can be obtained by using instrumental variable (IV) estimation method.

3. Data and related statistics

This paper uses data from the Living Standard Measurement Survey (LSMS) of Côte d'Ivoire conducted in 2015 by the National Statistics Office. The LSMS is a nationally and regionally representative survey that covered a sample of 12,899 households and 47,635 individuals. The survey collected information of household characteristics and living condition, especially on devices for energy use. Table 7 in appendix provides some statistics on the socioeconomics characteristics of the households surveyed. The correlation matrix in Table 8 in appendix shows that the indicator of deprivation for radio has the lower correlation with other indicators (at most 0.2).

Table 2 provides statistics on deprivation by indicator and dimension. Households experience high deprivations for almost all the dimensions considered in this analysis. Except for the lighting and mobile phone indicators for which the deprivation rates are 37.42 percent and 20.34 percent respectively, the deprivation rates for all the indicators are higher than 60 percent.

Table 2: Deprivation rates per indicator and energy poverty

Dimension	Indicators	Proportion	Standard error	Min	Max
Light	Lighting	0.3742	0.0059	0	1
Cook	Cooking	0.8089	0.0058	0	1
Communication	Computer	0.9583	0.0028	0	1
	Mobile phone	0.2034	0.0047	0	1
Education	TV	0.5966	0.0065	0	1
	Radio	0.6596	0.0060	0	1
Services	Fan	0.6576	0.0064	0	1
	Refrigerator	0.8825	0.0049	0	1

Source: Authors' calculation using data from the LSMS 2015

4. Estimation results

4.1. Weights and distribution of energy poverty indexes

The computed weights for PEPI and the weights set for MEPI are presented in Table 3 below. The weights are assumed symmetrical for each dimension in the MEPI approach. The weights computed with the PEPI methodology for the lighting, cooking, mobile phone, and radio are lower than that set for the MEPI approach. As described in the methodology section, the indicators of deprivation for computer and refrigerator have the highest weights from the PEPI method (0.1877 and 0.1658 respectively) due to the high deprivation observed. Also, the indicators with lower deprivation rates (lighting and mobile phone) as well as the indicator with lower correlation with others (radio) have the lowest weights (0.1154, 0.0879, and 0.0356 respectively).

Table 3: Weighting sets by approach

Dimension	Indicators	Weight MEPI	Weight PEPI
Light	Lighting	0.2	0.1154
Cook	Cooking	0.2	0.1277
Communication	Computer	0.1	0.1877
	Mobile phone	0.1	0.0879
Education	TV	0.1	0.1358
	Radio	0.1	0.0356
Services	Fan	0.1	0.1442
	Refrigerator	0.1	0.1658

Source: Authors' calculation using data from the LSMS 2015

Even there are differences in the weighting sets, the computed MEPI and PEPI are highly correlated as excepted. The computed correlations with the parametric Pearson coefficient and the non-parametric Spearman and Kendall coefficients are presented Table 9 in appendix. The correlation varies between 0.9548 and 0.9904 according to the method used. However, the analysis of the distribution of MEPI and PEPI points out some differences. Figure 2 in appendix plots the cumulative distribution functions for both MEPI and PEPI while Table 10 the displays the concordance rates between MEPI and PEPI per interval. It appears that there is a stochastic dominance of the MEPI distribution on the PEPI's one for scores varying between 0.4 and 0.8, justifying the rejection of the hypothesis of equal distribution by the Kolmogorov-Smirnov test.

4.2. Overview of energy poverty state

The Figure 1 below plots the energy poverty rates with 95 percent confidence interval computed for both MEPI and PEPI according to several. The estimates show that the differences between the poverty rates are lower than 5 percentage points when the selected threshold is up to 0.6. However, when the threshold is above 0.6, the poverty rates computed from MEPI is lower than that computed with PEPI by 12 to 17.3 percentage points. This result implies that the analysis of energy poverty status is quite similar with both MEPI and PEPI. Contrarily, when analysing the extreme energy poverty, the PEPI is likely to exacerbate the phenomenon.

The analysis of the poverty rate with 0.5 as threshold shows that 74.89 percent of population are poor (75.45 percent if the PEPI is used). Table 11 in appendix shows that the misclassification rates while using the two approaches is 1.56 percent. That is 1.06 percent of the population are classified as poor using the PEPI approach and non-poor using the MEPI while 0.5 percent of the population are classified as non-poor using PEPI and poor using MEPI.

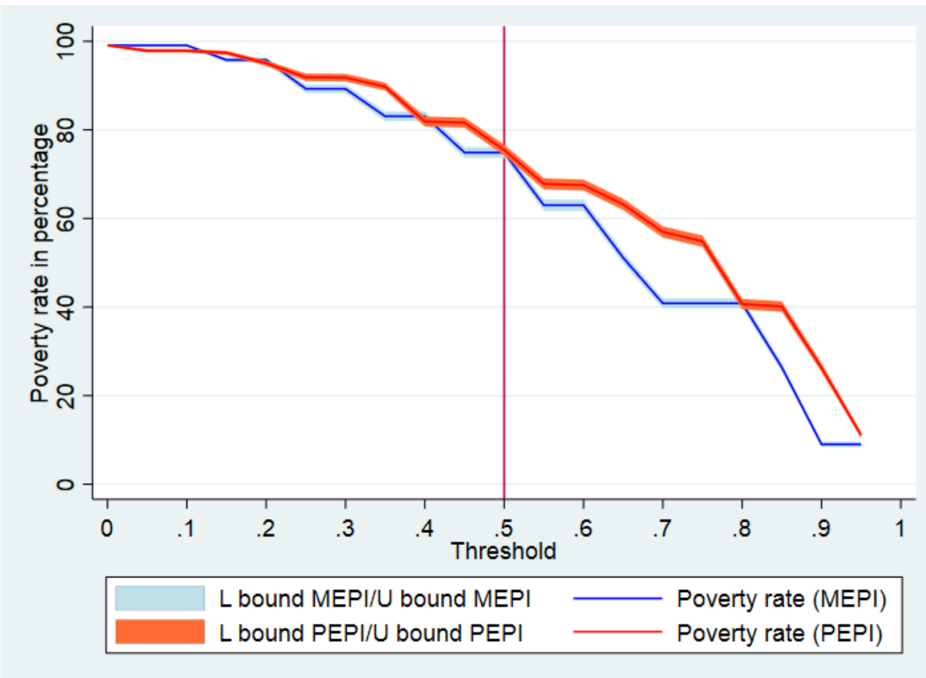

Figure 1: Poverty rates by threshold level

Source: Authors' calculation using data from the LSMS 2015
Note: 95% confidence intervals are used. The red line indicates the selected threshold.

To allow for comparison, the rest of the analysis focuses on the energy poverty measured according to the MEPI approach. Table 4 provides the mean comparison tests for the energy poverty indicators among income poor and non-poor. The energy poverty rate and the intensity of the energy poverty for income poor are higher by at least 20 percentage points. The average deprivation score is 0.6324 and the difference in deprivation score between poor and non-poor is 0.1578. The average energy poverty rate is 74.89 percent and is 22.98 percentage points higher for poor than non-poor.

Table 4: Mean or proportion comparison test of energy poverty between income poor and non-poor

Variables	Overall sample	Income poor (A)	Income non poor (B)	Difference (A) – (B)
Number of deprivations	5.1411 (0.0270)	5.7671 (0.0368)	4.6006 (0.0363)	1.1665*** (0.0517)
Deprivation score (MEPI)	0.6324 (0.0035)	0.7171 (0.0048)	0.5593 (0.0047)	0.1578*** (0.0067)
Energy poverty rate (MEPI)	0.7489 (0.0061)	0.8723 (0.0081)	0.6424 (0.0085)	0.2298*** (0.0117)
Intensity of energy poverty (MEPI)	0.5648 (0.0048)	0.6757 (0.0068)	0.4691 (0.0063)	0.2066*** (0.0093)

Source: Authors' calculation using data from the LSMS 2015
Note: standard errors are in parenthesis. *** denotes significance at 1 percent level

The significant differences in deprivation score and energy poverty rate between poor and non-poor have been further investigated using an Oaxaca-Blinder decomposition method to identify the part of the difference in deprivation score due to characteristics differences between the two groups. Table 5 below presents the results of the Oaxaca-Blinder decomposition. It appears that when controlling the three groups of variables namely household's characteristics, household's head demographics characteristics, and household's location, a difference of 0.0595 in deprivation score (i.e., one third of the total average difference) and 9.43 percent in energy poverty rate between poor and non-poor is due to the differences in their characteristics.

The results obtained while controlling for each group of variables separately reveal that the differences in household's location and in household's head demographics exacerbate the difference in energy poverty rate between poor and non-poor while the differences in household's characteristics reduce the difference in energy poverty rate between poor and non-poor. These results imply that 12.99 percentage points of the whole 22.98 percentage points of difference in energy poverty rate between non-poor and poor is due to the location of poor households in unfavourited areas, i.e. this difference belongs to accessibility issues. Furthermore, 6.49 percentage points of the difference in energy poverty rate between non-poor and poor is due to poor household's head being less educated, older, female or not living in couple. Contrarily, poor households having less children, high size and lower share of expenditures devoted to food reduce by 4.51 percentage points the gap in energy poverty rate between them and non-poor households.

Table 5 : Oaxaca-Blinder decomposition of income poverty effects on deprivation score and energy poverty

	model 1	model 2	model 3	model 4
Income poverty effects on deprivation score	-0.0442*** (0.0037)	0.0311*** (0.0073)	-0.0871*** (0.0053)	-0.0595*** (0.0072)
Income poverty effects on energy poverty	-0.0649*** (0.0056)	0.0451*** (0.0116)	-0.1299*** (0.0067)	-0.0943*** (0.0113)
Control variables included				
Demographics of household's head+	Yes	No	No	Yes
Household's characteristics++	No	Yes	No	Yes
Household's location+++	No	No	Yes	Yes

Source: Authors' calculation using data from the LSMS 2015

Note: standard errors are in parenthesis. *** denotes significance at 1 percent level. + includes age, gender, education, and marital status of the household's head, ++ includes the number of workers in the household, the share of food expenditures in percentage of total expenditures, the household size, and the number of children under 18, +++ includes dummy for rural area and regional dummies.

4.3. Determinants of energy poverty

The results of the estimated probit model with endogenous binary covariate are presented Table 6 below. The estimated model is globally significant and the test for exogeneity confirms our instrument used. Both the coefficients and the marginal effects are reported. We find that income poverty has a positive effect on energy poverty. Being poor increases by 0.1305 point the probability of energy poverty for households. This result is in line with the Oaxaca-Blinder decomposition conducted in the previous section. After controlling for differences in characteristics between poor and non-poor, the income poverty for a household increases his probability of energy poverty. This result is mainly due to the lack of capability for poor households are unable to connect to the electricity grid and afford electric equipment.

The estimates highlight the important role played by the accessibility, proxied by a dummy for rural areas and some dummies for regions. Living in rural areas increases by 18.73 percentage points the probability of energy poverty. In fact, urban populations have easier access to infrastructure (for LPG and electricity) than those in rural areas. This results is consistent with Ogwumike and Ozughalu (2015), who found that residing in urban areas reduces the odds in favor of being energy poor in Nigeria. It implies that accessibility is the main issue to be addressed for an effective policy to combating energy poverty.

The estimates show a U-shaped relationship between the age of household's head and energy poverty, with a threshold at age 53. This result implies that for younger' household head, an increase in the age reduces the probability of energy poverty while for older, the probability of energy poverty increases with age. The education level of the household's head also plays an important role: each one-year increase in the education level reduces by 0.88 percentage point the probability of energy poverty. This result is expected since higher education levels are associated with higher income levels, and as high schools, colleges, and universities are in big cities, people settle in these cities after studying there. This situation increases their probability of access to electricity and LPG and therefore reduces their probability of energy poverty. Furthermore, living in couple reduces the probability of energy poverty by 6.74 percentage points. This result is consistent with the findings of Ismail and Khembo (2015) and can be explained by the fact that married couples and committed partners combine their incomes and share the expenses of the household, including energy expenditures. There is weak evidence that being headed by a female reduces the probability of energy poverty for a household. Except for the gender, the results find for the household's head characteristics are consistent with that of Ogwumike and Ozughalu (2015).

In terms of household's characteristics, no evidence of an effect of the number of children or the number of workers in the household on energy poverty has been found. However, a one-unit increase in household's size reduces by 1.16 percentage point the probability of income poverty. This result is not consistent with the findings of Ozughalu and Ogwumike (2018) on extreme energy poverty but not consistent with that of Ogwumike and Ozughalu (2015) for energy poverty. The share of food expenditure in total expenditures, used as a proxy of affordability, is positively associated with energy poverty. A one percentage point increase in the share of food expenditure in total expenditures increases the probability of energy poverty by 0.27 percentage point.

Table 6: Determinants of household's energy poverty

Explanatory variables	Main model		Robustness check	
	Coefficients	Marginal effects	Model 1	Model 2
Household's poverty status (income poor)	1.7966***	0.1305***	2.0427***	0.6622***
	(0.0723)	(0.0230)	(0.1136)	(0.0586)
Household's head age	-0.0253***	-0.0012***	-0.0224***	-0.0356***
	(0.0069)	(0.0003)	(0.0076)	(0.0091)
Square of household's head age	0.0002***	-	0.0002***	0.0003***
	(0.00007)		(0.0001)	(0.0001)
Household's head is female	-0.0890*	-0.0226*	-0.1041*	-0.0870
	(0.0511)	(0.0131)	(0.0564)	(0.0678)
Household's head living in couple	-0.2820***	-0.0674***	-0.3430***	-0.3885***
	(0.0516)	(0.0110)	(0.0563)	(0.0646)
Household's head year of education	-0.0350***	-0.0088***	-0.0113*	-0.0451***
	(0.0034)	(0.0008)	(0.0056)	(0.0041)

Number of workers	0.0094	0.0023	0.0245	0.0159
	(0.0162)	(0.0041)	(0.0194)	(0.0213)
Share of food expenditures in total expenditure	0.0107***	0.0027***	0.0134***	0.0146***
	(0.0011)	(0.0002)	(0.0012)	(0.0012)
Household's size	-0.0465***	-0.0116***	-0.0899***	-0.06***
	(0.0149)	(0.0037)	(0.0169)	(0.0193)
Number of children	0.0080	0.0020	0.0185	0.0068
	(0.0200)	(0.0050)	(0.0395)	(0.0259)
Living in rural area	0.6766***	0.1873***	0.5012***	0.8966***
	(0.0560)	(0.0120)	(0.0757)	(0.0529)
Intercept	-0.1694	-		
	(0.1656)			
Threshold for household's head age	52.5787***	-		
	(3.3765)			
Test for exogeneity statistics [p-value]	-3.21 [0.001]	-	55.80 [0.000]	-
Regional dummies included	YES	YES	YES	YES

Source: Authors' calculation using data from the LSMS 2015

Note: standard errors are in parenthesis. *** denotes significance at 1 percent level, * denotes significance at 10 percent level. Model 1 is an IV probit model, and Model 2 is the standard probit model

5. Concluding remarks

The aim of this paper is twofold: (i) comparing two approaches for the computation of an energy poverty index, and (ii) investigating the determinants of the energy poverty using data from the Living Standard Measurement Survey (LSMS) of Côte d'Ivoire in 2015. Energy poverty indices are constructed by aggregating a set of indicators for deprivation that are weighted according to the MEPI and PCA approaches. For investigating the determinants of energy poverty, a probit model with endogenous binary covariate approach has been used. It appears from the estimates that the two approaches result in a quite similar conclusion while dealing with energy poverty; however, the conclusions are different when analysing the extreme energy poverty. Furthermore, even if the PCA approach allocates scientifically weights that are contextualized, this approach lacks a comparability property. In terms of determinants of energy poverty, the estimates point out that income poverty is the main household characteristic that determines energy poverty since been poor increase by 0.1305 point the probability of energy poverty for a household. Energy poverty is negatively associated with education and household's size. The estimates also highlight the nonlinear effect of household's head age on energy poverty. For household's head aged 53 or more, the probability of energy poverty increases with age.

The results call for paying attention to the method used when addressing policy implementation issues. For temporal and spatial comparisons, the MEPI performs well. In addition, it does not exacerbate the situation of extreme energy poverty like for the PEPI.

In terms of policy recommendations, the results of the paper call for jointly designing of policies for alleviating income poverty and energy poverty. For alleviating the energy poverty, policies designed to combat income poverty should particularly address elderly situation.

Furthermore, rural areas, mainly remoted from the national energy distribution network, must be considered by some specific programs that aim at making others energy sources accessible and affordable.

Our study has two main limitations. On the one hand, the analysis could be improved when a panel data will be available. This could help investigating the dynamics of energy poverty and its determinants and helps improving the identification of the role of income poverty in energy poverty. On the other hand, since several policies are implemented to combat energy poverty, it is important to implement a clear impact evaluation strategy to assess how these efforts change the role of classical determinants on energy poverty.

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Appendices

Table 7: Summary statistics on the sample

Variables	Mean or proportion	Standard error	Min.	Max.
Household's head age	42.84	0.1671	12	120
Household's head is female	0.1874	0.0050	0	1
Living in couple	0.7982	0.0048	0	1
Household's head year of education	4.15	0.0745	0	18
Number of workers	1.69	0.0217	0	23
Share of food expenditures in total expenditure	0.4724	0.0027	0	0.9786
Number of children	2.40	0.0294	0	17
Household's size	5.14	0.0467	1	36
Living in rural area	0.4992	0.0064	0	1
Poor (income)	0.4634	0.0064	0	1
Owner of motorized transportation	0.1469	0.0044	0	1

Source: Authors' calculation using data from the LSMS 2015

Table 8: Correlation matrix

	Lighting	Cooking	Computer	Mobile phone	TV	Radio	Fan	Refrigerator
Lighting	1.0000							
Cooking	0.3232	1.0000						
Computer	0.1595	0.2996	1.0000					
Mobile phone	0.1957	0.1079	0.0994	1.0000				
TV	0.5620	0.3695	0.2169	0.3397	1.0000			
Radio	0.0317	0.0228	0.0405	0.2028	0.1743	1.0000		
Fan	0.5581	0.4368	0.2621	0.3097	0.7022	0.1241	1.0000	
Refrigerator	0.2778	0.3749	0.3783	0.1648	0.4162	0.0848	0.4576	1.0000

Source: Authors' calculation using data from the LSMS 2015

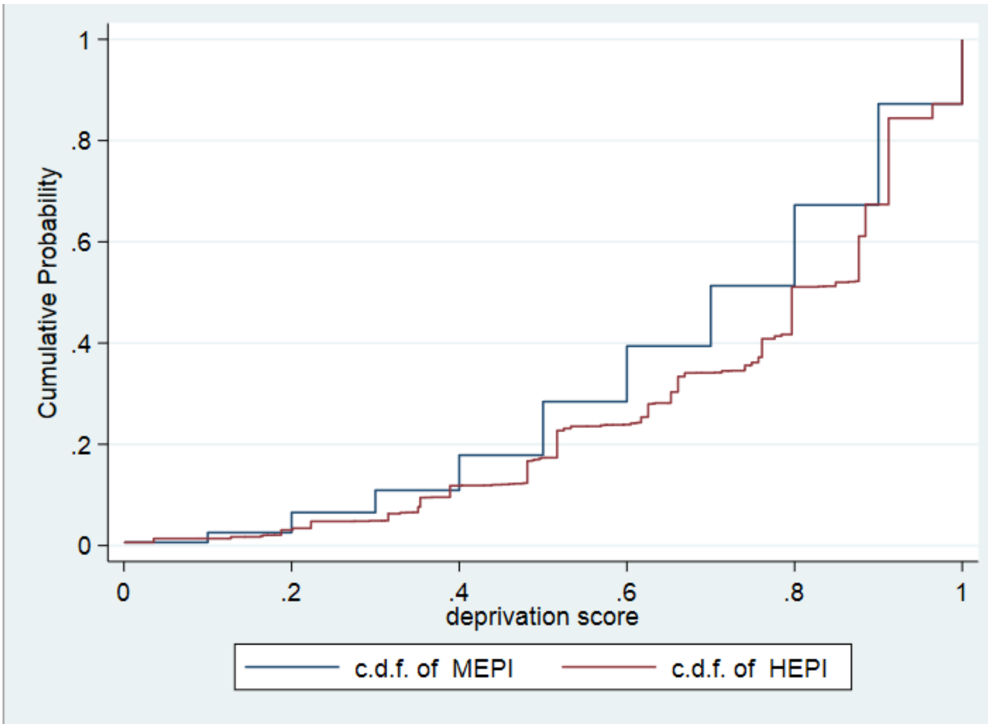

Figure 2 : Cumulative distribution function of MEPI and PEPI

Source: Authors' calculation using data from the LSMS 2015

Note: The application of a Kolmogorov-Smirnov test for equality of distribution functions allows to conclude that there is significant difference in the distribution functions (D statistics is equal to 0.1987 and the difference is significant at 0.1 percent level).

Table 9: Correlation between MEPI and PEPI

	Pearson correlation	Spearman correlation	Kendall correlation*
Correlation between MEPI and PEPI	0.9759	0.9904	0.9548

Source: Authors' calculation using data from the LSMS 2015

Note: * the reported Kendall's tau is adjusted for ties.

Table 10: Comparison of MEPI and PEPI per interval

	PEPI<0.2	0.2≤PEPI <0.4	0.4≤PEPI <0.6	0.6≤PEPI <0.8	PEPI≥0.8	Row total
MEPI <0.2	100					100
0.2≤MEPI <0.4	5.77	90.71	3.51			100
0.4≤MEPI <0.6		8.08	68.91	23.02		100
0.6≤MEPI <0.8			0.31	97.69	2.00	100
MEPI≥0.8				1.48	98.52	100

Source: Authors' calculation using data from the LSMS 2015

Note: It is worth noting that 91.46 percent of scores fall in the same interval.

Table 11: Differences in poverty rates by method

		Energy poverty (using PEPI)		
		Non poor	Poor	Total
Energy poverty (using MEPI)	Non poor	24.05	1.06	25.11
	Poor	0.50	74.39	74.89
	Total	24.55	75.45	100.00

Source: Authors' calculation using data from the LSMS 2015
Note: Poverty rates are computed using 0.5 as threshold.