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Evaluating the effect of economic crisis on energy poverty in Europe

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ABSTRACT

Energy poverty is an issue that concerns developing as well as developed countries and its mitigation is essential for social welfare. European countries are also affected by energy poverty problems and lately policy-makers are trying to address this issue, especially after the recent economic crisis. In order for strategies and policies implementation to be effective, it is important that energy poverty is measured and evaluated. In this paper, energy poverty is examined for the time-period 2004–2019 for 28 selected European countries, using a consensual approach and a composite measurement, based on the main indicators proposed in the literature. The Scandinavian countries are found to have the lowest levels of energy poverty, while the highest levels have been observed in Bulgaria and in the Balkans in general throughout the whole studied time-period. In addition, the drivers of energy poverty conditions are identified; electricity prices were found to be the main driving force for all three main indicators, while unemployment and the percentage of people at risk of poverty followed, for certain indicators. GDP per capita is found to be linked with an inverse relationship with issues related to energy poverty, confirming thus that the economic recession affected energy poverty conditions in Europe.

1. Introduction

Energy is essential for the satisfaction of basic human needs such as human health, food security, education, mobility and communications [1,2]. It is linked directly to economic growth, while it is considered important for well-being and social development and vital for the eradication of poverty [3]. World's energy consumption has grown rapidly over the last decades, reaching 9.72 kilotonnes of oil equivalent in 2017 [4]. Despite that, many countries in the world, including European countries, are still not able to ensure the necessary supply of energy for every household, something that affects people's health and everyday living [5,6].

Energy poverty is defined as the situation in which individuals or households can not keep their homes adequately warm or meet other required energy needs at a cost that they can afford [7]. In other words, energy poverty refers to the lack of sufficient, affordable and safe energy services [8] and leads to social injustice [9]. Energy poverty is also often referred to as "fuel poverty" although, according to Bouzarovski et al. [5] fuel poverty is mainly used to describe low energy affordability, while energy poverty is a wider term that includes problems related to energy accessibility.

Energy poverty can be a result of the rising energy prices that occur worldwide, combined with low incomes and the inefficiency of buildings and appliances. In addition, factors such as tax systems and low energy infrastructure investments, as well as the lack of awareness and knowledge regarding energy efficiency can be considered as driving forces of energy poverty [10].

The global economic crisis that erupted in 2008 had major negative economic impacts worldwide. The banking system collapsed, debt skyrocketed and global economic growth suffered major setbacks. In addition, unemployment rates were increased and economic and social inequalities grew even more [11]. The issue of energy poverty was also raised, since problems to modern energy services access were arisen and the economic crisis is now considered to be one of energy poverty's driving forces. The negative impact on developing countries was more intense, but several developed countries also suffered from energy poverty during and post-crisis [12].

The 7th Sustainable Development Goal that the United Nations have proposed, refers to the accessibility to affordable and sustainable energy. More specifically, the United Nations have set a target of ensuring access to energy services worldwide by 2030, especially of supplying modern and reliable energy for all developing and least developed countries [13]. Energy poverty seems to be an issue that concerns governments and policy makers and its eradication is considered essential for social welfare [14].

Energy poverty is an issue that concerns European countries, too. It is

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estimated that about 50–125 million people in Europe could be characterized as “fuel poor” and a plethora of policy measures have been promoted, in order to prevent energy consumers’ vulnerability [15]. Especially Southern-Eastern European countries are found to be more vulnerable in terms of energy poverty and it is important that policies are implemented in order to provide help for the households that need it. The Energy Community Treaty was established in 2006 for EU members and concerns, among others, the topics of energy security and energy efficiency [5].

In this paper, energy poverty in 28 European countries is measured, for the period 2004–2019. A consensual approach, that is based on EU-SILC survey data, and a composite measurement are used to calculate energy poverty, and 4 different scenarios are created, where a different weight is assigned to each indicator. In addition, panel data model specifications are used, in order to identify energy poverty’s drivers, and three linear regression models are constructed, where the main energy poverty indicators are used as dependent variables.

This paper is organized as follows: Section 2 presents all the approaches for measuring energy poverty, based on the current literature, and Section 3 includes recent studies that focus on energy poverty worldwide. Section 4 contains the indicators and econometric methodology that were used in this study, and Section 5 presents and discusses all the results. In Section 6, the paper is concluded, and policy implications are discussed.

2. Approaches to measure energy poverty

Two main approaches of defining and measuring energy poverty are identified in the literature: the *expenditure approach* and the *consensual approach*.

In the *expenditure approach*, an expenditure indicator, such as a household’s expenditure on energy or its share on income, is compared to a certain critical threshold for evaluation [15]. This means that a household is energy poor when its expenditure metric is above or below the certain threshold. The metrics that use those thresholds can be categorized into 3 different kinds:

1. **High share of energy costs metrics**: when a household has high energy expenditures
2. **Low available income metrics**: when little income is left in a household after energy costs
3. **Insufficient energy spending metrics**: when energy costs of a household are less than the minimum level of basic energy services.

The identification and the setup of a threshold is a difficult task and has led to a number of debates. According to Trinomics [16], the following options of thresholds are proposed:

- **10% of income**: a household is energy poor when its energy expenditures are more than 10% of total household income.
- **Above the median share**: a household is energy poor when its energy expenditures (as a % of income) are above the national median and its income is below the poverty line, after energy costs.
- **Twice the national median**: a household is energy poor when its energy expenditures (as a % of income or in euros) are above the national median multiplied by two.
- **Minimum Income Standard**: a household is energy poor when its income is lower than the minimum income that is necessary for its members to be integrated in society or when its income is lower than its necessary energy and housing costs.
- **No threshold**: instead, a scale of severity is proposed, of energy expenditure for households with low income.

The expenditure approach is based on objective measures and data, that can be easily compared over time and location. However, the differences in metrics’ definitions can lead to differences in the estimation of energy poverty [16]. There is a significant possibility that the results estimated with the expenditure approach might be misleading and, in addition, it does not capture other important elements of energy poverty [10].

The *consensual approach* uses measures and metrics to identify those households that meet basic energy services with difficulty. These measures and metrics can include various indicators, such as energy affordability, thermal comfort and dwelling efficiency, which are used and evaluated [15]. This approach is based on surveys and each household can make assessments about each one of the studied indicators. In Europe, the Statistics on Income and Living Conditions (EU-SILC) provides data on the three main indicators that can help measure energy poverty:

- **Inability to keep home adequately warm**
- **Arrears on utility bills**
- **Presence of leak, damp, rot in the dwelling**

In the European level, the collection of data for the consensual approach is considered to be much easier, compared to the expenditure approach, due to the EU-SILC, while there can be an easier comparison over time and country [16]. In addition, using the consensual approach has the best potential to capture the wider elements of energy poverty. However, the limitations that come with the consensual approach include mainly the error that could occur due to the subjectivity of the indicators that are used to assess energy poverty [10].

There are a few more approaches presented in current literature, but they are not widely used, due to their significant disadvantages and limitations. These are the *temperature-based approach*, that takes into consideration internal temperature measurements, and the *outcome-based approach*, which relies on the outcomes that could be associated with energy poverty. The significant lack of data in the first case and the lack of national statistics and the causality problem in the second case, are the main weaknesses of these two approaches and the reasons why they are not further explored [16]. Also, a *direct measurement* has been proposed, in which every energy service that exists and is achieved in a household is compared to a set standard [10].

3. Literature review

According to Santillán et al. [9], the issue of energy poverty was not widely discussed in the literature until recently and the interest in it was risen mainly since 2011. In some papers, energy poverty is seen from the perspective of energy and sustainability while in others it is seen from a health perspective. In general, energy poverty can be addressed either directly or as a secondary issue.

Nussbaumer et al. [2] developed a new composite index to capture the deprivation of households’ access to modern energy services. The Multidimensional Energy Poverty Index (MEPI) takes into consideration the multidimensional nature that energy poverty has and includes variables that represent basic energy needs, including: type of cooking fuel, food cooked on stove or open fire using other fuels beside electricity, LPG, natural gas or biogas, access to electricity, existence of fridge, existence of television or radio, existence of land line phone or mobile phone. Based on that, energy poverty was estimated for selected African countries. They found that the MEPI was highest in Ethiopia, meaning that there is an intense energy poverty problem there, followed by Niger and Rwanda. They also compared these results with previous data and concluded that there was a reduction in energy poverty over the years in all countries (for which data were available), except Zimbabwe.

Santillán et al. [9] examined energy poverty in Latin American countries based on the Multidimensional Energy Poverty Index (MEPI) that Nussbaumer et al. had developed. After collecting the necessary data for the six MEPI variables, they evaluated energy poverty for 7 Latin American countries and were able to compare countries with different social and economic backgrounds. They estimated that Haiti has the biggest problem, since the percentage of people living on energy poverty is estimated at 98%, while Guatemala and Honduras follow. They also support that measures that would reduce energy positive could have a positive impact on economic and social development, as well.

Focusing on energy poverty in Europe, Thomson and Snell [17] used the consensual approach that was described before and the three main indicators from EU-SILC to estimate energy poverty in 25 European countries for 2007. They presented four different scenarios in which they assigned different weights to each indicator. They concluded that the countries that had the worst levels of fuel poverty in every scenario were Bulgaria, Cyprus and Romania. They also found, through a logistic linear regression, that location was one of energy poverty's main drivers, since it was linked to people's inability to keep home adequately warm.

Those main three indicators, combined with two more, were used by Bollino and Botti [15] in their analysis of energy poverty in European countries for 2012 and 2014. More specifically, the authors also took into consideration whether a household has a heating system that can keep the dwelling warm in the winter and whether a household has a cooling system that can keep the dwelling cold in the summer. Subsequently, they used the fuzzy set approach, in order to overcome the limitations of existing energy poverty measures, and developed the Energy Poverty Multidimensional Index (EPMI), an innovative indicator that considers the two most important dimensions of energy poverty: affordability and efficiency. They found that Eastern and Southern European countries are the most affected and have the highest levels of energy poverty, while Scandinavian countries are the least effected by energy poverty. They also found that the main drivers of energy poverty include low income levels, dwelling type, home localization and living in thinly populated areas. In addition, women and migrants are found to be more affected from energy poverty, while older people seem to suffer less.

Additional studies that focus on different European countries have also been conducted. For example, Phimister et al. [18] examined energy poverty in Spain for the period 2007–2010, using the expenditure approach and a subjective self-reported measure. According to the first approach, the percentage of people in Spain that lived in energy poverty in 2010 was calculated just over 10%, while using the second approach it was calculated at 28%. Papada and Kaliampakos [19] used also the expenditure approach to examine energy poverty in Greece in 2015, using a sample of 400 Greek households. They estimated that 58% of population lives under the threat of energy poverty and people that have low incomes or that live in detached houses, in colder places and in high altitudes are more vulnerable to energy poverty.

4. Methodology

In order to calculate and examine energy poverty in 28 European countries, the consensual approach and the methodology proposed by Thomson and Snell [17] were followed and a larger time period was analyzed. Thomson and Snell, as it was mentioned in Section 3, proposed a composite measurement, presenting four different scenarios in which the three indicators were assigned a different weight.

4.1. Indicators

The three main indicators that are proposed in the literature [16,17] for the evaluation of energy poverty with the consensual approach, as mentioned in Section 2, are the following: inability to keep home adequately warm, arrears on utility bills and presence of leak, damp or rot in the dwelling [20]. Their combination and joint study allow us to have a wider understanding of energy poverty, capturing its multidimensional nature.

Subsequently, a set of secondary indicators is used, to identify the drivers that lead to energy poverty. These indicators are: Gini coefficient of equivalised disposable income, GDP per capita (current $US), unemployment (%), people at risk of poverty (%), urban population (%), average rooms per person in dwellings and average electricity prices for consumption between 2500 and 5000 kWh (euro/kWh).

The Gini coefficient, as well as GDP per capita, have been identified in the literature as predictors of households' ability to keep home adequately warm in EU studies for different time-periods [21]. In addition, urbanization level was also found to have an impact on the ability to keep home adequately warm (higher levels of inability in rural areas) [17], while indicators such as GDP, unemployment rate and people at risk of poverty are also linked to energy poverty in various studies in the literature [12,22,23]. In addition, according to Eurostat data, a large percentage of households' final energy consumption comes from electricity [24], indicating that electricity prices could have a potential impact on energy poverty conditions. This study takes into consideration these indicators, in order to examine whether they can be characterized as energy poverty drivers for the 28 studied European countries and the studied time-period.

4.2. Data

The EU-SILC provides data that can be combined and used to measure energy poverty. Data were retrieved for 28 European countries (Fig. 1) for the years 2004–2019, concerning three main indicators: inability to keep home adequately warm, arrears on utility bills and presence of leak, damp or rot in the dwelling [20]. Data were also retrieved from Eurostat for the following secondary indicators: Gini coefficient, rooms per person, people at risk of poverty, average electricity prices [25–28]. Data for GDP per capita, urban population and unemployment were retrieved from the World Bank database, for the same 28 countries and the same years [29–31]. In the few case of missing values, adequate interpolations were applied with moving average and single and double exponential smoothing techniques, to provide forecasts for the missing values. The determination of the appropriate method was chosen based on the measures of accuracy like Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD) and Mean Squared Deviation (MSD). Data for electricity prices were available only since 2007, so middle tendency was calculated and missing data were filled in based on that.

4.3. Composite measurement

As it was mentioned before, Thomson and Snell [17] proposed an approach in which they assigned a different weight to each of the three main indicators and created 4 different scenarios, in order to explore the usefulness of each indicator and the interaction between them. Their approach is also used in this study; 4 different scenarios are created, with different assigned weights, giving a strong performance in a different indicator each time (Table 1).

As presented in Table 1, the percentage of population that is unable to keep home adequately warm is given a strong performance in Scenario 1; the percentage of population facing arrears on utility bills is given a strong performance in Scenario 2, while the percentage of dwellings where leak, damp or rot exist is given a strong performance in Scenario 3. In Scenario 4, the same weight is assigned to all three indicators. According to Thomson and Snell [17], this approach can assist in examining the usefulness of each one of the used indicators.

4.4. Drivers of energy poverty

After the calculations for energy poverty, panel data are analyzed, in order to determine which of the selected secondary indicators can be considered as drivers of energy poverty. By using panel data, complex models can be studied more efficiently and more reliable estimations are provided [32]. In order to compare linear and logarithmic forms, Box-Cox specifications were used. Three linear regression models are

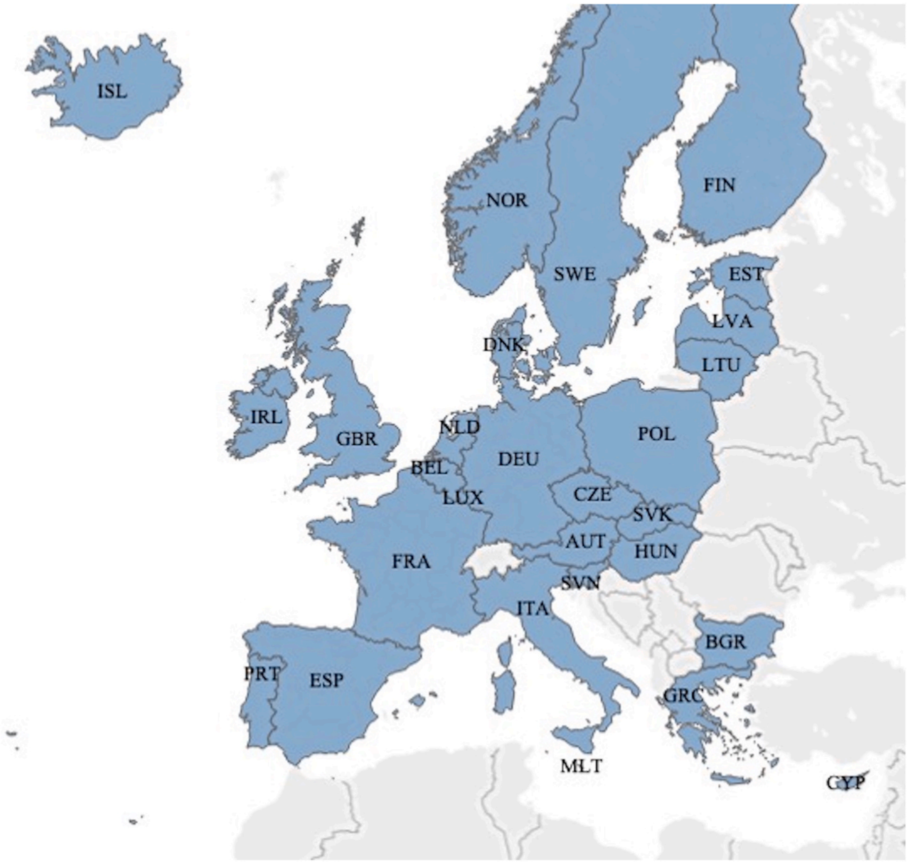

Fig. 1. The 28 studied European countries[11].

Table 1
Weights assigned in each indicator in 4 different scenarios.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Inability to keep home adequately warm	0.5	0.25	0.25	0.33
Arrears on utility bills	0.25	0.5	0.25	0.33
Leak, damp or rot in the dwelling	0.25	0.25	0.5	0.33

constructed, considering each one of the indicators used to estimate energy poverty as a dependent variable and seven secondary indicators as independent variables. The general form of the proposed model can be presented as:

$$Y_{it} = \alpha + X_{it}\beta_{it} + \delta_i + \gamma_i + \varepsilon_{it} \quad (1)$$

where Y_{it} is the dependent variable, X_{it} is a k-vector of independent variables and ε_{it} the disturbance terms. Additionally, δ_i and γ_i are the cross-section and period specific effects respectively, which can be used as random or fixed. By modifying equation (1), the proposed model, that includes only the statistically significant variables, is now:

$$(\text{IndicJ})_{i,t} = \alpha_{i,t} + \beta_{1i,t}(\text{gini})_{i,t} + \beta_{2i,t}(\text{gdppc})_{i,t} + \beta_{3i,t}(\text{unempl})_{i,t} + \beta_{4i,t}(\text{pov\_risk})_{i,t} + \beta_{5i,t}(\text{urban\_pop})_{i,t} + \beta_{6i,t}(\text{roomspp})_{i,t} + \beta_{7i,t}(\text{electr\_prices})_{i,t} + \gamma_i + \delta_t + \varepsilon_{i,t} \quad (2)$$

In this regression, *gini* indicates Gini coefficient, *gdppc* indicated GDP per capita, *unempl* indicates unemployment rate, *pov_risk* indicates people at risk of poverty, *urban_pop* is the population living in urban areas, *roomspp* indicates the number of rooms per person and *electr_prices* the average electricity prices for consumption. In addition, *i* represents the country and *t* the year, while J represents the number of the main indicators (1–3).

Panel data models are estimated by using Fixed and Random Effects methods. This choice depends on whether α_i is handled as fixed predefined numbers or random expulsions from a particular distribution. More specifically, in the Fixed Effects Approach, each individual cross-section unit has a different constant term and y_i (and δ_t) are considered as regression parameters. This means that the characteristics of the sections are fixed long-term differences and not results of random changes. In the Random Effects Approach, individual effects are treated as random and y_i (and δ_t) are considered as factors of random errors. Hausman test can be performed, in order to check for inconsistency in the RE estimate [33]. In case of heteroscedasticity, both those approaches are inefficient [34] and in order to address such problems, the application of Generalized Least Squares (GLS) specifications is required

[35]. For the efficient estimation of β, the GLS estimator is:

$$\hat{\beta} = (X'\varphi^{-1}X)^{-1}X'\varphi^{-1}\gamma \quad (3)$$

where the covariance matrix as block diagonal is:

$$\varphi = [(\mu \otimes j_T + e)(\mu \otimes j_T + e)'] = I_N \otimes \varphi_i \quad (4)$$

In addition to Fixed and Random Effects methods, Generalized Method of Moments is used, a method that can be used in dynamic models and that minimizes equation (5) regarding β:

$$M(\beta) = \left(\sum_{i=1}^{N} \Psi_i' u_i(\beta)\right) W \left(\sum_{i=1}^{N} \Psi_i' u_i(\beta)\right) = \zeta(\beta)' W \zeta(\beta) \quad (5)$$

where: W is a pxp weighting matrix, Ψ_i is a $T_i xp$ instruments matrix for cross section i and $u_i(\beta) = (Y_i - f(X_{it}, \beta))$. To calculate the weighting of matrix W, White robust covariances are used; the coefficient covariance estimates are:

$$\left(\frac{M^*}{M^* - k^*}\right)\left(\sum_t X_t' X_t\right)^{-1}\left(\sum_t X_t' \hat{u}_t \hat{u}_t' X_t\right)\left(\sum_t X_t' X_t\right)^{-1} \quad (6)$$

In orthogonal deviations, according to Arellano and Bond [36], each observation is indicated as a deviation from the average of the sample's future observations, while each deviation is weighted to standardize the variance:

$$x_{it}^* = [x_{it} - (x_{i(t+1)} + \ldots + x_{iT}) / (T-t)]\sqrt{(T-t)} \Big/ \sqrt{T-t+1}, \ t = 1, \ldots T-1 \quad (7)$$

The (T_i -q) equations for individual units i are:

$$Y_i = \delta w_i + d_i \eta_i + v_i \quad (8)$$

where δ is a parameter vector that includes α_k, β and λ. In addition, w_i is a data matrix that includes the endogenous variables' time series, the interpretive variables x and the time dummies, and d_i is a (T_i-q)x1 vector of ones.

Pesaran's cross-section dependence test is used to determine whether the used time series are cross-sectional independent, since variables' correlation is a usual problem present in panel data. In cases where the time series are cross-sectional dependent and in order to correct the variance-covariance matrix, OLS Dummy estimator (FEM) allowing for individual fixed effects with Driscoll-Kraay standard errors is used. In Random Effects approaches, after a Breusch-Pagan LM test for individual effects, robust standard errors are used.

Additionally, unit root tests are performed, that take into consideration the cross-section dependence of errors. Unit root tests are applied in order to examine the stochastic nature and properties of each variable. Dickey-Fuller and Augmented Dickey-Fuller tests can be performed when analyzing panel data, with the issue of homogeneity in the autoregressive parameter. This restrictive assumption is not adopted by *Fisher* type tests, where strongly balanced panels are not required. When conducting unit root tests, the asymptotic behavior of the time series (T) and the cross-section dimensions (N) should be taken into consideration; if T and N tend to infinity, Fisher type test can be used, but the number of panels that do not have a unit root must raise at the same rate as N.

Panel co-integration tests are also performed in this panel data analysis; Pedroni suggested seven test statistics for the null hypothesis of no cointegration, with four panel statistics and three group statistics, in order to test panel co-integration or co-integration across cross-sections. In addition, Westerlund tests are performed for panel cointegration, that are based on the significance of the error correction term in the error correction model. Westerlund proposes four tests that check for panel cointegration. The Gt and Ga statistics test for no cointegration (null hypothesis) of all cross-sectional units and a rejection implies cointegration for at least one unit. The null hypothesis is rejected from the Pt and Pa statistics when cointegration is implied for the panel in total [33, 37].

5. Results

5.1. Energy poverty in 2004–2008

Based on the previously described methodology, energy poverty was estimated for 28 European countries for the years 2004–2008, before the outbreak of the global economic crisis. The countries that seem to have suffered less from energy poverty issues this time-period were mainly the Scandinavian countries: Sweden, Finland and Denmark, as well as Austria. More specifically, Sweden had the lowest levels of energy poverty in most of the scenarios for the years 2004–2006, while Finland and Denmark had the lowest levels in most of the 4 scenarios for 2007 and 2008 respectively.[2] In contrast, Bulgaria was the country that had the highest levels of energy poverty among the studied European countries, for every scenario, throughout this time-period. In addition, high levels of energy poverty were observed in Poland, Lithuania, Latvia, Cyprus and Portugal.

In most of these countries, energy poverty was lower in 2008 than it was in 2004. This can be confirmed by the fact that the average energy poverty of the studied countries for 2004 was higher, in every scenario, compared to the average energy poverty in 2008 (Table 2). The most notable reduction was the one of Poland, that managed to significantly reduce energy poverty more than any other country, according to all 4 scenarios. Additional notable reductions in energy poverty are the ones of Latvia and Lithuania. Slovenia was the country that had the highest increase from 2004 to 2008 while generally, energy poverty increased only in a few more countries (e.g. Bulgaria, Belgium), but their increases were smaller.

5.2. Energy poverty in 2009–2013

Subsequently, energy poverty is examined for the years 2009–2013, a time period where the effects of global economic crisis were visible in most European countries. The Scandinavian countries were once again the ones

Table 2
Descriptive statistics of energy poverty in 2004–2008.

		Scenario 1	Scenario 2	Scenario 3	Scenario 4
2004	Mean	14.345	13.290	15.719	14.307
	Median	10.375	9.875	12.263	10.577
	Maximum	47.175	34.550	37.475	39.336
	Minimum	3.550	4.125	4.500	4.158
	Std. Dev.	10.933	8.621	9.687	9.564
2005	Mean	14.303	13.121	15.491	14.162
	Median	10.275	9.738	12.438	10.890
	Maximum	47.175	34.550	37.475	39.336
	Minimum	3.400	4.250	4.500	4.026
	Std. Dev.	11.042	8.707	9.740	9.646
2006	Mean	13.297	12.033	14.491	13.141
	Median	9.300	8.825	11.313	10.016
	Maximum	47.175	34.550	37.475	39.336
	Minimum	3.975	4.425	4.500	4.455
	Std. Dev.	10.152	7.747	8.636	8.672
2007	Mean	12.038	10.864	13.026	11.856
	Median	8.313	7.713	10.188	8.316
	Maximum	44.600	34.950	31.450	36.630
	Minimum	2.975	3.625	3.925	3.564
	Std. Dev.	9.480	7.201	7.351	7.834
2008	Mean	11.566	10.798	13.161	11.723
	Median	7.675	7.788	10.425	8.217
	Maximum	49.100	40.875	40.125	42.933
	Minimum	3.575	3.700	4.325	4.158
	Std. Dev.	9.478	7.545	7.661	8.076

[1] All figures were created with Tableau Software.

that had the lowest percentages of people living under energy poverty. More specifically, Denmark had the lowest levels in 2009, according to three of the four scenarios, while Norway had the lowest levels for the years 2012–2013, according to most scenarios. Low levels of energy poverty were also observed in Finland, Sweden and the Netherlands. Bulgaria was the country with the highest levels of energy poverty according to most scenarios, during the whole time-period 2009–2013. High levels were also observed in Greece, Cyprus and Portugal.

By comparing the average energy poverty for 2009 and 2013, it can be observed that energy poverty was, overall, higher in 2013 and that most of the countries suffered an increase in their population living under energy poverty conditions. The biggest increase was observed in Greece, according to three out of four scenarios; energy poverty was radically increased over this time-period in the country. Hungary, as well as Malta, Portugal and Cyprus, were also some of the countries where energy poverty increased a lot. The biggest decrease was noted in Bulgaria but, despite that, Bulgaria was still the country with the highest energy poverty over this period, compared to the other European countries. A significant decrease in energy poverty was also observed in Poland (Table 3).

5.3. Energy poverty in 2014–2019

Finally, energy poverty is examined for the years 2014–2019, when the effects of global economic crisis had faded. The Scandinavian countries were again the ones with the lowest levels of people living under energy poverty, with Norway having the lowest levels of energy poverty for most of these years and almost every scenario. Bulgaria was, once again, the country with the highest levels of energy poverty, while a few scenarios indicate that Greece had equally high levels in certain years. More specifically, Greece had some of the highest levels of energy poverty in 2014–2016 but managed to reduce it over the next three years. High energy poverty levels were also observed in Cyprus and Portugal.

By comparing these results for the years 2014 and 2019, energy poverty was reduced in most of the studied countries over the years. The biggest reductions were observed in Malta, Latvia and Italy, depending on each scenario. Energy poverty kept decreasing in Bulgaria, as it was in the previously studied period, but remained the country where the highest levels were observed. Increases in energy poverty were observed in only a few countries and were really low; Slovakia was the country where the highest increase was noted (Table 4).

Table 3
Descriptive statistics of energy poverty in 2009–2013.

		Scenario 1	Scenario 2	Scenario 3	Scenario 4
2009	Mean	11.349	11.245	12.917	11.719
	Median	7.988	8.725	10.188	9.026
	Maximum	46.100	38.075	36.025	39.666
	Minimum	3.350	3.625	4.650	3.927
	Std. Dev.	8.784	7.159	6.915	7.466
2010	Mean	12.005	11.821	13.366	12.274
	Median	9.000	9.525	11.238	10.296
	Maximum	45.000	36.275	32.225	37.455
	Minimum	3.675	4.075	4.575	4.323
	Std. Dev.	8.916	7.316	6.868	7.525
2011	Mean	12.160	11.965	13.450	12.400
	Median	8.975	9.288	11.025	10.065
	Maximum	34.025	29.600	26.175	29.634
	Minimum	4.225	4.950	5.250	5.016
	Std. Dev.	7.931	6.843	6.475	6.912
2012	Mean	12.774	12.513	13.838	12.911
	Median	9.588	10.075	12.300	10.824
	Maximum	33.800	29.275	27.275	29.271
	Minimum	3.550	4.525	5.350	4.455
	Std. Dev.	8.271	7.332	6.652	7.242
2013	Mean	12.944	12.866	14.076	13.162
	Median	9.463	10.313	11.913	10.527
	Maximum	34.175	31.450	28.650	30.294
	Minimum	3.325	4.225	4.850	4.092
	Std. Dev.	8.606	7.866	7.131	7.694

Table 4
Descriptive statistics of energy poverty in 2014–2019.

		Scenario 1	Scenario 2	Scenario 3	Scenario 4
2014	Mean	12.447	12.521	13.649	12.744
	Median	9.463	9.750	11.213	10.115
	Maximum	31.775	30.300	25.600	28.578
	Minimum	2.575	3.200	3.925	3.201
	Std. Dev.	8.261	7.680	6.987	7.465
2015	Mean	11.644	11.650	12.935	11.955
	Median	8.725	8.813	11.113	9.422
	Maximum	30.675	32.075	25.350	28.479
	Minimum	2.750	3.425	4.325	3.465
	Std. Dev.	7.915	7.522	6.580	7.171
2016	Mean	10.963	11.003	12.510	11.377
	Median	8.200	8.488	10.938	8.976
	Maximum	30.600	32.050	25.175	28.380
	Minimum	2.525	2.900	3.775	3.036
	Std. Dev.	7.568	7.162	6.267	6.827
2017	Mean	10.018	9.952	11.516	10.390
	Median	7.288	7.725	9.600	8.498
	Maximum	29.075	29.050	23.800	26.334
	Minimum	2.550	3.100	3.750	3.102
	Std. Dev.	7.000	6.642	5.807	6.313
2018	Mean	9.733	9.729	11.409	10.188
	Median	7.288	7.513	10.400	8.019
	Maximum	27.625	26.725	23.625	25.344
	Minimum	2.825	3.275	4.300	3.432
	Std. Dev.	6.501	6.115	5.485	5.861
2019	Mean	9.119	9.063	10.714	9.536
	Median	7.400	7.400	9.513	7.811
	Maximum	24.850	24.225	23.400	22.869
	Minimum	2.925	3.375	4.300	3.531
	Std. Dev.	5.817	5.458	4.994	5.255

5.4. Comparative study of energy poverty

It was expected that, due to the financial issues that occurred worldwide and their effects, energy poverty would be higher in the period 2009–2013 than the previously studied time-period (2004–2008). Indeed, if 2007 data (just before the outbreak of economic crisis) are compared to 2012 data, it is observed that energy poverty was, in general, a little higher in 2012. The countries that suffered the highest increases in their energy poverty were Greece, Slovenia, Malta and Hungary. In contrast, in Poland and Bulgaria were observed high decreases, despite the global economic situation. In total, the percentage of people living under energy poverty conditions increased in most of the studied countries and its general level was higher: average energy poverty in 2012 was higher than the average energy poverty in 2007, in all 4 scenarios that were examined.

In a comparison between 2004 and 2013 data, the results show that energy poverty was overall lower in 2013, compared to 2004, for most countries. The most notable decrease was the case of Poland and the countries with the biggest increases were Greece, Malta and Slovenia. In Greece and Malta, energy poverty was decreasing during the period 2004–2008 and increased rapidly after the outbreak of the global economic crisis, while energy poverty in Slovenia was continually increasing since 2004. In general, these results indicate that, despite the economic crisis that occurred, over these years the average energy poverty was decreased and most of the countries managed to reduce their individual levels.

If year 2017 is added to the comparative study, as a representative of the post-crisis time-period, it is observed that the lowest energy poverty levels were presented in 2017, among these three years. This result indicates that most of the European countries were able not only to recover from the negative impacts that economic crisis had on energy related issues, but to reduce energy poverty even more, compared to 2004 (Fig. 2).

Fig. 2. Mean values of energy poverty, according to all 4 scenarios, throughout the time-period 2004–2019.

5.5. *Drivers of energy poverty*

Subsequently, seven secondary indicators are used to estimate which of them can be considered as drivers of energy poverty. The methodology described in Section 4.4. is used and panel data are examined for the whole time-period (2004–2019).

Before the econometric methodology, the descriptive statistics of the used indicators were analyzed. For the studied time-period (2004–2019), it is observed that high differences exist among the 28 European countries regarding the percentage of people that are not able to keep their home adequately warm: the highest percentages are mainly observed in Bulgaria, while Portugal and Lithuania also present high levels in certain years. In contrast, the lowest percentages are observed mainly in Luxembourg and Norway. Lower standard deviations are observed for the other two indicators: in the case of arrears on utility bills, the highest percentages were observed in Greece and Bulgaria, while the lowest percentages were observed in Luxembourg, the Netherlands and Austria. The highest percentages of dwellings with leak, damp or rot were observed mainly in Poland and Latvia, with Cyprus, Slovenia and Hungary also presenting high percentages for certain years, while the lowest percentages were observed in Finland. The indicator regarding dwellings with leak, damp or rot presented the highest mean among the three main indicators, for the studied countries and years (Table 5).

The highest levels of the Gini coefficient were observed in Bulgaria, as well as in Latvia and Portugal, while some of the lowest levels were observed in Slovakia, Norway and Iceland. Luxembourg had the highest GDP/capita for most years, while Bulgaria had the lowest. Greece presented the highest levels of unemployment, with Spain also having significantly high percentages, while Czechia presented the lowest levels; Iceland and Norway's levels were also significantly low. At the same time, some of the highest percentages of people living at risk of poverty were found in Latvia, followed by Bulgaria and Greece, while some of the lowest percentages were found in Iceland and Czechia. Belgium was the country with the highest percentage of urban population and Slovenia the country with the lowest percentage. In addition, Belgium was the country with the highest average rooms per person, while Latvia was the country with the lowest average. Electricity prices were higher in Denmark, while they were significantly high in Germany as well; the lowest electricity prices were found in Latvia and Bulgaria (Table 6).

Table 5
Descriptive Statistics (main indicators).

	Inability to keep home adequately warm	Arrears on utility bills	Leak, damp or rot in the dwelling
Mean	10.96333	9.395647	16.35397
Median	5.9	6.9	15
Maximum	69.5	42.2	43.9
Minimum	0.3	1.1	4.1
Std. Dev.	12.40343	7.57837	7.577198
Skewness	2.141631	1.787271	0.84492
Kurtosis	8.557032	6.234138	3.687255
Jarque-Bera	918.9029	433.7574	62.12044
Prob.	0.0000	0.0000	0.0000

As described in Section 4.4, cross-section dependence is tested and a Pesaran CD test is performed. The results reject the null hypothesis (cross-section independence) in all cases except of the Gini coefficient. This indicates the evidence of cross-sectional dependence in the data (Table 7). A non-randomly selection of individuals, common shocks that happen as a result of single currency or common policies, or the fact that some groups might be interrelated, can explain such dependance [37].

Unit root tests were also performed with the results indicating the examined variables are I(1) having evidence of stationarity in first differences (Table 8). According to the results from the Pedroni cointegration tests that were performed, with a lag length being selected based on Schwarz Info Criterion, it is observed that in six out of eleven cases the null hypothesis of no-cointegration is rejected. Table 9 presents the results regarding inability to keep home adequately warm; the results of the other two dependent variables are exactly the same, with six out of eleven cases rejecting the null hypothesis. Table 10 presents the results of the Westerlund panel cointegration tests: the Gt and Ga statistics, as well as the Pt and Pa statistics, reject the null hypothesis in most cases, implying cointegration for at least one unit and cointegration for the whole panel respectively.

Regression results (Table 11) indicate that electricity prices were the main driving force of all three main indicators of energy poverty, for the period 2004–2019, especially for arrears on utility bills. This confirms the fact that higher electricity prices can lead to more intense energy poverty conditions and that it is significantly difficult for households to pay bills on time, as well as to keep their home adequately warm, while it indicates that higher electricity prices can lead to more dwellings with leak, damp or rot.

GDP per capita is linked with an inverse relationship to each one of the three main indicators and is statistically significant in every case, meaning that an increase in GDP per capita, would lead to a reduction of the percentage of population that face energy poverty-related issues. These results highlight the fact that economic growth is linked to energy poverty and that the economic recession affected energy poverty conditions in Europe. At the same time, unemployment rate can be

Table 6
Descriptive Statistics (secondary indicators).

	Gini	GDPpc	Unemployment	Urban population	Poverty Risk	Rooms per person	Electricity prices
Mean	29.34828	37614.54	8.187147	74.8671	15.60556	1.615179	0.165403
Median	28.65	34871.32	7.2395	74.748	15.2	1.7	0.1608
Maximum	40.8	121292.7	27.466	98.04	26.4	2.3	0.31245
Minimum	20.9	9193.156	1.933	51.308	7.9	0.9	0.071347
Std. Dev.	4.020866	16592.75	4.332169	12.13488	3.782436	0.365995	0.051
Skewness	0.360667	1.771641	1.730413	0.038123	0.2301888	−0.290912	0.629502
Kurtosis	2.225003	8.131495	6.706735	2.100929	2.234888	1.823829	3.334845
Jarque-Bera	20.92429	725.8923	480.0545	15.19733	14.88374	32.14205	31.68131
Prob.	0.000029	0.0000	0.0000	0.000501	0.000586	0.0000	0.0000

Table 7
Cross-section dependence (Pesaran CD test).

Variables	CD test	P-value
Inability to keep home adequately warm	12.75***	0.0000
Arrears on utility bills	19.99***	0.0000
Leak, damp or rot in the dwelling	5.754***	0.0000
Gini coefficient	−0.743	0.4576
GDP per capita	70.45***	0.0000
Unemployment rate	28.52***	0.0000
Urban population	32.67***	0.0000
Poverty Risk	4.871***	0.0000
Rooms per person	25.60***	0.0000
Electricity Prices	42.79***	0.0000

*Note: The null hypothesis assumes that there exists no cross-section dependence (correlation). Significance at ***1%.*

considered as a driver of a household's inability to keep home adequately warm, as well as a driver of arrears on utility bills; unemployment is statistically insignificant in the case of presence of leak, damp or rot in the dwelling.

Poverty risk can also be considered as a driving force of inability to keep home adequately warm, according to the static model, and of arrears on utility bills and of the presence of leak, damp or rot in the dwelling, according to the dynamic models. This means that highest percentages of people at risk of poverty in a country can lead to higher energy poverty-related problems, but to a lesser extent, compared to high electricity prices.

The Gini coefficient is statistically insignificant in the case of inability to keep home adequately warm. The results regarding arrears on utility bills and the presence of leak, damp or rot in the dwelling are controversial; both static models indicate that the Gini coefficient is a driver of energy poverty problems, while the dynamic models indicate the opposite. This implies a static rather than a dynamic influence of the Gini coefficient in such analyses.

The average number of rooms in a household is linked with an inverse relationship with the presence of leak, damp or rot in the dwelling, which can be explained by the fact that a house with a bigger number of rooms per person might be richer, compared to households with less rooms per person, and thus, less affected by this problem. At the same time, the number of rooms per person is considered to be a driver of arrears on utility bills; this can indicate that a household with a bigger number of rooms per person has more energy expenses, which can be hard to cover. In the case of inability to keep home adequately warm, the results are controversial, indicating a dynamic rather than a static

Table 9
Pedroni residual cointegration test.

	Statistic	Prob	Weighted Statistic	Prob
Panel v-Statistic	−2.513071	0.9940	−4.049323	1.0000
Panel rho-Statistic	5.346341	1.0000	5.262699	1.0000
Panel PP-Statistic	−6.0231***	0.0000	−6.3298***	0.0000
Panel ADF-Statistic	−3.6113***	0.0002	−3.8698***	0.0001
Group rho-Statistic	6.843332	1.0000		
Group PP-Statistic	−12.292***	0.0000		
Group ADF-Statistic	−4.1342***	0.0000		

Note: The null hypothesis assumes no cointegration. Significance at ***1%, ** 5% and *10%.

Table 8
ADF Fisher and PP Fisher panel unit root tests.

Variables	Fisher - ADF	Fisher - PP	Variables	Fisher - ADF	Fisher - PP
Levels			First Differences		
Inability to keep home adequately warm	61.7860	66.4179	Inability to keep home adequately warm	125.57***	261.99***
	[0.2771]	[0.1608]		[0.0000]	[0.0000]
Arrears on utility bills	65.8610	47.1452	Arrears on utility bills	131.53***	220.85***
	[0.1725]	[0.7943]		[0.0000]	[0.0000]
Leak, damp or rot in the dwelling	78.7127**	112.31***	Leak, damp or rot in the dwelling	196.92***	355.76***
	[0.0244]	[0.0000]		[0.0000]	[0.0000]
Gini coefficient	60.7053	54.5085	Gini coefficient	179.8***	317.48***
	[0.3102]	[0.5315]		[0.0000]	[0.0000]
GDP per capita	43.3453	18.5522	GDP per capita	105.27***	119.06***
	[0.8917]	[1.0000]		[0.0001]	[0.0000]
Unemployment rate	63.0193	15.8798	Unemployment rate	116.64***	92.003***
	[0.2420]	[1.0000]		[0.0000]	[0.0017]
Urban population	63.6135	46.3023	Urban population	83.191**	139.98***
	[0.2262]	[0.8189]		[0.0106]	[0.0000]
Poverty Risk	60.2671	53.4903	Poverty Risk	141.35***	254.71***
	[0.3242]	[0.5704]		[0.0000]	[0.0000]
Rooms per person	58.5308	5.42019	Rooms per person	160.15***	295.11***
	[0.1909]	[1.0000]		[0.0000]	[0.0000]
Electricity Prices	50.9160	30.8240	Electricity Prices	110.85***	134.37***
	[0.6672]	[0.9975]		[0.0000]	[0.0000]

Note: The null hypothesis assumes that the variable contains unit root. P-values in brackets. Significance at ***1%, ** 5% and *10%.

Table 10
Westerlund ECM panel cointegration tests.

	Gt	Ga	Pt	Pa
Inadeq_warm = f(Gini)	−4.173*** [0.000]	−15.048*** [0.006]	−19.094*** [0.000]	−18.267*** [0.000]
Inadeq_warm = f(GDPpc)	−4.629*** [0.000]	−14.127** [0.038]	−17.872*** [0.000]	−13.235*** [0.000]
Inadeq_warm = f(Unempl)	−6.878*** [0.000]	−17.796*** [0.000]	−26.775*** [0.000]	−24.649*** [0.000]
Inadeq_warm = f(Urban)	−6.691*** [0.000]	−8.198 [0.998]	−18.539*** [0.000]	−5.467 [0.999]
Inadeq_warm = f(PovRisk)	−4.953*** [0.000]	−16.202*** [0.000]	−26.507*** [0.000]	−18.51*** [0.000]
Inadeq_warm = f(Rooms)	−5.292*** [0.000]	−18.832*** [0.000]	−17.695*** [0.000]	−14.913*** [0.000]
Inadeq_warm = f(Electr)	−5.221*** [0.000]	−23.278*** [0.000]	−22.309*** [0.000]	−20.433*** [0.000]
Arrears = f(Gini)	−5.46*** [0.000]	−15.138*** [0.005]	−22.533*** [0.000]	−16.778*** [0.000]
Arrears = f(GDPpc)	−5.001*** [0.000]	−11.604 [0.592]	−20.891*** [0.000]	−12.999*** [0.000]
Arrears = f(Unempl)	−6.005*** [0.000]	−14.737** [0.012]	−17.829*** [0.000]	−14.946*** [0.000]
Arrears = f(Urban)	−7.127*** [0.000]	−3.07 [1.000]	−17.279*** [0.000]	−3.097 [1.000]
Arrears = f(PovRisk)	−4.992*** [0.000]	−19.199*** [0.000]	−20.602*** [0.000]	−20.001*** [0.000]
Arrears = f(Rooms)	−5.056*** [0.000]	−14.29** [0.029]	−18.116*** [0.000]	−16.212*** [0.000]
Arrears = f(Electr)	−5.346*** [0.000]	−14.452** [0.021]	−17.996*** [0.000]	−15.481*** [0.000]
Leak_damp = f(Gini)	−5.769*** [0.000]	−19.509*** [0.000]	−23.795*** [0.000]	−16.948*** [0.000]
Leak_damp = f(GDPpc)	−5.753*** [0.000]	−15.112*** [0.005]	−22.105*** [0.000]	11.318** [0.018]
Leak_damp = f(Unempl)	−5.946*** [0.000]	−19.416*** [0.000]	−25.293*** [0.000]	−19.579*** [0.000]
Leak_damp = f(Urban)	−6.704*** [0.000]	−10.048 [0.929]	−18.044*** [0.000]	−6.244 [0.992]
Leak_damp = f(PovRisk)	−6.266*** [0.000]	−20.71*** [0.000]	−26.433*** [0.000]	−19.084*** [0.000]
Leak_damp = f(Rooms)	−5.961*** [0.000]	−23.035*** [0.000]	−26.554*** [0.000]	−20.007*** [0.000]
Leak_damp = f(Electr)	−5.993*** [0.000]	−22.89*** [0.000]	−22.92*** [0.000]	−24.692*** [0.000]

Note: Test regression fitted on a constant and trend with 1 lag and lead. The null hypothesis assumes no cointegration. P-values in brackets. Significance at ***1%, ** 5% and *10%.

influence of the number of rooms per person in the analysis.

Regarding urban population, it is considered to be a driving force for arrears on utility bills and the presence of leak, damp or rot in the dwelling. In contrast, urban population is found to be linked with an inverse relationship to inability to keep home adequately warm, confirming the findings in the literature [17]; this can be explained by the fact that dwellings in urban areas are usually not detached and big cities are not located in high-altitude areas and thus, are easier to heat (Table 11).

The lags of the three dependent variables are an autoregressive-distributed lag specification that ends up to an AD (1,0) formulation, so that insignificant variables dynamics are not included. All variables, except the lagged dependents, are assumed to be strictly exogenous.

In the case of inability to keep home adequately warm, the adjustment coefficient equals to 1–0.6034; in the case of arrears on utility bills the adjustment coefficient equals to 1–0.4718, while in the case of leak, damp, rot in the dwelling the coefficient equals to 1–0.556. Since the lag coefficients can show the adjustment to equilibrium values, it can be concluded that the adjustment of each variable equals to 39.7%, 52.8% and 44.4% respectively. This means that 39.7% of the discrepancy that exists between the actual and desired levels in the case of inability to keep home adequately warm are eliminated in a year. Similarly, for arrears on utility bills and the presence of leak, damp or rot in the dwelling, the annual eliminated discrepancy is estimated at 52.8% and 44.4%. It is, therefore, observed, that less than three periods are required for the adjustment of inability to keep home adequately warm, less than two periods for the adjustment of arrears on utility bills and two periods for the adjustment of the presence of leak, damp or rot in the dwelling.

Wald tests of joint significance are asymptotically distributed as χ^2 variables, as are Sargan tests of over-identifying restrictions. According to Table 11, Sargan statistics do not reject the null hypothesis of over-identifying restrictions, implying evidence of serially uncorrelated errors. First and second order serial autocorrelations tests AR(1) and AR(2) indicate that the hypothesis that assumes absence of autocorrelation is not rejected.

6. Conclusions and policy implications

The problem of energy poverty has been concerning not only developing but developed countries as well, especially during and after the global economic crisis. European countries suffered also from energy problems and 50 to 125 million people in Europe could be characterized as "fuel poor" [15]. This has risen the need for new policies and strategies that could prevent energy poverty issues and, in order for them to be efficiently implemented, it is important that energy poverty rates are accurately measured.

This paper estimates energy poverty in 28 European countries, before and after the economic crisis. Three main energy poverty indicators are used, that characterize a household's inability to keep home adequately warm, arrears on utility bills and problems (leak, damp, rot) in the dwelling. Then four different scenarios are created, assigning a different weight to each indicator, in order to evaluate energy poverty, as proposed by Thomson and Snell [17].

These results indicate that the Scandinavian countries had the lowest levels of people suffering from energy poverty issues in all three studied time periods, while the highest levels were observed in Bulgaria and in the Balkans in general. It is noted that energy poverty in Bulgaria was radically decreased over the years, but still remained the country with the highest levels among the rest of the European countries. Poland also radically decreased its energy poverty levels from 2004 to 2019, as did Latvia and Hungary. Greece was the country that had the biggest increase in energy poverty, starting from 2011, and these high levels lasted until 2016, but the country managed to significantly reduce them over the last three years (2017–2019). Despite the reduction, energy poverty levels in Greece in 2019 were higher, compared to 2004, according to 3 out of 4 scenarios.

Average energy poverty was reduced from 2004 to 2008, but was then again increased. More specifically, in a comparison between 2007 and 2012 data, it is observed that a small increase occurred between those years. Despite the economic crisis, European countries managed to overcome their energy problems and energy poverty in the period 2014–2019 was significantly lower, even compared to the years before the economic crisis.

In addition, the driving forces of energy poverty in European countries were studied. Electricity prices were found to be the main driver of problems related to energy poverty, since higher electricity prices equal higher energy poverty. High percentages of people at risk of poverty, as well as high unemployment rates can also worsen certain issues related to energy poverty. On the other hand, GDP per capita is linked with an inverse relationship to problems related to energy poverty, meaning that economic growth can improve such conditions. Based on that, it can also be concluded that the economic crisis indeed affected energy poverty

Table 11
Regression results with the three main indicators as dependent variables. (t-Statistics in parentheses and p-values in square brackets)

	Inability to keep home adequately warm		Arrears on utility bills		Leak, damp, rot in the dwelling	
	Fixed Effects DK se	GMM-Orthogonal	Fixed Effects DK se	GMM-Orthogonal	EGLS-Random	GMM-Orthogonal
Inability to keep home adequately warm (−1)		0.6034*** (38.86853) [0.0000]				
Arrears on utility bills (−1)				0.4718*** (27.60977) [0.0000]		
Leak, damp, rot in the dwelling (−1)						0.555959*** (32.61768) [0.0000]
Gini			0.28243* (1.74) [0.100]	−0.4055*** (−10.45333) [0.0000]	0.262151** (2.191972) [0.0289]	−0.275916** (−2.301765) [0.0219]
GDPpc	−0.0000573* (−1.71) [0.100]	−8.58E-05** (−2.210734) [0.0276]	−0.000081*** (−5.95) [0.000]	−0.000166*** (−7.570519) [0.0000]	−0.0000924*** (−2.950871) [0.0033]	−0.000155*** (−5.624087) [0.0000]
Unemployment	0.47842*** (3.51) [0.003]	0.121*** (4.292191) [0.0000]	0.545379*** (10.19) [0.000]	0.3949*** (15.55078) [0.0000]		
Poverty Risk	0.277041*** (5.563931) [0.000]			0.0971 (1.615106) [0.1071]		0.219873* (1.7535) [0.0803]
Urban population	−0.5185*** (−5.93) [0.000]	−2.3895*** (−10.06339) [0.0000]		0.21045** (2.283103) [0.023]		0.461427*** (2.950704) [0.0034]
Rooms per person	−7.6558** (−2.22) [0.043]	5.2326*** (6.672654) [0.0000]		3.4527*** (6.68218) [0.0000]	−9.438674*** (−4.972356) [0.0000]	−5.621812*** (−3.498) [0.0005]
Electricity prices		13.609*** (3.289957) [0.0011]	27.8266*** (12.35) [0.000]	22.9185*** (3.147073) [0.0018]	17.52629** (1.985785) [0.0477]	17.56669*** (3.6) [0.0004]
within R^2	0.197		0.4269		0.126	
Hausman	25.52*** [0.0001]		11.03** [0.0115]		9.61 [0.1423]	
Wald		1762.49 (5)		2262.298 (7)		330.25 (5)
Sargan		25.4549 (22)		21.837 (21)		20.5858 (22)
AR(1)		−1.9137* [0.0557]		−3.5459*** [0.0004]		−2.1338** [0.0329]
AR(2)		0.9484 [0.3429]		−1.1001 [0.2713]		0.9316 [0.3516]

Note: t-Statistics in parentheses and p-values in square brackets. Parentheses in Wald and Sargan tests indicate degrees of freedom. Critical values for the Wald test of overall significance of the explanatory variables: $\chi^{21}_{0.05,5} = 11.07$, $\chi^{2}_{0.05,7} = 14.067$. Critical values for the Sargan test for over-identifying restrictions: $\chi^{2}_{0.05,21} = 32.671$, $\chi^{2}_{0.05,22} = 33.924$. Significance at ***1%, **5% and *10%.

conditions and that a possible future economic recession will have an impact on energy poverty levels in Europe.

As it has been already highlighted, the limitations of this methodology are found mainly on EU-SILC data weaknesses, that include sampling issues and data anomalies [17]. The use of macro-data could also be a possible limitation, since they do not provide information regarding individual households, as primary data would do. Despite that, the use of the indicators provided by the EU-SILC allows us to retrieve data regarding a significant number of European countries and compare them across time and space. In addition, as mentioned in Section 2, a problem that comes with the use of a consensual approach is the subjectivity of the used indicators; some definitions, such as "adequately warm" are subjective and households view and translate this differently, something that could lead to errors in measuring energy poverty objectively. However, thermal comfort is a subjective term and people's opinions on whether they are suffering from energy poverty or not might be more representative than a fixed expenditure measurement. Afterall, the most important aspect when measuring energy poverty is the effect that it has on people. Thus, despite its limitations, the usage of the consensual approach and of EU-SILC indicators is an accepted and widely used method for energy poverty estimations in European countries [10].

The 7th SDG aims to reinsure access to affordable and reliable energy services [13]; in addition to that, focus should be given in combating energy poverty issues that are present not only in developing, but in developed countries as well. When assessing a country's progress on the achievement of the 7th SDG, evaluation should not stop on the assessment of lack of access to electricity and reliance on clean fuels; a wider context of fuel problems should be taken into consideration and more factors should be evaluated, including inability to maintain an adequate temperature in the household, inability to pay utility bills on time and problems in the dwelling.

It would be interesting to assess these results from the scope of renewables as well. Studies have shown that an increase in the production of renewables could lead to a significant decrease in electricity prices (the merit order effect) [38–40]. Since the results indicate that electricity prices were the main driving force of energy poverty-related issues in Europe, it could be possible that higher percentages of renewables' usage could lead to the mitigation of energy poverty. At the same time, some studies exist that have found linkages between the consumption of renewable electricity and electricity's regressive pricing [41]. Only a few studies in the literature have studied the relationship between energy poverty and renewables [42, 43] and, therefore, further investigation is suggested in this area, that would focus not only on the effects that fossil fuels and renewables have on energy poverty, but on the impact of energy transition on energy poverty as well.

After all, these results could be useful for governments and policymakers, since they can evaluate how energy poverty has evolved during the last 16 years, especially considering the financial crisis, in European countries, which countries were (and are) most affected and which parameters can be considered as energy poverty drivers. Based on that, the implementation of strategies and measures will be more effective and direct, something that could lead to a successful mitigation and eradication of energy poverty in Europe. These results will also be proven helpful in building resilience and in successfully preventing a rise in energy poverty levels that might result from a future economic downturn. Especially after the recent COVID-19 pandemic, that had severe and direct socioeconomic impacts on primary, secondary and tertiary sectors [44] which could possibly worsen energy poverty conditions, the identification of energy poverty drivers is significantly important, in order to successfully reduce negative outcomes through targeted policies.

Further investigation in the field of energy poverty that includes more parameters could also help to better understand, assess and address this topic, not only in Europe but worldwide.

Credit author statement

Both authors contributed equally.

Declaration of competing interest

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

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[2] All tables concerning energy poverty extractions per year are available upon request.