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An Empirical Analysis of the Household Energy Situation in Benin

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Abstract: This study assesses household energy deprivation in urban and rural areas of Benin using the data of Demographic and Health Surveys (DHS) program for Benin in its latest version of 2018. As a methodology, the paper estimates the multidimensional Energy Poverty Index (IPEM) for rural and urban areas based on Alkire & Foster (2011). Findings from the paper reveal that 9.2 percent of households are energy poor while 69.6 percent are multidimensionally energy poor. While the estimated value of the IPEM is 0.064 at the national level, its value revolves around 0.586 and 0.414 at the urban and rural levels respectively. Poor energy access for rural populations can lead in the long term to excessive degradation of forest ecosystems and loss of environmentally friendly habitats, compounding the problem of climate change. The study reveals that consuming households are increasingly becoming energy producers. To mitigate these negative external effects for the environment, there is an urgent need to improve access to modern energy resources in rural areas. It urgent to strength the policy of introducing renewable energies, such as solar, wind and hydraulic energy, as well as promoting energy-efficient techniques and energy efficiency solutions adapted to the needs of rural populations.

Keywords*:* Energy poverty, household, composite index, energy deprivation, principal component analysis.

JEL Classification*:* C21, I32, Q49, C38

Introduction

A great share of individuals without energy in developing countries live in sub-Saharan Africa and Asia (International Energy Agency, 2017). The inability of a household to meet its energy need was termed energy poverty. Such an energy poverty has emerged as a major concern in those countries (Charlier & Legendre, 2019), as evidence suggests that energy-poor household are exposed to health deterioration (Betto & al., 2020; Delugas & Brau, 2019).

The low economic growth in Benin has fueled the growing number of households trapped in energy poverty. At the national level, only 43.1 % of households has access to electricity in 2019. The electricity consumption per capita is very low and is around 42kWh/in habitant/year (International Energy Agency, 2017; IEA & World Bank, 2019). Several households in urban areas still live in the darkness owing to their financial inability to afford electricity bills and connection fees. The energy sector is characterized by low energy consumption per capita, a predominance of traditional biomass and poor access of populations to modern energies. However, further investigation is needed to fully understand the energy poverty in Benin in a multidimensional way. Benin being a developing country in West Africa, and this study aims to unravel the challenges and opportunities related to household access to energy in an African context.

The paper aims to assess the level of household energy deprivation by considering both the urban and rural levels. The motivation of this research is to highlight the effect of energy poverty on the living conditions of households in Benin. The novelty of the paper lies in the use of Principal Component Analysis (PCA) to retain the indicators and the number of dimensions of the multidimensional Energy Poverty Index (IPEM).

The remainder of the paper is organized as follows. Section 1 presents the literature review. Section 2 addresses the theoretical and methodological approaches. The third section presents and discusses the main findings and the fourth section concludes the paper.

1. Literature review

Analytical approaches to measuring energy poverty can be broadly classified into two categories which are the energy affordability and the energy deprivation. The first refers to the monetary thresholds that define the maximum level of income or share of expenditure spent on energy that can be considered affordable by households. In 1991, Boardman provides a starting point to this approach, stating that energy poverty occurs when a household has to spend more than 10 % of its income on total energy consumption (Moore, 2012). Variations of this basic approach, known as "2M indicators: double mean or double median", count as energy poor individuals whose share of energy expenditure is greater than the double of the mean (or median). Other studies propose a composite indicator of low income and high costs, which considers that individuals are energy poor if they spend more than 60% of the median of the disposable income distribution, and if they fall below a given income poverty line (Hills, 2011, 2012) . Ultimately, affordability was observed in a minimum income norm framework that considers energy-poor people who do not have the minimum income required to meet basic needs after paying housing and energy costs (Moore, 2012). The residual income indicator (Miniaci & al., 2014), close to Moore, aims to understand how many (non-energy related) goods an individual can buy apart from energy. This approach has also been developed with several thresholds to improve its adaptability to a differentiated energy demand, such as the two-threshold accessibility measure of Faiella & al., (2017). In addition, Betto & al., (2020) proposed a new index based on the household energy expenditure threshold. This index measures the actual percentage of hidden energy poverty by focusing on the main characteristics of households. From a different perspective, the energy deprivation approach underscores the importance of considering the different dimensions of energy poverty, alongside the debate that characterizes the comparison between multidimensional approaches to measuring poverty and. unidimensional poverty based on income (Alkire & Foster, 2011; Atkinson, 2003; Chakravarty, 2003). The analysis focuses on how people are affected by living in energy efficient homes. In this regard, both material manifestations of energy poverty and subjective indicators of discomfort associated with living in substandard housing are considered. Several indices and indicators have been used in that regard. Thomson & Snell, (2013) perform cross-sectional and intra-country analyzes considering information often included in household surveys. A few studies have compared objective and subjective measures of energy poverty. This is particularly the case of Waddams Price & al., (2012), who point out the large differences that appear in the identification of the energy poor among British citizens when using information from self-report energy poverty instead of the 10 percent rule. They conclude that both sources of information should be used by policy makers to detect the actual occurrence of energy poverty in the economy. Similar remarks have been made by Lawson et al., (2015) in New Zealand, and by Papada & Kaliampakos, (2016) in Greece. Waddams Price & al., (2012), also highlight the need for a multidimensional objective and subjective indicator to give a more complete picture of the incidence of energy poverty.

The literature informs that the multidimensional deprivation approaches can be used to assess even the intensity of the energy poverty for the purpose of enriching the information on incidence typically provided by affordability measures. Recent contributions also show that this can also be done by combining affordability and energy deprivation approaches. Such approach was adopted by Nussbaumer (2012) & Nussbaumer et al., (2013). Both authors use the methodology proposed by Alkire & Foster, (2011) to develop a multidimensional energy poverty index (MEPI) focusing on the deprivations experienced by households from several African countries. Later applications are those of Nussbaumer & al., (2013) in developing countries and Okushima, (2017) in Japan. Another multidimensional index of energy poverty which considers subjective and objective measures has been proposed by Charlier &

Legendre, (2019) and Delugas & Brau, (2019). Both authors study the relationship between energy poverty and subjective well-being by combining objective and subjective indicators in a multidimensional energy poverty index, and showing how this information tool can be used in the econometric analysis.

2. Methodology

2.1. Model Specification

To construct the household multidimensional Energy Poverty Index (IPEM), we adopt the approach proposed by Alkire & Foster, (2011). Innspired by Amartya Sen's contribution to the discussion on deprivation and capacity, this approach fits well with the characteristics of African countries and particularly those of Benin, since it is based on the variables that measures household access to energy services. IPEM offers several advantages. First, the IPEM focuses on energy services and is based on data related to energy deprivations, as opposed to proxy data using variables such as energy or electricity consumption that can be correlated. Second, the IPEM capture both the incidence and the intensity of energy poverty.

Table 1 below provides information on all the dimensions and the indicators selected for each dimension used by Nussbaumer et al., (2013) to calculate the IPEM. These authors retain five (05) dimensions as shown by Table 1, each dimension being composed of indicators.

Table 1: Structure of the Multidimensional Energy Poverty Index

Dimensions	*Indicators*
Access to energy	Electricity
	Generator
Access to energy services (services provided by means of household appliances)	Fridge
	Washing machine
Access to leisure/Education	Music hi-fi system
	VCD/DVD player
	Television
Access to modern energies for cooking	Electricity
	Liquefied Petroleum Gas
(LPG)	
	Natural gas
	Biogas
	Petroleum
Communication access	Cellphone
	Radio
	Internet connection

Source: Adapted from Nussbaumer et al., (2013) These indicators include the use of electricity or a generator for access to light, the use of a refrigerator or a washing machine for access to services provided by means of household appliances, the use of Hi-Fi music, DVD/VCD player and television for access to leisure/education, the use of electricity, liquefied petroleum gas, natural gas, biogas and oil for access to modern energies for cooking and the use of cell phones, radios and internet connections for access to communication. We use a multidimensional approach that includes device-related indicators to capture end-use, i.e., deprivation-related elements that are typically excluded from the traditional energy access metrics. The integration of variables related to the ownership of devices also brings out the notion of affordability. Indeed, access to electricity, or to modern fuels, is of limited use if the potential users (the household) do not have the financial means to pay for the fuel or to invest in the appliance to provide the desired service. We therefore include variables related to the possession of a radio or television and a refrigerator. We also include an indicator for telecommunications. Recent trend has shown the crucial role of the use of telephones and mobile phones in particular for socio-economic development.

The IPEM captures the incidence and intensity of household energy poverty. It defines household deprivation (and access to energy services in the five (05) dimensions selected above. Once the dimensions of multidimensional poverty are identified, the IPEM (M_0) according to Alkire & Foster (2011) combines two main sub-indices that are the proportion of households that are in multidimensional energy poverty (denoted H, also called incidence of energy poverty) and the intensity of energy poverty, denoted A, given by the average of the deprivation indices.

$$c_i = \sum_{j=1}^{d} w_{ij} \tag{1}$$

where c_i is the sum of household i deprivation weight for each dimensions j (w_{ij}). Mathematically, we can write:

i) Incidence of Energy Poverty :

$$H = \frac{q}{n} \tag{2}$$

where q is the number of households identified as energy poor and n the total number of households.

ii) Intensity of Energy Poverty:

$$A = \sum_{i=1}^{n} c_i / q \tag{3}$$

iii) Multidimensional Energy Poverty Index

$$IPEM = M_o = H \times A = \frac{1}{n}\sum\nolimits_{i=1}^{n}\sum\nolimits_{j=1}^{d} w_{ij}(k) \tag{4}$$

where d is the number of dimensions retained and k the level of the chosen threshold.

To estimate the IPEM, we rely on the estimation method proposed by Nussbaumer & al., (2013). The multidimensional energy poverty line, k of ½ (= 0.5), is adopted in the context of this study with the intuition of the literature. A household is energy poor if it is deprived of more than 50% of the indicators. Therefore, a household whose sum of weighted deprivations is greater than or equal to 0.5 is classified as energy poor and the household whose sum of weighted deprivations is less than 0.5 is not energy poor. Energy poverty for households is qualified as intense if the IPEM is higher than 0.7, moderate if the IPEM is between 0.3 and 0.7 and very weak if the IPEM is lower than 0.3 (Nussbaumer & al., 2013). Weights are assigned with intuition from the literature as well. Here we assign weights fairly to the different dimensions and indicators, recognizing the arbitrary nature of such a process. Arguably, not all criteria considered in an index necessarily have the same relative or symmetric importance (in the jargon of the decision theory literature). However, theoretically sound frameworks for deriving rational weighting approaches are difficult to construct (Freudenberg, 2003). Assigning weights can be difficult though arbitrary. Some have suggested participatory methods for this purpose. However, consensus on the relative importance of various dimensions has not been reached, especially in the case of conflicting objectives.

That said, the process of including or excluding criteria, even without weights, is a value judgment on the relative importance of variables. Like any synthetic index, the IPEM is subject to criticisms addressed to the Human Development Index, which mainly revolve around the choice of indicators and their weightings (Freudenberg, 2003). Generally, we are often faced with correlated variables that we seek to introduce into the index. When variables are highly correlated, principal component analysis (PCA) is often used to reduce the dimension of these variables. This dimensionality reduction technique is also used to feed the model with only a relatively limited number of uncorrelated components.

The PCA consists in converting the initial inter-correlated variables into a smaller number of uncorrelated linear combinations of each other called "principal components" or "factor axes", minimizing the loss of information due to this reduction. mass data (Dunteman, 1989). It would therefore be strongly recommended in our multidimensional analysis of energy poverty, to want to reduce the complexity of the five dimensions retained by extracting the most important main components which will be aggregated thereafter to arrive at the IPEM. In more detail, a PCA is performed on the indicator correlation matrix to extract, according to a chosen extraction criterion, the principal components most representative of the initial data (Cho & al., 2010). Finally, the IPEM is calculated by aggregating the components selected according to their share of total data variability (Jemmali, 2013). However, three statistics can be calculated before starting the multivariate analysis: the determinant of the correlation matrix, the overall Kaiser-Meyer-Olkin sampling adequacy measure, and the Bartlett sphericity test statistic.

2.2. Data

We mainly use data from the 2017-2018 Demographic and Health Surveys' database (EDSB-V), designed to study social exclusion and monitor poverty in Benin. The sample size is of 74,673 households. We use this dataset because it is nationally representative and covers both rural and urban households. As a rich dataset, it contained relevant information on household energy poverty. In addition, the dataset contains information on variables used to assess multidimensional poverty in the literature. Therefore, the dataset is useful to construct an index based on objective dimensions.

3. Empirical results

3.1. Descriptive statistics of the selected indicators

Figure 1 shows the descriptive statistics for the indicators used in the calculation of the IPEM at the national, urban, and rural level.

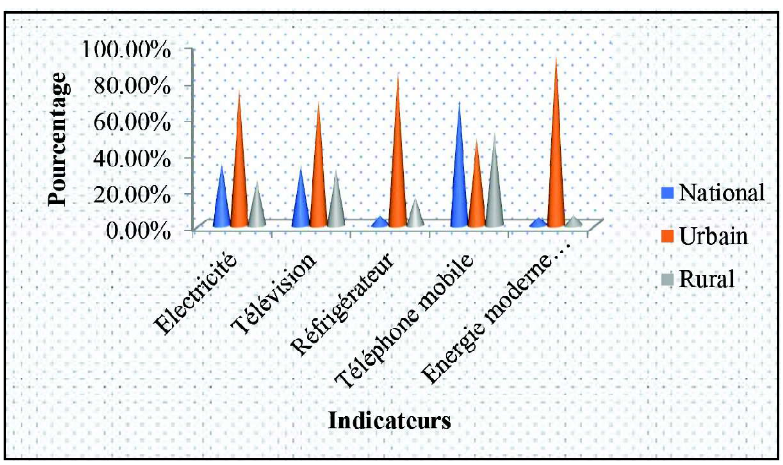


Figure 1: Access to IPEM indicators at national, urban, and rural level (EDSB-V, 2018)

Figure 1 shows that access to energy resources is more improved in urban than in rural areas. For instance, rural areas' electricity access rate revolves around 25.03%. This suggests a low use of household appliances in rural zones. A tiny share of households relies on modern energy sources for cooking. Figure 1 indicates 5.68% as the rate of access to modern cooking energy. These households benefit less from advantages provided by modern energy services, which lead to their energy poverty. This could contribute in the long term to an increase in greenhouse gas emissions, compounding the problem of climate change. Poor access for rural populations can lead to excessive deforestation and degradation of forest ecosystems in the long term. As a result, biomass energy production in rural settings will lead to the loss of environmentally friendly habitats and indoor air pollution affecting the well-being of rural households.

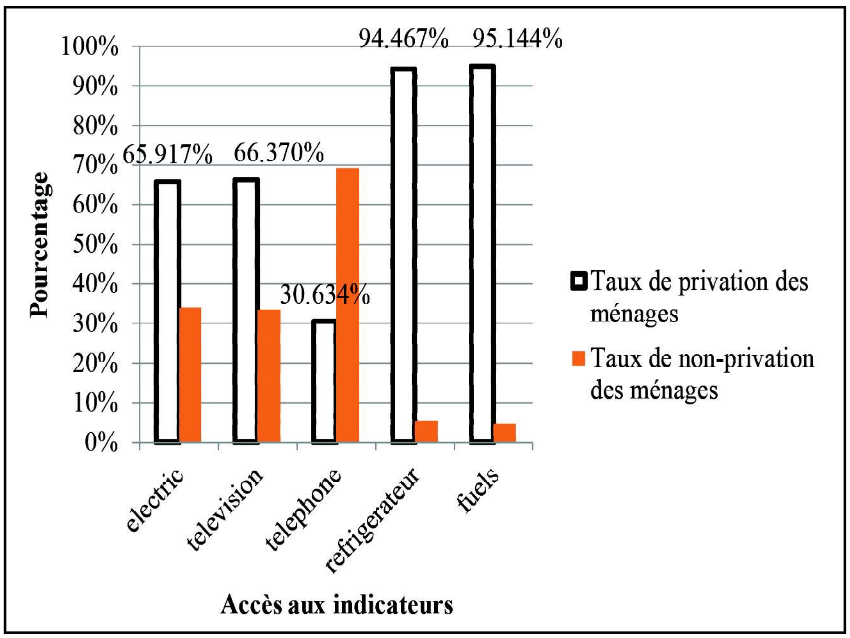


Figure 2: Household deprivation and non-deprivation rates by dimension of the IPEM (EDSB-V, 2018)

Figure 2 shows that Beninese households are more deprived of the services provided by household appliances (94.47%) and clean fuels for cooking (95.14%). According to the International Energy Agency, the average number of hours spent collecting fuel per day and per household in Benin is between 2 and 3 hours and more than 80% of the population uses traditional biomass (firewood and charcoal) for cooking (International Energy Agency, 2017). According to the report of the Integrated Regional

Survey on Employment and the Informal Sector, only 4.4% of the Beninese population has access to clean fuels for cooking (INSAE, 2018). This reveals the low household incomes and the increase in the price of domestic energy in housing in Benin. Thus, households will not be able to acquire energy-efficient equipment that guarantees energy efficiency in residences.

2.2. Results of Principal Component Analysis

Table 2 below presents the correlation matrix for the eleven indicators of the five dimensions selected. Analysis of this matrix reveals that none of the correlations is particularly significant in absolute value, with the exception of the value 0.7633 for the VCD/DVD player and television indicators. The results of the preliminary analysis of the factorability of the data show that the correlation matrix is far from being singular, otherwise the data could come from all independent variables and the multivariate analysis will therefore be of no use.

Table 2: Correlation matrix of the indicators of the dimensions of the IPEM

Matrice of correlation (n=74673)											
electricite |	1.0000										
groupelect~e |	0.061	1.000									
refrigerat~r |	0.291	0.178	1.000								
machineala~r |	0.029	0.088	0.120	1.000							
hifisytemu~c |	0.288	0.162	0.341	0.084	1.000						
lecteurvcd~d |	0.534	0.301	0.324	0.056	0.398	1.000					
television |	0.643	0.305	0.329	0.052	0.359	0.763	1.000				
ModEner |	0.253	0.088	0.403	0.111	0.268	0.258	0.263	1.000			
telephonpo~e |	0.211	0.099	0.084	0.014	0.092	0.188	0.219	0.069	1.000		
radio |	0.277	0.159	0.136	0.014	0.150	0.285	0.327	0.101	0.220	1.000	
connection~t |	0.244	0.099	0.290	0.137	0.260	0.276	0.270	0.255	0.082	0.089	1.000

Source: EDSB-V, 2018

Table 3 presents the Kaiser-Meyer-Olkin (KMO) statistic which measures the adequacy of the sampling. It emerges from this preliminary analysis that the five dimensions can be factored since the overall KMO index of 0.814 exceeds the threshold of 0.5 and reveals good adequacy of the sampling. Moreover, most of the individual KMO indices of the eleven indicators for the five dimensions of the multidimensional energy poverty index are above this threshold. The PCA results tell us that together, the first seven components explain 82.63% of the cumulative variance of the eleven indicators.

Table 3: Kaiser Meyer-Olkin adequacy measure

Variables	*Coefficient*
Global Adequacy Index (KMO).	0,814

Source: ECEB, 2015

The simplest and most common technique for deciding how many components to keep is to interpret the scree plot (Bartholomew, 2010). The graph of the eigenvalues (see appendix) shows that that the first three components (among the seven identified) meet the requirement while the fourth component is already in the lower part of the figure. In summary, the main extraction criteria, based mainly on the inspection of the spectrum of eigenvalues, reveal that it is worth extracting the first three components namely electricity, ModEner and television. Households therefore use electricity for access to energy, modern energies for cooking and televisions for leisure and/or education. Consequently, we retain for the measurement of the energy poverty index, these three dimensions.

2.3. *Multidimensional Energy Poverty Index*

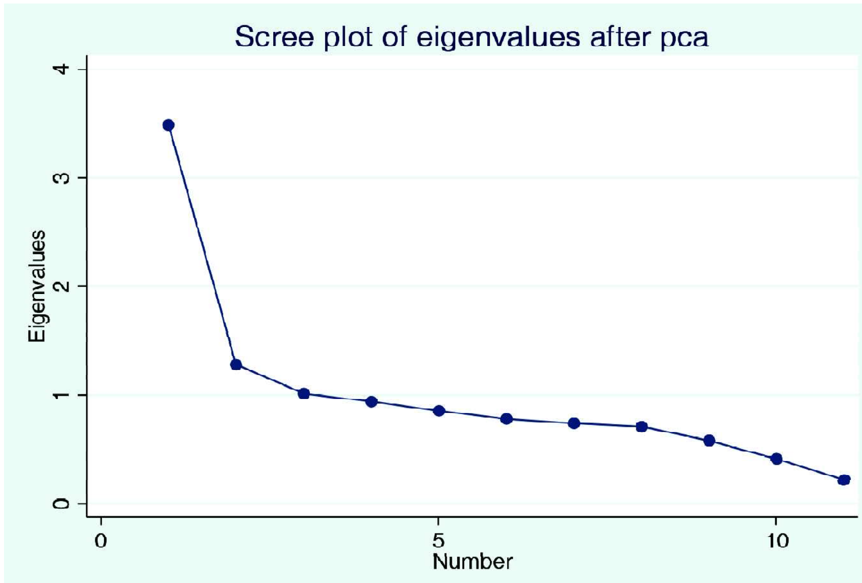
Table 4 summarizes the estimated values of the IPEM and of these two main components (H) and (A).

Table 4: Calculation of the IPEM in Benin

Levels	*Incidence of household energy poverty (H)*	*Intensity of energy poverty (A)*	*Multidimensional Energy Poverty Index (IPEM=H*A)*	*Degree of household energy poverty*	*Contribution to IPEM (en %)*
National	0.092	0.696	0.064	Very weak	100
Urban	0.575	1.019	0.586	Moderate	41.900
Rural	0.425	1.018	0.414	Moderate	58.100

Source : EDSB-V, 2017-2018

The results at the national level reveal that 9.2% of households are energy poor and 69.6% are deprived of the IPEM indicators. This means that these households are deprived of television for their leisure/education, modern energies for cooking and generators for the supply of electricity. Depriving households of long-term energy resources is a source of deforestation, air and water pollution in habitats, increased greenhouse gas emissions and loss of biodiversity. The adjusted value of the energy poverty index of 0.064 is less than 0.3. The degree of energy poverty is therefore very low at the national level and moderate for households in urban and rural areas. Indeed, these results obtained are explained by 58.1% of surveyed households living in rural areas against 41.9% living in



Annex 2 : Eigenvalue scree

urban areas. In the sub-group of households, the incidence of energy poverty is significantly higher in urban areas (57.5%) than in rural areas (42.5%). This is also true of the level of IPEM (0.586 against 0.414). This result shows that urban households live in energy poverty compared to rural ones that have more access to unsuitable substitute energies to compensate for the existence of the energy divide between urban and rural areas in Benin. This could lead to increased migration of rural populations to urban areas where access to energy is easier on the one hand and could increase the risk of accidents and insecurity in rural areas. Moreover, with households' limited access to modern energy, it would be difficult to achieve the sustainable development goals and lift the country out of poverty. This result also shows that households (especially urban ones) are becoming energy producers because they increasingly invest in modern energies (emergency generators) for domestic activities. For a long time, households were seen as consumers. Nowadays, households are both consumers and producers of energy. The rate of the IPEM (0.064) find in this current paper is lower than that found by Nussbaumer & al., (2012) which is 0.83 in African countries. This difference could be explained by the methodology used to identify the main components of the IPEM. In addition, the difference in the period of data can be a reason. Finally, this difference could be explained by the fact that the indicators used to calculate the IPEM in this study differ from those used by these authors.

Conclusion

The paper has assessed multidimensional energy poverty among households in Benin. Findings show that while energy poverty is low at the household level, it is moderate at urban and rural areas. As a policy implication, policymakers should facilitate access to renewable energy for urban and rural households. The policy support must be oriented to both consumption and production of renewable energy because households have been shifting from being consumer of energy to producer of energy. As the current paper is not exempt of limitations, future research may investigate the level of household energy investment that is not captured in this study.

References

Alkire, S., & Foster, J. (2011). Counting and multidimensional poverty measurement. *Journal of Public Economics*, *95*(7–8), 476–487. https://doi.org/10.1016/j.jpubeco.2010.11.006

Atkinson, A. B. (2003). Multidimensional deprivation: contrasting social welfare and counting approaches. *Journal of Economic Inequality*, *1*(1), 51–65. https://doi.org/10.1023/A:1023903525276

Bartholomew, D. J. (2010). Principal Components Analysis. *International Encyclopedia of Education*, 374–377.

Betto, F., Garengo, P., & Lorenzoni, A. (2020). A new measure of Italian hidden energy poverty. *Energy Policy*, *138*(February 2019), 1–7. https://doi.org/10.1016/j.enpol.2019.111237

Chakravarty, S. R. (2003). The measurement of multidimensional poverty. *Journal of Economic Inequality*, *1*(1), 25–49. https://doi.org/10.1007/978-0-387-79253-8_6

Charlier, D., & Legendre, B. (2019). A Multidimensional Approach to Measuring Fuel Poverty. *The Energy Journal*, *40*(27–53).

Cho, D. I., Ogwang, T., & Opio, C. (2010). Simplifying the water poverty index. *Social Indicators Research*, *97*(2), 257–267. https://doi.org/10.1007/s11205-009-9501-2

Delugas, E., & Brau, R. (2019). Evaluating the Impact of Energy Poverty in a Multidimensional Setting. In *The Energy Journal* (Vol. 42, Issue 1). https://doi.org/10.5547/01956574.42.1.edel

Dunteman, G. H. (1989). *Principal component analysis (Quantitative Applications in the Social Sciences) issue 69* (U. of L. Michael S. Lewis-Beck, Ed.). Sara Miller McCune, Sage Publications, Inc.

Faiella, I., Lavecchia, L., & Borgarello, M. (2017). Una nuova misura della povertà energetica delle famiglie (A new measure of households' energy poverty). *Bank of Italy Reasearch Papers Series*, *404*, 1–18. https://doi.org/http://dx.doi.org/10.2139/ssrn.3073102

Freudenberg, M. (2003). Composite indicators of country performance: a critical assessment. In *OECD Science, Technology and Industry Working Papers* (Vol. 16). https://doi.org/10.1787/405566708255

Hills, J. (2011). Fuel poverty: the problem and its measurement. In *Annals of Physics*. http://sticerd.lse.ac.uk/dps/case/cr/CASEreport69.pdf

Hills, J. (2012). Getting the measure of fuel poverty. In *Fuel Poverty Review*.

INSAE. (2018). *RAPPORT DE SYNTHESE*. www.afristat.org

International Energy Agency. (2017). *World Energy Outlook*. www.iea.org/t&c/

Jemmali, H. (2013). Mesures de la pauvreté en eau/ : analyse comparative et développement de l'indice de pauvreté en eau. *VertigO*, *13*(2), 1–9. https://doi.org/10.4000/vertigo.13982

Lawson, R., Williams, J., & Wooliscroft, B. (2015). Contrasting approaches to fuel poverty in New Zealand. *Energy Policy*, *81*, 38–42. https://doi.org/10.1016/j.enpol.2015.02.009

Miniaci, R., Scarpa, C., & Valbonesi, P. (2014). Energy affordability and the benefits system in Italy. *Energy Policy*, *75*, 289–300. https://doi.org/10.1016/j.enpol.2014.09.008

Moore, R. (2012). Definitions of fuel poverty: Implications for policy. *Energy Policy*. https://doi.org/10.1016/j.enpol.2012.01.057

Nussbaumer, P. (2012). *Energy for Sustainable Development —An Assessment of the Energy-Poverty-Development Nexus*.

Nussbaumer, P., Bazilian, M., & Modi, V. (2012). Measuring energy poverty: Focusing on what matters. *Renewable and Sustainable Energy Reviews*, *16*(1), 231–243. https://doi.org/10.1016/j.rser.2011.07.150

Nussbaumer, P., Nerini, F. F., Onyeji, I., & Howells, M. (2013). Global Insights Based on the Multidimensional Energy Poverty Index (MEPI). *Sustainability*, *5*, 2060–2076. https://doi.org/10.3390/su5052060

Okushima, S. (2017). Gauging energy poverty: A multidimensional approach. *Energy*, *137*, 1159–1166. https://doi.org/10.1016/j.energy.2017.05.137

Papada, L., & Kaliampakos, D. (2016). Measuring energy poverty in Greece. *Energy Policy*, *94*, 157–165. https://doi.org/10.1016/j.enpol.2016.04.004

Thomson, H., & Snell, C. (2013). Quantifying the prevalence of fuel poverty across the European Union. *Energy Policy*, *52*(2013), 563–572. https://doi.org/10.1016/j.enpol.2012.10.009

Waddams Price, C., Brazier, K., & Wang, W. (2012). Objective and subjective measures of fuel poverty. *Energy Policy*, *49*, 33–39. https://doi.org/10.1016/j.enpol.2011.11.095