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# Invisible energy poverty? Analysing housing costs in Central and Eastern Europe

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ABSTRACT

The paper presents a comprehensive approach to capturing the scale of exposure to hidden energy poverty at a household level in 11 Central and Eastern European countries. Despite constant refinements, the currently used energy poverty metrics remain highly controversial when it comes to inter-country comparisons. Scarce data and the lack of agreement on the energy poverty definition among the EU countries impedes operationalization of energy poverty measures on a global scale.

Instead, we propose a reliable tool for tracking hidden energy poverty based on the existing micro-level data compiled by Eurostat. The paper assumes that the energy poor limit their energy consumption to the level below what is reasonably assumed a decent life. To estimate the expected energy costs, the paper introduces a new statistical approach. We consider multiple aspects of exposure to hidden energy poverty, including dwelling parameters and location, households' structure, and regional specificity.

Our findings confirm that on average 23.57% of the Central and Eastern European population is exposed to hidden energy poverty. The examined profiles are quite heterogeneous. In general, the affected are single-person households or living in detached houses and remote areas households with dependent children. The paper provides suggestions for targeted policy action.

## 1. Introduction

Energy poverty is a recognized form of material deprivation distinct from income poverty. Energy poverty encompasses multiple dimensions of life and impacts health, social inclusion, environmental quality, mental well-being, and, ultimately, productivity [1]. Recent studies suggest that energy poverty also refers to insufficient cooling during summertime, which is an aggravating factor in cities experiencing the urban heat island effect [2,3].

The EU Commission estimates that roughly 50 million, which is about 11.2% of the EU population is affected by energy poverty [4]. It is widely recognized in the respective EU legislation that the issue needs to be defined and measured at national and the EU-wide scale [5]. The suggested by the EU Energy Poverty Observatory primary energy poverty metrics include two self-reported or indirect indicators, such as arrears on utility bills and inability to keep home warm, and two direct or expenditure-based indicators, i.e. a high share of energy costs in income and low absolute energy costs [6]. Although there are multiple single-country studies assessing the scale of energy poverty, comparative energy poverty studies are not so numerous. Some of the latter studies are based on aggregated macro indicators [7–10]. And the existing micro-level cross-country researches employ indirect energy poverty metrics [11,12]. However, indirect energy poverty measures have some important drawbacks. Namely, subjective indicators are criticised for being biased, dependent on the socio-cultural environment and individual perceptions [11,13,14]. Expenditure-based energy poverty measures are left without proper attention when it comes to micro-level cross-country estimations. To the best of our knowledge, this paper is the first attempt to apply expenditure-based metrics in assessing households' energy poverty in cross-country analysis.

Given such a lacuna, we propose to estimate the level of households' energy under-consumption based on the EU-SILC micro-level data. In this study, we focus on Central and Eastern European countries and consider a hidden aspect of energy poverty. The aims of the study are two-fold.

First, we put forward an expenditure-based metrics to estimate the expected consumption of energy in households. These estimates are used to identify households, who under-consume energy. To model the expected energy expenditures, we use households' and dwellings' attributes and rely on some assumptions. Since the study approximates energy expenditures and operates on housing costs, we measure exposure to hidden energy poverty.

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Second, we apply this approach to estimate and compare the scale of exposure to hidden energy poverty across Central and Eastern European countries. We define a household to be exposed to hidden energy poverty if after deducting the expected housing costs from a total disposable income, this income falls below 60% of a national median. We rely at this point on Eurostat's definition of a relative poverty line [15].

In addition, a micro-level approach allows profiling exposed to hidden energy poverty households across Central and Eastern Europe. Several variables are used to make the decryption effective.

We choose Central and Eastern European countries as a target for several reasons.

The problem of energy poverty in Central and Eastern European countries is exacerbated by infrastructural problems, income inequality, energy inefficient building stock, and deficiencies resulting from a socialist economy [16]. Also, the air quality in the Central and Eastern European region leaves much to be desired. The world air quality report reveals that cities from Central and Eastern Europe represent 88% of the most polluted places in Europe [17]. This could be attributed to insufficient usage of renewables and little public awareness of energy poverty prevention. Particulate matter, which is a measure of air pollution, is generated, among others, by the combustion of solid fuels in the household sector. The complex interaction between residential energy usage, climate change and thermal efficiency of the buildings in Eastern Europe are identified by Urge-Vorsatz and Tirado-Herrero [18].

Studies on energy poverty in the EU measured by indirect metrics confirm that Central and Eastern European countries are affected by this problem to a greater extent than other countries [16,7]. This can be attributed not only to a socio-cultural environment but also to the spread of income poverty, significant energy burden on households' budget, and failures of the transition period. Overall, the studies suggest that energy poverty in the Central and Eastern European region is prevalent and depends on economic, socio-political and environmental issues [19]. Dubois and Meier [8] provide almost the same conclusion stating that Eastern and Southern European countries demonstrate a higher incidence of energy service deprivation due to low income and old dwellings.

The hidden aspect of energy poverty is of special interest to us because of the following reasoning. First, income poverty is widely spread in Central and Eastern European countries. Households experiencing challenges of making ends meet prioritize other basic needs and cannot afford to maintain a comfortable temperature inside. Thus, energy poverty in Central and Eastern European countries is hard to detect because of abnormally low energy expenditures in many households. Second, the quality of building stock in Central and Eastern European countries, especially in urban areas with district heating, requires significant improvement [19,21]. There are a lot of decayed buildings and houses in poor thermal condition, which means that low energy expenditures are less likely to be driven by pre-bound effect in this region.

We make an inference about the scale of exposure to hidden energy poverty at the Central and Eastern European level based on the following assumptions.

Firstly, modelling housing costs captures the variability attributed to energy usage. According to the EU-SILC description, the varying component of housing costs comprises costs of gas, electricity, heating and water. Except for water, all utility components are related to energy services. To account for the energy-related component of housing costs, we include in a model a set of parameters specific to energy consumption.

Secondly, we assume that energy poor households refrain from consuming energy at the level necessary for a comfortable life. We acknowledge that the actual level of energy spending provides no grounds for determining energy poverty prevalence until we take into account the parameters of housing. Expected housing costs serve as a proxy of costs needed to achieve an adequate level of necessary energy services [1] as compared to actual ones. This way we reveal a hidden aspect of energy poverty.

The study is divided into several stages.

In the first stage of our analysis, we select the best set of indicators from the EU-SILC database. Expected housing costs are calculated for 11 Central and Eastern European countries in 2017, which is the latest available cross-sectional dataset. To compile the data, the study makes use of two files, i.e. household register and household data files, which contain information on, among others, household composition, expenditures, and dwelling types. For our analysis, we choose 16 indicators.

In the second stage of the analysis, we model housing costs following multiple linear, lasso, and robust regressions. We then find out which households fall below relative poverty line after deducting the expected housing costs from income. We consider energy costs to be the main component of housing costs which could be cut down by households experiencing material and financial difficulties.

In the third stage of the analysis, we describe the profile of the exposed to hidden energy poverty households. Utilizing a set of sociodemographic indicators, the study provides a cross-country comparison of the results in Central and Eastern European countries.

The rest of the paper is organized as follows. In the second section, we review the literature on the topic. The third section describes the data used in the analysis. The fourth section focuses on methodology. In section five we present and discuss the results. The last section concludes and provides policy implications.

## 2. Literature review

Few Central and Eastern European countries have been a subject of energy poverty discussions so far [2,20,22,23]. In Poland, the incidence of energy poverty based on a set of conventional energy poverty metrics varies between 2.1% and 18.6%, whereas the multidimensional index is estimated at 9.8% [24]. In Bulgaria, households are facing challenges of excessive energy burden with the highest rates of energy poverty within the EU-27 countries [25]. In Hungary, energy poverty is exacerbated by district heating of energy inefficient panel blocks of flats [26]. This type of poverty is linked to the supplier-switch problem and the lack of investments in building modernization. energy poverty is also claimed to be a path-dependent phenomenon resulting from the legacy of the former economy [27]. In Czechia, energy poverty is estimated at a level of 16% [28]. Karásek and Pojar [28] claim that, despite the existence of policy mechanisms aimed at increasing energy efficiency and reducing energy consumption in the household sector, energy poverty needs to be addressed separately. In Slovenia, the qualitative comparative analysis indicates that energy poverty is driven mainly by poor building stock and inefficiencies of the labour market [29].

In line with the literature, we acknowledge that the nature of energy poverty in Central and Eastern European countries is determined by energy under-consumption exacerbated by low income and poor living conditions. Abnormally low energy expenditures point at hidden energy poverty [30] and are observed in many countries especially among vulnerable groups of the population [31,32]. energy poverty is often characterized by reduced energy usage and self-disconnections [33,34]. The lived experience of the energy poor illustrated in the literature demonstrates that such people prefer to satisfy their other basic needs at the expense of energy consumption among other things [35–37]. What is more, the energy poor are often incapable of making capital investments in the energy efficiency of houses or housing refurbishment [38].

The existing comparative empirical studies on energy poverty either take a macro-economic approach to the problem or rely on subjective energy poverty indicators, i.e. ability to keep home adequately warm and a composition of several proxy indicators. Expenditure-based metrics, including hidden energy poverty indicators, has not been used in micro-level cross-country comparisons. Instead, hidden energy poverty analysis is dominated by singe-country studies [30,31,32].

The first group of literature on energy poverty are macro-level comparative studies.

Consensual metrics complemented with some variables related to macro-regional differences are applied by Bouzarovski and Tirado Herrero [7]. To measure energy poverty, the authors design a composite index as a weighted sum of three indirect energy poverty indicators [7]. In the same vein, Dubois and Meier [8] consider a composite index as a viable Pan-European measure of energy deprivation. The authors put forward the concept of energy services deprivation and inequality in heating service. The analysis is conducted with the usage of proxy energy poverty indicators. Similarly, the recent research on energy poverty vulnerability in the EU is also conducted at a macro-level [10]. The authors estimate structural energy poverty vulnerability in the EU based on a set of indicators related to labour, housing, and energy markets, which allows identifying similar groups of countries in cluster analysis.

The second group of literature are micro-level comparative studies.

Energy poverty prevalence across the EU was for the first time studied in 2002 [11]. According to Healy and Clinch estimations [11], the incidence of energy poverty in the EU14 measured by composite indices oscillates between 11.3% and 16.3% on average. The authors rely on subjective energy poverty indicators complemented with some dwellings characteristics available in the ECHP dataset. After almost a decade, Thomson and Snell [12] conduct a subsequent Pan-European study on the prevalence of energy poverty in the EU27. The authors explore subjective energy poverty indicators and compute a composite indicator in four scenarios. Besides, the study utilizes three logistic models assessing the propensity of households to suffer from energy poverty. An extended version of the composite index is a compound energy poverty indicator [39]. The indicator consists of the same self-reporting metrics from the EU-SILC and, additionally, includes cooling during summertime and dark dwelling variables.

A couple of reasons determine lack of micro-level Pan-European energy poverty research based on other than subjective indicators. The first reason is the vagueness of the definition of energy poverty itself. The EU as a whole has adopted the concept created within the framework of Energy Poverty Observatory [1]. But member states can use their definitions. The second reason is a methodological issue associated with the implementation of direct energy poverty metrics and a scarcity of relevant micro-level data [40,41]. The micro-data on residential energy consumption and energy efficiency of the housing stock is not available at EU level. And the purpose of the EU-SILC database is to monitor poverty and social inclusion in the EU [42], which makes it less suitable in studying complex research questions, such as energy poverty. To overcome the problem, many researchers use unconventional data or specifically-tailored energy poverty surveys [43,44] that is problematic to implement the EU-wide.

## 3. Data description

In our analysis, we explore household registers and household data, so-called D- and H-files of cross-sectional data. The selected set covers observations in 11 Central and Eastern European countries reported in 2017. There are two reasons why cross-sectional data are chosen. First, the cross-sectional component of the EU-SILC is more sizable compared to longitudinal observations[1]. Second, there is no need to retain data describing households observed over some time to conduct a static analysis. The EU-SILC is an acknowledged source of high-quality data on income, poverty, living conditions and social exclusion, which implies that the data is harmonized and suitable for comparisons. Nevertheless, not all information is gathered in and delivered by all countries. Some countries do not compile HH031, DB040, or DB100 (Estonia, Latvia, Slovenia, Croatia, Lithuania, and Slovakia). Some datasets contain missing values, which requires cleaning procedures. We decide not to impute any values, as the datasets contain a sufficient number of observations.

The variables that we choose account for either the housing or the income aspect of exposure to hidden energy poverty. The housing aspect refers to a type and quality of homes, while the income aspect describes household's needs and the level of its' welfare. These two aspects are suggested by the energy poverty ratio, which includes income and energy efficiency components and provides the simplest basic estimation of energy poverty [45].

We select 16 variables from the EU-SILC database to model housing costs (Table 1). Most of the EU-SILC variables used in the analysis are categorical variables. Our set of variables accounts for under- or over-occupancy (variables HX060, HX040, HH030), heating regime and regional socio-economic differences (DB040, DB100), income (variables HX090, HS120, HS021, HH050), as well as includes several housing-related indicators (variables HH010, HH021, HH040, HH081, HH091, HS160, HH031). Among all income variables available in the EU-SILC dataset, we choose HX090, because it adjusts the total disposable income to the equivalised household size.

Continuous variables represent income, housing costs, and a year of purchasing installation. The summary statistics of HX090 and HH070 variables are shown in Fig. 1 and in Fig. 2.

Because the variables are expressed in absolute terms and do not account for the purchasing power of a currency, the living standards in different countries are hard to compare. However, the statistics give an insight into the income and housing costs distribution in the respective datasets. Outliers and extreme outliers are numerous, especially in the upper quartile. We handle the outlying observations in the later part of the analysis.

The Central and Eastern European median equivalised disposable income equals 5875.85 euro per year, and the Central and Eastern European median housing costs equal 135.66 euro per month[2]. The distribution of HX090 variable across countries is presented in Fig. 1. Two groups of countries are identified concerning the level of income. The first group consists of countries with a low income, which is below the Central and Eastern European median value. The second group includes countries with a high income, i.e. Czechia, Estonia, Slovenia, and Slovakia. In 2017 median equivalised disposable income was characterized by higher variance within the second group of countries, ranging from 12483.33 euros in Slovenia to 6921.28 euros in Slovakia. In the first group, the highest median income is observed in Lithuania (5651.59 euro), and the lowest one - in Romania (2850.52 euro).

When considering housing costs distribution (Fig. 2), the composition of groups slightly changes. The median value in the second group is relatively low, reaching its maximum in Estonia (131.00 euro) and minimum in Romania (75.72 euro). In the first group, Czechia (203.45 euro), Poland (137.51 euro) and Slovakia (200.00 euro) have median values above the Central and Eastern European one. Maximum is found in Slovenia (225.83 euro).

As noted above, variables HX090 and HH070 are given in euro and not in purchasing power parity. To overcome this problem, the distribution of two relative measures is presented in Figs. 3 and 4. The first one describes the income poverty rate, and the second one - the housing costs overburden rate, which is a percentage of households whose share of total housing costs in HX090 is above 40% [46][3].

Two measures of income poverty are presented in Fig. 3. The income poverty rate calculated as the share of households falling below the threshold of 60% median HX090 is presented on the left panel, and

[1] For example, in 2017 cross-sectional household panel for Poland encompasses 13,057 observations, while the corresponding longitudinal panel, i.e. waves 2014–2017, consists of 2681 unique observations.

[2] According to Eurostat, variable HH070 refers to monthly costs, and variable HX090 refers to an annual income.

[3] Housing costs overburden does not account for housing allowances.

**Table 1**
Variables.

| Housing aspect | Income aspect |
|---|---|
| HH010 Dwelling type<br>• 1. detached house<br>• 2. semi-detached or terraced house<br>• 3. apartments or flat in a building with less than 10 dwellings<br>• 4. apartments or flat in a building with 10 or more dwellings | HS120 Ability to make ends meet<br>• 1. with great difficulty<br>• 2. with difficulty<br>• 3. with some difficulty<br>• 4. fairly easily<br>• 5. easily<br>• 6. very easily |
| HH021 Tenure status<br>• 1. outright owner<br>• 2. owner paying mortgage<br>• 3. tenant or subtenant paying rent at prevailing or market rate<br>• 4. accommodations are rented at a reduced rate (lower price than the market price)<br>• 5. accommodations are provided free | HX060 Household type<br>• 5. one-person household<br>• 6. 2 adults, no dependent children, both adults under 65 years<br>• 7. 2 adults, no dependent children, at least one adult 65 years or more<br>• 8. other households without dependent children<br>• 9. single parent household, one or more dependent children<br>• 10. 2 adults, one dependent child<br>• 11. 2 adults, two dependent children<br>• 12. 2 adults, three or more dependent children<br>• 13. other households with dependent children<br>• 16. other |
| HH030 Number of rooms available to the household<br>HH040 Leaking roofs, damp walls/floors/foundation, or rot in window frames or floor<br>• 1. yes<br>• 2. no<br>HH081 Bath or shower in dwelling<br>• 1. yes, for sole use<br>• 2. yes, shared<br>• 3. no<br>HH091 Indoor flushing toilet for sole use of household<br>• 1. yes, for sole use<br>• 2. yes, shared<br>• 3. no<br>HS160 Problems with the dwelling: too dark, not enough light<br>• 1. yes<br>• 2. no<br>DB040 Region<br>DB100 Degree of urbanization<br>• 1. densely populated area<br>• 2. intermediate area<br>• 3. thinly populated area<br>HH031 Year of contract or purchasing of installation | HX040 Household size<br>HS021 Arrears on utility bills<br>• 1. yes, once<br>• 2. yes, twice or more<br>• 3. no<br>• HH050 Ability to keep home adequately warm<br>• 1. yes<br>• 2. no |

the at-risk-of-poverty indicator is presented on the right panel. The income poverty measure indicates that the most affected countries are Croatia (21.96%), Latvia (21.90%), and Bulgaria (21.16%). Czechia (6.49%), Slovakia (10.49%), and Hungary (10.58%) are the countries which are less likely to become poor. The at-risk-of-poverty indicator provides slightly different results, i.e. the highest shares of the poor are obtained for Latvia (33.82%), Bulgaria (28.93%), and Croatia (27.03%), while the lowest rates are found for Czechia (11.59%), Slovakia (11.77%), and Slovenia (13.58%). The median value of the at-risk-of-poverty variable (HX080) is 19.28% with the standard deviation being equal to 7.67%. However, the income inequality measure has a lower median (19.16%) and standard deviation (5.55%), which signify slightly lower dispersion.

Fig. 4 describes the patterns of housing costs overburden. The highest rates are recorded in Bulgaria (48.52%) and Slovakia (37.63%), the lowest are observed in Estonia (10.82%) and Lithuania (15.20%). In 2017 the median housing costs overburden was 28.16% for Central and Eastern Europe. Listed in ascending order, above the median are Czechia, Poland, Romania, Slovakia, and Bulgaria. On average, 26.50% of the Central and Eastern European population experiences difficulties associated with housing costs. According to the same measure, the variation within Central and Eastern European countries measured by standard deviation is 10.77%, indicating a wide spread of values obtained.

## 4. Methodology

We develop a model that predicts total housing costs (variable HH070) based on a set of 16 variables that capture variability in total housing costs related to energy consumption. Three estimation approaches, namely the ordinary least squares, lasso and M-estimator (robust regression) are used in the study.

The formula of linear regression is given by:

$$\mathrm{Y} = \mathrm{X}\beta + \varepsilon$$

where Y is an $\mathrm{n} \times 1$ vector of response,$\beta$ is an m-dimensional vector of coefficients, $\mathrm{X} = (\mathrm{X}_1, \cdots, \mathrm{X}_\mathrm{m})$ is an $\mathrm{n} \times \mathrm{m}$ matrix of predictors, $\varepsilon = (\varepsilon_1, \cdots, \varepsilon_\mathrm{m})$ is a vector of i.i.d. random error with mean zero and variance . OLS estimates minimize the residual sum of squares, however, they do not always provide an accurate prediction. The model contains a large number of variables, some of which are interrelated with others or exert less influence on the response variable. To improve the prediction power of the model and to verify the accuracy of multiple linear regression results, lasso regression is used in the second step of the analysis.

Lasso regression is an alternative statistical method that yields better results in terms of prediction accuracy and interpretability of the model. It resolves the problem of predictor selection by constraining the set of variables to the most influential ones. Lasso regression is based on

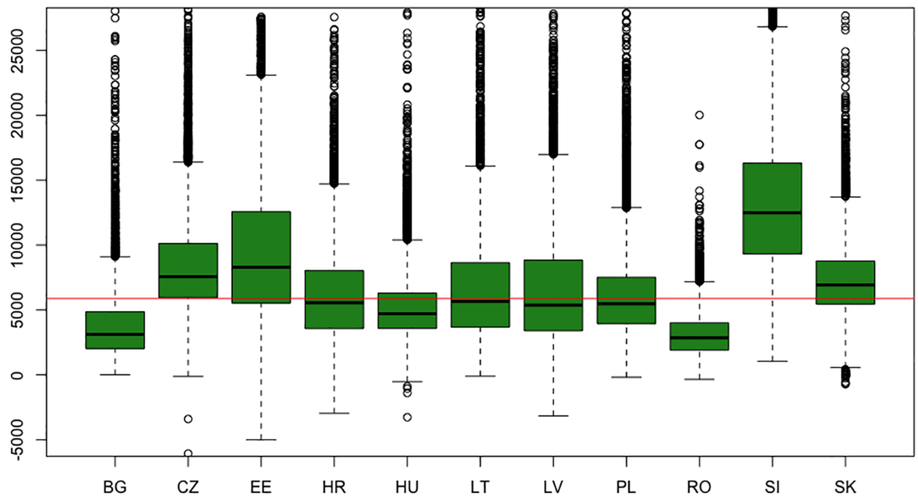


**Fig. 1.** Equivalised disposable income distribution and the Central and Eastern European median value, EUR per year.

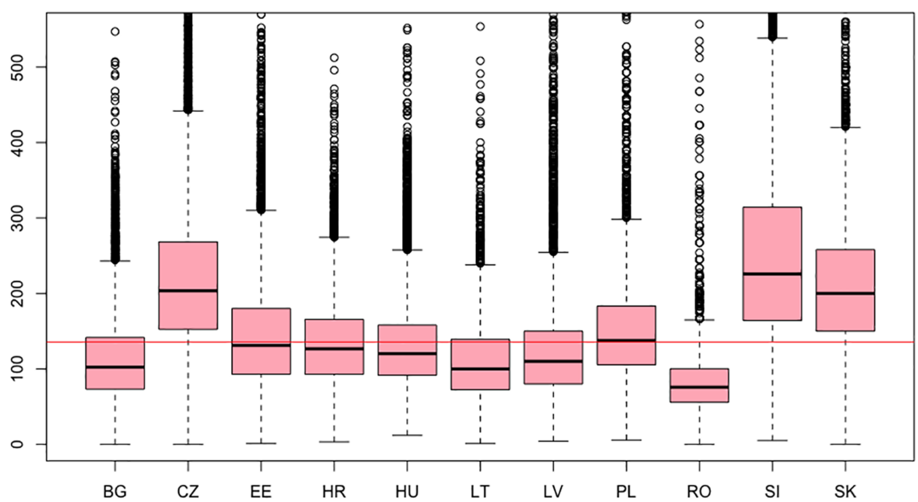


**Fig. 2.** Housing costs distribution and the Central and Eastern European median value, EUR per month.

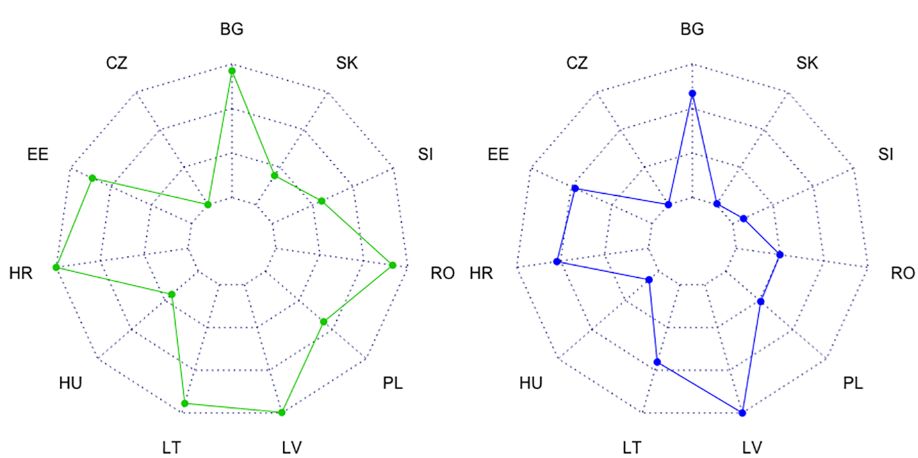


**Fig. 3.** Income poverty in Central and Eastern European countries.

regularization or shrinkage as a way to conduct variable selection. Compared to OLS, the variance of coefficients is significantly reduced. Some of the coefficients are estimated to be equal to zero. The author of lasso regression claims that the method retains the best properties of subset and rigid regression, such as interpretability and stability [47]. Contrary to OLS, lasso regression minimizes the following expression based on a tuning parameter: $\lambda \geq 0$:

$$\hat{\beta}(\lambda) = \underset{\beta}{\operatorname{argmin}} \|Y - X\beta\|_2^2 + \lambda\|\beta\|_1$$

where $\|\bullet\|_1$ is $\ell_1$-norm (penalty in lasso), and $|\bullet\|_2$ is a $\ell_2$-norm. Penalty in lasso is obtained by summing the absolute values of the coefficients.

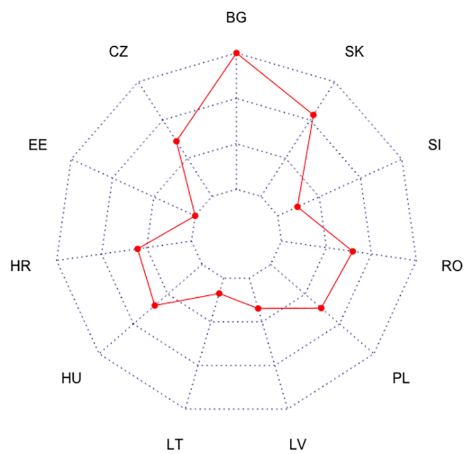


**Fig. 4.** Housing costs overburden in Central and Eastern European countries.

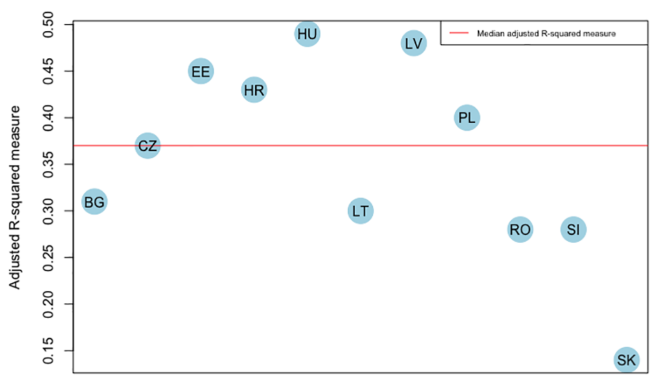


**Fig. 5.** Adjusted R-squared measures obtained in multiple linear regressions.

Setting the respective hypermeter $\lambda$, we can achieve an acceptable level of information loss and, at the same time, to retain only those variables which are the most valuable in the model. Lasso regression serves as an additional robustness check of the model we build. Among all other sparse models, lasso regression has features that make it suitable for the purpose of our analysis, and it produces more interpretable models [48]. To ensure the results are properly validated, we perform robust regression. Huber M-estimator with the scale estimated by iterated MAD is used [49]. This type of estimation adjusts for multiple outliers we observe in the dataset. Robust regression is also applied when some of the linear regression assumptions are violated [50].

After estimating the model parameters, we identify the exposed to hidden energy poverty, i.e. those households, who's after-housing-costs disposable income falls below the established level. To compare the groups obtained in various models, we use statistical measures of classification comparisons. Specifically, we apply the adjusted Rand index to compare classifications from the first, second and third models and to compare groups of exposed to hidden energy poverty and poor households. The Rand index is a pair-counting measure of comparison. The adjusted version of the same index is refined to account for the normalized difference between the Rand index and its expected value under generalized hypergeometric distribution [51]. The adjusted Rand index assumes values between zero and 1, where 1 means a total agreement between two partitions.

## 5. Results and discussion

This section focuses on estimating the expected housing costs in Central and Eastern European countries using cross-sectional data from the EU-SILC and on discussing the prevalence of exposure to hidden energy poverty across Central and Eastern European countries.

In the first step of the analysis, we conduct the same multiple linear regression for all countries (model 1). However, we skip missing variables in formulas in some countries. The regression results, including adjusted R-squared measure, are presented in Table A1. The goodness-of-fit value ranges from 0.14 (Slovakia) to 0.49 (Hungary). On average, the model explains 0.35 of variability in the response variable. As a rule, the lower adjusted R-squared measure is obtained for regressions with fewer variables. Due to a specificity of datasets, coefficients are not interpretable. Fig. 5 shows the distribution of the adjusted R-squared measure calculated for each regression. The lowest values are obtained in Slovakia, Slovenia, and Romania, while the highest values are noted in Hungary, Latvia, and Estonia. The analysis of the results should account for Slovakia's goodness-of-fit value being the lowest among Central and Eastern European countries.

In the second step of the analysis, we verify the results of multiple linear regression with lasso shrinkage (model 2). The cross-validation procedure is performed for the most regularized model based on $\lambda$. 1se. Lasso regression estimates are presented in Table A2. The restricted model reveals the sets of variables with the highest predicting power. Lasso procedure applied in all countries selects up to fifteen most important variables. In Slovenia, lasso regression estimates only six variables. Each country might have its own specific legal, infrastructural or socio-economic arrangements that are not captured by the model, which explains the results of the restricted model. It is worth noting that the most significant variables according to multiple linear regression are also selected by lasso shrinkage. The most significant variables identified in lasso regression in almost all countries include HX090, HH030, HH021, and HX040, while the less important - HH010, HX060, DB040, HH081, and DB100. Tables A3 and A4 contain robust regression results as well as regression evaluation metrics. The robustness check confirms that multiple linear regression provides accurate predictions.

Table 2 shows that the actual housing costs are lower than the estimated ones, especially in the lower income deciles. The difference diminishes as income grows. We note that people from the upper income deciles in almost all countries spend more on housing costs than is

**Table 2**
The difference between the actual and modelled housing costs per income decile, EUR per year.

| Countries | 1st | 2nd | 3rd | 4th | 5th | 6th | 7th | 8th | 9th | 10th |
|---|---|---|---|---|---|---|---|---|---|---|
| **BG** | −213.10 | −189.87 | −180.23 | −178.93 | −161.60 | −114.91 | −47.86 | 101.83 | 409.12 | 4114.88 |
| **CZ** | −303.45 | −249.05 | −219.92 | −194.56 | −146.62 | −99.67 | −37.91 | 60.08 | 420.75 | 12889.31 |
| **EE** | −244.77 | −229.84 | −212.04 | −146.41 | −97.83 | −32.11 | 38.58 | 77.41 | 231.59 | 8270.27 |
| **HR** | −212.53 | −171.94 | −179.48 | −136.28 | −85.10 | −24.68 | 27.08 | 134.30 | 326.34 | 2021.67 |
| **HU** | −198.52 | −149.28 | −116.47 | −80.76 | −22.98 | 25.60 | 68.95 | 94.01 | 127.59 | 2968.09 |
| **LT** | −233.00 | −236.40 | −171.66 | −153.44 | −123.16 | −44.09 | 54.77 | 185.33 | 350.62 | 10914.93 |
| **LV** | −158.55 | −202.70 | −160.85 | −98.12 | −109.49 | −118.01 | −44.03 | −21.34 | 272.53 | 14184.21 |
| **PL** | −245.61 | −238.73 | −179.67 | −163.06 | −147.41 | −24.57 | 35.00 | 123.34 | 248.86 | 6737.83 |
| **RO** | −300.70 | −163.54 | −133.56 | −215.21 | −41.44 | −74.54 | −5.97 | 152.76 | 332.78 | 3675.95 |
| **SI** | −644.44 | −640.15 | −516.15 | −391.97 | −227.75 | −34.38 | 222.36 | 546.00 | 426.29 | 12846.99 |
| **SK** | −830.70 | −552.00 | −362.77 | −245.19 | −118.08 | 13.33 | 142.31 | 371.59 | 879.69 | 5881.20 |

**Table 3**
Agreement of classifications between three models and income poverty.

| | Model 1 & Model 2 | Model 1 & Income poverty | Model 2 & Income poverty | Model 3 & Model 1 | Model 3 & Model 2 | Model 3 & Income poverty |
|---|---|---|---|---|---|---|
| **BG** | 0.83 | 0.55 | 0.60 | 0.94 | 0.82 | 0.58 |
| **CZ** | 0.86 | 0.46 | 0.48 | 0.95 | 0.88 | 0.47 |
| **EE** | 0.90 | 0.74 | 0.76 | 0.96 | 0.91 | 0.75 |
| **HR** | 0.95 | 0.73 | 0.75 | 0.99 | 0.95 | 0.73 |
| **HU** | 0.91 | 0.49 | 0.48 | 0.97 | 0.92 | 0.50 |
| **LT** | 0.91 | 0.74 | 0.74 | 0.97 | 0.91 | 0.76 |
| **LV** | 0.86 | 0.69 | 0.73 | 0.93 | 0.89 | 0.72 |
| **PL** | 0.93 | 0.61 | 0.62 | 0.96 | 0.94 | 0.63 |
| **RO** | 0.91 | 0.71 | 0.71 | 0.97 | 0.92 | 0.72 |
| **SI** | 0.91 | 0.68 | 0.69 | 0.97 | 0.92 | 0.70 |
| **SK** | 0.89 | 0.61 | 0.60 | 0.97 | 0.89 | 0.63 |

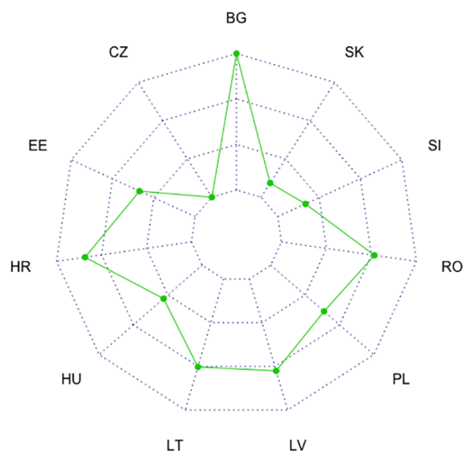


**Fig. 6.** Exposure to hidden energy poverty in Central and Eastern European countries.

computed by the model.

After estimating the expected housing costs, the scale of exposure to hidden energy poverty is computed. Households are classified as exposed to hidden energy poverty if their total equivalised disposable income after deducting the estimated housing costs is lower than 60% of a national median value. The level of agreement between classifications in two models measured by the adjusted Rand index reveals that multiple linear, lasso and robust regressions generate almost the same results (Table 3). The index varies from 0.83 to 0.95. The lowest values are observed in Bulgaria (0.83) and Czechia (0.86). The same index demonstrates that model 1, model 2, and model 3 are close in terms of grouping the results in all countries. As far as income poverty is concerned, the pair-wise comparisons between groupings indicate that exposed to hidden energy poverty households are not necessarily poor and vice versa. Given the similarity between classifications obtained in model 1, model 2, and model 3, multiple linear regression results are used in the latter part of the analysis.

Fig. 6 presents the scale of exposure to hidden energy poverty in Central and Eastern European countries. In 2017 the share of under-consuming energy households (model 1) ranges from 15.69% (Czechia) to 31.35% (Bulgaria). The median value is 23.77%, while the standard deviation is 4.76%. The lower exposure to hidden energy poverty rates are also noted in Slovakia (17.62%) and Slovenia (19.18%). The high share of households under-consuming energy is found in Croatia (28.05), Latvia (26.66%), and Romania (26.47%). Income poverty and exposure to hidden energy poverty patterns are similar. In general, more households in the Central and Eastern European region are exposed to hidden energy poverty than experience income poverty.

Income poverty is unevenly distributed among exposed to hidden energy poverty households (Fig. 7). As a rule, most poor households are also those, who under-consume energy. This is not the case in such countries as Czechia and Hungary, where more than 50% of the identified households are not classified as the poor. This could be partially attributed to the fact that income poverty in those countries is below the Central and Eastern European median value. The share of poor households exposed to hidden energy poverty households is significant in Estonia, Croatia, Latvia, Lithuania, and Romania.

The distribution of income per income deciles across exposed to hidden energy poverty households indicates (Fig. 8) that the latter households are mostly those with low income. There is an evidence that energy under-consumption is widely spread in the lower income deciles. Fig. 8 reveals that energy under-consumption affects up to seven income deciles. However, in the vast majority of countries, the exposed to hidden energy poverty belong to the first four income deciles. The proportion of exposed to hidden energy poverty people not earning much is significant in all countries. In Bulgaria and Romania households from the upper income deciles face problems related to energy under-consumption. In Czechia, Croatia, Hungary, Lithuania, and Poland energy under-consumption is recorded in the sixth income decile, while in Estonia the exposed to hidden energy poverty are identified in the fifth income decile.

Following Ward's minimum variance method, we perform

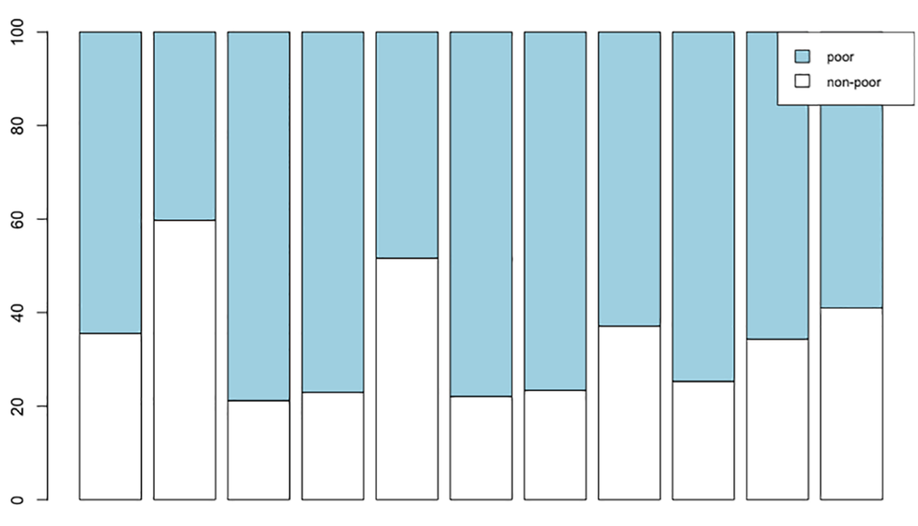


**Fig. 7.** Distribution of income poverty among exposed to hidden energy poverty households in Central and Eastern European countries.

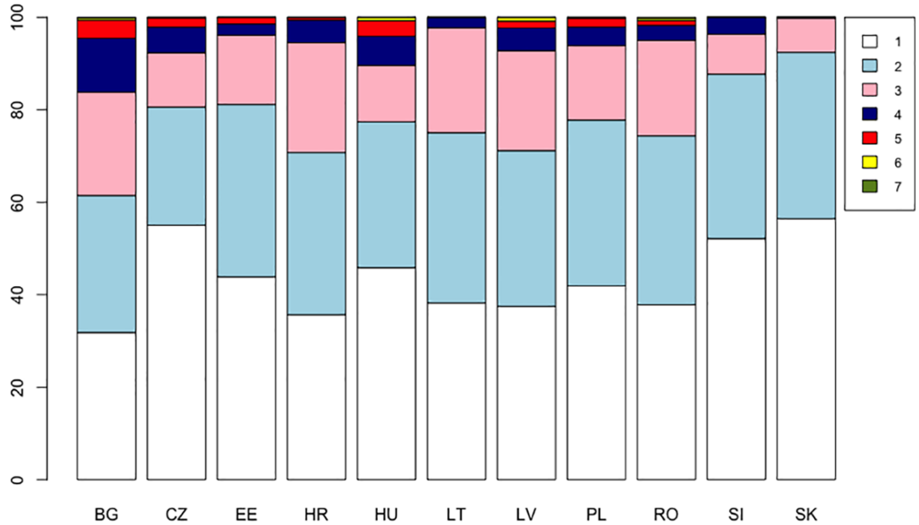


**Fig. 8.** Distribution of income per income deciles across exposed to hidden energy poverty households in Central and Eastern European countries.

hierarchical clustering based on the distribution of income among exposed to hidden energy poverty households. Fig. A1 shows the results of groupings conducted for a set of indicators used in the description stage of our study. We identify three clusters for income deciles, household types, and the degree of urbanization grouping, and four clusters for dwelling types grouping. Clustering displays countries which are the most similar in terms of parameters distribution. It is worth highlighting that there is not exactly the same group in all four dendrograms, which means that the characteristics of exposed to hidden energy poverty households are rather heterogeneous among Central and Eastern European countries.

It is interesting to see the distribution of subjective energy poverty indicator, i.e. ability to keep home warm, across exposed to hidden energy poverty households (Fig. 9). In contrast to income poverty, HH050 is a subjective measure which depends on the socio-cultural environment. This variable captures the degree of problem-awareness among people. It is worth noting that the question on the ability to keep home warm does not take into account whether the dwelling needs to be kept warm. In 2017 the average share of 'no' answers provided by under-consuming energy households is 20.59%. The remaining households do not acknowledge their inability to maintain an adequate temperature in a house/flat. According to this measure, energy poverty affects 52.50% (max) and 7.21% (min) of the exposed to hidden energy poverty in Bulgaria and Estonia, respectively.

In the last step of the analysis, we describe the profile of exposed to hidden energy poverty households. For that purpose, we examine what types of households are the most exposed, in what dwellings their members live, and in what areas. Ten household types are identified among exposed to hidden energy poverty households. Fig. 10 illustrates the distribution of household types among exposed to hidden energy poverty population. One-person households predominate in most of the analysed countries. Living alone increases exposure to hidden energy poverty as the burden of housing spending and energy services falls on a single budget. On average, in Central and Eastern European countries, 39.57% of the exposed to hidden energy poverty are single-person households. The highest share is recorded in Lithuania (57.92%) and the lowest in Slovakia (23.25%).

Sharing housing costs reduces exposure to hidden energy poverty. Two-adult households without dependent children from the sixth and seventh categories seem to be equally represented in the exposed to hidden energy poverty group with a mean value of 9.80% and 10.39% respectively. The seventh category constitutes the largest group of the exposed to hidden energy poverty in Bulgaria (17.26%) and the smallest group in Slovakia (6.04%). Among the remaining categories, households with dependent children reach maximum at 18.85% (Slovakia), while single persons with dependent children are exposed to hidden energy poverty in Czechia (11.94%). The last category is poorly represented among households under-consuming energy.

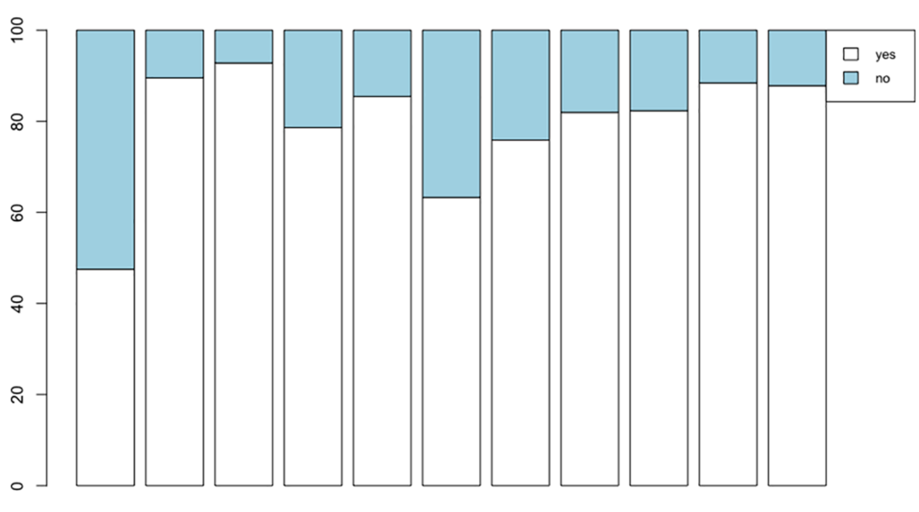


**Fig. 9.** Distribution of the ability to keep home warm indicator across exposed to hidden energy poverty households in Central and Eastern European countries.

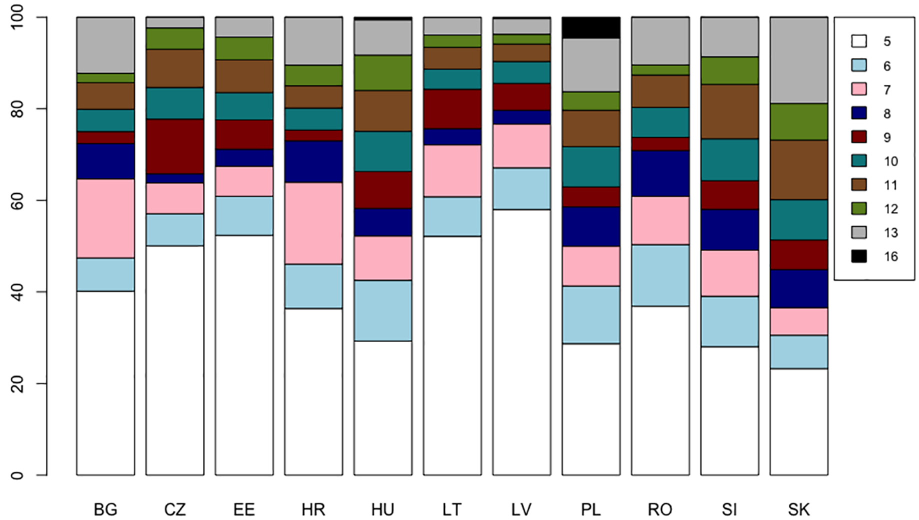


**Fig. 10.** Distribution of household types across exposed to hidden energy poverty households in Central and Eastern European countries.

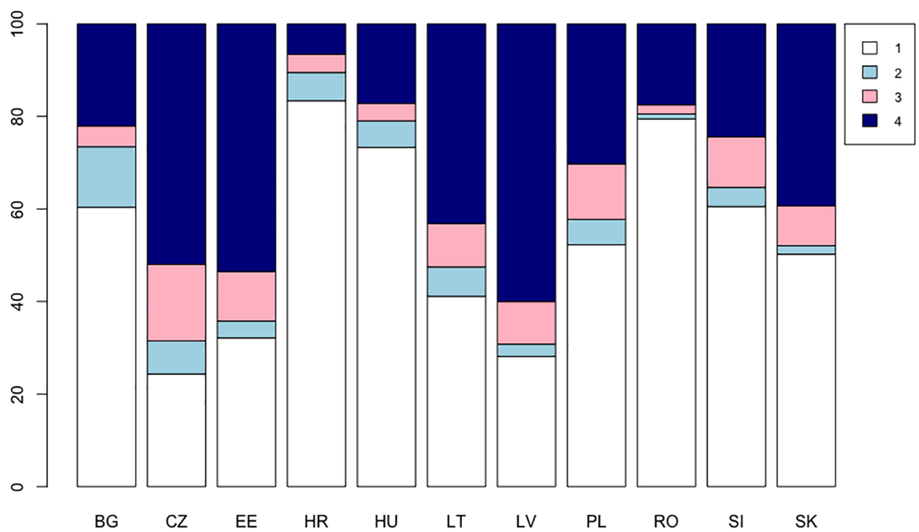


**Fig. 11.** Distribution of dwelling types across exposed to hidden energy poverty households in Central and Eastern European countries.

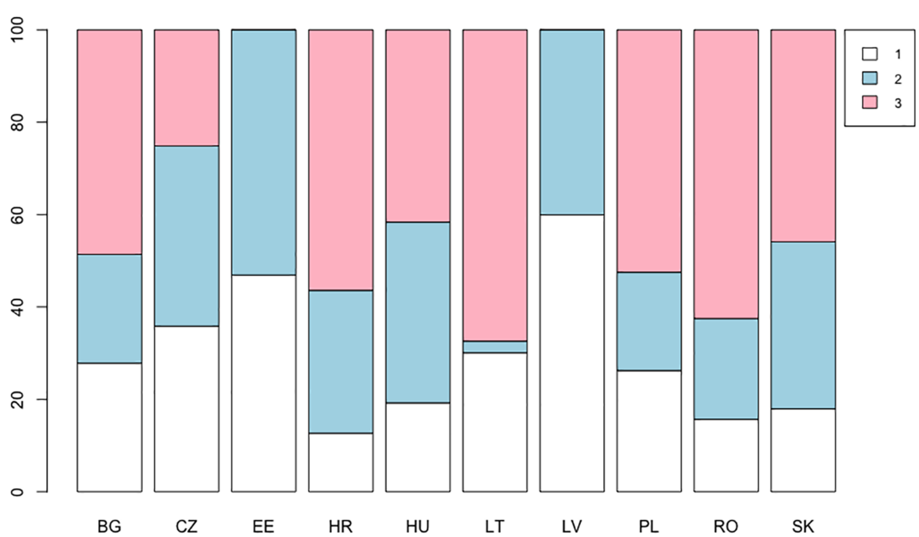


**Fig. 12.** Degree of urbanization distribution across exposed to hidden energy poverty households in Central and Eastern European countries. Without SI.

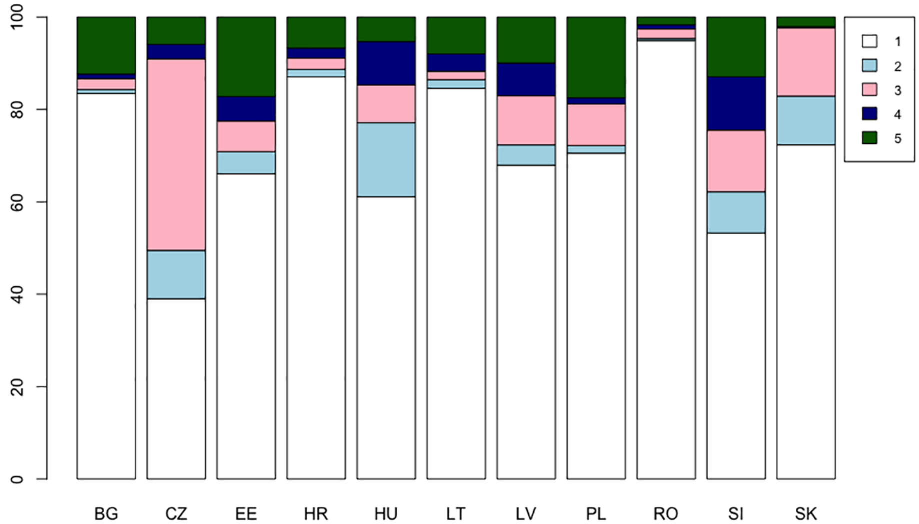


**Fig. 13.** Distribution of tenure status across exposed to hidden energy poverty households in Central and Eastern European countries.

A great variety of dwelling types is observed among exposed to hidden energy poverty households (Fig. 11). In Bulgaria, Croatia, Hungary, Poland, Romania, Slovenia, and Slovakia more than 50% of the affected households live in detached houses. This type of home requires more energy to maintain a comfortable temperature than apartments or flats. The share of the first category ranges from 24.33% in Czechia to 79.46% in Romania and reaches a peak of 83.37% in Hungary. By contrast, in Lithuania, Estonia, and Czechia a high share of exposed to hidden energy poverty population inhabits blocks of flats, i.e. 60.00%, 53.53%, and 51.99%, respectively. Across Central and Eastern European countries, the mean share of exposed to hidden energy poverty households living in single-family houses is 53.20%. On average, 5.20% and 8.31 of the affected households occupy respectively semi-detached houses and apartments in small buildings, while 33.28% of the households inhabit large blocks of flats. The maximum value for the third category of a dwelling type is noted for Czechia (16.51%), while the minimum is observed in Romania (1.96%).

As far as the degree of urbanization is concerned, the statistics confirm the previous findings. Thinly and moderately populated areas are mainly associated with single-family houses, while densely populated areas are occupied by buildings with more than ten dwellings (Fig. 12). This variable also depends on the territory of the country and the size of its population. In general, households categorized as exposed to hidden energy poverty predominantly occupy buildings in remote and intermediate populated areas, except for Lithuania. The average share of the exposed to hidden energy poverty living in rural regions is 40.02% at the Central and Eastern European level. The mean value for the first category is 29.23%. When combining these two categories, the majority of the exposed to hidden energy poverty is found outside large agglomerations and populous regions.

The vast majority of exposed to hidden energy poverty households belong to outright owners or owners paying a mortgage (Fig. 13). The average share of the affected households in the first and second tenure status category is 70.93% and 5.59%, respectively. In Czechia, a significant number of tenants are exposed to hidden energy poverty (41.44%). A large group of such tenants is found in Slovenia (37.84%). Such tenure profile corresponds to the existing housing structure in Central and Eastern European countries.

## 6. Conclusions and policy implications

Summing up, the study presents the cross-country comparison of hidden energy poverty prevalence in 11 Central and Eastern European countries-members of the EU based on the estimated housing costs.

We compute those costs using the data from the EU-SILC dataset. By assuming that people in economic hardship put other basic needs above energy consumption, we focus on a hidden aspect of energy poverty. The study overcomes the problem of direct energy poverty metrics associated with the difference between actual and expected energy costs. We calculate the expected housing costs following multiple linear regression and test the results with the lasso and robust regressions. The predictors in our model account for a varying component of housing costs related to energy consumption.

The results of the study suggest that, on average, 23.57% of the Central and Eastern European population is exposed to hidden energy poverty, while commonly used consensual metrics, i.e. the inability to keep home warm, yields the number of 12.63%. What is more, only 20.59% of exposed to hidden energy poverty households admit that they are unable to keep home warm. The dissimilarity between the subjective indicator and other energy poverty metrics revealed in our study is consistent with the findings of Dubois and Meier [8].

It is worth noting that households exposed to hidden energy poverty constitute distinct from the poor group of population. Although there is a significant number of poor households among the exposed to hidden energy poverty, in some countries the share is lower than 50%. On average, the level of association between exposure to hidden energy poverty and income poverty measured by the adjusted Rand index is 63.72%.

This result is important in terms of political implications. If some of the exposed to hidden energy poverty households are not poor, they could contribute to the costs of energy efficiency improvements of the houses they live in. Such a situation would allow a wider group of households to be covered by state programmes of buildings' modernization.

The profile of exposed to hidden energy poverty households is highly heterogeneous. However, several common traits can be identified. First, exposed to hidden energy poverty households are mostly single-person households. Those households subsist on a sole budget, which makes coping with energy-related issues a challenge. There are also other types of households threatened by hidden energy poverty, such as households with dependent children or single-parent households.

Second, as a rule, households exposed to hidden energy poverty live in remote rural areas in detached and semi-detached houses. In some countries (Lithuania, Estonia, and Czechia) the identified households inhabit multi-family houses, which is in line with Healy and Clinch's results [11].

Third, the problem of hidden energy poverty is acute among households living in thinly- and intermediately-populated areas. Single-family dwellings and buildings with fewer than ten flats have a higher incidence of energy under-consumption and are mostly located in less urbanized regions.

Fourth, in all countries except Bulgaria, fewer than 50% of exposed to hidden energy poverty households acknowledge problems with the ability to keep home warm. Hence, the scale of energy poverty presented by the self-reporting indicator should be interpreted with great caution, given its behavioural and cultural nature.

Fifth, there are some links between exposure to hidden energy poverty and income poverty. In many countries, hidden energy poverty affects not only the lowest income decile (Bulgaria, Romania, Czechia, Croatia, Hungary, Lithuania, and Poland). Nevertheless, income poverty remains the key factor in exerting an impact on exposure to hidden energy poverty.

From a policy-making perspective, the relationship between income poverty and exposure to hidden energy poverty found in the study seems the most important. Income poverty is often cited as a major driving force of hidden energy poverty. This is partially supported by our findings. As is mentioned above, not all poor are exposed to hidden energy poverty. A comparison of exposure to hidden energy poverty and income poverty rates reveals that the former prevails in Central and Eastern European countries. Housing costs have a decisive impact on exposure to hidden energy poverty, which can be attributed to the housing stock quality, i.e. its energy efficiency.

A broad set of policies is required to counteract hidden energy poverty. Traditional social allowances must be complemented with energy efficiency improvements, educational campaigns raising awareness of energy poverty, and national housing stock renovation plans [25,52,53]. Many households inhabiting remote arrears are affected by hidden energy poverty. Those households are left with limited possibilities to find employment as most of the good-paid jobs in Central and Eastern European countries are concentrated in large agglomerations. We would suggest taking policy actions with regards to promoting employment in small areas and lessen the concentration of economic activities in metropolitan regions inter alia.

We also believe that the issue of hidden energy poverty is much more complex than the issue of income poverty, as it is difficult to observe and tackle. The scale of exposure to hidden energy poverty in the Central and Eastern European region is also higher compared to income poverty. The study suggests that Central and Eastern European countries should monitor exposure to hidden energy poverty continuously. According to the current assessment, almost a quarter of the Central and Eastern European population is affected by hidden energy poverty. Thus, Central and Eastern European countries should accommodate their policies to the needs of the target group. Undoubtedly, hidden energy poverty requires multiple policy instruments and a comprehensive policy-making approach.

The limitations of the study are attributed to the lack of some indicators. This lack exerts a non-negligible impact on the predictive power of a statistical model as in the case of Slovakia.

Multiple extensions to our methodology are possible. First, the statistical approach to measuring exposure to hidden energy poverty could be applied to other regions of the EU given the assumptions are modified to fit the respective economies. For instance, the high energy efficiency of housing stock and a pre-bound effect, pro-environmental behaviour, conscious consuming and other beliefs drive self-restricted strategies with regards to energy consumption in some countries [54].

Second, we could model the expected energy costs with the same methodology, which allows estimating energy poverty directly. This possibility requires modification of the EU-SILC questionnaire to include energy poverty in the scope.

Lastly, either hidden energy poverty or energy poverty modelling could be further utilized to assess their persistence based on the respective longitudinal microdata.

## 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.

## Acknowledgements

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## Appendix A

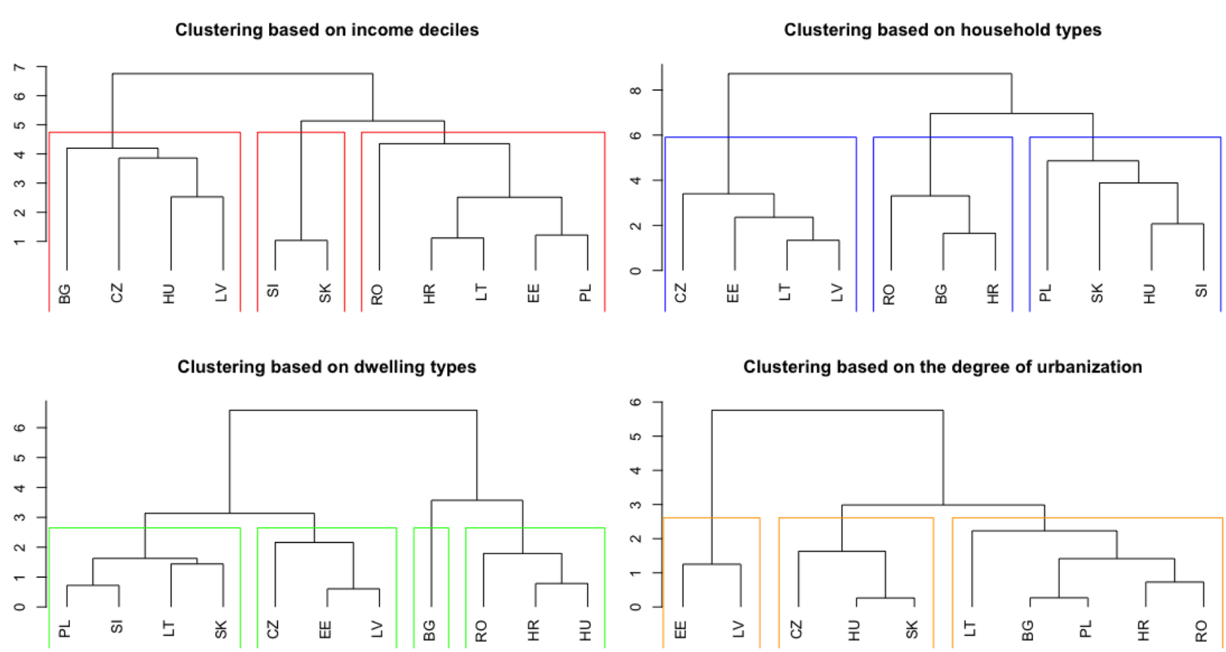


**Fig. A1.** Hierarchical clustering of Central and Eastern European countries based on the distribution of different variables across exposed to hidden energy poverty households.

**Table A1**
Multiple linear regression results for Central and Eastern European countries.

| Variables | BG | CZ | EE | HR | HU | LT | LV | PL | RO | SI | SK |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | | | ** | . | | * | *** | | * | | |
| HH010(2) | | | * | | *** | | * | ** | | | |
| HH010(3) | . | * | * | | *** | | ** | | | | |
| HH010(4) | ** | | *** | * | *** | *** | | *** | | | |
| HS120(2) | . | | | | | | | | * | | |
| HS120(3) | *** | | | ** | . | | *** | | *** | . | |
| HS120(4) | ** | *** | * | | *** | *** | *** | | *** | * | |
| HS120(5) | * | *** | | | | | * | | *** | * | |
| HS120(6) | | * | | | . | ** | ** | * | * | . | |
| HX090 | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** |
| HS160 | * | | | | | | | | | | . |
| HH030 | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** |
| DB040(2) | | *** | | | *** | | | ** | *** | | |
| DB040(3) | | *** | | | *** | | | *** | | | |
| DB040(4) | | *** | | | | | | *** | *** | | |
| DB040(5) | | *** | | | | | | * | | | |
| DB040(6) | | *** | | | | | | | | | |
| DB040(7) | | *** | | | | | | | | | |
| DB040(8) | | *** | | | | | | | | | |
| HX060(6) | *** | *** | | *** | *** | *** | ** | *** | * | *** | *** |
| HX060(7) | *** | ** | | *** | *** | *** | . | *** | | *** | ** |
| HX060(8) | *** | . | | *** | *** | | * | *** | * | *** | *** |
| HX060(9) | *** | ** | | *** | *** | ** | *** | *** | | ** | * |
| HX060(10) | *** | * | | *** | *** | * | *** | *** | * | *** | *** |
| HX060(11) | *** | | | *** | *** | * | *** | *** | . | *** | *** |
| HX060(12) | | | | *** | *** | | ** | *** | * | *** | * |
| HX060(13) | *** | | | *** | *** | | ** | *** | | *** | *** |
| HX060(16) | | | | | | | * | *** | | | |
| HH031 | | * | | | | * | | . | ** | | |
| HH081(2) | | ** | * | | | | ** | | | | . |
| HH081(3) | *** | . | *** | *** | * | ** | *** | *** | ** | | . |
| HH091(2) | . | . | * | | | | | | | | |
| HH091(3) | *** | | *** | * | * | *** | *** | | . | | |
| HH021(2) | *** | *** | *** | ** | *** | *** | *** | *** | *** | *** | *** |
| HH021(3) | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** | *** |
| HH021(4) | . | *** | *** | *** | *** | *** | | *** | *** | *** | |
| HH021(5) | ** | . | | * | ** | * | | | | * | . |
| HX040 | *** | *** | *** | *** | *** | ** | | *** | ** | * | * |
| DB100(2) | *** | *** | | | | | | *** | *** | | . |
| DB100(3) | *** | *** | *** | *** | *** | *** | *** | *** | *** | | *** |
| HH040(2) | | | | . | *** | | | | | . | |
| HH050 | *** | | * | | ** | | | | | | |
| HS021(2) | | | | . | | ** | | | . | | |
| HS021(3) | * | | | | | . | | | . | | |
| Adj. $R^2$ | **0.31** | **0.37** | **0.45** | **0.43** | **0.49** | **0.30** | **0.48** | **0.40** | **0.28** | **0.28** | **0.14** |

Notes: Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

**Table A2**
Lasso regression results for Central and Eastern European countries.

| Variables | BG | CZ | EE | HR | HU | LT | LV | PL | RO | SI | SK |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Intercept** | 1078.42 | −2852.06 | 1040.55 | 720.12 | 739.00 | 967.01 | 862.97 | −1159.38 | −1294.58 | 1736.84 | 265.61 |
| **HH010(4)** | | 1.38 | 12.79 | | −11.33 | | | 138.63 | | | |
| **HS120(3)** | | | | | | | | | | | |
| **HX090** | 0.02 | 0.03 | 0.02 | 0.02 | 0.01 | 0.01 | 0.03 | 0.03 | 0.04 | 0.01 | 0.03 |
| **HS160** | | | | | | | | | | | |
| **HH030** | 45.01 | 110.53 | 56.95 | 107.96 | 118.80 | 63.61 | 84.37 | 160.47 | 33.53 | 112.97 | 91.12 |
| **DB040(2)** | | −75.41 | | | | | | | | | |
| **DB040(3)** | | | | | −29.70 | | | −200.99 | | | |
| **HX060(6)** | | 74.61 | | 37.06 | 0.30 | | | 7.30 | | | |
| **HX060(7)** | | | | 0.42 | | | | | | | |
| **HX060(8)** | | | | | 20.46 | | | | | | |
| **HX060(11)** | | | 21.45 | | | | | | | | |
| **HX060(12)** | −27.01 | | | | | | | | | | |
| **HX060(16)** | | | | | | | | 6.27 | | | |
| **HH031** | | 2.15 | | | | | | 1.05 | 1.00 | | 0.71 |
| **HH081(2)** | | | | − 28.94 | | | | −2.11 | | | |
| **HH081(3)** | −130.10 | | −272.05 | 205.37 | −95.63 | −100.03 | −222.43 | −236.00 | −124.91 | | −72.33 |
| **HH091(2)** | | | | | | | | | | | |
| **HH091(3)** | −107.67 | | −232.08 | −114.07 | −156.99 | −213.08 | −158.86 | | −62.37 | | −133.70 |

(*continued on next page*)

**Table A2** (*continued*)

| Variables | BG | CZ | EE | HR | HU | LT | LV | PL | RO | SI | SK |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **HH021(2)** | | 694.07 | 675.91 | 20.25 | 685.80 | 385.64 | 1708.62 | 1036.22 | 190.84 | 1748.58 | 200.51 |
| **HH021(3)** | 884.73 | 1265.11 | 2053.79 | 1655.41 | 1510.63 | 479.92 | 400.26 | 1260.76 | 1214.01 | 1922.94 | 126.70 |
| **HH021(4)** | | | 862.84 | 155.84 | 1179.48 | | | 209.16 | 547.26 | 896.95 | |
| **HH021(5)** | −8.37 | −69.10 | | | −35.68 | | | | | | |
| **HX040** | 131.32 | 220.19 | 105.49 | 173.28 | 119.50 | 63.19 | 76.22 | 96.88 | 45.20 | 152.53 | 94.40 |
| **DB100(2)** | | −144.21 | | | | | | −50.94 | | | |
| **DB100(3)** | −37.14 | −353.71 | | −54.72 | −11.51 | −84.50 | | −246.62 | −104.53 | | −73.09 |
| **HH050** | −75.17 | | | | −3.65 | | | | | | |
| **HS021(2)** | | | | 23.94 | | | | | | | |

**Table A3**
Robust regression results for Central and Eastern European countries (t-value).

| Variables | BG | CZ | EE | HR | HU | LT | LV | PL | RO | SI | SK |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Intercept** | 1.17 | 0.61 | 4.43 | 1.06 | 0.66 | −1.27 | 8.45 | 0.68 | −1.53 | 4.11 | −0.11 |
| **HH010(2)** | −1.16 | −0.84 | 3.46 | −0.47 | −4.70 | 1.64 | −1.87 | 1.60 | 2.39 | 0.28 | −1.48 |
| **HH010(3)** | −1.04 | 6.21 | −0.94 | −1.42 | −4.72 | −0.52 | −0.40 | 3.32 | 1.59 | −1.22 | 2.08 |
| **HH010(4)** | −2.15 | 5.92 | 10.46 | −2.45 | −6.07 | 7.66 | 6.40 | 14.41 | 0.61 | −0.46 | 0.86 |
| **HS120(2)** | 2.71 | −0.40 | −0.77 | 0.46 | −0.95 | −0.76 | −0.05 | 2.21 | 1.90 | −1.55 | 1.03 |
| **HS120(3)** | 5.98 | −1.90 | −2.05 | 1.95 | −2.01 | −2.21 | −3.36 | 1.82 | 4.22 | −2.21 | 0.22 |
| **HS120(4)** | 2.36 | −4.80 | −4.31 | −0.30 | −4.26 | −5.38 | −5.07 | −0.72 | 4.19 | −3.43 | −1.34 |
| **HS120(5)** | 0.83 | −5.73 | −2.21 | 0.46 | −2.77 | −3.49 | −5.33 | 0.09 | 3.42 | −2.80 | −0.07 |
| **HS120(6)** | −0.77 | −3.11 | −3.01 | −1.99 | −2.02 | 0.38 | −1.85 | −1.44 | 1.56 | −2.99 | 1.15 |
| **HX090** | 17.97 | 13.95 | 17.35 | 18.81 | 9.30 | 11.68 | 20.04 | 19.65 | 10.25 | 13.22 | 8.00 |
| **HS160** | 1.87 | 0.20 | −0.17 | 1.33 | −0.61 | 0.32 | −1.98 | 0.32 | 0.13 | 0.05 | 2.16 |
| **HH030** | 11.91 | 20.54 | 15.75 | 20.27 | 20.40 | 16.67 | 20.09 | 32.43 | 12.24 | 14.24 | 10.35 |
| **DB040(2)** | | −8.38 | | | −7.05 | | | 4.58 | −4.65 | | |
| **DB040(3)** | | −13.11 | | | −9.67 | | | −8.91 | −3.06 | | |
| **DB040(4)** | 0.35 | −7.37 | | | | | | 4.75 | −5.31 | | |
| **DB040(5)** | | −11.12 | | | | | | 3.00 | | | |
| **DB040(6)** | | −9.71 | | | | | | 0.58 | | | |
| **DB040(7)** | | −9.04 | | | | | | | | | |
| **DB040(8)** | | −10.42 | | | | | | | | | |
| **HX060(6)** | 10.11 | 7.02 | 2.27 | 10.03 | 9.73 | 6.14 | 4.91 | 9.54 | 2.97 | 7.61 | 4.04 |
| **HX060(7)** | 10.17 | 3.34 | 0.29 | 9.93 | 9.15 | 5.16 | 4.02 | 8.17 | 2.18 | 9.06 | 4.01 |
| **HX060(8)** | 10.69 | 1.89 | 0.81 | 7.26 | 8.98 | 3.89 | 4.39 | 7.35 | 2.66 | 7.05 | 4.82 |
| **HX060(9)** | 5.87 | 3.54 | 2.44 | 4.93 | 5.24 | 5.54 | 5.06 | 5.56 | −0.15 | 4.82 | 2.96 |
| **HX060(10)** | 10.95 | 3.00 | 1.83 | 6.79 | 7.90 | 4.15 | 5.90 | 7.52 | 2.09 | 8.69 | 5.48 |
| **HX060(11)** | 9.55 | 0.78 | 3.57 | 6.72 | 6.82 | 3.55 | 6.18 | 5.32 | 2.26 | 7.34 | 5.02 |
| **HX060(12)** | 1.03 | 0.06 | 1.43 | 3.72 | 5.36 | 3.21 | 5.23 | 3.68 | 2.49 | 5.81 | 2.27 |
| **HX060(13)** | 9.65 | 0.77 | 1.26 | 5.52 | 7.73 | 2.94 | 5.55 | 4.68 | 1.76 | 6.52 | 5.22 |
| **HX060(16)** | 0.16 | | −0.37 | | 1.85 | 1.26 | 3.90 | 7.22 | | | |
| **HH031** | −0.15 | 0.48 | | −0.33 | 0.69 | 1.70 | | 0.24 | 2.60 | −3.50 | 0.69 |
| **HH081(2)** | 0.94 | −2.94 | −2.57 | −0.47 | −1.63 | 0.43 | −3.43 | −1.49 | −0.22 | −1.79 | −1.80 |
| **HH081(3)** | −7.35 | −1.91 | −7.04 | −3.53 | −3.06 | −3.56 | −5.85 | −4.37 | −3.64 | −1.39 | −2.17 |
| **HH091(2)** | −1.48 | 2.10 | −2.79 | −0.18 | 1.29 | −0.96 | −0.54 | 0.46 | −0.94 | 0.80 | −0.17 |
| **HH091(3)** | −4.45 | −0.34 | −6.91 | −2.34 | −2.55 | −4.94 | −7.33 | −0.62 | −1.98 | −1.68 | −1.67 |
| **HH021(2)** | 4.45 | 28.58 | 27.38 | 3.00 | 36.18 | 14.15 | 62.36 | 29.98 | 8.25 | 43.22 | 5.60 |
| **HH021(3)** | 27.00 | 45.39 | 51.60 | 34.72 | 54.28 | 17.45 | 16.21 | 46.61 | 26.33 | 41.22 | 6.50 |
| **HH021(4)** | 2.69 | 6.05 | 23.87 | 6.46 | 43.51 | 4.84 | −2.04 | 8.63 | 13.27 | 23.14 | −1.90 |
| **HH021(5)** | −3.23 | −2.68 | −0.97 | −3.11 | −2.96 | −2.43 | −0.56 | 0.85 | −2.04 | −4.32 | −2.63 |
| **HX040** | 3.29 | 6.26 | 4.49 | 10.05 | 3.95 | 2.50 | 1.47 | 6.45 | 3.37 | 2.16 | 1.91 |
| **DB100(2)** | −6.24 | −6.57 | | −0.95 | 1.70 | 1.72 | | −9.18 | −8.59 | | −1.56 |
| **DB100(3)** | −10.74 | −13.35 | −7.63 | −6.87 | −2.21 | −7.27 | −13.33 | −18.74 | −13.75 | | −5.41 |
| **HH040(2)** | 1.78 | 0.85 | −0.009 | 1.98 | 6.34 | 1.52 | 0.25 | 1.75 | −1.17 | −2.10 | −0.17 |
| **HH050** | −6.00 | 0.05 | 3.13 | −1.11 | −3.68 | 1.57 | 2.14 | −0.82 | −1.76 | 0.57 | −1.16 |
| **HS021(2)** | −1.05 | 0.32 | 0.02 | 2.57 | 0.46 | 1.83 | −0.67 | −0.43 | 2.94 | 0.18 | −1.18 |
| **HS021(3)** | −1.89 | −0.60 | −1.07 | −0.02 | 0.27 | 2.84 | 0.12 | 0.20 | −1.86 | −1.86 | 0.29 |

**Table A4**
Robust regression accuracy metrics.

| | Mean absolute error | Root mean squared error | Mean absolute percent error |
|---|---|---|---|
| **BG** | 431.44 | 654.30 | 0.33 |
| **CZ** | 682.21 | 1043.84 | 0.26 |
| **EE** | 522.03 | 817.32 | 0.31 |
| **HR** | 396.16 | 539.97 | 0.26 |
| **HU** | 380.44 | 547.10 | 0.24 |
| **LT** | 400.84 | 620.39 | 0.32 |
| **LV** | 470.35 | 821.65 | 0.32 |
| **PL** | 481.97 | 691.31 | 0.27 |
| **RO** | 329.90 | 494.02 | 0.37 |
| **SI** | 977.57 | 1512.69 | 0.34 |
| **SK** | 769.73 | 1051.37 | 0.31 |

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