Energy poverty in the European Union. State of play

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Abstract

The article explores the concept of Pan-European composite index as a measure of energy poverty. Only indirect energy poverty indicators are selected. The study pursues two goals. The first one is to discover the possibilities of a composite energy poverty index as a simple tool delivered to policy- and decision-makers. The second one is to depict the most contributing energy poverty factors. To that end, the paper considers two dimensions of energy poverty, housing and income ones. The variables for the composite index and logistic regression are selected to cover both dimensions. Several assumptions are made with regards to the number and choice of indicators employed in the construction of the composite energy poverty index. The results show that energy poverty is strongly affected by general poverty prevalence in the EU26 countries. Hierarchical clustering reveals four groups of countries, including outliers. The EU-SILC micro-data is provided by the EU Commission within the Research Project Proposal 204/2018-EU-SILC.

Key words: *energy poverty, composite energy poverty index, indirect energy poverty metrics*

JEL Classification: *I31, I32, Q40, Q42*

1. Introduction

Energy poverty has recently received a lot of attention in the EU policy-makers primarily due to a wide range of political commitments starting from combatting social exclusion, health improvement, environmental protection, building stock renovation, vulnerable consumer protection, energy market integration, usage of renewables, prosumer role, households' energy efficiency and savings. The paper aims at describing the current situation of energy poverty prevalence in the EU. It is worth highlighting that energy poverty is a cross-cutting issue. There are a few EU policies mentioned in the founding EU treaties that cover at least one of the energy poverty dimension (Consolidated version of the Treaty on the Functioning of the European Union). Social policy, public health, consumer policy, environment, energy policy those are policy domains largely associated with the predicament. In most of the documents energy poverty is measured with indirect metrics from the EU-SILC database. The EU-SILC is a primary European survey on poverty and social exclusion. The key questions form the EU-SILC, which are related to insufficient energy consumption, are ability to keep home adequately warm; arrears on utility bills; leaks/damp/rot in the dwelling, and problems with the dwelling being too dark. The definition of energy poverty provided on the EU energy poverty observatory web-site, launched by the EU Commission in the early 2018, states that energy poor households experience inadequate level of essential energy services, which results in aggravation of diseases and poor wellbeing ("EU Energy Poverty Observatory", 2018). The EU Commission emphasises the distinct character of energy poverty and puts the phenomenon into

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the broad context of energy consumer vulnerability and single energy market integration (Clean Energy for All Europeans).

2. Literature survey

Many studies on energy poverty are country-specific and based on national household energy consumption surveys. Not so much is done in relation to estimating energy poverty at the EU level not to mention the ongoing debate on the appropriate metrics. The literature on energy poverty in the EU could be roughly divided into two broad categories, policy-centered and metrics-centered. When it comes to energy poverty metrics in cross-countries comparisons, the vast majority of studies explore consensual metrics. Some authors deny possibility of single energy poverty measure as it is ill-suited to countries' specificity and could possible impede effective policy targeting (Deller, 2018).

Failures of direct energy poverty metrics are widely discussed in the literature (Moore, 2012; Heindl and Schuessler, 2015). Each indicator is based on several assumptions that are not always possible to maintain. Direct energy poverty metrics could be demanding in terms of data sophistication, i.e. detailed technical parameters of housing stock and data availability, which is the major problem for the EU analysis (Fuel poverty, 2018). Besides, direct energy poverty metrics provides inconsistent results ranging from too low to incredibly high rates of energy poverty depending on the thresholds and assumptions (Karpinska, 2018).

Cross-country comparisons are mainly constrained by lack of relevant micro data collected at the EU level. To that end EU-SILC is used. The survey is the only available micro-dataset suitable for Pan-European energy poverty assessment. The studies on the EU energy poverty prevalence go back to 2002. In the first Pan-European energy poverty assessment, the authors model the probability of energy poverty based on probit regression and build a composite measure of the predicament (Healy and Clinch, 2002). Various scenarios with different weights assigned to each variable are tested and different sets of variables are considered in the construction of a composite measure. The similar studies are conducted afterwards (Thomson, Bouzarovski and Snell, 2017). When exploring logistic regression and statistics from EU-SILC dataset, the authors discovered the propensity of households to energy poverty across the EU countries (Thomson and Snell, 2013). The research carried out under the auspices of the Commission, concludes that consensual-based metrics is the only easily accessible energy poverty metrics for the EU (Rademaekers et al., 2016).

Considering the limitations associated with single energy poverty metrics, the study discovers the possibility of a composite index as a practical and easily understandable tool for policy action. Besides, composite indices are proved to be the most influential and transparent measure, when it comes to energy poverty metrics. Composite or multidimensional energy poverty index (MEPI) was introduced within the context of energy access debate and achievement of the UN seventh millennium development goal, which is to "ensure access to affordable, reliable, sustainable, and modern energy for all" ("International Energy Agency", 2018). Initially the index was designed as a tool to estimate the depth and scale of modern energy services deprivation in the least developed and developing countries (Nussbaumer, Bazilian and Modi, 2012). The index is an aggregated measure that captures several dimensions of energy poverty. It resembles multiple human and sustainable development metrics used by the international organizations.

The study contributes to the literature on Pan-European energy poverty assessment by introducing hierarchical clustering to group the EU26 countries based on the results of a composite index and log regression estimates. Two classifications are conducted. The first one makes use of composite index results. The second one is based on the logistic regression estimates. The clusters are then compared. To conduct the first grouping, composite energy poverty index is computed at micro-level. The obtained results help to depict the profile of energy poor and to reveal the determinants of the predicament. This study supports the idea that energy poverty is complex and is related to both, energy efficiency of houses and income poverty.

The second grouping is performed based on log regression results. In line with previous researchers, log regression analysis is conducted for a set of EU-SILC variables. The set of variables used in a composite index and in log regression is almost the same. Ability to keep home warm variable is predicted with two variables related to energy efficiency of building stock, such as leaking roofs, and darkness in a house. The income component is covered by arrear on utility bills and poverty indicator.

3. Methodology and data

The study is based on the latest available cross-sectional EU-SILC variables from household data section. The EU-SILC survey is conducted by national statistical offices using harmonized procedures and is compiled by Eurostat. The latest data upgrade was released in November 2018. The number of observations depends on the country and varies between around 3,9 thousand for Malta and Luxembourg to 22 thousand for Italy. Household data for Poland-2017 contains around 13 thousand records. The survey is initially designed to cover income poverty and social inclusions with the purpose to monitor progress on 2020 goals. However, as discussed earlier the database contains questions that intuitively fit for energy poverty and vulnerability measurement. To build composite energy poverty index, three indirect energy poverty measures were selected accompanied with poverty indicator. Weighted sum model is adopted with equal weights being assigned to each indicator. The weights are arbitrary. The study makes usage of weighted additive models developed in the literature on the topic. The experts' cut off line is adopted at 0.5 points. Each indicator has weight of 0.25. The variables are transformed into binary, where 1 means energy poverty. Both types of "yes" answers to question HS021 are simplified to "yes" in a composite index analysis. Summary statistics of the chosen indicators is presented in Table 1.

Table 1. Descriptive statistics

Variable	Value	Dimension
HH040 Leaking roof, damp walls/ floors/foundation, or rot in window frames or floor	1-yes 2-no	Housing
HH050 Ability to keep home adequately warm	1-yes 2-no	Housing/ income poverty
HS021 Arrears on utility bills	1 yes, once 2 yes, twice or more 3 no	Income poverty
HS160 Problems with the dwelling: too dark	1 yes 2 no	Housing
HX080 Poverty indicator	0 when >= at risk of poverty threshold 1 when < at risk of poverty threshold	Income poverty

Each household is assigned composite energy poverty index. The chosen variables are HH040, HH050, HS021 and HX080. In addition, variables HH040, HS160, HS021 and HX080 are regressed against the probability of HH050. The log regression is computed for each country. The output variable has value 1 for energy poverty and 0 otherwise. In our case, all input variables except HS021 are binary. For clustering purposes, the study uses hierarchical (agglomerative) method. The results are presented on dendrograms depicting similarities within groups. Ward's minimum variance within the group method is deployed.

4. Results

In the first step of the analysis the composite energy poverty index is calculated. The index captures both the scale and the intensity of the phenomenon. As mentioned earlier four drivers of energy poverty are considered. All of them account for either energy efficiency of housing stock or income poverty of a household. Three indicators are objective in nature, because they impartially describe the real fact, whereas the ability to keep home warm is a subjective indicator that depends on various country-specific factors. This aspect of cultural and behavioral differences between countries should be considered in the first place when analysing the results of estimations. Energy poverty rate for EU26 is presented in Fig. 1. The rate ranges from 3,8% to 21,1%. Median is around 8%. The distribution is right-skewed, and the interquartile range is 7,97 pp. The worst performing countries are Bulgaria, Greece, Portugal, Cyprus, Lithuania, Latvia and Hungary. The lowest energy poverty rates are observed in Finland, Sweden, Czech Republic, Denmark, Netherlands, Slovakia, and Austria.

Energy poverty depth is the prevalence of the phenomenon across the respective equivalised income quartiles, i.e. the lower the quartile the deeper energy poverty is. The most affected countries are Bulgaria, Greece, Lithuania, Portugal and Croatia. The ratio of energy poor to non energy poor in each quartile is calculated. In the first income quartile median value of the ratio is 0,4017. In the second quartile the number of energy poor decreases, and the ratio varies between 0,0013 (Austria) to 0,4112 (Bulgaria). The distribution of the aforementioned ratio in the second quartile slightly differs, however the most vulnerable countries are practically the same. The upper quartiles in Austria and Belgium are not affected by energy poverty at all. The results of the discussed distributions are depicted in Fig. 2. Bulgaria is removed as an extreme outlier.

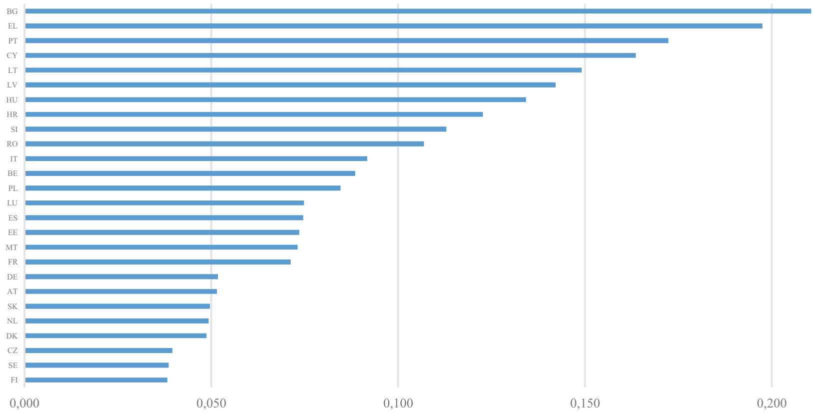

Fig. 1. Energy poverty rate

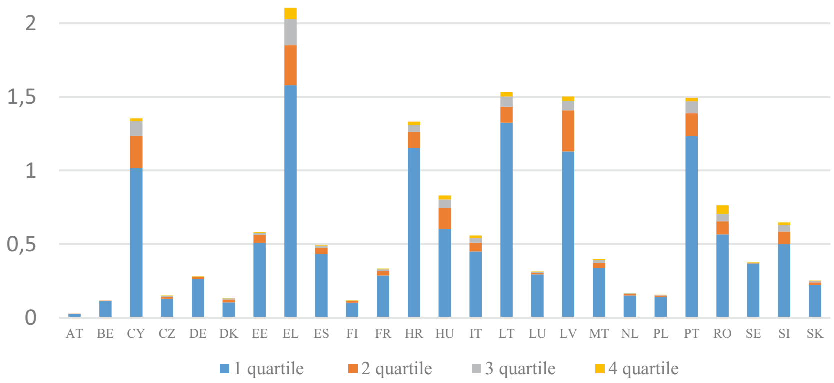

Fig. 2. Distribution of energy poverty by income quartile (without BG)

It is worth mentioning that some of the variables have greater impact on output than others. In Fig. 3 indicators have been sorted as being related mostly to energy efficiency dimension (HH040) or income poverty dimension (HS021, HX080).

Ability to keep home warm is equally divided between housing and poverty dimensions of energy poverty. Poverty domains are a bit of more importance in this analysis, meaning that countries experience energy poverty primarily due to general poverty. Croatia, Hungary, Poland and Slovenia appear to be in the forefront of energy poor countries where energy poverty is caused by poor dwellings.

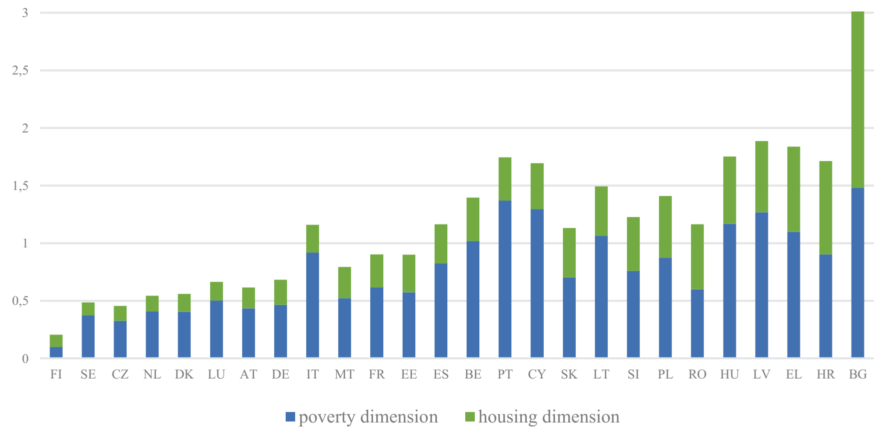

Fig. 3. Energy poverty determinants

In the second step of the analysis, logistic regression is computed[2]. In addition to index variables, HS160 is added. Ability to keep home warm is a predicted value. Given the limited number of determinants included into the model the predicting power of the model is around 53%. Variables have different significance levels across the countries. HX080 has high p-value for Lithuania and Luxembourg, slightly lower for Denmark and is not significant for Finland. It means that ability to keep home warm in those countries is impacted by other factors than income poverty. When it comes to HH040 and HS160 they are significant for most of the countries. It is worth highlighting that in the models HS021 has adverse impact on the odd ratio. In the logistic regression variables are not transformed to 0-1 binary variable. Hence, the interpretation depends on the initial values.

Table 2. Distribution of energy poverty determinants in groups of countries (min, max, median)

Countries/variables	Housing dimension		Income poverty dimension	
	HH040	HH050	HS021	HX080
AT, CZ, DE, DK, EE, ES, FI, FR, LU, MT, NL, RO, SE, SK	0.03/0.39/ 0.08	0.06/0.46/ 0.25	0.04/0.50/ 0.27	0.03/0.19/ 0.06
BE, EL, HR, HU, LV, PL, SI	**0.13/0.51/ 0.28**	**0.45/0.76/ 0.67**	0.21/0.72/ 0.44	0.17/0.55/ 0.22
BG	1.31	0.44	0.65	0.61
CY, IT, LT, PT	0.15/0.35/ 0.22	0.17/0.36/ 0.25	**0.68/0.89/ 0.71**	**0.14/0.43/ 0.29**
EU26	0.03/1.31/ 0.15	0.06/0.76/ 0.32	0.04/0.89/ 0.33	0.03/0.61/ 0.15

In the third step grouping of the EU26 countries is performed. Hierarchical clustering results are presented in Table 2 and 3. The analysis reveals four groups of countries, including two

[2] The results are available upon request.

groups of one outlier in each clustering. Distribution of variables across groups represents the most influential factors for each group of countries. Groups are not similar in each clustering. One representative group is identified in each clustering. As outlined previously, the study focuses on two dimensions of energy poverty, housing and income poverty-related. HH040 is an objective criterion used to describe poor houses. It has the highest values for the second group and the lowest for the first one. Another variable that is partially related to housing dimension is HH050, which has also the greatest impact in the second group, and a lower impact in the rest of the groups including Bulgaria. HS021 and HX080 are associated with income poverty. Income poverty is an issue in the fourth group, and the same group has highest arrears on utility bills. Bulgaria is an outlier and has extremely high values for all indicators, except HH050. It should be remembered that HH050 is the only indicator that has strong socio-behavioral specificity.

Grouping countries based on log regression estimates indicates that housing dimension plays an important role in the first group (HH040) and in the fourth group (HS160). Income poverty mostly affects the second group (HX080. There is strong evidence that income poverty is a key energy poverty driver. It is no surprise that energy poverty in the countries richer in terms of social welfare is driven mainly by energy inefficient housing stock.

Table 3. Distribution of logistic regression coefficients in groups of countries (min, max, median)

Countries/ coefficients	Housing dimension		Income poverty dimension		
	HH040	**HS160**	**HS021**	**HS021**	**HX080**
AT, BE, CZ, DE, ES, FR, HR, HU, LV, MT, NL, PL, RO, SI, SK	**0.32/ 1.08/ 0.79**	0.24/ 0.87/ 0.44	-1.28/ 0.08/ -0.40	0.23/ 1.24/ 0.76	-1.42/ -0.32/ -0.97
BG, CY, EL, IT, LT, LU, PT	0.18/ 0.51/ 0.37	0.15/ 0.70/ 0.24	-0.41/ 0.37/ -0.06	0.36/ 1.55/ 0.54	-0.74/ -0.15/- 0.53
DK	1.14	1.39	0.22	1.39	-0.71
EE, FI, SE	0.60/ 0.67/ 0.61	**0.62/ 0.88/ 0.84**	**-1.98/ -0.91/ -1.75**	-0.71/ 0.12/ 0.02	-1.27/ -0.26/ -0.81
EU26	0.18/1.14/ 0.69	0.15/ 1.39/ 0.45	-1.98/ 0.37/ -0.30	-0.71/ 1.55/ 0.73	-1.42/ -0.15/ -0.81

Conclusions

The paper relies on the EU-SILC database and makes use of self-reporting energy poverty indicators. Due to some shortcomings of direct metrics, the paper adopts indirect approach. Thus, concerns related to single energy poverty metrics, especially lack of cross-country comparability are mitigated. The paper addresses the problem of measuring energy poverty at the EU level exploring the concept of multidimensional energy poverty index and indirect metrics. The study begins by computing composite energy poverty index to obtain the distribution of the energy poverty across income groups and estimate the contribution of each variable to the final energy poverty score. The first aspect sheds light on the gap of energy poverty being the deepest in the first income quartile. The second aspect allows the author to characterise the underlying reasons of the predicament. In addition, log regression is conducted to predict the ability to keep home warm. The respective model for each EU country is built using three most popular indirect energy poverty metrics, and poverty indicator. The study concludes by comparing the results of hierarchical clustering of the EU countries based on log regression parameters on the one hand and composite index variables on the other.

To sum up, the main findings of the study are as follows. Firstly, housing and income poverty-related dimensions equally contribute to energy poverty prevalence. Secondly, the first income decile seems to be the most affected by energy poverty with the deepest gap notified for poor countries of the EU. Thirdly, energy poverty is also a concern in upper income quartile groups. In this regard, it is worth highlighting that energy poverty is distinct from income poverty. Fourthly, energy poverty in richer countries is determined more by poor housing conditions than income poverty. The analysis was constrained by a number of assumptions, including limitations of indirect energy poverty metrics, dependency of self-reported metrics on country-specific socio-behavioral patterns, finite number of energy poverty variables.

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