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Impact of energy transitions on energy poverty in the European Union

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ABSTRACT

While there is a consensus on the importance of energy transitions for achieving a zero-carbon economy, concerns about unfavorable social impacts on most vulnerable groups have often been raised. This study examines the complex links between energy transitions, economic growth, income inequality, and energy poverty in 27 EU countries, based on panel data from 2011 to 2020. The study introduces a new energy poverty measure incorporating six indicators using principal components analysis (PCA). Our method of moments quantile regression (MMQR) model captures asymmetries in the data collected from Eurostat and the World Bank without compromising accuracy.

The results reveal the significant impact of income inequality measured by the Gini coefficient and economic wealth measured by GDP per capita on the energy poverty rate. The predicament is exacerbated by long-term unemployment in countries experiencing high levels of energy poverty. GDP growth remains unexplained by the model suggesting the weak connection between households' vulnerability and macroeconomic cycles. Ultimately, energy transitions exhibit an ambiguous influence on energy poverty. In the countries heavily impacted by energy poverty, energy transitions have a mitigating role. We recommend focusing on income inequality and long-term unemployment when targeting energy poverty.

1. Introduction

Achieving climate neutrality by 2050 requires an ambitious and transformative energy transition across EU countries – one that must gain broad societal acceptance to succeed. However, this transition poses significant challenges, particularly its potential impact on energy affordability. Substantial investments in the energy sector, necessary for this transformation, could lead to higher energy prices and strain household budgets. These economic pressures risk exacerbating energy poverty, leaving more households struggling to meet their basic energy needs. To ensure a socially equitable transition, it is crucial to understand how the energy transition translates into energy poverty and address these impacts effectively.

Energy transitions, understood as shifts away from fossil fuels towards renewable energy, can impact household economics through two channels. Firstly, the increase in the share of renewable energy influences electricity prices, although this impact is not straightforward. When examining energy markets in the short term, many researchers point to the merit order effect, which demonstrates a decrease in electricity prices with a higher share of renewable energy [1,2], in the longer term, this is not so clear-cut. Utilizing renewable energy requires costly investments in infrastructure, energy storage, and power grids [3]. However, measuring the energy transition itself poses challenges due to varied energy structures and the different stages of renewable adoption across countries. Indicators such as renewable energy share, production levels, or installed capacity each capture distinct facets of this transition, yet often lack comparability or miss recent investments. Additionally, data inconsistencies between countries can hinder accurate cross-sectional analyses, as variations in technology adoption and legacy systems may obscure trends. Such phenomena have been observed in recent years in EU countries. From 2018 to 2022, in 22 out of 27 EU countries, electricity prices for households increased, with an increase of more than 20 percent recorded in 11 countries and over 50 percent in four (Czech Republic, Estonia, Italy, Romania) [4]. The second channel of impact is the change in energy sources within households themselves. Households equipped with residential solar photovoltaic panels or residing in energy-efficient homes can largely mitigate energy costs. However, this situation is more prevalent among higher-income households, as evidenced in the case of the US [5,6]. Conversely,

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Nomenclature

Abbreviations

AT	Austria
BE	Belgium
BFP	Building Fuel Poverty Index
BG	Bulgaria
CEPI	Composite Energy Poverty Indicator
Const	Constance
CP04	HICP category: Housing, water, electricity, gas and other fuels
CP045	HICP category: Electricity, gas and other fuels
CY	Cyprus
CZ	Czechia
DE	Germany
DK	Denmark
EE	Estonia
EL	Greece
EP	Energy Poverty
EPVI	Energy Poverty Vulnerability Index
ES	Spain
EU	European Union
EU-LFS	EU Labor Force Survey
EU-SILC	European Union Survey on Income and Living Conditions
FA	Factor Analysis
FI	Finland
FR	France
GDP	Gross Domestic Product
GDP GR	Gross Domestic Product Growth
HC	Housing costs overburden
HICP	Harmonized Index of Consumer Prices
HR	Croatia
HU	Hungary
IE	Ireland
IR	Interquartile Range
IT	Italy
LN	Long-term unemployment rate
LT	Lithuania
LU	Luxembourg
LV	Latvia
MEPI	Multidimensional Energy Poverty Index
Min	Minimum
MMQR	Method of Moments Quantile Regression
MT	Malta
NL	Netherlands
OECD	Organisation for Economic Co-operation and Development
PC	Principal Component
PCA	Principal Components Analysis
PL	Poland
PPP	Purchasing Power Parity
PT	Portugal
Qtile	Quantile
Qu	quartile
Ren	Renewable energies in gross final energy consumption
RenE	Low-carbon energies in gross electricity generation
RenEC	Low-carbon energies in total installed electricity capacity
RenWS	Wind and solar energies in gross electricity generation
RenWSC	Wind and solar energies in total installed electricity capacity
RO	Romania
SD	Standard Deviation
SE	Sweden
SI	Slovenia
SK	Slovakia

poorer households in Poland, if they decide to switch from solid fuels used for heating to gas, may find themselves in an even more challenging economic situation [7].

Our analysis is also rooted in sociotechnical transition theories, which assume that successful energy transitions require not only technological advancements but also the integration of social, economic, and institutional dimensions to foster inclusivity and fairness" [8]. Thus, the energy transition must address the socioeconomic barriers faced by vulnerable populations, ensuring that the shift to renewables actively reduces energy poverty. This shift is impossible without considering the path dependency of some countries that are trapped in cheap fossil fuel consumption. Path dependency often leads to sustained energy poverty as more affordable and efficient energy sources are reserved for wealthier areas or urban centers [9]. In this context, some EU countries are characterized by higher levels of income poverty and lower macroeconomic performance, while others are forerunners to the adoption of renewable energy with a good targeting of vulnerable populations, which constitutes a perfect case to study.

There is a lack of cross-sectional research in this area, describing multiple countries simultaneously. Therefore, this study aims to illuminate the impact of the energy transitions on energy poverty across EU countries. Specifically, the study focuses on two research objectives. Firstly, it presents an energy poverty index constructed from panel data that maximizes the differentiation of countries based on energy poverty. Secondly, the study demonstrates the influence of the energy transitions in EU countries on the level of energy poverty. In doing so, it provides policymakers and decision-makers with a better understanding of the relationship between the energy sector transformation process and its social consequences.

To conduct an in-depth empirical analysis, we utilize data from 27 European Union countries spanning from 2011 to 2020. The energy poverty index is constructed using Principal Component Analysis (PCA), employing six variables commonly used to measure this phenomenon. Inference is performed using a Method of Moments Quantile Regression (MMQR), technique proposed by [10]. The MMQR is particularly suitable when the model includes endogenous explanatory variables, and the panel data exhibits individual-specific effects. The energy transition is approximated using five indicators related to the share of renewable energy in primary energy consumption, electricity and installed capacity. The models also include variables that potentially influence the level of energy poverty, such as economic development, economic wealth, long-term unemployment and social inequalities. Model estimation is preceded by checking the statistical properties of the time series, which aids in better understanding any issues related to acceptance.

The estimated models allowed for drawing a number of important conclusions. Firstly, it revealed that income inequality plays a crucial role in determining the extent of energy poverty, while the level of wealth of the economy displayed a negative correlation with this phenomenon. Secondly, in nations with higher prevalence of energy poverty, long-term unemployment was identified as a contributing factor exacerbating the situation. Thirdly, the study indicated that economic wealth does not significantly influence energy poverty, implying that the fluctuations in the economy do not notably affect the social groups experiencing this form of deprivation. Lastly, the research clearly demonstrated the unicameral positive impact of energy transitions in mitigating energy poverty especially in countries where it was highest.

The study is structured as follows. The second section reviews the literature that supports the basis of the composite indicator and macromodeling of energy poverty. The third section provides an overview of the data. The fourth section explains the statistical methods. The fifth section discusses the results. The last section concludes the analysis.

2. Literature overview

This study pioneers in several respects. Firstly, we introduce the composite energy poverty indicator (CEPI) constructed by the means of well-designed statistical approach. Our measure stands out because the following: i) we compile massive information in our panel dataset of 27 countries from 2011 through 2020; ii) we account for many facets of energy poverty and rely on suitable statistical tool to reveal the most meaningful combinations of factors; iii) our measure is suitable for comparative and intertemporal analysis. Secondly, we forge a bridge between clean energy transitions and energy poverty. Our model accounts for a complex process of moving towards carbon taken place during a ten-year period of time in 27 EU countries. This process is accompanied with societal changes and impacts people's welfare and life in general. We discover neutrality links between energy poverty and energy transitions with special emphasis put on inequality and economic development. In light of the preceding, we identify two strands of literature our study contributes to and discuss them point by point.

2.1. Composite energy poverty indicator

Much effort has been put into disclosing the complex nature of energy poverty [11,12,13]. and many others provide a thorough review of the definitions and indicators of energy poverty. Most researchers agree that energy poverty is determined by income, energy prices, and energy efficiency of buildings [14]. Energy poverty is also related to a subjective feeling of thermal discomfort in winter or summer, depending on the geographical area or country [15,16]. However, self-assessed and objective metrics of energy poverty capture different population strata [17], [18]. Comprising all the aspects of energy poverty poses a serious obstacle to implementing a single measure across Europe, which stirs the debate about the necessity of a single measure [19].

While there are no controversies surrounding the concept of energy poverty, defined as the situation where a household experiences inadequate levels of energy services in the home, measuring this phenomenon itself is challenging. In practice, three approaches are employed to measure energy poverty:

1. The expenditure approach evaluates energy poverty by comparing household energy costs to established thresholds, providing insight into financial constraints.
2. The consensual approach relies on self-reported assessments of living conditions and the ability to meet basic needs within a community context, offering a subjective view of deprivation.
3. Direct measurement, on the other hand, directly assesses the level of energy services attained by households against predefined standards, offering a tangible measure of energy poverty based on actual energy access and usage.

Each of these approaches offers specific metrics that allow us to view energy poverty from a particular perspective. However, no measure is universal and should be applied more locally, within a specific geographic or social context (politically and culturally contingent) [16]. For this reason, efforts have been made to devise composite measures that consider various facets of this form of deprivation [20]. put forward a multidimensional energy poverty index (MEPI), which comprises three dimensions: "energy," "income," and "energy efficiency of housing." While this index delineates energy poverty in Japan, its dimensions could be applicable to developed nations provided accurate data is amassed. Additionally, there exist alternative proposals for a comprehensive assessment of energy poverty [21]. introduced an index encompassing aspects such as cooking, lighting, household appliances, entertainment/education, and communication, tailored specifically for developing countries [22]. introduced the Building Fuel Poverty Index (BFP) for Italy, which concentrates on the interaction between building energy performance and fuel poverty. It highlights energy efficiency, housing affordability, and housing conditions as key factors.

[23] delved into the structural vulnerability of energy poverty in the EU, examining its correlation with excess winter mortality [24]. introduced the Energy Poverty Vulnerability Index (EPVI) for Portugal, which maps energy-poor regions and identifies intervention hotspots by integrating socioeconomic indicators, building characteristics, and energy performance, advocating for localized strategies to tackle energy poverty challenges. Lastly [25], proposed a composite index that acknowledges the drivers and consequences of energy poverty to rank the Member States of the European Union. A key limitation of these approaches is either their applicability to individual countries or their lack of a temporal dimension.

2.2. Macro-factor models of energy poverty

Energy poverty macro-models focusing on countries and large regions differ in terms of goals and indicator selection. Most of the studies contain temporal dimension and include panels of data. Vast majority of macro-models center around economic development, GDP growth, crises.

For example [26], study the impact of economic crises on the EU countries during 2004–2019. The authors consider electricity prices, GDP, unemployment, the at-risk of poverty, urbanization and the number of rooms in the model to find out strong effect of the first indicator on the levels of energy poverty measured by the consensual and composite metrics. Economic growth is noted to have a significant impact on energy poverty. The same idea is supported by [27], who previously assessed the case of Greece by approximating energy poverty with electricity consumption. The authors document negative consequences of economic crisis for the people's ability to pay electric bills. In line with prior findings [28], assume electricity prices are key to understanding energy poverty trends. The study claims that energy poverty levels in Spain were influenced by economic crisis as demonstrated by the data for the period of 2004–2012 [29]. builds a macro model for 28 EU countries with the goal to investigate energy poverty and the Gini coefficient, GDP causal relationships inter alia. The model reveals strong dependency between the energy poverty rate on the one hand, and inequality and GDP per capita on the other. Some authors go further in the macroeconomic analysis and examine the link between energy poverty and public spending [30] or particular governmental programs and social aids schemes [31,32].

Yet, little attention is devoted to studying the impact of energy transitions on the prevalence of energy poverty in the EU, especially in the context of the recent developments. The importance of the topic has already been raised by some scholars [3,33,34]. In particular [3], emphasize such issues as limited access to energy transitions benefits and disproportioned burden put on vulnerable people [35] discuss environmental justice, which should be ensured in the process of energy transitions [34]. construct a theoretical framework of energy transitions within the sustainability and circularity discourse. The emerging insights from the literature inspire us to build the model, which explains the impact of energy transitions on energy poverty and goes beyond the macro-economic development.

3. Data description

In this research we use panel data aggregated at a country level – the data span from 2011 to 2020. We consciously limit the time range to avoid unusual sharp declines and peaks as well as missing values. Additionally, in 2021 some countries experienced breaks in the time series of the EU-SILC, which is one of the primary sources of our data. The last fact further explains the choice of a time range. Our dataset contains 27 EU countries, such as Austria (AT), Belgium (BE), Bulgaria (BG), Cyprus (CY), Czechia (CZ), Germany (DE), Denmark (DK), Estonia

(EE), Greece (EL), Spain (ES), Finland (FI), France (FR), Croatia (HR), Hungary (HU), Ireland (IE), Italy (IT), Lithuania (LT), Luxembourg (LU), Latvia (LV), Malta (MT), Netherlands (NL), Poland (PL), Portugal (PT), Romania (RO), Sweden (SE), Slovenia (SI), and Slovakia (SK).

Different sets of variables are selected to construct the CEPI and build mixed quantile regression models. We collect most of the indicators from the Eurostat database except GDP per capita in PPP, which is derived from the World Bank database. The data fulfill multiple criteria of accessibility and clarity, quality, relevance, accuracy, coherence, and comparability. The last feature of the data is crucial in comparative analysis, like the present one.

3.1. Composite energy poverty indicator data

This study is designed in a two-stage way. In the first stage, we assess energy poverty using a composite indicator approach. In the second stage, we build a model, where energy poverty is a response variable, and six other variables are independent. We propose different methods to estimate energy poverty described in detail in the methodology section. Our approach is driven by the need to ensure a comprehensive and comparable measurement of energy poverty across time and space. We emphasize the policy soundness and feasibility of energy poverty assessment.

Table 1 describes the variables selected for a CEPI. We propose to measure energy poverty based on six variables commonly estimated in the EU statistics. The choice of the variables is determined by a strong intention to embrace the most recognized and accepted by the research community aspects of energy poverty. The indicators capture various manifestations of energy poverty, such as subjective assessment, over-indebtedness, housing deprivation, natural and living environment, housing costs, and energy consumption. Since energy poverty is measured at a household level, the data are gathered through questionnaires.

Except HICP, all variables are collected from the EU-SILC, a well-known source of the EU annual micro-data available in cross-sectional and longitudinal formats since 2001. Despite some deficiencies, e.g. lack of energy poverty target, the EU-SILC represents the most harmonized and updated survey available for comparative analysis of energy poverty in Europe by now. The household and individual data are transmitted from the national statistical offices to Eurostat and the whole process is regulated by the EU law (Regulation EU 2019/1700).

Fig. 1 shows boxplots of the descriptive statistics of the energy poverty indicators, such as mean, median, maximum, minimum, the first and the third quantiles. The biggest spread in values is observed in the inability indicator. In this case the interquartile range equals 11.93 pp. The less scattered are values in the dark indicator signifying homogeneity of households' answers close to the median value 5.6 %. The highest median value is 13.2 % for the grime indicator, which points at the gravity of the environmental problems. And the lowest median is 1.35 for the HICP indicator. We note upper boundary outliers in all indicators, and lower boundary outliers in the HICP variable. In the latter case negative values mean decline in consumer prices from the previous year.

Table 1
Description of the variables included into the composite energy poverty indicator.

Shortcut	Variable name	Variable description
Inability	Inability to keep home warm	Households provide a yes-no answer to the question about affordability of warmth in a dwelling and does not necessarily reflect the current situation of a cold dwelling. Eurostat includes this indicator of household's material deprivation (EU-SILC).
Arrears	Arrears on utility bills	Households assess their situation within the last 12 month and can respond yes, once/yes, twice or more/no to the question about arrears on utility bills. Utility bills include electricity, heating, gas, waste disposal, water, etc. This variable measures the economic strain and refers to the inability to pay (EU-SILC).
Dark	Total population considering their dwelling as too dark	The indicator represents the share of the population considering their dwelling as too dark, not having enough light. Eurostat collects this variable as a part of housing deprivation monitoring within income and living conditions analysis (EU-SILC).
Grime	Pollution, grime or other environmental problems	Eurostat collects this indicator of subjective well-being as a percentage of households reporting exposure to pollution, grime or other environmental problems. The variable indicates quality of life, especially natural and living environment (EU-SILC).
HC	Housing costs overburden	This variable is aggregated by Eurostat under the domain income and living conditions (EU-SILC). It represents a total percentage of households, which spend more than 40 % of their disposable income on housing costs in a given year. Both disposable income and housing costs are net of housing allowances. The variable captures the expenses related to the right to live, including utilities and rental payments in the case of tenants.
HICP	HICP: harmonized index of consumer prices	HICP is an official measure of inflation based on consumer prices by different purposes. We use annual average rate of change in individual consumption of electricity, gas and other fuels (CP045), i.e. a subcategory of housing, water, electricity, gas and other fuels (CP04). This variable correctly reflects inflation attributed to the energy component of housing costs.

3.2. Method of moments quantile regression data

Our MMQR model includes six independent variables, which are key to understanding the macro-economic impact of energy transitions on energy poverty. The description of the variables is provided in Table 2. We further justify the choice of the variables for the model.

The first indicator is the Gini coefficient is considered a good indicator of inequality in a society and is monitored by Eurostat regularly as a part of the income and living conditions statistics [36]. documents that the Gini indicator is robustly correlated with energy poverty measured by the inability to keep home warm indicator. Another good measure of a country's wealth is GDP. GDP shows the wealth of a country each year, while the GDP growth reveals the dynamics of economic growth. The Gini coefficient, together with the GDP indicator, is frequently employed in a similar macro-level analysis of energy poverty [26,27,28].

Since the clean energy transitions is central to this study, we introduce five renewable energy variables. All renewable indicators, described in Section 3.2, are used in separate models and capture energy transitions from various perspectives.

The impact of income on energy poverty cannot be overstated and is recognized by many researchers [37,38,39,40]. Our last variable is long-term unemployment, which is supposed to indicate the income situation of vulnerable households. The long-term unemployment signifies a serious dysfunction of the labor market and represents a greater challenge to policymakers compared to unemployment in general. Being unemployed for more than a year negatively affects the mental and physical condition of households and individuals. Accounting for unemployment is a common point in energy poverty macro-research [26,41].

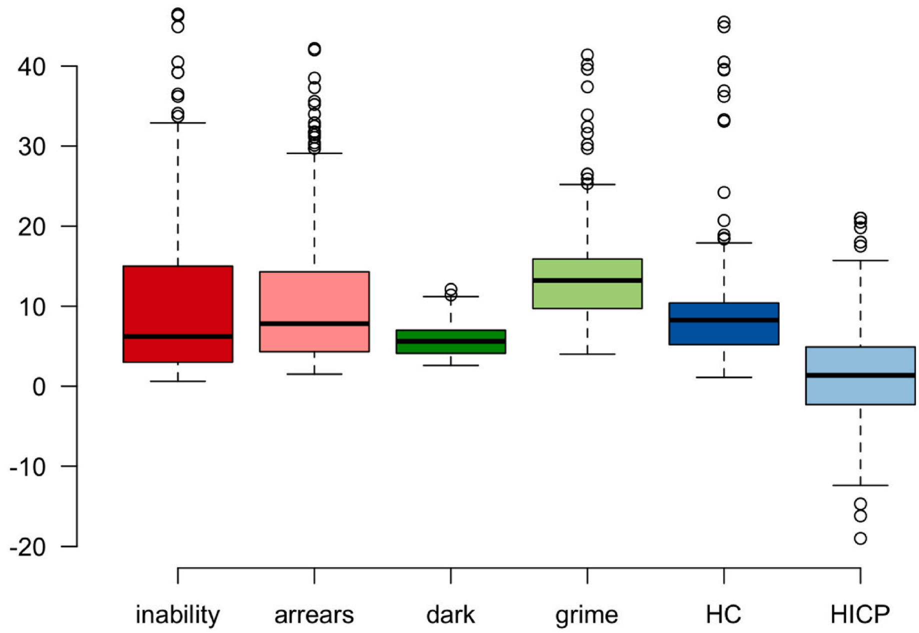

Fig. 1. Boxplots of the variables comprising composite energy poverty indicator.

Table 3 presents the descriptive statistics of key independent variables used in the regression analysis. All of our variables are skewed but to a different extent. We observe that the distribution of most of the indicators except GDP and LN is approximately normal. Both GDP and LN are right-skewed higher concentrations around lower values, which is a good sign in the case of LN. Gini informs about relatively low to moderate inequality within European countries. Multiple upper boundary outliers are observed in Ren, LN and GDP, while many extremely low values are noted in GDP GR. We report that on average from 2011 to 2020 in the EU countries, the Gini coefficient was about 29.7 %, GDP growth was about 1.5, and long-term unemployment equaled 4 %. The share of renewables in final energy consumption amounted to around 20 % on average. The mean values for RenE and RenEC are close to 0.5, while average RenWS and RenWSC reach 0.11 and 0.16 respectively.

4. Methodology

4.1. Composite index of energy poverty

Following the definition provide by the European Commission's first state-of-the-art report [42], composite indicators are '[…] based on sub-indicators that have no common meaningful unit of measurement and there is no obvious way of weighting these sub-indicators'. This suggests that constructing a composite index involves gathering a suitable set of features and appropriately weighting them. Equal weighting, the most common approach in composite indicator development [43], treats all variables as equally important, which may not reflect their true significance. To address this issue, data-driven weighting methods like Principal Component Analysis (PCA) are utilized [44]. In PCA, the original dataset can be depicted through a series of equations, correlating with the number of indicators. These equations act as linear transformations of the original data, systematically designed to reveal the maximum variance in the initial equation, followed by the explanation of subsequent variances in successive equations. In this study, the standard procedure, where the factor loadings of first principal component as used as weights [45]. In results the composite index indicates the direction in the data space that maximally differentiates countries over time and space due to energy poverty.

4.2. Method of moments quantile regression

To analyze the determinants of energy poverty in this study, a Method of Moments Quantile Regression (MMQR) technique proposed by [10] is applied. The traditional panel regression technique, as outlined by [46], allows for the analysis of the diverse impacts of covariates across different conditional quantiles of the dependent variable. However, it overlooks the fixed effects contributed by individuals within the system. Addressing this gap, [10] introduced the MMQR approach, which incorporates individual effects into the total distribution, thereby enabling us to discern conditional heterogeneous impacts of covariates on energy poverty. This innovative method suggests that individual characteristics within the panel may have distinct heterogeneous impacts on the conditional distributions of dependent variables, potentially yielding more robust insights compared to traditional quantile regression techniques pioneered by [47,48,49]. Additionally, the MMQR has the capacity to identify asymmetries in covariates based on their positions and alleviate the impact of their endogenous properties, as observed by [50]. Furthermore, in a nonlinear context, estimates derived from the MMQR exhibit enhanced robustness, reliability, comparability, and reproducibility. Expanding on the research conducted by [10], the fixed-effects panel quantile model can be articulated as follows:

$$Y_{it} = \alpha_i + X_{it}'\beta + \left(\delta_i + Z_{it}'\gamma\right)U_{it} \tag{1}$$

Where it is assumed that $P\left\{\delta_i + z_{it}'\gamma > 0\right\} = 1$. Vector $(\alpha, \beta', \delta, \gamma')$ comprise the estimated model parameters. The individual fixed effects are determined by (α_i, δ_i), for $i = 1, .., n$ and k-vector of known subset of X is denoted by Z, specifically:

$$Z_l = Z_l(X), l = 1, \ldots k. \tag{2}$$

It is assumed that in equation (1), Z_{it} is distributed identically for any fixed effect across different units over time. Similarly, U_{it} is identically and independently for individuals distributed through time, however it is orthogonal to Z_{it} standardized to complete the standard conditions [10]. equation (1) expressed in terms of quantile of dependent variables, is given by:

$$Q_{Y_{i,t}}(\tau|X_{i,t}) = (\alpha_i + \delta_i(\tau)) + X_{i,t}'\beta + Z_{it}'\gamma q(\tau), i = 1, .., N, t = 1, .., T \tag{3}$$

Table 2
Description of the variables in the MMQR model.

Shortcut	Variable name	Variable description
Gini	Gini coefficient of equivalised disposable income	The Gini coefficient is measured on the scale from 0 to 100, where 0 indicates perfect equality and 100 means full inequality. The equivalised disposable income, which is the total income of a household minus tax and other deductions, from the EU-SILC is used to calculate this measure. The modified OECD equivalence scale applies.
GDP	GDP per capita, PPP (constant 2017 international $)	The World Bank defines this measure as the GDP per capita in international dollars based on purchasing power rates and fixed to 2017 prices, which makes this measure comparable across countries. The values are divided by the number of a population in a country.
GDP GR	Real GDP growth rate – volume, per capita	The annual growth rate of the real GDP is computed in terms of chain linked volumes at the prices of a previous year. The value is given per capita. Eurostat uses this measure to compare the dynamics of GDP development over time and between different countries.
Ren	Renewable energies in gross final energy consumption	The indicator gives the share of renewable energy as defined by Eurostat (2024) in gross final energy consumption in percentage. The gross final energy consumption is calculated as an end-used consumption of energy in addition to grid losses and power plants consumption. The EU introduced this indicator to monitor progress towards Sustainable Development Goals as well as the achievement of Fit for 55 targets.
RenE	Low-carbon energies in gross electricity generation	The indicator represents the share of low-carbon energies, i.e. renewables and biofuels as well as nuclear energy, in gross electricity generation measured in Terawatt hours (TWH). Renewables and biofuels category includes hydro, wind, solid biofuels and renewable wastes, biogases liquid biofuels, solar, geothermal, geothermal, tide, wave and ocean, and other. The indicator is calculated based on the Eurostat energy statistics.
RenEC	Low-carbon energies in total installed electricity capacity	This measure is calculated as a share of low-carbon energy sources in total installed electricity capacity (MW). We deduct combustible fuels and retain, such energies as nuclear, hydro, wind, solar PV, solar thermal, geothermal, tide, wave and ocean, and others. The data drives from the Eurostat energy statistics.
RenWS	Wind and solar energies in gross electricity generation	The indicator represents the share of combined wind and solar energies in gross electricity generation measured in Terawatt hours (TWH).
RenWSC	Wind and solar energies in total installed electricity capacity	This measure is calculated as a share of combined solar and wind capacity in total installed electricity capacity (MW).
LN	Long-term unemployment rate	Long-term unemployment refers to unemployment for 12 months and more. The variable is counted as a percentage of the population in labor force at the age class from 15 to 74 years. Eurostat collects this indicator from the EU Labor Force Survey (EU-LFS).

In equation (3), the outcome variable Y_{it} (Energy poverty index) and its distribution represented by quantiles $Q_{Y_{i,t}}(\tau|X_{i,t})$ is subjected to locational distribution of predictors (GDP, GDP GR, Gini, Ren) for any individual (i) and is time invariant. This fixed effects for given country is represented by $\alpha_i(\tau) = \alpha_i + \delta_i q(\tau)$. The model parameters are obtained by numeric optimization techniques.

5. Results and discussion

In this section, we report empirical results and discuss findings. Our first task is to create the energy poverty measure, which we pass to the model later as a response variable. We employ several methods, including PCA, FA and equal weights approach. The latter two methods are used to ensure the PCA results are robust. Our second task is to build a model, which examines the link between energy poverty and clean energy transitions. We also enrich the model to include a set of inequality and economic growth variables.

5.1. Composite energy poverty indicator

We construct our CEPI using a couple of statistical techniques, such as PCA and FA, and an equal weights approach frequently applied in the energy poverty research [51,52]. The main method of this study is PCA. The panel data include observations by countries and years (long format). Our goal is to retain the most information (variance in data) by reducing the number of variables to one. Before identifying the principal components, we explore the relationships between the variables. As shown in Table 4, we observe a positive correlation between all the variables, except dark and HC. The strongest link is found between arrears and inability as well as arrears and HC. Other variables are not strongly related to each other, which means that they do not contain a lot of redundant information.

The results of the PCA analysis are presented in Table 5. The first component explains 37.2 % of all the variance in the data; the second one represents 19.7 % of the variance and so on in the diminishing order of significance. The PCA allows us to reduce the number of variables and retain only the most informative one as a CEPI. The proportion of the variance in each variable explained by the first component varies from 0.555 (arrears) and 0.545 (inability) to 0 (HICP).

Table 6 provides the descriptive statistics of the CEPI for all years and countries. The values range between −1.9 and 5.7, where positive numbers and negative numbers signify the level of energy poverty above and below the average respectively. The distribution is asymmetric with the most outliers on the right side, i.e. high levels of energy poverty.

Fig. 2 displays the more detailed distribution of the CEPI by year and country. The heatmap shows the magnitude of energy poverty, ranging from the lowest to the highest depending on the intensity of the color. Our results confirm that two countries, Greece and Bulgaria, report high energy poverty rates throughout the period. Generally, the two upper boundary outliers face positive changes in the reduction of energy poverty. In contrast, Finland and Sweden have the lowest CEPI based on PCA calculations. Since the situation in each country changes dynamically, we analyze the problem in each country-year observation.

Fig. 3 captures the distribution of CEPI by quantiles. Six quantiles correspond to the 10th, 25th, 50th, 75th, and 90th quantiles used in the MMQR models. Most countries, with rare exceptions, experience a significant reduction in CEPI at the end of the observation period. Slovenia, Poland, Cyprus, Croatia, and Ireland show remarkable progress moving from higher to lower distribution quantiles. We also observe a marked improvement in Latvia, where CEPI dropped from 2.9 in 2011 to −0.73 in 2020. The results for other countries oscillate within certain limits, with a noticeable decrease in the level of energy poverty in 2016–2017 compared to 2011. Falling trends in most countries, including troubled Bulgaria, indicate progress in counteracting energy poverty. Some countries, such as Belgium, Luxembourg, Spain, and France, experience

Table 3
Descriptive statistics of the variables used in the MMQR model.

Variable	Min	1st qu.	Median	Mean	3rd qu.	Max	SD	Skew	Range
Gini	20.9	26.9	29.2	29.73	32.7	40.8	3.87	0.36	5.8
GDP	18662	29168	37791	41947	50320	116284	18870.99	2.18	21152
GDP GR	−11.6	0.025	1.5	1.484	3.6	23.3	3.57	0.06	3.575
Ren	1.85	11.68	16.95	20.04	26.06	60.12	11.69	0.97	14.38
RenE	0.0045	0.302	0.531	0.511	0.687	0.985	0.26	−0.17	0.385
RenEC	0.0091	0.321	0.493	0.473	0.621	0.925	0.21	−0.15	0.3
RenWS	0.0022	0.0341	0.0783	0.1113	0.1447	0.6095	0.11	1.94	0.61
RenWSC	0.0004	0.0806	0.146	0.167	0.2308	0.495	0.11	0.9	0.5
LN	0.600	1.925	2.900	4.088	5.1	17.5	3.26	1.7	3.175

Note: Min – minimum; max – maximum; qu. – quartile; SD – standard deviation; skew – skewness. The values are truncated.

Table 4
The correlation matrix of the energy poverty indicators.

	HICP	arrears	inability	dark	grime	HC
HICP	1.000	0.055	0.031	0.019	0.017	0.060
arrears		1.000	0.640	0.217	0.154	0.512
inability			1.000	0.283	0.298	0.296
dark				1.000	0.353	−0.039
grime					1.000	0.194
HC						1.000

fluctuations in energy poverty rates. In 2020, Spain, France, and Denmark experienced an increase in CEPI, which can be attributed to the impact of indicators with the highest weights. Our analysis also reveals that the number of observations in the highest quantile fell by 14.8 p.p. in 2020 compared to 2011. The highest CEPI is reported in Greece throughout the period.

We perform a robustness check of the PCA results by following two alternative approaches. The first approach is FA, which is based on Bartlett's scores. The arrears variable is almost entirely explained by the first factor. The share of inability and HC is equal to 0.7 and 0.5, respectively. Some commonalities can be found between PCA and FA loadings. In both cases, we observe the strong presence of arrears, inability, and HC variables. The marginal role of HICP is confirmed in the first component and the first factor results, which aligns with the findings obtained from the PCA analysis. Detailed statistics and graphs are available upon request. The description of CEPI (FA) statistics is presented in Table 7. According to both methods, Greece and Bulgaria are the countries most affected by energy poverty, with Greece leading the ranking. France, Finland, and Greece belong to the same quantiles over all years. We observe almost the same recovery rate at the end of the period. In general, there are no striking dissimilarities in the PCA and FA results.

The second approach assigns equal weights to the six indicators of energy poverty. This method produces results presented in Table 8. In this case, the standard deviation and the interquartile range are much higher than before, highlighting the differences between countries. Yet, the pattern of the trend with two extreme upper outliers (Greece and Bulgaria) measured by the equal weights approach is like the one discussed above. The quantile distribution of country-year observations provides the same insight as the PCA and FA methods demonstrating the robustness of the results. Detailed statistics and graphs are available upon request.

5.2. *Method of moments quantile regression models*

5.2.1. *Model specification*

To examine the relationship between the progress of energy

Table 5
PCA loadings and importance of components.

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6
HICP		0.134	0.987			
arrears	0.555	0.282		0.293		−0.719
inability	0.545			0.344	0.547	0.529
dark	0.312	−0.658		0.289	−0.600	0.141
grime	0.355	−0.478		−0.696	0.326	−0.231
HC	0.410	0.492		−0.477	−0.478	0.362
Standard deviation	1.494	1.087	0.996	0.879	0.734	0.526
Proportion of variance	0.372	0.197	0.165	0.128	0.089	0.046
Cumulative proportion	0.372	0.569	0.734	0.863	0.953	1.000

Note: Comp. – component. The values are truncated to 3 decimal places.

Table 6
Descriptive statistics of the CEPI (PCA).

Min	1st qu.	Median	Mean	3rd qu.	Max	SD	Skew	IR
−1.891	−1.105	−0.439	0.000	0.753	5.650	1.5	1.44	1.858

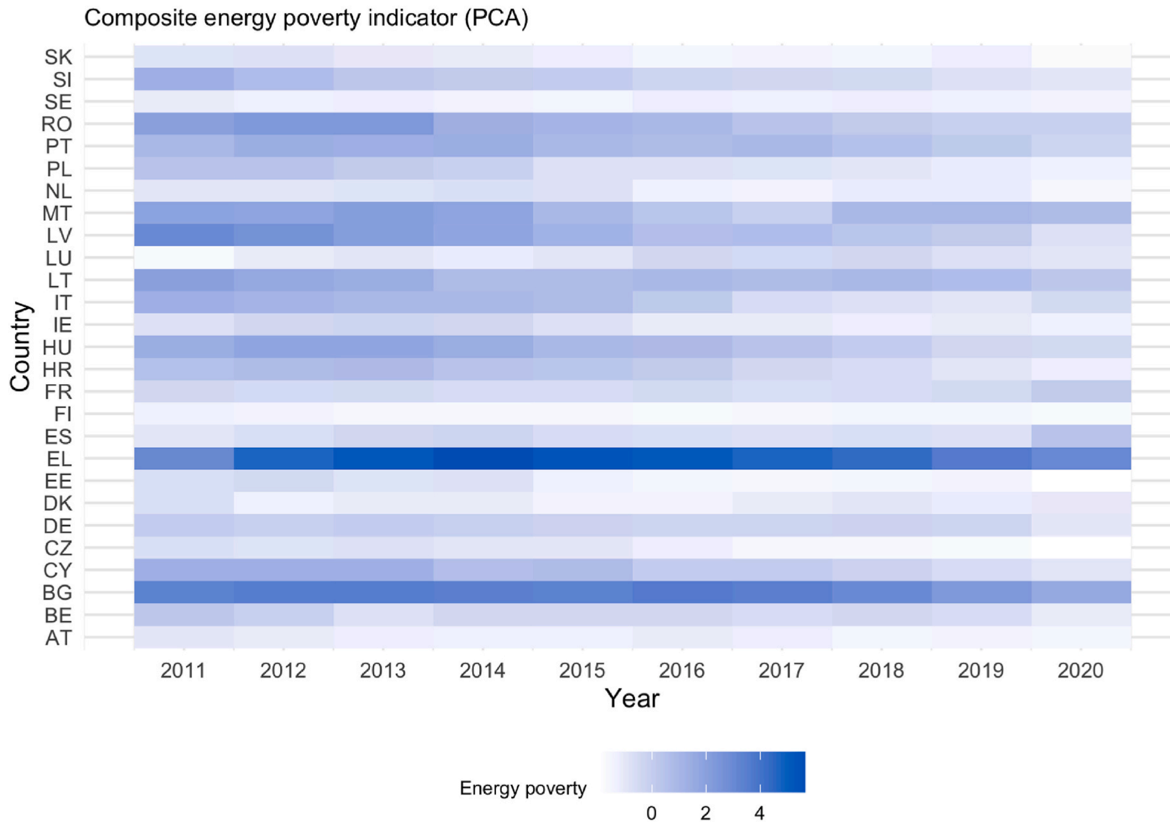

Fig. 2. CEPI by country and year, based on PCA.

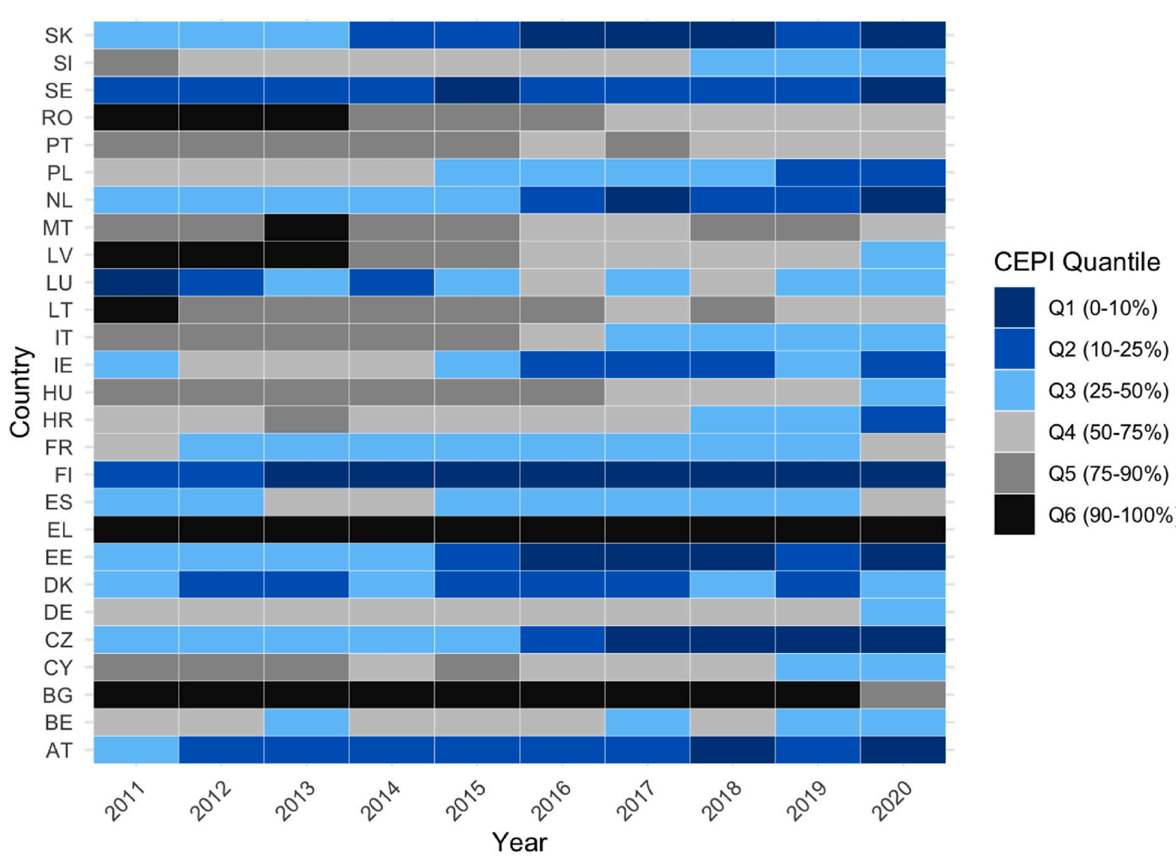

Fig. 3. Heatmap of CEPI quantiles, based on PCA.

Table 7
Descriptive statistics of the CEPI (FA).

Min	1st qu.	Median	Mean	3rd qu.	Max	SD	Skew	IR
−1.163	−0.739	−0.423	0.000	0.363	3.972	1.08	1.55	1.102

Table 8
Descriptive statistics of the CEPI (equal weights).

Min	1st qu.	Median	Mean	3rd qu.	Max	SD	Skew	IR
−5.344	−2.624	−0.928	0.000	1.530	13.312	3.49	1.24	4.154

transitions and energy poverty, we consider five models, with the differences between them stemming from how we understand energy transitions. The detailed specification of these models has been presented in Table 9. As can be seen, each of the models shares the same set of control variables, namely Gini, GDP, GDP GR, LN and five proxies for energy transitions: Ren, RenE, RenEC, RenWS and RenWSC, which take into account: renewable energies in gross final energy consumption, low-carbon energies in gross electricity generation, low-carbon energies in total installed electricity capacity, wind and solar energies in gross electricity generation, and wind and solar energies in total installed electricity capacity.

5.2.2. *Preliminary tests*

In this section, we present empirical results and discuss our findings. Before delving into the main results, we provide details of the standard preliminary tests. We initially assess the presence of cross-sectional dependence (CD) within the panel. CD has the potential to distort the true parameter values of coefficient estimates. Neglecting cross-sectional dependence, which may stem from unobserved common factors, can significantly reduce the efficiency gains of panel data if disregarded [53]. In this study, we evaluate cross-sectional dependence (CD) using the [54] CD test. The results from the CD test are presented in Table 10, revealing a presence of CD in the data. Specifically, the test statistics are significant for four out of five variables, with Gini being the exception. Next, we examine the homogeneity of slopes in our models using the Pesaran and Yamagata test [55].

The test statistics presented in Table 11 demonstrate high significance, thereby supporting the alternative hypothesis of heterogeneous slopes for both models. Next, we apply the second-generation unit root test (CIPS) developed by [56], with the results presented in Table 12. We consider two commonly adopted specifications: one with an intercept and another with both an intercept and a linear trend. Based on the test results, it appears that the only stationary variable is GDP GR. The other variables exhibit a unit root. The non-stationarity of the variables in the panel implies that it is only meaningful to analyze the models estimated at the levels if they are in long-run equilibrium.

Therefore, in the subsequent step, we apply two panel cointegration tests. The first test proposed by [57] permits the inclusion of panel-specific cointegrating vectors. In contrast, the second test introduced by [58] does not necessitate any correction for the temporal dependencies of the data. However, it allows for the accommodation of individual-specific short-run dynamics, individual-specific intercept and trend terms, as well as individual-specific slope parameters. The results of both types of tests are displayed in Table 13, indicating, for majority of specification the presence of a long-term relationship.

Table 9
List of models considered in the study.

Model 1	$EP_{it,q} = \alpha_{0,q} + \alpha_{1,q}Gini_{it} + \alpha_{2,q}logGDP_{it} + \alpha_{3,q}GDPGR_{it} + \alpha_{4,q}LN_{it} + \alpha_{5,q}Ren_{it} + \varepsilon_{it}$
Model 2	$EP_{it,q} = \alpha_{0,q} + \alpha_{1,q}Gini_{it} + \alpha_{2,q}logGDP_{it} + \alpha_{3,q}GDPGR_{it} + \alpha_{4,q}LN_{it} + \alpha_{5,q}RenE_{it} + \varepsilon_{it}$
Model 3	$EP_{it,q} = \alpha_{0,q} + \alpha_{1,q}Gini_{it} + \alpha_{2,q}logGDP_{it} + \alpha_{3,q}GDPGR_{it} + \alpha_{4,q}LN_{it} + \alpha_{5,q}RenEC_{it} + \varepsilon_{it}$
Model 4	$EP_{it,q} = \alpha_{0,q} + \alpha_{1,q}Gini_{it} + \alpha_{2,q}logGDP_{it} + \alpha_{3,q}GDPGR_{it} + \alpha_{4,q}LN_{it} + \alpha_{5,q}RenWS_{it} + \varepsilon_{it}$
Model 5	$EP_{it,q} = \alpha_{0,q} + \alpha_{1,q}Gini_{it} + \alpha_{2,q}logGDP_{it} + \alpha_{3,q}GDPGR_{it} + \alpha_{4,q}LN_{it} + \alpha_{5,q}RenWSC_{it} + \varepsilon_{it}$

Table 10
Cross-sectional dependence test (CD) (the null hypothesis: no cross-sectional dependence) and correlation.

Variables	CD	Corr	Abs Corr
EP	26.02***	0.439	0.564
Gini	−0.69	−0.012	0.4660
GDP	43.78***	0.739	0.744
GDP GR	39.70***	0.67	0.67
Ren	43.38***	0.732	0.804
RenE	32.15***	0.56	0.58
RenEC	33.72***	0.59	0.74
RenWS	47.199***	0.83	0.83
RenWSC	49.53***	0.87	0.87

Note: *, **, *** indicate the level of significance at 10, 5, and 1 %, respectively; Pesaran's (2021, 2015) CD test is performed using the Stata 'xtcdf' command., CD means - CD-test; Corr - average correlation coefficient; Abs corr - average absolute correlation coefficient.

Table 11
Slope homogeneity test (the null hypothesis: slope coefficients are homogenous).

Test statistics/ Model	Model 1	Model 2	Model 3	Model 4	Model 5
Delta tilde	3.033 ***	3.427***	3.436***	3.602***	3.432***
Delta tilde adjusted	5.537 ***	6.256***	6.274***	6.576***	6.266***

Note: *, **, *** indicate the level of significance at 10, 5, and 1 %, respectively. Pesaran and Yamagata's (2008) CD test is performed using the Stata 'xthst' command.

Table 12
Panel unit root CIPS test (the null hypothesis: series are nonstationary).

Variables	constant	constant and trend
EP	−2.350**	−2.533
Gini	−1.678	−3.209***
logGDP	−2.083*	−2.394
GDP GR	−2.777***	−2.596
Ren	−1.841	−2.590
RenE	−1.848	−2.123
RenEC	−1.500	−1.536
RenWS	−1.575	−1.947
RenWSC	−2.194*	−2.335

Note: The critical values at 10 %, 5 %, and 1 % significance levels for the constant specification are −2.1, −2.22, and −2.44 respectively. For the constant and trend specification, the critical values are −2.67, −2.82, and −3.1 respectively; *, **, *** indicate the level of significance at 10, 5, and 1 %, respectively; Pesaran's (2007) test is performed using the Stata 'xtcips' command. We specified: maxl [1], bglag [1].

5.2.3. Method of moments quantile regression

The parameters of quantile regression models are estimated for the 10th, 25th, 50th, 75th, and 90th quantiles, allowing for an assessment of the significance of the relationships between individual variables and energy poverty depending on its prevalence.

Table 14 presents the coefficients derived from the initial specification of the model. For three variables, specifically Gini, GDP, and Ren, a uniformly significant relationship is discerned across all quantiles. Concerning the remaining variables, their impact varies as a function of the degree of energy poverty. The findings suggest that an augmentation in income inequality (Gini) is positively correlated with energy poverty, with regression coefficients spanning from 0.134 to 0.190, and the coefficient is greater for higher quantiles of poverty. This observation is consistent with the findings of (Galvin, 2019). The results for prosperity levels (GDP) also accord with prior studies [16,17], demonstrating that an increase in national prosperity generally results in a reduction in energy poverty, with regression coefficients ranging from −0.887 for the 10th quantile to −1.660 for the 90th quantile. In the context of economic growth, the results are less unambiguous. Despite negative coefficients being obtained for all quantiles, significant relationships are evidenced only for the uppermost quantiles, with coefficient values of −0.029 and −0.036, respectively. This suggests that in nations where energy poverty is pronounced, economic growth ameliorates the conditions of groups contending with this form of exclusion. Comparable results, i.e., significant coefficients for higher quantiles (beginning from the 50th quantile), were identified for long-term unemployment. An escalation in this indicator, with coefficients ranging from 0.105 for the median to 0.252 for the 90th quantile, corresponds with an increase in energy poverty in countries where it is relatively elevated. The significant coefficients obtained for the share of renewable energy (Ren) are significant across all quantiles, demonstrating an inverse relationship, wherein an elevated share of renewable energy corresponds to lower poverty levels. This relationship intensifies as the quantile of the energy poverty distribution increases, with coefficients ranging from −0.011 for the 10th quantile to −0.031 for the 90th.

Table 15 presents the findings derived from Model 2, which integrates the proportion of renewable energy within electricity generation. The findings of this model largely corroborate those of Model 1, particularly highlighting the pivotal role of social inequality and overall economic prosperity in mitigating energy poverty. Analogous to Model 1, long-term unemployment is associated with poverty at higher quartiles. Nevertheless, Model 2 exhibits its distinctiveness in two aspects. It suggests that the extent of energy poverty is independent of economic affluence, as the parameters across all quantiles lack statistical significance. Furthermore, it reveals that augmenting the proportion of renewable energy in electricity production is linked to poverty alleviation only for elevated levels of this phenomenon, specifically for levels exceeding the median, with an increasing correlation corresponding to higher quantiles (regression coefficients range from −0.504 for the median to −1.46 for the 90th quantile).

In Table 16, the results for Model 3 are presented. In this case, the analysis includes the relationship between energy poverty and the share of installed renewable energy capacity in the overall installed electricity capacity. Installed capacity does not necessarily indicate electricity production but rather refers to the level of investment. Therefore, high installed capacity, in the case of low utilization due to weaker wind conditions or less sunlight, signifies poor efficiency, high costs, and relatively lower financial benefits. It may even contribute to the increase of energy poverty. The obtained results from quantile regression suggest that this assumption may hold true. The regression coefficient for RenEC is positive for low quantiles (qtile_10, qtile_25), respectively 0.744 and 0.489 (both significant), and negative for the highest ones (qtile_75,

Table 14
Model 1 (quantile regression).

	qtile_10	qtile_25	qtile_50	qtile_75	qtile_90
Gini	0.135***	0.139***	0.143***	0.149***	0.152***
logGDP	−0.887***	−1.073***	−1.260***	−1.522***	−1.660***
LN	−0.033	0.036	0.105***	0.201***	0.252***
GDP GR	−0.000	−0.009	−0.017	−0.029*	−0.036*
Ren	−0.011**	−0.016***	−0.021***	−0.027***	−0.031***
Const	4.628***	6.818***	9.015***	12.081***	13.707***

Table 15
Model 2 (quantile regression).

	qtile_10	qtile_25	qtile_50	qtile_75	qtile_90
Gini	0.120***	0.123***	0.131***	0.140***	0.147***
logGDP	−0.870***	−0.949***	−1.108***	−1.233***	−1.342***
LN	0.005	0.040	0.109***	0.197***	0.258***
GDP GR	0.013	0.003	−0.012	−0.032	−0.045
RenE	0.231	−0.053	−0.504***	−1.070***	−1.460***
Const	4.488***	5.531***	7.189***	9.267***	10.701***

Table 16
Model 3 (quantile regression).

	qtile_10	qtile_25	qtile_50	qtile_75	qtile_90
Gini	0.123***	0.129***	0.137***	0.149***	0.159***
logGDP	−0.995***	−1.026***	−1.076**	−1.152***	−1.199***
LN	−0.008	0.036	0.111***	0.222***	0.290***
GDP GR	0.022	0.012	−0.005	−0.031	−0.047
RenEC	0.744***	0.489**	0.062	−0.576	−0.968**
Const	5.417***	5.875***	6.643***	7.790***	8.495***

Table 13
Co-integration test results (the null hypothesis: No cointegration).

	Model 1	Model 2	Model 3	Model 4	Model 5
Pedroni (1999, 2004)					
Modified Phillips-Perron t	7.36 ***	6.97 ***	7.16***	7.175***	7.160***
Phillips–Perron t	−15.49***	−16.32 ***	−20.26***	−17.337***	−24.482***
Augmented Dickey-Fuller t	−12.67 ***	−11.22 ***	−16.05***	−11.563***	−18.356***
Westerlund (2005)					
Variance ratio	−0.16	0.52	−0.38	−0.355	−0.361
Variance ratio, trend included	3.50***	2.25**	4.13***	3.953***	3.907***

Note: *, **, *** indicate the level of significance at 10, 5, and 1 %, respectively. Pedroni (1999, 2004) and Westerlund (2005) tests are performed using the Stata 'xtcointtest' command.

qtile_90): −0.576, −0.968 – (the latter being statistically significant). Parameters for the remaining variables are similar to those noted in Models 2 and 3.

Table 17 investigates the relationship between energy poverty and the proportion of wind and solar energy within overall electricity generation (RenWS), demonstrating the extent to which these renewable sources are integrated into the existing energy mix. The regression coefficients for RenWS are negative across all quantiles, ranging from −0.360 at the 10th quantile to −0.295 at the 90th quantile; however, none of these coefficients are statistically significant. This indicates that although a higher proportion of wind and solar energy in electricity generation might be intuitively regarded as reducing energy poverty, the quantile regression results do not support this assumption. It is important to recognize that wind and solar energy sources are inherently reliant on environmental conditions, such as solar irradiation and wind availability, which can be highly variable. As a result, exclusive reliance on these energy sources is challenging unless a nation has well-developed sources (such as hydropower) to stabilize the energy supply. In countries lacking such infrastructure, maintaining a parallel system based on fossil fuels is often essential to ensure continuous energy availability during periods of inadequate solar or wind energy production. This requirement for a dual-system can hinder the immediate benefits of renewable energy in reducing energy poverty and potentially increase costs for energy consumers. Model 4 confirms that social inequality, measured by the Gini Index, is a primary factor in exacerbating energy poverty, with a significantly positive effect across all quantiles. In countries facing high levels of energy deprivation, long-term unemployment further worsens the issue, particularly in the upper quantiles. Conversely, economic prosperity, as measured by logGDP, significantly alleviates energy poverty, highlighting the critical need to address inequalities and promote economic growth to effectively tackle this challenge.

Table 18 elucidates the effect of wind and solar capacity as a proportion of total electricity capacity (RenWSC) on energy poverty across disparate quantiles. The model aims to discern the association between the aggregated capacity of wind and solar—integral elements of the energy transition—and energy poverty. Analogous to Model 4, these outcomes do not demonstrate a beneficial impact of the energy transition, as assessed through the installed capacity of wind and solar energy, in diminishing energy poverty. This consistency is further reinforced when considering diverse geographical conditions and the potential of wind and solar energy, factors that do not inherently lead to the generation of affordable electricity. The recurrent need for energy storage emerges, with large-scale technical solutions remaining absent. Crucially, the model reveals that while RenWSC fails to yield statistically significant coefficients for any quantile, this indicator persists as a pivotal component of the broader energy transition strategy within EU countries. The parameters for other variables closely correspond with those in preceding models, demonstrating significant, positive correlations between income inequality (Gini) and energy poverty across all quantiles, underscoring the vulnerability of energy-impoverished households as income inequality escalates. Economic prosperity, measured via log GDP, consistently exhibits a negative correlation with energy poverty, implying that enhanced GDP levels are associated with reductions in energy poverty across all quantiles, with values ranging from −0.833 at the 10th quantile to −1.330 at the 90th quantile. The significance of long-term unemployment (LN) is also pronounced in higher quantiles, further highlighting that, notably in countries exhibiting elevated levels of energy poverty, increased long-term unemployment rates tend to aggravate the issue. Nevertheless, the RenWSC variable, albeit not statistically significant, suggests a more intricate relationship that may necessitate further examination within the context of disparate dependencies on renewable resources and grid stability.

Table 17
Model 4 (quantile regression).

	qtile_10	qtile_25	qtile_50	qtile_75	qtile_90
Gini	0.136***	0.140***	0.146***	0.155***	0.159***
logGDP	−0.784**	−0.863**	−0.985***	−1.156***	−1.237***
LN	0.004	0.052	0.124***	0.226***	0.275***
GDP GR	0.001	−0.003	−0.009	−0.018	−0.022
RenWS	−2.202	−1.934	−1.525	−0.951	−0.679
Const	3.361	4.246***	5.600***	7.500***	8.401***

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

Table 18
Model 5 (quantile regression).

	qtile_10	qtile_25	qtile_50	qtile_75	qtile_90
Gini	0.129***	0.134***	0.140***	0.149***	0.154***
logGDP	−0.833***	−0.929***	−1.045**	−1.237***	−1.330***
LN	−0.001	0.053	0.118***	0.227***	0.279***
GDP GR	0.006	−0.001	−0.008	−0.020	−0.027
RenWSC	−0.360	−0.348	−0.332	−0.307	−0.295
Const	3.937*	5.003	6.304**	8.461***	9.504***

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

6. Conclusions

In this study, we proposed a synthetic indicator for energy poverty in European countries and examined whether it is correlated with advancements in energy transitions. The synthetic variable for energy poverty was obtained by combining information from six variables which often appear separately as proxies for this type of deprivation. Energy transitions was described by the share of renewable energies in gross final energy consumption, renewable energies in electricity generation and renewable energies capacity in total installed electricity capacity. Estimated panel quantile regression models considered important predictors of macroeconomic origins for energy poverty previously tested in literature.

The conducted research enabled the derivation of several conclusions. The primary findings pertain to the role of energy transition in addressing energy poverty. The investigation revealed that the effect of energy transition on energy poverty is unequivocally dependent upon the criteria employed in measuring the transition. When energy transition is assessed by the proportion of zero-emission sources in gross final energy consumption or the share of low-emission sources in electricity production or installed capacity, its influence on alleviating energy poverty is anticipated to be positive. Conversely, when the focus is confined to low-emission sources that have experienced swift growth in the past decade, notably wind and solar energy, their effect on diminishing energy poverty appears less significant. An energy transition predicated solely on weather-dependent sources presents challenges concerning social costs, potentially hindering public acceptance. This underscores the imperative of constructing inclusive support mechanisms within energy transitions to aid vulnerable demographics and avert their marginalization.

Moreover, the study underscores the significance of macroeconomic factors in shaping energy poverty. Income inequality emerged as a substantial factor positively correlated with energy poverty, whereas economic wealth exhibited a negative correlation. In nations where energy poverty is more prevalent, prolonged unemployment was identified as an exacerbating factor. Furthermore, economic wealth demonstrated no significant impact on energy poverty, suggesting that the benefits and costs of economic transformations are not uniformly distributed among those experiencing this deprivation.

Our analysis is subject to certain limitations predominantly associated with the data employed for estimating energy poverty. This subject is extensively addressed in the literature section and is characterized by ambiguity. While our methodology is deemed robust, it would be significantly enhanced by the availability of data encompassing all dimensions of energy poverty. Currently, such comprehensive data for international comparisons is unavailable.

CRediT authorship contribution statement

Sławomir Śmiech: Conceptualization, Software, Investigation, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Supervision, Preparation of the review, Visualization, Project administration. **Lilia Karpinska:** Conceptualization, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Preparation of the review, Visualization. **Stefan Bouzarovski:** Writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Slawomir Smiech reports financial support was provided by National Science Centre Poland. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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