Principal Component Analysis for Some Energy Poverty Indicators for EU27

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Abstract

In this article, the correlation relationships between the normalized values of the main energy poverty indicators for the EU27 countries were tested, for the period 2010-2024. Thus, a Principal Component Analysis (PCA) was applied in EViews 9 to check the eigenvalues, the eigenvector loadings of the correlation matrix. The purpose of applying this method is to identify the correlations between variables as well as to reduce the dimension of variation by simplifying the number of factors. Regarding the dimension reduction, it was found that components 1 and 2 have eigenvalues greater than 1. Specifically, factor 1 has a value of 3.3157, and factor 2 has a value of 1.8076. Thus, the factors retained are two. Regarding the eigenvalues, we found that the proportion for factor 1 is 41.45%, for factor 2 it is 22.60% of the total variance, summing the two components 64.04% of the total variance.

Key words: energy poverty, correlation matrix, Principal component analysis (PCA)
J.E.L. classification: C38, I32, Q01

1. Introduction

Energy poverty is a complex notion, with no universally accepted concept by the literature or authorities, encompassing aspects related to poverty and inequality of opportunity, aspects related to energy, prices and energy infrastructure, but also to housing conditions, more precisely the typologies of housing infrastructure of each country. Thus, the concept assimilates information related to socio-economic conditions, historical (e.g. at the level of EU27 countries, membership or not of the communist bloc), geographical conditions (e.g. predominantly mountain, hill or plain, desert etc.), cultural (e.g. through the prism of local traditions and customs), geopolitical, etc. In general, energy poverty is difficult to monitor carefully, with forms sometimes difficult to detect by the authorities. For example, according to a recent study, which studies satellite data (mainly in Sub-Saharan Africa), it is found that at least 1.18 billion citizens are in energy poverty, far above the officially recognized number of people (733 million) who do not have access to electricity (Min et al., 2024). In addition to precarious access to electricity (related rather to underdeveloped energy infrastructure), lack of provision of electricity services, frequent failures and power outages, or distribution problems, there is also a problem with those who practice under-consumption, due to the lack of financial resources to pay electricity bills.

The consequences of energy poverty can be direct or indirect, immediate or long-term, sometimes seriously and in the long term affecting physical and mental health, educational, work, social, economic and political opportunities, and the development of a generation or a large number of generations of people.

In this context, the article aims to analyze the issue of energy poverty through the lens of energy poverty indicators at EU27 level, using Energy Poverty Advisory Hub (EPAH) data, through the principal component method.

The work is ordered as follows: first describes the general context, the literature review, the methodology used and the description of the data, then in the second part is proceeded to analyze the statistical and econometric tests and in the end the conclusions are presented.

2. Literature review

Energy poverty is a multi-dimensional concept encompassing life expectancy, housing quality, caloric intake, literacy, inability to cook with modern cooking fuels and the lack of a bare minimum of electric lighting to read and many other controversial factors, being considered more a fundamental right (Reddy, 2000; Gaye, 2007; United Nations Development Program, 2010; Jones, 2010; Sovacool et al., 2014; Bouzarovski and Petrova, 2015; Bridge et al., 2018; Rafi et al., 2021; Koďousková and David, 2023). Beyond the regional level, energy poverty creates vulnerabilities that require specific actions at the zonal, local level, more precisely personalized, well-calibrated policies and strategies. In order to improve and reduce the problem over time, it is extremely valuable to understand the most important components that expose the population to energy poverty, framing, classifying and analyzing a set of variables that describe energy poverty. In general, energy poverty can be substantially reduced by a good energy infrastructure, centralized heating, high access to heating and lighting resources, a family budget covering bills and utilities, technology, but it can equally be aggravated by belonging to vulnerable groups (retirees, unemployed, young people, single parents, etc.), migration, poor energy infrastructure, climate, climate change, etc.

In terms of measurement, the use of indicators is more than useful in providing valuable information to authorities for the design of local and national policies, for rural or urban space, aiming to capture information on sustainable development, energy infrastructure, building infrastructure, but also household habits, so that they can complete the picture of energy poverty beyond classic statistics. It is generally considered that indicators can be grouped into individual indicators (Chen and Ravallion, 2008; IAEA, 2005; Vera and Langlois, 2007), indicators displayed in a dashboard structure, but not aggregated (IEA, 2010; UNDP 2010, with his Human Development Report), and composite indices (Freudenberg, 2003; Ebert and Welsch, 2004; Mirza and Szirmai, 2010; Nussbaumer, 2011).

If we refer to principal component analysis (PCA), it is a statistical analysis method that reduces a large, multivariate set of indicators into principal components, allowing the assessment of relative details between smaller areas, being used in various methodological forms across various geographical areas (Jolliffe, 1986; Buzar, 2007; Obeng et al., 2008; Doukas et al., 2012; Gonzalez-Mejia et al., 2012; Gollini et al., 2014; Robinson et al., 2018, Robinson et al., 2019, Korkmaz and Kurkcuoglu, 2025 etc.). Thus, the present article aims to deepen the study of energy poverty using the principal component method at the EU27 level.

3. Research methodology

In this article, we will test the relationship of the energy poverty indicators proposed by the Energy Poverty Advisory Hub (EPAH) by applying a principal component analysis (PCA). PCA aims to reduce the size of the data set by performing a covariance analysis between factors, through an orthogonal linear approach, based on the correlation or covariance matrix. By transforming a large set of variables into a smaller one, which still contains most of the information from the larger data set, additional simplification and clarity is achieved. However, reducing the number of variables in a data set still leads to a reduction in precision. Taking these limitations into account, PCA still offers enough simplicity, but also precision to be considered, making data analysis easier, faster to process, clearer. Since the variables included in the analysis have different measurements, even if they come from the same sphere of energy poverty indicators, a simple normalization of the data sets was previously performed.

The data are obtained from the Eurostat database, for the period 2010-2024. Where data were missing, interpolation was made, and where the data set stopped in 2023, extrapolation was done for 2024, and the systematization of the information is panel type, taking into account all countries of the European Union with 27 countries (EU27). The lack of data, but also the presence of adjustments, may make the results of the study be viewed with caution.

In the analysis, we can begin with a description of the macroeconomic variables which will be used in the analysis of the main components.

Table no. 1 Presentation of variables for energy poverty analysis for PCA

Variables name	**Acronym**	**Unit of measure**	**Data source**
Heating degree days	HDD	Number of days	Energy Poverty Advisory Hub (EPAH)
Pop. Liv. dwelling with presence of leak, damp and rot - Total	PLDPLDR	% of population	EPAH
Final consumption expenditure of households - Total	FCEH	k€/capita	EPAH
At risk of poverty or social exclusion - Total	ARPSE	% of population	EPAH
Inability to keep home adequately warm - Total (Unit: % of households)	IKHAW	% of households	EPAH
Arrears on utility bills - No disaggregation	AUB	% of households	EPAH
High share of energy expenditure in income (2M)(% of households)	2M	% of households	EPAH
Low absolute energy expenditure (M/2) - No disaggregation	M2	% of households	EPAH
Data are in a normalization procedure (i.e. value minus the minimum value on the difference between the maximum and minimum value).			

Source: Energy Poverty Advisory Hub (EPAH), author's selection

4. Findings

In this part of the paper, the descriptive statistics are presented, and to test normality, the Jarque-Bera statistical test is analyzed. The null hypothesis (H0) is that the selected variables have a normal distribution, and the alternative hypothesis (H1) is that they do not have a normal distribution. According to Table 2, the Jarque-Bera information for all selected variables is highly statistically significant at a significance level of 5%, confirming the normal distribution. But if we assume that the null hypothesis requires that the Skewness be 0 and the kurtosis be 3, this is not valid for all selected variables. Thus, the Skewness is generally below 1, except for the ARPSE, IKHAW and AUB indicators, and the Kurtosis is positive and extremely high (above 3) for most indicators, indicating a leptokurtic distribution. If we consider that for a normal distribution the value of the mean and median are close, suggesting a relatively symmetric distribution of the series, the null hypothesis is confirmed. At the same time, the standard deviation also oscillates around the mean and median values, which indicates that the values are spread within a small range, close to the mean, but below it.

Table no. 2 Descriptive statistics for energy poverty indicators selected

	HDD	PLDPLDR	FCEH	ARPSE	IKHAW	AUB	2M	M2
Mean	0.416763	0.311347	0.307200	0.300170	0.145369	0.214605	0.392799	0.348615
Median	0.416394	0.282857	0.298212	0.248082	0.086364	0.143902	0.379702	0.322515
Maximum	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000
Minimum	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Std. Dev.	0.196143	0.193440	0.186550	0.179606	0.144417	0.203286	0.187725	0.190047
Skewness	0.234117	0.797493	0.707390	1.429809	1.776555	1.593135	0.758847	0.820339
Kurtosis	3.289387	3.428550	3.622547	5.533580	7.004782	5.009671	3.897581	3.399060
Jarque-Bera	5.11291	46.02884	40.31724	246.31500	483.68590	239.47470	52.46514	48.11184
Probability	0.047579	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Sum	168.7890	126.0954	124.4161	121.5689	58.8745	86.9152	159.0837	141.1890
Sum Sq. Dev.	15.54268	15.11736	14.05962	13.03239	8.42594	16.69545	14.23720	14.59161
Observations	405	405	405	405	405	405	405	405

Source: Energy Poverty Advisory Hub (EPAH) indicators, author's calculation in Eview9

According to the correlation matrix table, most of the correlation coefficients of the macroeconomic variables are less than 0.5 and have a relatively weak positive and negative linear correlation, thus eliminating questions related to collinearity. Only, for example, IKHAW is positively and strongly correlated with ARPSE (0.6694), AUB with ARPSE (0.6895), AUB with IKHAW (0.6271) and M2 with 2M (0.6994), confirming the information that is also validated by the theory regarding the fact that there are multiple forms of poverty, which overlap and potentiate each other. Where the correlation is negative, it should be understood not necessarily as divergent elements, but as an alternative, a preference, choosing one element in favor of another, for example FCEH (Final consumption expenditure of households, k€/capita) is negatively correlated with IKHAW (Inability to keep home adequately warm, % of households) does not necessarily mean that the inadequacy of home heating cannot increase the final consumption expenditure of the home (because on the long-term this is the direction), but rather that it is preferred not to heat the home adequately to reduce final consumption expenditure. Based on the correlation matrix, information is successively obtained that helps us achieve the objective of the article which is to reduce the size of the information by eliminating variations, correlating the factors through PCA analysis.

Table no. 3 Correlation matrix for energy poverty indicators selected

	HDD	*PLDPLDR*	*FCEH*	*ARPSE*	*IKHAW*	*AUB*	*2M*	*M2*
HDD	1							
PLDPLDR	-0.4123	1						
FCEH	0.0648	-0.0464	1					
ARPSE	-0.1816	0.1968	-0.4624	1				
IKHAW	-0.4023	0.3440	-0.4382	0.6694	1			
AUB	-0.2325	0.1884	-0.5142	0.6895	0.6271	1		
2M	0.3841	-0.3379	0.2852	-0.0755	-0.1662	-0.2073	1	
M2	0.5008	-0.3704	0.1040	-0.1121	-0.2084	-0.1709	0.6994	1

Source: Energy Poverty Advisory Hub (EPAH) indicators, author's calculation in Eview9

The stationarity of the series was also checked by applying a clustered unit root summarization test to calculate and compare the statistical values with the p-values. In order to reduce the number of ADF tests from 8 to 1, the pool unit root summarization test was used.

Using a common unit root method, the study observed that all the statistical methods mentioned in Table 4 regarding Levin, Lin & Chu T*, IM, Pesaran and Shin W-Stat, ADF-FISHER Chi-Square and PP-Fisher Chi-Square have significant statistics and probabilities. For example, ADF - Fisher Chi-Square has a statistical value of 1242.87 and a probability of 0.0000. In other words, the selected indicators are presented as a stationary series.

Table no. 4 Pool unit root test for energy poverty selected indicators

Group unit root test: Summary				
Series: HDD, PLDPLDR, FCEH, ARPSE, IKHAW, AUB, _2M, M2, Sample: 1 405				
Exogenous variables: Individual effects				
Automatic selection of maximum lags				
Automatic lag length selection based on SIC: 0				
Newey-West automatic bandwidth selection and Bartlett kernel				
Balanced observations for each test				
Method	**Statistic**	**Prob.****	**Cross-sections**	**Obs**
Null: Unit root (assumes common unit root process)				
Levin, Lin & Chu t*	-76.2016	0.0000	8	3224
Null: Unit root (assumes individual unit root process)				
Im, Pesaran and Shin W-stat	-62.7196	0.0000	8	3224
ADF - Fisher Chi-square	1242.87	0.0000	8	3224
PP - Fisher Chi-square	1240.24	0.0000	8	3224
** Probabilities for Fisher tests are computed using an asymptotic Chi				
-square distribution. All other tests assume asymptotic normality.				

Source: Energy Poverty Advisory Hub (EPAH) indicators, author's calculation in Eview9

The PCA results table in the first section summarizes the eigenvalues or standardized variance associated with each factor, and the last two sections present the eigenvector loadings and correlations. For example, the proportion for factor 1 is 41.45%, and for factor 2 it is 22.60% of the total variance. The proportion of the first factor is calculated as 3.315705 / 8 = 0.4145. The first two components account for 64.04% of the total variance.

The patterns in the data are shown by the eigenvector loadings. For example, the eigenvector loading of the first principal component labeled PC1 is -0.32 for HDD and 0.29 for PLDPLDR. The first component, considering the eigenvector loadings, has 4 negative values out of 8. The principal component PC2 has only two negative values and six positive values. For example, PLDPLDR has a value of 0.29 at PC1, then a value of -0.29 at PC2, then a value of 0.48 at PC3, then a value of 0.76 at PC4, a value of -0.08 at PC5, a value of 0.11 at PC6, a value of -0.10 at PC7, and a value of -0.08 at PC8. The correlation matrix shows that most of the correlation coefficients of the energy poverty indicators are below 0.50 and negative, but there are also quite numerous positive correlations between the variables, some of them with strong intensity, as we explained in detail earlier when we analyzed the correlation matrix.

The decision on the number of factors to be retained can be based on the eigenvalues. As we can see from Table 5, factors 1 and 2 have eigenvalues greater than 1. Specifically, factor 1 has the value of 3.315705, factor 2 has the value of 1.807662, and factor 3 has the value of less than one. Therefore, the factors that we will retain are two.

Table no. 5 Results of the principal component analysis (PCA), computed by using ordinary correlations for the selected energy poverty indicators

Principal Components Analysis
Date: 05/14/25 Time: 16:48
Sample: 1 405
Included observations: 405
Computed using: Ordinary correlations
Extracting 8 of 8 possible components

Eigenvalues: (Sum = 8, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	3.315705	1.508043	0.4145	3.315705	0.4145
2	1.807662	0.861524	0.2260	5.123367	0.6404
3	0.946138	0.343067	0.1183	6.069505	0.7587
4	0.603071	0.122434	0.0754	6.672576	0.8341
5	0.480637	0.149732	0.0601	7.153212	0.8942
6	0.330904	0.054846	0.0414	7.484116	0.9355
7	0.276058	0.036233	0.0345	7.760175	0.9700
8	0.239825	---	0.0300	8.000000	1.0000

Eigenvectors (loadings):

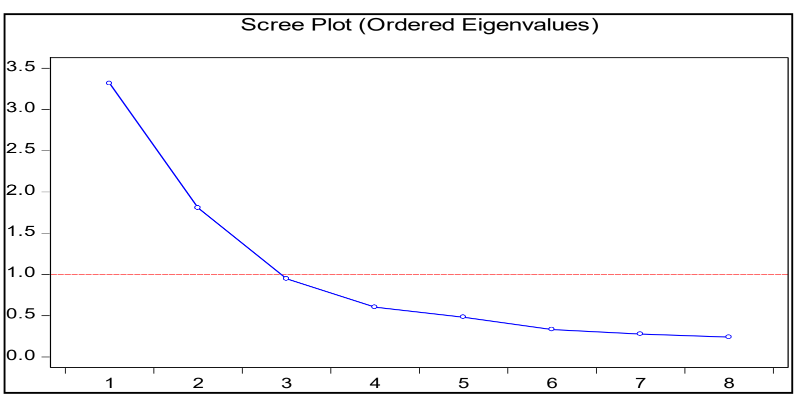
Variable	PC 1	PC 2	PC 3	PC 4	PC 5	PC 6	PC 7	PC 8
HDD	-0.327982	0.330565	-0.338513	0.566179	0.473758	-0.217420	0.248606	-0.120341
PLDPLDR	0.291728	-0.284953	0.476553	0.756297	-0.077372	0.109168	-0.103978	-0.076765
FCEH	-0.318825	-0.295417	0.534377	-0.221508	0.606467	0.086242	0.230257	0.219536
ARPSE	0.387976	0.385032	0.114347	-0.036019	0.391580	-0.271063	-0.561470	0.380518
IKHAW	0.435049	0.231007	0.269031	-0.104018	-0.111727	-0.473976	0.660905	-0.015484
AUB	0.411915	0.322531	-0.047630	-0.080654	0.296385	0.731449	0.191848	-0.240539
_2M	-0.311970	0.425826	0.485042	-0.119159	-0.090739	-0.094366	-0.257299	-0.623331
M2	-0.314454	0.485066	0.223069	0.159906	-0.373990	0.302197	0.138972	0.583092

Ordinary correlations:

	HDD	PLDPLDR	FCEH	ARPSE	IKHAW	AUB	2M	M2
HDD	1.000000							
PLDPLDR	-0.412314	1.000000						
FCEH	0.064768	-0.046402	1.000000					
ARPSE	-0.181615	0.196839	-0.462377	1.000000				
IKHAW	-0.402291	0.344031	-0.438247	0.669434	1.000000			
AUB	-0.232537	0.188364	-0.514194	0.689463	0.627062	1.000000		
_2M	0.384140	-0.337930	0.285231	-0.075496	-0.166215	-0.207314	1.000000	
M2	0.500780	-0.370411	0.103951	-0.112070	-0.208416	-0.170911	0.699366	1.000000

Source: Energy Poverty Advisory Hub (EPAH) indicators, author’s calculation in Eview9

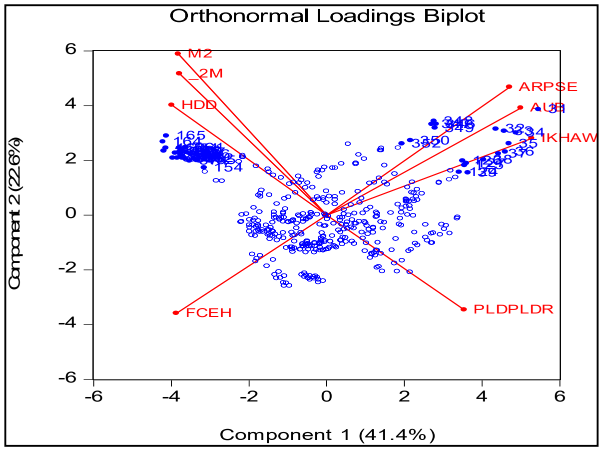
Figure no. 1. The observed eigenvalue matrix of the principal component analysis (PCA) for selected energy poverty indicators



Source: Authors’ calculation based on EViews 9 software

Combining Figure 1 with Table 5, we can see the number of eigenvalues plotted. Therefore, we should only retain two factors whose eigenvalues are greater than 1. If we consider only two factors, the results are presented as in Figure 2.

Figure no. 2. The orthonormal loadings of the principal component analysis (PCA) for selected energy poverty indicators



Source: Authors' calculation based on EViews 9 software

According to Figure 2, the component scores are displayed as circles, and the loadings of the macroeconomic factors are presented as lines. The first component has the largest proportion of the total variation, which is 41.4%, and positive loadings for four of the variables, except for the variables HDD, FCEH, 2M and M2. The second component has a value of 22.6% of the total variation. It has positive loadings for six variables and negative loadings for PLDPLDR and FCEH.

5. Conclusions

The article tested the correlation relationships between the normalized values of the main energy poverty indicators. The total data set includes annual data from 2010 to 2024, with systematized panel data for the EU27, so that the total number of observations is 405. The main data source is Eurostat.

Thus, a principal component analysis (PCA) was applied in EViews 9 to check the eigenvalues and eigenvector loadings of the correlation matrix. It was found, through the correlation matrix, that most of the correlation coefficients of the energy poverty indicators show a negative linear correlation, and where the correlation is positive, there are enough indicators with a positive and strong correlation.

Regarding dimensionality reduction, the study found that factors 1 and 2 have eigenvalues greater than 1. Specifically, factor 1 has a value of 3.315705, and factor 2 has a value of 1.807662. Thus, the factors that we will retain are two. Regarding the eigenvalues, we found that the proportion for factor 1 is 41.45%, for factor 2 it is 22.60%. The first two components represent 64.04% of the total variation. The orthonormal loadings show that the first component has the highest proportion of total variation, namely 41.45%, and positive loadings for four of the 8 selected variables. The second component has a value of 22.60% of the total variation and has positive loadings for six of the 8 selected variables.

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