A new composite indicator for assessing energy poverty using normalized entropy[1]

Pedro Macedo[1*], Mara Madaleno[2], Victor Moutinho[3]

[1]CIDMA – Center for Research and Development in Mathematics and Applications, Department of Mathematics, University of Aveiro, 3810-193 Aveiro, Portugal; pmacedo@ua.pt; https://orcid.org/0000-0002-4371-8069
*Corresponding author

[2]GOVCOPP – Research Unit in Governance, Competitiveness and Public Policy, Department of Economics, Management, Industrial Engineering and Tourism (DEGEIT), University of Aveiro, 3810-193 Aveiro, Portugal; maramadaleno@ua.pt; https://orcid.org/0000-0002-4905-2771

[3]NECE – Research Unit in Business Sciences, Department of Management and Economics, University of Beira Interior, 6200-209 Covilhã, Portugal; ferreira.moutinho@ubi.pt; https://orcid.org/0000-0003-0811-9033

Abstract

Using a unique or common measure of energy poverty is very limited for the true classification of a household being in energy poverty. Thus, this study proposes a composite indicator, whose weights will be determined from the estimation of two relationships using a robust and stable methodology based on information theory. This work considers two regression models, where the two dependent variables are the gross domestic product and greenhouse gas, and the 12 energy poverty explanatory variables are based on those proposed by Recalde et al. (2019), for the period 2008-2018. Hence, the study presents a more comprehensive measurement with additional dimensions, weights, and indicators. Probably most important, in addition to the discussed proposal with a specific choice of models and variables, this work reveals a promising methodology that can be replicated in any other theoretical configuration. This approach is suitable for the discussion and design of new energy, environmental and social policies. Findings can be used to assess in advance the effectiveness of energy poverty measures, turning the model into a valuable policy tool.

Keywords: European Countries, Index, Info-Metrics, Maximum Entropy, Regression Analysis

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1. Introduction

Three major energy challenges are to be faced by countries all around the world (González-Eguino, 2015): energy security, climate change, and energy poverty. Energy poverty refers to a "level of energy consumption that is insufficient to meet certain basic needs" (González-Eguino, 2015, p. 379). Reddy (2000, p. 49) defines energy poverty as "the absence of sufficient choice in accessing adequate, affordable, reliable, high-quality, safe and environmentally benign energy services to support economic and human development". Being a complete definition in our view, it will be the adopted definition in this paper as in González-Eguino (2015), provided the major contribution is the creation of an energy poverty index, which captures many, if not all, of these elements.

As highlighted recently by Halkos and Gkampoura (2021), energy poverty represents a challenge to both the developing (Ozughalu and Ogwumike, 2019; Qurat-ul-Ann and Mirza, 2021) and the developed (Streimikiene et al., 2021; Castaño-Rosa et al., 2019) countries. Thus, energy poverty problems are faced by all countries and the European ones are no exception. Erasing it is essential for social welfare. Recently, in Europe, policy-makers are trying to address this issue, while facing climate change and pollution mitigation challenges. When fighting climate change, ensuring energy security, and supplying to face all the demand requirements in terms of energy, countries are realizing that energy poverty is increasing (Halkos and Gkampoura, 2021; Thomson et al., 2017), especially after an economic crisis. To be able to implement policies and strategies effectively, energy poverty should be measured and evaluated appropriately. Moreover, energy poverty could be the result of increased energy prices, fossil fuel prices rising worldwide, combined with low incomes and the older age of buildings and appliances turning these inadequate and inefficient to satisfy human needs of heating, comfort, and health (Halkos and Gkampoura, 2021; Thomson et al., 2017; González-Eguino, 2015). Additionally, inadequate tax systems, low energy infrastructure investments, and lack of awareness and knowledge regarding energy efficiency, all could be determinants of energy poverty. But how can we effectively measure energy poverty? The literature points to several measures (Lewis, 1982; Boardman, 1991; Leach, 1992), but including all these proxies individually may be inadequate (Recalde et al., 2019). Thus, the emergence of energy poverty indicators is necessary to create an adequate and efficient measure, gathering several dispersed pieces of information. With a unique index, it will be possible to infer the state of energy poverty in different contexts and also advise wisely policymakers to implement the most correct strategies to reduce these numbers to a null existence.

Energy poverty analysis in the European Union has been made using the Eurostat available information sources, such as the European Union Statistics on Income and Living Conditions (EU-SILC). However, this kind of metric based on expenses may be a vehicle for underestimation of the energy poverty incidence, by not being considered concrete situations of energy consumption privation in face of the physical needs of a household, in specific economic, environmental and social contexts. These limitations amplify the hardness in an international comparison of indicators based on the options expenses/income, even on a restricted scale as the European reality.

The definition of energy poverty can be broad, as suggested by Day et al. (2016, p. 260), who define energy poverty as "an inability to realize essential capacities as a direct or indirect result of insufficient access to reliable, safe and accessible energy services, and taking into account the reasonable alternatives available to realize these capacities". What the authors call capacities were divided into secondary (e.g., washing clothes, access to information, use of machinery) and basic (e.g., education, health, access to energy resources, among others). In these basic capacities, for example, Rehman et al. (2012) noted that non-access to energy is an obstacle to economic development since there is a strong correlation between GDP and access to energy. Access to energy is a consequence of economic growth and a fair redistribution of wealth among the population. In this alignment, the study by Achour and Belloumi (2016) proposes that energy can be seen as the main driver of economic growth provided that access to services that energy ensures such as lighting, heat for cooking, heating, transport fuels, water pumping, and food grinding are essential for measuring energy poverty and the consequent effect on economic growth.

In the EU Regulation 2018/1999, on the Governance of the Energy Union and Climate Action, the fundamental character of combating energy poverty as part of the fight against climate change is highlighted in several points. Day et al. (2016) consider that this approach to the concept of energy poverty, with the inclusion and subdivision of capacities, could be particularly useful in studies of energy poverty that are introduced in the context of climate change. From another perspective, Ürge-Vorsatz and Herrero (2012) justify the need to study the nexus between energy poverty and climate change (greenhouse gas emissions), admitting that this relationship can be analyzed from the point of view of policies to combat climate change aimed at increasing energy prices, thereby increasing energy poverty. They also argue that social tariffs will serve as a disincentive to investment in energy efficiency at the household level, while they offer no benefit in terms of greenhouse gas emissions. Therefore, betting on energy efficiency is the best way to align the objectives of combating climate change and reducing energy poverty. In this alignment of the study by Ürge-Vorsatz and Herrero (2012), as suggested by Thomson et al. (2017), the measurement of energy poverty has broader implications when considering its interaction with other public policies and economic contexts in terms of their effects on energy poverty itself - as is the case, for example, of the effects of economic recessions and the economic policies that respond to them, or the recurring effects of environmental policies aimed at reducing polluting emissions. Additionally, Chakravarty and Tavoni (2013) conclude that universal access to modern energy increases energy demand, consumption, emissions, and global warming.

There are two basic and different types of indicators usually used in the literature to measure energy poverty (objective and subjective measures), but still no consensus as to the best measurement. Llorca et al. (2020) mention that classifying households using subjective measures of energy poverty leads to different results than when objective measures are to be used. Therefore, the authors suggest a combination of the two measures to capture the adverse effect of fuel poverty on health. The measurement of energy poverty, mainly based on indicators, is not consensual, and several authors resort to the creation of specific indices to measure energy poverty (among others, Nussbaumer et al., 2012; Okushima, 2017; Recalde et al., 2019). In this study, we propose a composite indicator, whose weights will be determined from the estimation of two relationships using generalized maximum entropy and the corresponding normalized entropy measure. In these two relationships, energy poverty measures (or indicators) are related to economic growth on the one hand, and on the other hand, we consider that the same determinants of energy poverty are related to greenhouse gas emissions.

According to the contributions referred to in the literature review on the importance of relating the determinants of energy poverty to economic growth and its implications for climate change, in our proposal, and to fulfill this objective, we consider, like Camarero et al. (2014), the gross domestic product (GDP; per capita) as an indicator of the added value of the productive activity, and as an indicator of environmental pressure, greenhouse gas emissions (GHG; per capita). Our selection of energy poverty indicators was based on the study by Recalde et al. (2019), in which these authors propose an index of structural energy poverty vulnerability (SEPV), consisting of 13 energy poverty variables, categorized as variables referring to labor, with a total weight of 64.84%, to housing, with a total weight of 24.97%, or energy, with a total weight of 10.20%. Recalde et al. (2019) proposed this very recent index by using Principal Component Analysis (PCA) applied initially to 47 variables. After the PCA analysis, the authors highlight 13 as being the most important in hierarchical terms, using these afterward to measure the structural vulnerability of energy poverty. It is over these variables that we set out for the analysis made in the present research work. Therefore, of the 13 variables that Recalde et al. (2019) used in the construction of the structural vulnerability index to energy poverty, the variables H16 (social rental stock as a percentage of the total housing stock) and E1 (switching rate in electricity services) were not included because we were not able to find the appropriate information. Ideally, the most desirable approach would be to provide the broadest combination of indicators generated from causal aspects and impacts of the phenomenon, to have the most complete and informative picture possible, not conditioned by the limited and unavailable access to information.

Thus, our main contribution as compared to Recalde et al.'s (2019) work is the novelty in the method used to create a weighted measure of energy poverty. Our theoretical reflection on the improvement of a mainstream of the metrics of energy poverty is the recognition that it is necessary to invest heavily in the production of statistical information, such as the proposal of a composite indicator that serves for international comparisons and that can be an instrument of specific analysis for decision-makers with political will in what is necessary for joint coordination to implement measures to combat energy poverty in the Member States.

Recalde et al. (2019) choose 13 variables that best represent energy poverty, creating a structural energy poverty vulnerability index. The novelty in this paper is that we stick with some of these 13 “best-ranked indicators” and apply the normalized entropy measure to define weights from the information content of different models and different variables, without any exclusion of models or variables (model or variable selection is not the goal here). The interest is to identify weights for each variable to construct a weighted measure of energy poverty. So, in addition to the discussed proposal with a specific choice of models and variables, this work reveals a promising methodology that can be replicated in any other theoretical configuration. Furthermore, the indicator framework used in this study is new, and it does have some unique characteristics.

The rest of the article develops as follows. Section 2 provides a literature review on the topic of constructing energy poverty measures. Section 3 presents our data and methodology, while section 4 discusses and presents the achieved results. Finally, section 5 concludes this work.

2. Literature Review

2.1 Definition and measurement

Defining energy poverty is far from generating consensus in the literature. A survey of energy poverty definitions is provided by Moore (2012), exemplifying how the size of the problem depends on the definition and chosen threshold. More recently, Siksnelyte-Butkiene et al. (2021) provide a recent systematic review and assessment of the available simple and composite indicators for measuring energy poverty, identifying a total of 71 (composite) indicators to measure it. The Structural Energy Poverty Vulnerability Index, Fuel Poverty Index, and Energy Vulnerability Composite Index are identified as the more valuable indicators for measurement purposes. Villalobos et al. (2021) explore the consequences that different energy poverty definitions and measures might have for the identification of energy-poor, proposing first- and second-order energy poverty measures classification. Also, Herrero (2017) provides a critical review of energy poverty indicators methods. The paper's author advocates that single energy poverty indicators are not suitable, and presents evidence to support the need for multiple-indicator approaches.

Energy poverty is also explored in the literature as fuel poverty or energy vulnerability, happening whenever a household experiences scarce levels of energy services (Thomson et al., 2017). It originates from low household income, high energy prices, bad warming and cooling conditions, and inefficient buildings and appliances (Ntaintasis et al., 2019). Its social consequences are well reported (social exclusion, disruption of social cohesion, degraded quality of life, damaging public health; Chakravarty and Tavoni, 2013; Llorca et al., 2020). Churchill and Smyth (2020) argue to be the first to study the impact of ethnic diversity on household energy poverty in Australia (using a panel setting composed of 12 waves). Still, there is no generally applicable definition of energy poverty (Lin and Wang, 2020), nor a commonly accepted method for measuring it (Llorca et al., 2020), even if a correct energy poverty definition and measurement is relevant for policy formulation. Only with its correct measurement, it would be possible for policymakers to determine the scale and the nature of the problem, target a strategy, help reduce the energy poverty trap and monitor progress. Primc et al. (2021) published an article providing a bibliometric and network analysis of the past 30 years of research, summarizing the differences and similarities between the concepts of energy poverty and fuel poverty. Social aspects of the energy transition are identified as a useful future research gap. Gatto and Busato (2020) found that GDP is not a strong driver for energy vulnerability and that green OECD and non-OECD countries are less vulnerable, exploring and analyzing the global energy vulnerability index.

Reduced access to modern energy is normally used as representative of energy poverty in developing countries (affordability and accessibility), while affordability is used in the context of developed countries (commonly known as fuel poverty). Despite being used interchangeably, energy poverty is associated with the scarce access to energy suppliers in developing countries, leading to economic, infrastructure, social equity, education, and health concerns. In opposition, those in fuel poverty refer to households suffering from insufficient monetary resources to pay for their basic energy needs. Still, consensus arises as to its possible classifications, which as well result in their measurement, namely, those in energy poverty are households unable to keep homes adequately warm (Lewis, 1982), delayed in the payment of utility bills (Boardman, 1991; Leach, 1992), and which live in defective dwellings.

To measure energy poverty the literature traditionally uses objective and subjective approaches. The objective approach relates household income and energy expenditure using four basic measures. The first was proposed by Boardman (1991), the 10% rule, where households are in energy expenditure if they spent more than 10% of their income on fuel costs to keep an appropriate home temperature. The second (Hills, 2012) refers to the after fuel cost poverty considering a household in fuel poverty if its income is 60% lower than the median income of the representative household. The third respect to the Low Income-High Costs (LIHC) indicator proposed by Hills (2012), which considers households to be in fuel poverty if they have energy needs above the median of the representative household and simultaneously income below the 60% of the median of the representative household. Finally, the Minimum Income Standard (MIS) measure considers that if the residual income after expenditure on energy and housing of the household is lower than or equal to the income after housing costs and expenditure on energy services (the MIS), then they are in fuel poverty.

The subjective approach considers an individual's perceptions and usually refers to survey data. It collects individuals’ perceptions about their perceived capacity to keep houses at an appropriate temperature. Since they are based on questionnaires, these measures could be inappropriate and subjectively biased (Llorca et al., 2020). Therefore, objective measures turn out to be more accurate than subjective measures. Even so, some studies argue that subjective measures can capture households’ feelings of material deprivation (Thomson et al., 2017). Still, there is no generally accepted measure, since they do not coincide or lead to different results (Llorca et al., 2020) and it has been reported that using a single metric is problematic considering the heterogeneity of EU countries (Deller, 2018). Fizaine and Kahouli (2019) explore the use of several objective and subjective measures to categorize fuel poverty, highlighting differences in the profiles of the households depending on the measure and threshold used. They suggest the combination of standard indicators, to exclude thresholds from expenditure-based measures, and innovative strategies based on more appropriate conceptual frameworks of fuel poverty.

Moreover, recently composite indicators have been reported in the literature, namely the multidimensional energy poverty index (MEPI), which combines both subjective and objective measures of energy poverty (see, for example, Koomson and Damquah, 2021). This MEPI was first proposed by Nussbaumer et al. (2012) that reviewed the relevant literature discussing the adequacy and applicability of existing instruments to measure energy poverty and propose a new composite index to measure energy poverty in Africa. To build the MEPI they resort to Monte Carlo methods for the computation of random weights. González-Eguino (2015) provides an overview of energy poverty, different ways of measuring it, and its implications, arguing that this concept cannot be dissociated from the general poverty definition. The present article proposes a new composite indicator (or measure) of energy poverty using methodologies from information theory. Based on previous findings of energy poverty indicators (Recalde et al., 2019), we build our framework and associate these with economic growth and greenhouse gas emissions, to define a weighted measure of energy poverty.

2.2 Different energy poverty measures

Burinson et al. (2018) identify three dimensions of fuel poverty using three economic variables (income, housing costs, energy costs) applying a multidimensional logit framework to data from the English Housing Survey, based on the LIHC indicator. Churchill et al. (2020) use 13 waves of the Australian Household, Income, and Labor Dynamics to conclude that fuel poverty lowers subjective well-being. They provide estimates for the shadow cost of fuel poverty using the expenditure-income approach and the LIHC indicator. Recently, Karpinska and Smiech (2021) provide novel evidence on the Polish energy-poor profiles and explored interactions between energy poverty and general poverty. They combine objective and subjective measures employing Markov chains and logistic regressions.

Meyer et al. (2018) follow O'Sullivan et al. (2015) and Dubois and Meier (2016) creating a composite measure of energy poverty combining objective and subjective measures, using data from Belgium and creating an energy poverty barometer (or an aggregation of indicators). Rehman et al. (2012) examine the accessibility of physical infrastructure, energy service delivery, and conformance to social goals in Asia and Sub-Saharan Africa, highlighting the need for policymakers to reorient the subsidy regime and incorporate energy service delivery indicators in monitoring and reporting mechanisms. Papada and Kaliampakos (2018) developed a stochastic model of energy poverty using household-level data and allowing its transition to the country level through Monte Carlo simulation. They found that energy poverty reaches 70.4% of households in Greece.

Romero et al. (2018) compare critically the different approaches to measuring energy poverty (objective versus subjective measures) using data from Spain and propose a new methodology, which is an MIS-based (minimum income standard) energy poverty indicator. Our methodology follows the developments and findings of Recalde et al. (2019) as stated previously. Recalde et al. (2019) created a structural energy poverty vulnerability index using principal component analysis (PCA) and ranking each of the EU-27 countries. A Poisson regression model was fitted to analyze the association between the proposed index and excess winter mortality. The proposed index allowed them to explore energy poverty geographically. They started with 47 indicators pre-selected through meetings with experts. After Spearman correlation analysis, 29 indicators were left and using PCA in the final stage only 13 indicators have been chosen.

We depart from some of these “13 best” indicators proposed by the authors to present and construct our energy poverty measure.

Nussbaumer et al. (2012), Fizaine and Kahouli (2019), and Kelly et al. (2020) mention that although many composite indicators emerged in the literature there is still room for advancing energy poverty measures. This is because new proposals are still needed to surpass the drawbacks of previous proposals, due to their still lack of applicability to multiple countries and to surpass the simplicity of using single measures and gain by the over-simplification nature of the association of multiple variables into a single measure. Aimed at defining a new measure of hidden energy poverty in Italy, Betto et al. (2020) considered low income, inadequate housing, and energy efficiency. Kelly et al. (2020) built a composite index using 10 indicators to assess home-heating energy-poverty risk in Ireland (weighting heating requirements at 40%, building characteristics at 20%, and householder characteristics at 40%).

Castaño-Rosa et al. (2019) provide a review of the concepts and indicators of fuel poverty across Europe. They also discuss how energy vulnerability issues fit fuel poverty situations highlighting that infrastructure aspects and comfort, energy efficiency, social and economic poverty, wellbeing, and wealth need to be considered jointly. They also discuss the need for a multiple-indicator, provided single indicators are not able to capture all possible factors at once to recognize the source of energy poverty in each EU member. Okushima (2017) developed a multidimensional energy poverty index composed of energy costs, income, and energy efficiency of housing for Japan proving the negative impact of energy price escalation on energy poverty, especially among vulnerable households and the elderly. Also, Sareen et al. (2020) reinforce that combining indicators at multiple scales is needed to capture the multi-dimensional aspects of energy poverty. However, challenges like database availability, coverage, and limited disaggregated resolution persist.

Proposing a new method, Llera-Sastresa et al. (2017) define an index for household energy vulnerability and improve social housing management. The index methodology was based on the analytic hierarchy process, where the relative weight of each factor was computed based on the average values reported by specialists in interviews associated with dwellings, installations, bills, and households’ characteristics. Robles-Bonilla and Cedano (2021) consider the MEPI index as an energy service deprivation calculation and try to understand the regional nature of thermal comfort in Mexico. Previously, Pelz et al.

(2018) mentioned that despite recent efforts to capture the multidimensional nature of energy poverty, the current existent measures are complex to be applied at the global level and too prescriptive to be accepted in several heterogeneous national contexts.

O´Meara (2016) reviewed the fuel poverty literature concerning definition and measurement, enhancing the impacts it has on health and well-being. The authors examine policy initiatives undertaken in Ireland to alleviate fuel poverty. Streimikiene et al. (2021), for Lithuania and Greece, develop indicators for assessing low carbon just energy transition. A framework of analysis is built to understand how climate change mitigation policies are affecting households' energy renovation in buildings, micro-generation technologies, and others, in terms of energy poverty and vulnerability. For Pakistan, Qurat-ul-Ann and Mirza (2021) used a multidimensional energy poverty index with seven dimensions weighted based on their relative importance. Results point out that 55% of the households are multi-dimensionally energy-deprived in 30% of the selected dimensions.

Building on the work of Recalde et al. (2019) and their "13 best" identified indicators for energy poverty measurement through dimensionality reduction techniques (namely, PCA), in this work we have collected data for 11 of these variables (the available ones), joining another (using in total 12 indicators) and by applying generalized maximum entropy and normalized entropy, we inferred about the weight of each of these indicators and their contribution to building a general energy poverty measure. It was possible to infer that even if being the best indicators pointed out in Recalde et al. (2019), under our proposed methodology some have an almost null weight in the overall index (considering our two regression models). Therefore, it was found that even for these top 13 energy poverty representatives, some have an almost residual weight, finding that the correct weighting of each variable or indicator used in composite energy poverty indicators to be built needs to consider the different variable weights, which change in accordance to the models, periods or countries analyzed. As will be evidenced afterward, the socio-economic dimensions were revealed to be those more related to energy poverty in the EU-26 countries analyzed. Thus, the indicator framework used in this study is new, easily adapted to any other theoretical framework, and it does have some unique characteristics.

2.3 Energy poverty, income, and emissions

Up to this moment, it was possible to infer that both macro and micro variables are used to infer energy poverty. More attention is paid to developed than developing countries mostly due to data scarcity, although recent research has placed increased attention on the developing group. Nussbaumer et al. (2013) apply the MEPI index to analyze energy poverty in developing countries reinforcing the need to develop appropriate tools to inform the development of interventions and keep progress tracking. Alem and Demeke (2020) use a dynamic probit estimator with data from Ethiopia to estimate the probability of being energy-poor and study the impact of energy price inflation on energy use and energy poverty. Karpinska and Smiech (2021) point out that to eliminate energy poverty there is the need to reinforce the employment, social, and building renovation policy, based on the EU-SILC data. Koomson and Danquah (2021) explore the financial inclusion-energy poverty nexus using data from Ghana and the MEPI index, using a linear probability model and the pooled ordinary least squares (OLS).

Ürge-Vorsatz and Herrero (2012) explore the link between energy poverty alleviation and climate change mitigation, evidence that the two cannot be reached jointly. Day et al. (2016) conceptualize energy use from a capabilities perspective, which argues to bring advantages when tempting to address energy poverty in the context of climate change by controlling aggregate consumption. Reyes et al. (2019) study assessed socio-economic variables, energy consumption, and indoor environments in households in Chile. They recommend policymakers consider heterogeneity, social inequalities, and energy consumption to reduce both energy poverty and air pollution.

Using the Johansen multivariate cointegration approach, impulse response functions, and variance decomposition methodologies, Achour and Belloumi (2016) studied the relationship between transportation infrastructure (when absent, another pointed in the literature indicator to measure energy poverty) on economic growth and the environment in Tunisia over the period 1971-2012. They show the need to invest in infrastructures to increase economic growth. Previously, Camarero et al. (2014) assessed convergence in eco-efficiency in greenhouse gas emissions in the EU using data envelopment analysis. Their results point to different clubs of convergence depending on the specific pollutant analyzed.

The association of energy poverty to economic growth and development as well as to emissions was already reported in the literature. Usually, we should not expect a reduction of energy poverty made at the expense of more growth and environmental improvements. In opposition, when fighting energy poverty, the literature reports that economic growth decreases and pollution increases (Alem and Demeke, 2020; Karpinska and Smiech, 2021; Koomson and Danquah, 2021). Santillán et al. (2020) used the MEPI index to measure the intensity of energy poverty in different Latin American countries finding a clear negative correlation between MEPI and the Human Development Index. Mendoza Aguilar et al. (2019) created the compound energy poverty indicator revealing regional singularities and disparities in the Canary Islands. Thema and Vondung (2021) find that expenditure-based energy poverty indicators in the EU increase or decrease after an income change and energy expenditure depending on specific country-wise income at the macro level, as well on the energy expenditure distribution between households at the micro-level.

Energy poverty is found to negatively impact income, education, life expectancy, and employment, but has a positive effect on poverty, income inequality, and sanitation risk. Renewable energy, on the other side, is found to exert exactly the opposite effects over these same measures (Adom et al., 2021). Moreover, energy poverty and economic vulnerability have mutual positive causalities (Nguyen and Thanh, 2022). Also, Ozughalu and Ogwumike (2019) found that the region of residence, household composition, age, gender, and education level of the household head to be determinants of extreme energy poverty. Zhao et al. (2022) explore how renewable energy alleviates energy poverty, finding it thus, assessing the energy poverty composite index across the globe. Churchill et al. (2020) found that being in fuel poverty lowers subjective well-being, being results robust to different measures of fuel poverty. Ehsamullah et al. (2021) estimate the nexus between energy insecurity and energy poverty using DEA and data for G7 countries. They combined individual indicators into a mathematical composite indicator to measure energy, economic, social, and environmental performance in what the authors called the EPI index. It is found that the USA has the lowest EPI average score of environmental vulnerability, despite its highest economic development.

It is also found in the literature that energy-poor households are characterized by the interdependence of socio-demographic and housing characteristics, not alone being able to explain energy poverty by itself (Primc et al., 2019). Primc et al. (2019) point to energy poverty as a structural issue arising from poor-energy-efficient buildings and labor market inefficiencies mostly. Zhao et al. (2021) found that energy poverty accelerates growth in CO2 emissions in China. For BRICS, Hassan et al. (2022) found that energy poverty intensifies the carbon emissions rate, but that education and globalization reduce pollution and improve energy poverty. Calvo et al. (2022) found that in Chile energy poverty conditions significantly reduce air quality policies' effectiveness. Apergis et al. (2022) found that education mitigates energy poverty in 30 developing countries. Raghutla and Chittedi (2022), for five emerging economies, found that access to electricity (lower energy poverty) promotes economic development. Rao et al. (2022) present some key influencing factors of energy poverty in N11 countries (emerging economies). For the effect, they combine 13 indicators capable of capturing energy availability, cleanability, and affordability dimensions, combining them via the GRA-SRA (Grey Relational Analysis – Sequential Relational Analysis) method. Results indicate that higher energy availability decreases energy poverty, which in turn lowers income inequality.

However, different solutions have as well been reported up to date. Murthy et al. (1997) conclude for different sectors of the Indian economy that while we reduce poverty targets, CO_2 emissions increase, only surpassed through energy efficiency. More recently, Baloch et al. (2020) analyze the relationship between poverty, income inequality, and CO_2 emissions, finding that increased poverty and income inequality drive environmental pollution in Sub-Saharan African countries. Bonatz et al. (2019) developed an energy poverty index to compare China and Germany. They mention that the development of low carbon strategies is linked to energy efficiency and renewable energy, reducing energy poverty through the decrease of energy consumption and promoting access to high-quality energy carriers. Bilan et al. (2019) employ data from the 1995-2015 period of potential EU candidates, finding that renewable energy sources increase GDP that still needs to be fostered while reducing pollution. Finally, Galvin (2020) highlights that addressing the low-income determinant of UK energy poverty through progressive income redistribution would not distort tax rates nor even increase emissions.

3. Data and Methodology

3.1. Data

This work considers two regression models, where the two dependent variables are the Gross Domestic Product (GDP; per capita) and Greenhouse Gas (GHG; per capita), and the 12 explanatory variables were inspired by the ones identified by Recalde et al. (2019) (from the 13 identified by the authors we were able to collect that for 11 of these in total; adding the final electricity consumption) in the creation of a structural energy poverty vulnerability index:

- long-term unemployment rate (X_1; in %);
- the median income (X_2; in PPS – Purchasing Power Standard);
- disposable income ratio S80/S20 (X_3; in %);
- young people neither in employment nor in education training (X_4; in %);
- the employment rate of recent graduates (X_5; in %);
- expenditure on social protection (X_6; in PPS per inhabitant);
- labor market policies - category 1 (X_7; as % of GDP);
- labor market policies - categories 2 to 7 (X_8; as % of GDP);
- tenants (X_9; rent at market price, in %);
- overcrowding rate (X_{10}; in %);
- final electricity consumption (X_{11}; KWh per capita);
- electricity prices for household consumers (X_{12}; in PPS).

Although most of them need no presentation, a detailed description can be found in Recalde et al. (2019). The data were collected from Eurostat and the countries considered are Austria, Belgium, Bulgaria, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden. Furthermore, and to improve the research work by making comparisons over different stages, three-time periods are considered: 2008-2018 (the entire period of the sample), 2008-2012, and 2013-2018. The average value of the variables is considered for each country accordingly to each period. The analyzed database consists of a panel of 26 European Union countries (where Croatia and the United Kingdom were excluded, due to data scarcity for some of the used variables), between 2008 and 2018, provided that only from 2008 onwards do we have complete data for all the mentioned variables. Although the logarithms of the values of the variables will be considered in the estimation procedure, Table 1 presents some descriptive statistics for the original values of the variables considered in the work. And, to simplify the presentation, the values refer to the entire panel (26 countries times 11 years; detailed statistics for each country, year or period are available upon request to the authors). Using nominal values for GDP could be analyzed in future research. However, real GDP per capita (in Euro), is widely used for comparison of living standards within the European Union (Rodriguez-Alvarez et al., 2021). Thus it makes more sense to use values deflated than nominal ones while assessing the effects of the proposed energy poverty index. Additionally, PPS is usually used in this context to remove the effect of exchange rate volatility and inflation (Che et al., 2021).

The highest mean value presented is for GDP, presenting also the highest standard deviation. The lowest presented mean is from labor market policies – Cat.1, but the lowest standard deviation is that of electricity prices for household consumers. Data differences observed in Table 1 lead us to work with logarithm values in regression modeling.

According to the Kyoto Protocol, developed countries were required to reduce their GHG by at least 5.2% compared to 1990 levels in the period 2008 and 2012 (also known as the "first commitment period"), as was described in the UNFCCC (2009) report, which is why we consider this separate period of 2008-2012 in our analysis. To comply with the imposed obligations, the European Union (EU) developed a measurement system for GHG emissions, as well as, implemented a trading system for emissions licenses, as mentioned by Brodny and Tutak (2020), so it is considered the "second commitment period", 2013 to 2020, where the countries participating in the Kyoto agreement agreed on a 20% reduction compared to the base year (1990). Given that our analysis is reported up to 2018, we consider this second commitment period 2013-2018. We also include a period where the two Kyoto commitment periods are jointly included, namely the entire 2008-2018 analysis time horizon. The goal is to observe changes in the weightings of each of the 12 energy poverty indicators considered in the analysis among the different periods.

Table 1. Some descriptive statistics.

	Symbol	Minimum	Maximum	Mean	Std. Deviation
GDP	GDP	4990.00	83470.00	25412.87	16298.37
GHG	GHG	4665.59	18191.50	8561.81	3026.28
Unemployment	X_1	0.50	19.50	4.05	3.14
Median income	X_2	3062.00	29596.00	14300.48	5842.97
Disposable income	X_3	3.04	8.33	4.85	1.17
Young people neither employment/education	X_4	3.90	22.10	11.33	4.35
Employment recent graduates	X_5	40.00	96.20	77.85	10.31
Expenditure social protection	X_6	1635.91	15773.48	6622.62	3297.00
Labor market policies – Cat. 1	X_7	0.01	0.52	0.13	0.11
Labor market policies – Cat. 2 to 7	X_8	0.02	1.43	0.42	0.30
Tenants	X_9	0.70	40.80	14.36	11.20
Overcrowding	X_{10}	1.40	57.40	19.60	16.35
Final electricity consumption	X_{11}	1839.85	15604.25	5937.82	2986.98
Electricity prices household consumers	X_{12}	0.10	0.31	0.20	0.04

Source: Own elaboration based on the data collected from Eurostat.

3.2. Generalized maximum entropy and normalized entropy

Considering a linear regression model defined as

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{e}, \tag{1}$$

where $\boldsymbol{y}$ denotes a $(N \times 1)$ vector of observations, $\boldsymbol{X}$ is a $(N \times K)$ matrix of explanatory variables, $\boldsymbol{\beta}$ is a $(K \times 1)$ vector of parameters to be estimated and $\boldsymbol{e}$ is a $(N \times 1)$ vector of errors, Golan et al. (1996) introduced a reformulation of the model in (1) as

$$\boldsymbol{y} = \boldsymbol{XZp} + \boldsymbol{Vw}, \tag{2}$$

where $\boldsymbol{\beta} = \boldsymbol{Zp}$ and $\boldsymbol{e} = \boldsymbol{Vw}$. In this reformulation of the linear regression model, $\boldsymbol{Z}$ is a $(K \times KM)$ matrix of support spaces for the parameters, $\boldsymbol{V}$ is a $(N \times NJ)$ matrix of support spaces for the errors, $\boldsymbol{p}$, and $\boldsymbol{w}$ are respectively a $(KM \times 1)$ and a $(NJ \times 1)$ vectors of probabilities to be estimated. Moreover, each β_k, $k = 1,2,\dots,K$, and each e_n, $n =$

$1,2,\ldots,N$, are considered as expected values of discrete random variables z_k and v_n respectively, with $M \geq 2$ and $J \geq 2$ possible outcomes, within the lower and upper bounds of the corresponding support spaces. Additional details can be found in Golan et al. (1996) and Golan (2018).

Given the model in (1) and the corresponding reparameterization in (2), Golan et al. (1996) defined the generalized maximum entropy (GME) estimator as

$$\operatorname{argmax}_{\boldsymbol{p},\boldsymbol{w}}\{-\boldsymbol{p}' \ln \boldsymbol{p} - \boldsymbol{w}' \ln \boldsymbol{w}\}, \tag{3}$$

subject to the model constraints,

$$\boldsymbol{y} = \boldsymbol{XZp} + \boldsymbol{Vw}, \tag{4}$$

the additivity constraints for $\boldsymbol{p}$,

$$\mathbf{1}_K = (\boldsymbol{I}_K \otimes \mathbf{1}'_M)\boldsymbol{p}, \tag{5}$$

and the additivity constraints for $\boldsymbol{w}$,

$$\mathbf{1}_N = \left(\boldsymbol{I}_N \otimes \mathbf{1}'_J\right)\boldsymbol{w}, \tag{6}$$

where $\otimes$ represents the Kronecker product. Thus, from the optimization problem in (3)-(6) and through numerical optimization techniques, the GME estimator finds the optimal probability vectors that are used to obtain point estimates of the unknown parameters and errors, by $\widehat{\boldsymbol{\beta}} = \boldsymbol{Z}\widehat{\boldsymbol{p}}$ and $\widehat{\boldsymbol{e}} = \boldsymbol{V}\widehat{\boldsymbol{w}}$.

To measure the information content of the signal component of the model in (1) using the GME estimator, Golan et al. (1996) defined normalized entropy as

$$S(\widehat{\boldsymbol{p}}) = \frac{-\widehat{\boldsymbol{p}}' \ln \widehat{\boldsymbol{p}}}{K \ln M}. \tag{7}$$

This measure lies between one (perfect uncertainty) and zero (no uncertainty). Concerning the information content of each specific variable, when all the $\boldsymbol{z}_k$ in $\mathbf{Z}$ are defined uniformly and symmetrically around zero, then $S(\widehat{\boldsymbol{p}}_k) \approx 1$ implies $\beta_k \approx 0$, because $\widehat{\boldsymbol{p}}_k$ is uniformly distributed. Thus, when normalized entropy associated with a specific variable is approximately one, its information content is considered irrelevant. The information index, defined as $1 - S(\widehat{\boldsymbol{p}})$, is a measure of uncertainty reduction and it is used in this work to establish the weights of each variable. It is important to note that no kind of judgment (including possible cut-off values; how irrelevant a variable is to justify its elimination from the model?) is used in this work to make a variable selection with normalized entropy; e.g., Macedo (2020). The novelty here is that the measure is used to define weights from the information content of different models and different variables, without any exclusion of models or variables.

Additional details on maximum entropy estimation and normalized entropy can be found in Golan et al. (1996), Jaynes (2003), Mittelhammer et al. (2013), and Golan (2018).

3.3. A weighted measure of energy poverty

The values of normalized entropy for each of the 12 explanatory variables, in the two regression models (with GDP and GHG as dependent variables) and each of the three time periods (2008-2018, 2008-2012, and 2013-2018), are first obtained.[1] In step 1, the GME estimator is performed with four different supports (centered on zero and with five equally spaced points each): [-1000, 1000], [-100, 100], [-10, 10] and [-5, 5] for all the parameters. Four scenarios are considered in the work because there is no prior information available. For each error support (centered on zero and with three points each) is used the three-sigma rule, considering the standard deviation of the noisy observations (the use of a sample scale statistic is the usual procedure).[2] It is important to note that just only one specific support could be considered in other problems, where this approach could be replicated with a possible different theoretical configuration if some prior information exists about the parameters of the model.

Next, in step 2, the values of normalized entropy are obtained considering the average of the values obtained with the four support spaces for the parameters, instead of considering the information just from a single support (avoiding possible difficulties in this choice). Although the absolute values are different between supports, the average circumvents the impact caused by the greater or lesser contraction implied by different supports. Again, it is important to note that model or variable selection is not the goal here. The interest is to identify weights for each variable to construct a weighted measure of energy poverty. Naturally, if just only one support was used, the values of normalized entropy to be considered are the ones obtained with that support.

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[1] A MATLAB code to compute the GME and normalized entropy is available in Macedo (2017) and Macedo (2020).

[2] The supports are defined as closed and bounded intervals in which each parameter (or error) is restricted to belong. The number of points in the supports is usually between three and seven, since there is likely no significant improvement in the estimation with more points in the supports; e.g., Golan (2018).

In step 3, with the values of normalized entropy previously obtained, the information index is computed for each variable in the two regression models and each of the three-time periods. In the final stage, step 4, the weights (w_i) for each variable in each period are easily determined considering the two (one for each model) information indexes of each variable, weighted by the information index of each of the two regression models, such that the sum of the 12 weights is equal to one. This final stage can be seen as a normalization of the information indexes. And, since there are two models, the information index of each model is introduced to provide an adequate weight of the information content of each one. Again, in other problems where this approach could be replicated, if just one model is used, then only the normalization of the information indexes of each variable is needed. Table 2 presents the weights (w_i) for each variable in each period (the original values are rounded to four decimals or presented as approximately zero when appropriate).

Finally, a weighted measure of energy poverty (WMEP), based on the dimension indexes of the Human Development Index from the United Nations Development Programme (UNDP, 2020), is proposed as

$$\mathrm{WMEP_c} = 1 - \sum_{i=1}^{12} w_i \frac{\ln(\mathrm{X}_{ic} + 1) - min\ln(\mathrm{X}_i + 1)}{max\ln(\mathrm{X}_i + 1) - min\ln(\mathrm{X}_i + 1)}, \tag{8}$$

where c represents the country, w_i represents the weight of variable X_i $(i = 1, 2, \dots, 12)$, $min\ln(\mathrm{X}_i + 1)$ represents the minimum value of $\ln(\mathrm{X}_i + 1)$ in the sample of countries, and $max\ln(\mathrm{X}_i + 1)$ represents the maximum value of $\ln(\mathrm{X}_i + 1)$ in the sample of countries. The interpretation is straightforward: a country with a higher value of WMEP has a lower performance on the explanatory variables considered, measured by $\ln(\mathrm{X}_{ic} + 1)$, when compared to the performance in the sample of countries, implying a lower value of the sum component. The values of the variables should be used in the sense that the higher the value greater the performance. The two extremes scenarios for a specific country: $\ln(\mathrm{X}_{ic} + 1) = min\ln(\mathrm{X}_i + 1)$, for all the variables X_i $(i = 1, 2, \dots, 12)$, implies $\mathrm{WMEP} = 1$; $\ln(\mathrm{X}_{ic} + 1) = max\ln(\mathrm{X}_i + 1)$, for all the variables X_i $(i = 1, 2, \dots, 12)$, implies $\mathrm{WMEP} = 0$. This issue is illustrated in the next section.

4. Results and Discussion

Considering the two regression models, where GDP and GHG are the dependent variables, from Table 2 it is clear that some variables are considered irrelevant (e.g., X_7,

X_8, and X_{12}), and others have a small contribution to the reduction of uncertainty (e.g., X_1, X_3, X_4, and X_9) in these models. The above strategy with a specific choice of models and variables represents a choice for simplicity over generality. It is intended to be possibly used upon replacing variables and models in any other possible theoretical configuration.

Table 2. Weights (w_i) for the 12 variables in each period.

	Symbol	**2008-2018**	**2008-2012**	**2013-2018**
Unemployment	X_1	0.0002	0.0004	0.0002
Median income	X_2	0.5319	0.5036	0.5483
Disposable income	X_3	0.0006	0.0004	0.0008
Young people neither employment/education	X_4	0.0010	0.0012	0.0012
Employment recent graduates	X_5	0.0817	0.0831	0.0831
Expenditure social protection	X_6	0.2172	0.2028	0.2309
Labor market policies – Cat. 1	X_7	≈ 0	≈ 0	≈ 0
Labor market policies – Cat. 2 to 7	X_8	≈ 0	≈ 0	≈ 0
Tenants	X_9	0.0013	0.0027	0.0005
Overcrowding	X_{10}	0.0234	0.0332	0.0152
Final electricity consumption	X_{11}	0.1427	0.1727	0.1197
Electricity prices for household consumers	X_{12}	≈ 0	≈ 0	≈ 0

Source: Own elaboration.

These results seem to indicate that there are different impacts from these 12 variables. The importance of, for example, median income in economic growth and GHG mitigation seem consensual in the literature on the nexus between GDP and GHG. Additionally, it is also relevant the weight of expenditures on social protection. This result may induce that in the different European countries social policies related to expenditures with social protection must promote programs that contribute to poverty reduction through unemployment reduction, and simultaneously reduce vulnerability in economic growth differentials. The studies of Dubois and Meier (2016) and Bouzarovski and Tirado Herrero (2017) consider socio-economic factors to measure energy poverty, as well as the possible structural energy poverty proposed by Recalde et al. (2019).

Besides, in the spectrum of energy poverty and economic growth, lower per capita income economies will have lower social and economic conditions to invest in energy efficiency and, consequently, will need to increase their emissions of polluting gases. As such, in Europe, the vulnerabilities associated with energy poverty will be associated with the highest or lower level of economic growth and with the highest or lowest impact on mitigating emissions.

Table 3 presents the results from the WMEP defined in (8) for the countries in the sample, for each period, and Table 5 presents some corresponding descriptive statistics. The first finding is that the mean and median values of WMEP increase from the first period (2008-2012) to the second (2013-2018), with the biggest increase being seen for the median value. The skewness value, although positive, is near zero (with a corresponding standard error of approximately 0.46). Naturally, the distributions of the WMEP values should have a strong positive asymmetry in this context, which is unfortunately not the case (e.g., Figure 1).

Table 3. Results from the WMEP for the countries in the sample.

2008-2018			**2008-2012**			**2013-2018**	
WMEP	**Country**		**WMEP**	**Country**		**WMEP**	**Country**
0.9244	Romania		0.9063	Romania		0.9350	Romania
0.7732	Bulgaria		0.7620	Bulgaria		0.7805	Bulgaria
0.7142	Latvia		0.7196	Latvia		0.7091	Latvia
0.6768	Lithuania		0.6942	Lithuania		0.6702	Hungary
0.6516	Hungary		0.6297	Hungary		0.6628	Lithuania
0.6048	Poland		0.6231	Poland		0.6536	Greece
0.5885	Estonia		0.6096	Estonia		0.5886	Poland
0.5685	Greece		0.5776	Slovakia		0.5702	Estonia
0.5678	Slovakia		0.5044	Portugal		0.5592	Slovakia
0.5322	Portugal		0.4846	Greece		0.5511	Portugal
0.4870	Czech Republic		0.4797	Czech Republic		0.4896	Czech Republic
0.4158	Malta		0.4254	Malta		0.4376	Cyprus
0.4156	Spain		0.3929	Spain		0.4337	Spain
0.3991	Slovenia		0.3774	Slovenia		0.4158	Slovenia
0.3932	Italy		0.3755	Italy		0.4098	Italy
0.3920	Cyprus		0.3400	Cyprus		0.4037	Malta
0.3315	Ireland		0.3236	Ireland		0.3386	Ireland
0.2497	France		0.2603	Belgium		0.2424	France
0.2471	Belgium		0.2556	France		0.2327	Belgium
0.2313	Denmark		0.2429	Germany		0.2230	Netherlands

0.2274	Germany		0.2410	Denmark		0.2208	Denmark
0.2244	Netherlands		0.2244	Netherlands		0.2122	Germany
0.2046	Finland		0.2039	Finland		0.2025	Finland
0.1877	Austria		0.1978	Austria		0.1841	Sweden
0.1826	Sweden		0.1794	Sweden		0.1776	Austria
0.0471	Luxembourg		0.0506	Luxembourg		0.0425	Luxembourg

Source: Own elaboration. WMEP stands for the weighted measure of energy poverty.

It is also worth noting that the rankings are very similar in the three periods under analysis, where at the top always are the same three countries (Romania, Bulgaria, and Latvia), and Luxembourg is always the country at the bottom with the best performance. Given the structure of the WMEP defined in (8) and, for example, considering the three variables with more weights in Table 2, the results are not surprising when the four countries are compared (mean values for the period 2008-2018) in Table 4. For example, Luxembourg with greater values on these three variables, measured by $\ln(X_{ic} + 1)$, and thus closer to $max \ln(X_i + 1)$, implies a higher value of the sum component and, as a consequence, a lower value of WMEP.

Table 4. A comparison of countries (with best and worst values of WMEP).

		2008-2018
Median income (X_2)	Romania	4179.00
	Bulgaria	6268.91
	Latvia	7507.73
	Luxembourg	27664.18
Expenditure social protection (X_6)	Romania	2395.45
	Bulgaria	2308.73
	Latvia	2584.56
	Luxembourg	14263.87
Final electricity consumption (X_{11})	Romania	2110.82
	Bulgaria	3885.35
	Latvia	3178.38
	Luxembourg	11826.90

Source: Own elaboration. WMEP stands for the weighted measure of energy poverty.

When the periods 2008-2012 and 2013-2018 are compared it is observed that 12 countries increase their values of the WMEP (the three biggest increases occurred for Greece, Cyprus, and Portugal) and 14 countries decrease their values of the WMEP (the three biggest decreases occurred for Estonia, Poland, and Lithuania).

Table 5. Some descriptive statistics for the results from the WMEP.

	2008-2018	2008-2012	2013-2018
Mean	0.4322	0.4262	0.4364
Median	0.4073	0.3852	0.4247
Standard Deviation	0.2173	0.2138	0.2227
Skewness	0.3515	0.4269	0.2897

Source: Own elaboration. WMEP stands for the weighted measure of energy poverty.

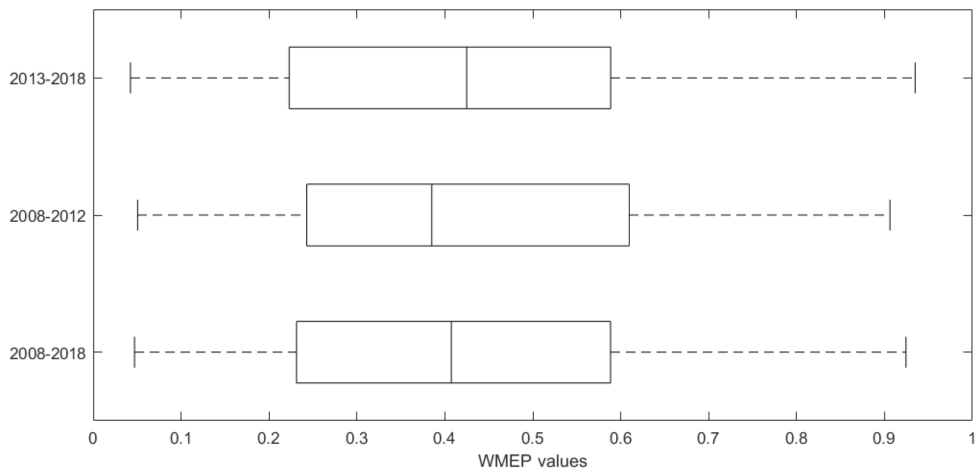

Fig. 1 Box plots with WMEP values for the countries in the sample

Source: Own elaboration. Figure 1 is created with MATLAB.

Fig. 2 Results from the WMEP for the countries in the sample

Source: Own elaboration. Figure 2 is created with mapchart.net.

Figure 2 illustrates the results from the WMEP defined in (8) using a greyscale, where Luxembourg corresponds to the lightest shade and Romania to the darkest shade, for the period 2008-2018. Countries with white color were not considered in the study.

Tundys et al. (2021), considering their sample of 35 European countries, conclude that relatively poorer countries with higher levels of energy poverty are closing the gap faster over the years, mainly due to the implementation of effective energy policies, by shifting toward more environmentally friendly energy use.

We consider that the differential values of energy poverty computed result from the aggregation of heterogeneous effects in the socio-economic variables included in the WMEP. Their weights may support and help political and governmental decision-makers in formulating social and economic policies that may contribute to the vulnerability of the vicious cycles of energy poverty. Tundys et al. (2021) assume differences in energy poverty between "old European Union countries" and "new European Union countries", as also suggested through our results of energy poverty scores.

To conclude, another weighted measure of energy poverty based on an updated science-wide author database of standardized citation indicators by Ioannidis et al. (2020)

was tested with similar results in terms of rankings, which provides additional support to the results discussed in this section. Details are available in the Appendix.

5. Conclusions

In the past, the literature used objective or subjective measures of energy poverty, using simple indicators. Afterward, multiple energy poverty indicators have been reported in the literature aiming at finding a reasonable measure for energy poverty, useful to be applied globally and considering as well national heterogeneities. This article builds upon the work of Recalde et al. (2019), where the authors choose 13 variables that best represent energy poverty, creating an index through principal component analysis, and afterward analyzing its impact on excess winter mortality. Using 11 of these variables, and adding another one, so 12 in total, provided data availability for 26 EU countries, we considered in the analysis the weightings of each of these variables across three specific periods using generalized maximum entropy estimation and normalized entropy. Therefore, this study contributes to the existent literature by proposing a new weighted measure of energy poverty (WMEP).

In any attempt to build a universal composite indicator (or measure), the two key issues are the variables used and their corresponding weights in the indicator. The proposal discussed here addresses these two issues through a statistical formulation almost free of restrictive assumptions, by using concepts from information theory. It is a promising methodology that can be replicated in any other theoretical configuration, regardless of the specific choice of models and variables that can be tested by researchers in different empirical scenarios (e.g., developed vs. developing countries; warmer vs. colder regions). The novelty here is that the normalized entropy with generalized maximum entropy estimation is used to define weights from the information content of different models and different variables, without any kind of judgment to make variable or model selection. This technical feature allows statistical modeling in different empirical scenarios, maintaining the same structure of the proposed universal composite indicator. Given the advantages of generalized maximum entropy in the estimation of ill-posed problems (including collinearity, outliers, non-normal errors, micronumerosity), this new proposal acquires an increased relevance in real-world empirical studies.[3]

[3] Golan et al. (1996), p. 3, mentioned that "[…] in applied mathematics, statistics and econometrics, ill-posed inverse problems may be the rule rather than the exception."

Results point out that the rankings are very similar in the three periods under analysis (2008-2018; 2008-2012; 2013-2018), where at the top always are the same three countries (Romania, Bulgaria, and Latvia) and Luxembourg is always the country at the bottom with the best performance. When the periods 2008-2012 and 2013-2018 are compared it is observed that 12 countries increase their values of the WMEP (the three biggest increases occurred for Greece, Cyprus, and Portugal) and 14 countries decrease their values of the WMEP (the three biggest decreases occurred for Estonia, Poland, and Lithuania).

Compared to previous research, the findings in this paper demonstrate that an alternative modeling strategy can be applied to better understand the various dimensions of energy poverty in EU countries. Policy measures could thus be designed by focusing on the variables of interest. For example, our results suggest that, from the policymaker's perspective, energy-related schemes could be targeted specifically at the private sector and/or households. Policies built upon energy efficiency are needed in the 26 EU countries analyzed, namely renewable energy source development to satisfy growing demand, ensure economic growth and development while decreasing GHG emissions, and improve pollution levels to fulfill the 2030 levels. Our tests also suggest that this approach could be applied across all the dimensions of fuel poverty.

Policymakers could design income, housing, and energy-related schemes that target specific types of house tenures for each dimension of poverty. This could be a more efficient method to allocate funds aimed at alleviating the burden of relatively high energy costs. In the future, we propose to explore the impact of the weighted measure of energy poverty here proposed with economic growth, environmental efficiency, fossil fuel consumption, and renewable energy production to infer the impacts of energy poverty on the overall economy, for both developed as well as developing countries, considering as well hot and colder country temperatures.

We have relied upon the 13 identified variables of Recalde et al. (2019) and this could be seen as a limitation of work. Indeed, future work should start with a large volume of potential predictors and the entire modeling process should be accomplished by maximum entropy procedures. Another possible limitation, that could turn into a new research opportunity, could be the use of the information obtained by the European Union Statistics on Income and Living Conditions. At this time, despite being a useful resource there are some possible shortcomings in the available information for some countries, preventing its use. Finally, the use of interval-based indexes may also be useful for comparison and robustness purposes, and should be investigated in future research.

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Appendix

Resorting to the same data set as in the article, the weights were obtained through maximum entropy being as well the same but another index structure was used; that proposed by Ioannidis et al. (2020). Thus, a new weighted measure of energy poverty (WMEP), based on an updated science-wide author database of standardized citation indicators by Ioannidis et al. (2020), is tested as

$$\mathrm{WMEP_c} = 1 - \sum_{i=1}^{12} w_i \frac{\ln(\mathrm{X}_{ic}+1)}{max\,\ln(\mathrm{X}_i+1)}, \tag{9}$$

where c represents the country, w_i represents the weight of the variable X_i $(i = 1, 2, \dots, 12)$, and $max\,\ln(\mathrm{X}_i + 1)$ represents the maximum value of $\ln(\mathrm{X}_i + 1)$ in the sample of countries. Table A1 shows that the rankings of countries (ordered from highest to lowest value) obtained by the weighted measures in (8) and (9) are very similar. Table A.1 presents a comparison of rankings between both weighted measures and for the three periods (entire 2008-2018; and subsamples 2008-2012 and 2013-2018). Therefore, the weights may support and help political and governmental decision-makers in formulating social and economic policies that may contribute to the vulnerability of the vicious cycles of energy poverty, independently of the index structure used. This also indicates that independently of the indexes or variables used to construct the poverty index, we will reach the same results in terms of weightings and index structure, validating the proposed method here applied and presented.

Table A1. Comparison of rankings between weighted measures in (8) and (9).

2008-2018			**2008-2012**			**2013-2018**	
Country by (8)	**Country by (9)**		**Country by (8)**	**Country by (9)**		**Country by (8)**	**Country by (9)**
Romania	Romania		Romania	Romania		Romania	Romania
Bulgaria	Bulgaria		Bulgaria	Bulgaria		Bulgaria	Bulgaria
Latvia	Latvia		Latvia	Latvia		Latvia	Latvia
Lithuania	Lithuania		Lithuania	Lithuania		Hungary	Lithuania
Hungary	Hungary		Hungary	Hungary		Lithuania	Hungary
Poland	Poland		Poland	Poland		Greece	Greece
Estonia	Estonia		Estonia	Estonia		Poland	Poland
Greece	Slovakia		Slovakia	Slovakia		Estonia	Estonia
Slovakia	Portugal		Portugal	Portugal		Slovakia	Portugal
Portugal	Greece		Greece	Malta		Portugal	Slovakia
Czech Republic	Czech Republic		Czech Republic	Czech Republic		Czech Republic	Czech Republic
Malta	Malta		Malta	Greece		Cyprus	Cyprus
Spain	Spain		Spain	Spain		Spain	Spain
Slovenia	Cyprus		Slovenia	Cyprus		Slovenia	Malta
Italy	Slovenia		Italy	Slovenia		Italy	Slovenia
Cyprus	Italy		Cyprus	Ireland		Malta	Italy
Ireland	Ireland		Ireland	Italy		Ireland	Ireland
France	Belgium		Belgium	Belgium		France	Belgium
Belgium	Netherlands		France	Netherlands		Belgium	France
Denmark	France		Germany	Germany		Netherlands	Netherlands
Germany	Germany		Denmark	France		Denmark	Denmark
Netherlands	Denmark		Netherlands	Denmark		Germany	Germany
Finland	Finland		Finland	Finland		Finland	Finland
Austria	Austria		Austria	Austria		Sweden	Sweden
Sweden	Sweden		Sweden	Sweden		Austria	Austria
Luxembourg	Luxembourg		Luxembourg	Luxembourg		Luxembourg	Luxembourg

Source: Own elaboration.