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Exploring the persistence and transience of energy poverty: evidence from a Greek household survey

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Abstract The present study uses four rounds of household panel data to investigate consensual-based energy poverty in Greece. Employing dynamic Probit random effects and Wooldridge conditional maximum likelihood (WCML) estimators, we find evidence of genuine state dependence effects in consensual-based energy poverty among Greek households. Poverty persistence (10-12%) effects are also evident in our data. Socioeconomic, demographic, market, household, and climatic characteristics are essential predictors of energy poverty. Around 9–10% of the households seem chronically energy poor, while education, income level, dwelling characteristics, migration background, and employment status affect the chances of suffering and exiting from energy poverty. Empirical results have significant policy implications that could mitigate residential energy poverty.

Keywords Energy poverty · Dynamic probit · WCML · Persistence · Transition

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Introduction

The seventh sustainable development goal refers to the accessibility to sustainable and affordable energy. The energy demand has been significantly rising globally (Wang et al., 2022), despite the efforts to improve energy efficiency. At the same time, energy poverty concerns academia and policymakers, while its elimination is considered essential for socioeconomic well-being. Especially nowadays, the recent pandemic crisis and more recent Russian–Ukraine war have settled the energy issue as a hot topic for everyone in Europe. Energy supply, demand, cost, and transition are only some concepts discussed daily in governmental and academic panels.

It is well known that energy poverty affects people, societies, and the environment at the macro and microlevels (Awan et al., 2022). However, despite the ambitious goals to achieve by 2030 (United Nations, 2015), in the European Union, it is estimated that over 34 million individuals are experiencing energy poverty to various degrees (Thema & Vondung, 2020). According to Eurostat for 2020, 17.1% of Greek households were not able to keep their homes adequately warm, 28.2% were in arrears on their utility bills, and 10.8% were living in a dwelling with leaking roofs, damp walls, floors, or foundation or rot in window frames of the floor (Eurostat, 2022a, 2022b, 2022c). This study calculates energy poverty in 4466 Greek households over 2017–2020. Based on EU-SILC survey data, three leading consensual-based

indicators are estimated, and panel data model techniques are employed to determine possible drivers of energy poverty. Specifically, two dynamic binary specifications are applied, where the prominent energy poverty consensual indicators are used as outcome variables.

Based on the authors' knowledge, the present study is the first in Greece to estimate persistence and transition effects on energy poverty using microeconometric analysis while highlighting the dynamic characteristics of energy poverty among Greek households. Furthermore, analyzing energy poverty among Greek households is a critical research topic with significant contributions to understanding the impacts of socioeconomic determinants on residential energy access. The current study highlights several key findings, including the prevalence of energy poverty among households with different income and education levels. Additionally, it identifies significant disparities in energy poverty levels, with households in different areas characterizing less or more vulnerable households. Thus, the study's insights provide valuable information for policymakers seeking to design effective strategies to mitigate energy poverty in Greece, such as targeted subsidies, energy efficiency programs, and improved access to renewable energy sources.

The remainder of the present paper is organized as follows. The "Research content" section presents research content illustrating the approaches for estimating energy poverty accordingly to the previous empirical literature. Correspondingly, it includes several recent studies that pay particular attention to energy poverty worldwide while presenting research gaps and highlights of the study. The "Data and methodological approach" section contains data and econometric specifications that are implemented in this study. The "Empirical results and discussion" section reveals and discusses all the findings. The "Conclusion" section concludes and provides policy implications.

Research content

Approaches to measuring energy poverty

Energy/fuel poverty has gained interest among academics, researchers, professionals, governments, and policymakers since the seminal paper of Bradshaw and Hutton (1983). Researchers across the globe have undertaken different measures in defining and measuring energy poverty (Wang et al., 2015) in both developing and developed countries. As far as defining energy poverty is concerned, all overlapping concepts of energy poverty are used to express a scarcity of energy services. International Energy Agency, Energy Poverty Observatory 2021, the UK government, and many other organizations, authors, researchers, and countries use different definitions of energy poverty (Rademaekers et al., 2016). Regarding measuring energy poverty, some engaged in energy poverty indicators, some carried out ad-hoc surveys, and others developed new indices to reflect the problem better.[1] In general, energy poverty mentions individuals or households unable to access the required energy services (Lowans et al., 2021). Even if there is not a precise and globally accepted definition of energy poverty, as it is a multi-dimensional concept that cannot be easily captured by a single indicator (Herrero, 2017; Simcock et al., 2016; Thema & Vondung, 2020), three main approaches of measuring and defining energy poverty are identified in the literature (Thomson et al., 2017).

a) Expenditure-based approach. This approach determines energy poverty based on energy real or theoretical expenditures required for keeping adequate indoor conditions relative to a threshold often of income level, poverty line, or national median energy cost.
b) Consensual-based approach. This approach determines energy poverty based on self-reported information about the inability of households to secure and cover a certain level of energy needs.
c) Outcome-based approach (direct measurement). This approach determines energy poverty by attempting to measure if actual energy consumption is sufficient to achieve an adequate standard of living.

All approaches mentioned above and indicators have advantages and disadvantages. For instance,

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[1] For a more detailed and in depth analysis about the energy poverty indicators, please see (Siksnelyte-Butkiene et al., 2021).

regarding expenditure-based indicators, wealthy households with a high level of energy expenditure might be considered energy-poor households. In contrast, normal-income level households often underestimate their energy needs and indicate a deficient level of energy consumption. Similarly, consensual-based indicators are based on self-reported data that may present several biases. Also, they imply very narrow definitions of energy needs focusing mainly on heating. The outcome-based approach focuses on utility data, such as arrears, or health outcomes, such as excess mortality in extreme climatic conditions. There are often practical constraints regarding measuring and collecting energy or climatic datasets (Palma & Gouveia, 2022).

In the expenditure approach, indicators are estimated considering household income and energy expenditure data (based on HBS data). They are mainly compared to a specific threshold for an appraisal (Bollino & Botti, 2017). This approach implies that a household is considered energy poor when its energy expenditure level is below or above this threshold. The metrics based on those thresholds (see inter alia Rademaekers et al., 2016; Thema & Vondung, 2020) can be categorized into five types.

i. Indicator M/2. The absolute (equivalized) energy expenditure is below half the national median.
ii. Indicator 2M. The share of (equivalized) energy expenditure (compared to equivalized disposable income) is above twice the national median.
iii. Ten-percent-rule. A household is characterized as energy poor when its energy expenditures are more than 10% of total household income.
iv. Low-income high-cost. A household is characterized as energy poor when its expenditures are above the median and its disposable income net of energy costs is below the national income poverty line.
v. Above the median share. A household is characterized as energy poor when its energy expenditures (as a % of income) are above the national median and its income is below the poverty line, after energy costs.

For our econometric analysis, we select the consensual-based approach. The consensual approach uses measures to recognize those individuals or households that cover their energy needs with difficulty. These measures involve several indicators, such as energy affordability and dwelling efficiency, which are utilized and measured (Halkos & Gkampoura, 2021a). Moreover, single consensual indicators are simple and make analyzing energy poverty easier to understand. At the same time, they can provide a more concise and consistent picture of the level of energy poverty in a particular region or country over time. Also, as many other studies have already employed a consensual-based approach, the same indicators make comparing results more straightforward and accessible to policymakers, making it easier for them to understand and engage with the energy poverty issue. The consensual approach is based on the Statistics on Income and Living Conditions (EU-SILC) dataset, which provides information on the three leading energy indicators as follows.

i. Inability to keep home adequately warm
ii. Arrears on utility bills
iii. Presence of leak, damp, rot in the dwelling

Concurrently, we also present some figures about a secondary indicator of energy poverty that captures the income conditions concerning the affordability of commodities or services. More specifically, we provide information on the material deprivation rate of the housing dimension. However, we do not include this indicator in our econometric analysis as it is out of the scope of the present study. Also, most households indicate 1-item deprivation that possibly refers to the leakages, which is already included in our consensual-based indicators empirical analysis. A few more approaches are presented in the literature but are not widely used due to their drawbacks and limitations. For instance, these are energy prices-based, temperature-based, dwelling, and equipment-based approaches. However, the significant lack of pertinent data and the fact that they are not direct indicators of energy poverty make them too widely used in previous empirical studies.

Related literature review

It is well known that the issue of energy poverty was not widely debated in the literature until the explosion of the recent global financial crisis. Especially nowadays, after a new unprecedented global health

crisis and the Russian–Ukraine war, energy poverty has been a hot topic for research. In general, energy poverty can be analyzed from an environmental (Chakravarty & Tavoni, 2013), economic, or health (Pan et al., 2021; Sokołowski et al., 2023) perspective. In addition, researchers across the globe have undertaken different measures in determining and measuring energy poverty in developing and developed countries, while the topic of energy solvency is also introduced in theory nowadays (Gallego Sánchez-Torija et al., 2022). Most of the previous empirical studies use datasets in a macroeconomic and aggregated level of analysis while investigating the energy poverty issue either in a specific country (Churchill & Smyth, 2021), or in a group of countries (Anastasiou & Zaroutieri, 2023; Halkos & Gkampoura, 2021b) or a local area (Sánchez-Torija & Nieto, 2022).

Significantly fewer studies have focused their interest on a household level of analysis, mainly due to a lack of appropriate longitudinal micro-level datasets. For instance, Pachauri et al. (2004), analyzing Indian households data for 1983–2000, provide an overview of different approaches to measuring energy poverty, highlighting that the relationship between energy and poverty is a two-way relationship. Churchill and Smyth (2020), taking into account twelve waves of longitudinal household-level data, found that apart from several socioeconomic household characteristics (such as age, income, and household size), ethnic diversity is highly and positively correlated to energy poverty in Australia. Qurat-ul-Ann and Mirza (2021), based on the Pakistan Social and Living Standards Measurement survey data for 2014–2015, supported that despite the increased electrification rate, a large proportion of Pakistani households do not have sufficient access to energy. Also, it was found that space temperature regulations, cooking, and mobility are the most significant factors in energy poverty in the country. Jayasinghe et al. (2021), using household income and expenditure survey data, examined energy poverty in Sri Lanka by constructing the Multi-dimensional Energy Poverty Index (MEPI). The results of this study reveal the vital role socioeconomic characteristics such as gender, age, ethnicity, income, and area of living can play on energy poverty levels across households. Alvarez and Tol (2021) analyzed 2715 Spanish households from 2008 to 2011. Employing a linear difference-in-differences model and propensity score matching approaches, the

authors investigated the impact of the *Bono Social de Electricidad* program on energy poverty. Empirical results supported that those transfers to other households have an insignificant effect regarding the subjective indexes of energy poverty. Awan et al. (2022) investigated energy poverty using data from eight waves of Pakistani household income and expenditure surveys from 1998 to 2019. Empirical results indicate that education, house ownership, gender, age, family size, and region of living matter to energy poverty.

Recently, there has been an increasing number of empirical studies investigating the issue of energy poverty in European countries (Bollino & Botti, 2017; Halkos & Gkampoura, 2021a; Thomson et al., 2017). In particular, based on a European group of countries analysis, Thomson and Snell (2013), considering the consensual approach in 25 European countries for 2007, found that Cyprus, Romania, and Bulgaria had the highest levels of fuel poverty. Also, a logistic approach concluded that location is one of the primary energy poverty factors related to people's inability to adequately warm homes. Bollino and Botti (2017), employing a fuzzy set approach over the period 2014–2021, found that Southern and Eastern European economies are the most affected and have the highest levels of energy poverty. On the contrary, Scandinavian countries are the least affected societies by energy poverty. Furthermore, it was supported that energy poverty highly depends on income level, dwelling type, living area, age, gender, and migration. Similarly, Halkos and Gkampoura (Halkos & Gkampoura, 2021b), considering 28 selected European countries over the period 2004–2019 and using a consensual approach, also found that Scandinavian countries present the lowest energy poverty levels, while the highest levels of energy poverty have been detected within Balkans. Moreover, electricity prices, unemployment rate, the number of people at risk of poverty, and income per capita are highly linked with problems related to energy poverty in Europe.

Regarding Greece, several studies have highlighted the issue of fuel and energy poverty (Lyra et al., 2022). For instance, Santamouris et al. (2013) analyzed the relationship between energy consumption and the economic crisis in Greece using a cross-section dataset from 598 households in 2012. Results showed that income level is crucial in adopting conservation measures and belonging to fuel poverty. Dagoumas and Kitsios (2014)

supported that per capita electricity consumption is the best indicator of energy poverty for developed countries. It was also found that there exists a delay in the effect of the economic crisis on electricity demand. This result is because consumers need time to respond to the new economic conditions and change their habits and lifestyle. Atsalis et al. (2016), employing data from National Statistical Authority and implementing objective and subjective measures, estimated that around 20–30% of Greek households were in fuel poverty in 2013. Furthermore, the authors supported that increased poverty levels significantly adversely impacted public health. Papada and Kaliampakos (2016) highlighted that around 58% of Greek households are energy poor, while three out of four households have decreased other essentials in favor of energy needs. More specifically, the authors used data (400 households) from a survey conducted via telephone interviews in 2015 at the household scale. Energy spending, poverty, climatic zone, altitude, and residence type are significant drivers of energy poverty.

Later on, the same authors (Papada & Kaliampakos, 2020), following a similar procedure but taking into account two samples proportionally distributed among the Greek regions—mountainous Municipalities and Communities of Greece, respectively, found that energy poverty is significantly related to income, heating system, building characteristics, area of living while not related to climatic zone and altitude. Boemi et al. (2017), based on a study of 762 questionnaires from Western and Central Macedonia, estimated the energy vulnerability concerning building and socioeconomic characteristics. Ntaintasis et al. (2019) considered several subjective, objective, and composite indicators estimating energy poverty within the Attica region. Gathering data from 451 households pointed out that the estimation of energy poverty can give divergent results based on the used indicators. Spiliotis et al. (2020), investigating data from Athens, found that energy consumption is highly related to economic and weather factors. Lyra et al. (2022), utilizing microdata within the framework of the EU-SILC survey, found that 40% of Greek households suffer from fuel poverty. Furthermore, employing logistic regression models, the authors estimated that several structural characteristics, including dwelling type, location of residence, household income, and educational level, are identified as the main drivers of fuel poverty in Greece.

More interestingly, even fewer studies have investigated the dynamic effects of energy poverty at a microeconomic level of analysis. Alem and Demeke (2020) researched the impact of increasing energy prices in Ethiopia during 2007–2009 on energy use and poverty. Employing several dynamic Probit techniques, the authors found strong evidence of energy poverty state dependence highlighting that a poor individual or household today is more likely to be also poor tomorrow. Moreover, their findings support that an increase in the price of energy use (use of kerosene here) drives households into energy poverty. Drescher and Janzen (2021) investigated the factors of energy poverty persistence using seven waves of the German Socioeconomic Panel dataset. Using dynamic models, the authors also confirmed energy poverty state dependence effects. In particular, it was found that households characterized as energy poor in a previous period have a higher probability (up to 7.5%) of facing energy poverty in the future. In addition, parameters that affect energy poverty are household composition, educational level, labor status, heating installation, and energy efficiency in homes. Karpinska and Śmiech (2021), based on EU Survey on Income and Living Conditions waves (2014–2017) and employing panel data analysis, investigated the dynamic approach of energy poverty in Poland. Energy poverty linked with poverty was found to be more persistent. In contrast, age, area of living, gender, labor status, and household structure were found to be significant determinants of escaping energy poverty.

Research gap and highlights

The previous discussion demonstrates a research gap in the literature that can provide national and international evidence about the critical role of energy poverty indicators and factors. Much of the research employs either cross-sectional data without considering the dynamic persistence of energy poverty or aggregated and macroeconomic datasets identifying energy poverty's drivers at the country level or groups of countries' data. In Greece, many empirical studies have been published focusing on the factors that affect energy poverty. However, to our knowledge, none of the previous studies have incorporated the

ideas of energy poverty persistence and transition in their analysis. To fill this gap, this work validates the notable impact of several disaggregated (at the household level) socioeconomic determinants on energy poverty using panel data from the Hellenic Statistical Authority 2020 dataset. It supports evidence of energy poverty dynamic persistence and transition in Greece. In addition, this is a study in which a balanced panel dataset with identical households takes place in the analysis. First, we filter and figure only on the same homogenous households in the national statistical observatory dataset over time. Consensual-based and material deprivation indicators are created based on EU-SILC dataset. Next, we proceed with the statistical and econometric analysis investigating the relationship between households, dwellings, and climatic and market characteristics with energy poverty in Greece. Furthermore, we evaluate the dynamic properties of energy poverty employing several dynamic panel data specifications. However, we should also mention that data availability is essential in the indicators' selection for our empirical analysis.

Data and methodological approach

Household data are retrieved from the annual EU-SILC Hellenic Statistical Authority 2020. Survey responders are responsible for the financial decisions at the household level and are requested to provide all required information (Kostakis & Lolos, 2022). Data comes from four large-scale independent annual surveys collected for 2017–2020 concerning three leading energy poverty indicators: (a) inability to keep home adequately warm, (b) arrears on utility bills, and (c) presence of a leak, dampness, or rot in the dwellings. This dataset's unique and distinguishing feature includes 4466 identical households over time, allowing us to observe the time trend of their behavior. EU-SILC dataset covers consensual energy poverty indices and information on income, social exclusion, housing conditions, etc., while enabling us to investigate poverty dynamics. As mentioned above, we restrict our sample to the period 2017–2020 as there are not the same households in the data before 2017; thus, the energy poverty dynamic analysis would be impossible. All in all, we obtain a fully balanced sample for four successive years covering 4466 households and 17,864 observations for our research.

The covariates are selected based on concrete empirical research on energy poverty (Alem, 2014; Awan et al., 2022; Pachauri et al., 2004; Papada & Kaliampakos, 2016). Thus, we add several socioeconomic characteristics that may affect the likelihood of experiencing energy poverty in Greece. In particular, we include three general categories of variables in our analysis: socioeconomic and dwelling characteristics, macroeconomic figures, and climatic conditions. Due to the structure of the data, we do not involve gender variable in our analysis. Age, educational level, family status, income level, labor force status, and ethnicity are proxy variables for socio-demographic and socioeconomic household characteristics that might affect the probability of facing and/or escaping energy poverty. Following the literature, we also involve variables relating to dwelling characteristics, such as a dummy variable associated with the type of housing (detached home), the size of the building (number of rooms), the existence of dark rooms, and the region of living that can influence energy demand and therefore energy poverty within households. Moreover, we embrace the energy cost proxied by the real price of electricity and natural gas and two environmental variables that consider climatic conditions (Li et al., 2023), the heating and cooling degree days, respectively.

To identify the parameters that can impact energy poverty persistence and transition effects, we follow standard poverty literature (Alem & Demeke, 2020) and employ the dynamic Probit panel data specifications (Drescher & Janzen, 2021) and the Wooldridge Conditional Maximum Likelihood estimator (Wooldridge, 2005). The idea of persistence is based on the genuine state dependence phenomenon. This means that a poor household or individual in any given period is likelier to be poor in the next period. Technically, our dependent response variable y_{it} represents an observed binary (dummy) variable of a household i at time t that takes the value of one if it is considered poor and zero otherwise. Thereupon, the specification of the general dynamic Probit model is presented as follows:

$$y_{it}^* = \gamma y_{it-1} + \beta x_{it}' + u_i + \varepsilon_{it} \tag{1}$$

where y_{it}^* is the latent index dependent variable, y_{it-1} is the lag of the observed binary outcome that captures the (genuine) state dependencies in energy

poverty, β is the vector of independent variables coefficients, x'_{it} represents the regressors of the models, including information on socioeconomic factors, household dwelling characteristics, and climatic and market conditions (considered strictly exogenous). Finally, u_i represents the unobserved household heterogeneity while ε_{it} is the normally distributed error term with normalized variance equal to one and mean zero. It is assumed that the number of cross-sectional units (N) is large and time is short, indicating that asymptotics depends on N alone. Furthermore, in the standard random effects Probit specification, it is assumed that conditional x'_{it}, u_i is independent of ε_{it} and x'_{it}. Thus, under the assumptions mentioned above, the probabilistic transition model for household i at time t is given by:

$$Prob\left(y_{iy}|x_{it}, y_{it-1}, u_i\right) = \Phi\left\{\left(\gamma y_{it-1} + \beta x'_{it} + u_i\right)\left(2y_{it} - 1\right)\right\}$$
(2)

where Φ is the cumulative function of the standard normal distribution. Nevertheless, a well-known issue when employing dynamic random effects models to acknowledge state dependence is the assumption that initial energy poverty status y_{it} is exogenous. In other words, it is assumed that initial observation y_{it}, and time-invariant specific effects are uncorrelated, which might be unrealistic (so-called initial condition problem).

This problem stems from the fact that initial observation might not correspond to the starting point of the process (stochastic), leading to the experience of the outcome. The initial condition problem is common in dynamic panel data and especially in short-panel datasets, as in our case. This is because dynamic panel models involve individual-specific fixed effects and time-varying independent variables. However, the initial value of the dependent variable may be correlated with the unobserved individual-specific fixed effect, which creates a potential endogeneity problem. Alternatively, this stems from the fact that the initial observation does not link to the beginning of the stochastic process (Drescher & Janzen, 2021; Grotti & Cutuli, 2018). In our case, poverty status is likely to start at a time before the period of analysis and lead to inconsistent estimates.

Three main estimators to address this initial condition problem have been proposed. The first approach was suggested by Hechman (1981), presenting a two-step maximum likelihood estimator. A linear reduced-form equation is estimated, including exogenous instruments and initial values. After that, the reduced equation is incorporated into the likelihood function, and the Gauss-Hermite approach can be applied. Orme (2001), similarly to Heckman's approach, suggests a two-step bias corrected procedure. Later, Wooldridge (2005) proposed a conditional on the initial response maximum likelihood estimator, mainly referred to as the Wooldridge Conditional Maximum Likelihood (WCML) estimator. This approach also has the advantage of parsimony without requiring a balanced panel. So, Heckman and Orme's estimators are limited in empirical studies because they require different programming due to their absence from standard packages. On the contrary, the Wooldridge approach is straightforward in several software packages; we use our analysis to employ the Wooldridge approach proposed by Rabe-Hesketh and Skrondal (2013) to investigate energy poverty persistence and transition over time in Greece. This estimator captures the initial value and the within-unit average of time-varying explanatory variables and the initial value of the outcome variable (initial condition) (Grotti & Cutuli, 2018).

Furthermore, following Grotti and Cutili (Grotti & Cutuli, 2018), we provide steady-state expected dynamics, including transition effects at different levels of the time-constant variables.[2] By so doing, using the prediction estimates of the model, we generate a range of statistics under specific individual situations, which describe how energy poverty indicators are expected to change over time. More specifically, the applied approach includes information on how possible someone can enter or exit the energy poverty issue, the duration of poverty, and the probability of being in a long-term state of poverty.

Empirical results and discussion

Based on the previously described methodology, Table 1 illustrates the descriptive statistics for the main variables used in the empirical part.

Based on the pooled sample of 17,864 observations, the average age of the household heads is 63.5; 17% have completed tertiary education, and

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[2] *Probat* command was used in Stata.

Table 1 Descriptive statistics, 2017–2020

Panel A: quantitative variables		
Variable	Mean	Stand. dev.
Age (years)	63.5	16.0
Real income (€)	7699	7000
Household size (number)	2.2	1.2
Household rooms (number)	3.2	0.9
Real price of natural gas per Kwh (€)	0.05	0.006
Real price of electricity per Kwh (€)	0.17	0.002
Heating degree days (number)	1345.6	438.6
Cooling degree days (number)	390.7	129.4

Panel B: qualitative variables (tabulation)			
Variable	Relative freq.	Variable	Relative freq.
Tertiary education	0.17	Detached house	0.48
Married	0.60	Dark rooms	0.06
Unemployed	0.07	Rural areas	0.49
Migration background	0.04	Islands	0.19

Real income refers to equivalized household income. Panel B presents categorical variables and its values refer to relative frequencies

Table 2 Consensual-based energy poverty rates and material deprivation rate of housing dimension, 2017–2020

Consensual-based indicators	2017	2018	2019	2020
Inability to keep home adequately warm	24.3%	22.0%	20.5%	23.5%
Arrears on utility bills	31.1%	29.0%	28.0%	24.7%
Presence of leak, damp, etc.	12.9%	15.2%	14.8%	16.8%
Material deprivation — housing dimension	2017	2018	2019	2020
1-item	11.6%	14.0%	14.3%	16.5%
2-items	3.7%	3.2%	3.3%	3.8%
3-items	0.2%	0.2%	0.2%	0.0%
4-items	0.1%	0.0%	0.0%	0.0%

7% are unemployed. Sixty percent of the sample are married, and the median equivalized income is 7699 euros. The average number of members is 2.2 per household, while each home has, on average, around 3.2 rooms. Six percent of the houses lack light, 48% live in detached houses, while almost half of the sample indicate that they live in rural areas and 19% in islands. Also, 4% of the households' heads have a migration background. Finally, regarding climatic conditions, the average heating and cooling degree days are equal to 1346 and 391, respectively. Concerning market information, the average real price of electricity and natural gas is 0.17 and 0.05 euros per kWh, respectively.

Table 2 presents the consensual-based indicators of energy poverty and the material deprivation rates of the housing dimension.

Regarding the consensual indices of energy poverty, we can see that around 22.5% of the households (average across time) cannot keep their home adequacy warm. Similarly, 28.2% declare that they delay paying utility bills, while around 14.9% indicate that their homes present building issues such as leaks, dampness, etc. Apart from 2020, an extraordinary year as COVID-19 was the main problem for the whole planet, consensual-based energy poverty indicators seem to be decreasing. Concerning the latter indicator, we can observe that despite an existing program for dwelling renovation in the country, there could be several reasons why the presence of a leak, dampness, and other related issues related to energy poverty might persist or increase. For instance, the lack of awareness, the amount of funding, the geographical coverage, and some other household

Table 3 Energy poverty rates according to different income levels, pooled sample 2017–2020

Variables	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	Aver.
Warm	40.0%	35.6%	30.4%	28.2%	22.5%	19.2%	16.7%	13.7%	11.0%	6.4%	22.6%
Arrears	44.6%	32.2%	33.7%	29.0%	28.4%	26.0%	24.6%	25.5%	20.8%	16.0%	28.2%
Leak, etc.	22.7%	20.2%	17.1%	16.7%	14.4%	14.0%	12.3%	12.8%	10.3%	7.6%	14.9%
1-item	20.1%	17.5%	16.2%	15.2%	13.1%	14.0%	12.7%	12.8%	10.1%	8.6%	13.2%
2-items	6.6%	5.3%	4.1%	4.1%	3.6%	3.2%	1.8%	2.6%	2.1%	1.4%	3.5%
3-items	0.3%	0.0%	0.5%	0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
4-items	0.0%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Authors' calculations

structural issues could explain the path of this energy poverty indicator. Also, it is worth noting that presenting energy poverty is a complex issue requiring a comprehensive approach beyond just describing only one indicator.

Regarding the second panel of the table, we present the material deprivation for the housing dimension. This dimension refers to the percentage of households which are materially deprived for the housing dimension, based on the dwelling problems suffered from one or more of a list of the material deprivation items (EU explanation), namely, (a) leaking roof/damp walls/floors/foundation or rot in window frames, (b) accommodation too dark, (c) no bath/shower, and (d) no indoor flushing toilet for the sole use of the household. This figure seems more complex. Interestingly, Greek households seem to avoid suffering from severe material deprivation (3 and 4 items out of 4). Nevertheless, it is very worrying that 1-item material deprivation follows an increasing path from 2017 to 2020. In particular, a rise of 5% in the 1-item material deprivation rate of the housing dimension is evident from 2017 to 2020. The 2-item deprivation fell from 3.7% to around 3.2–3.3% in 2018 and 2019 but increased again in 2020, reaching 3.8%. However, it should be noted that 2020 was a challenging period due to the pandemic crisis that formed several dwelling problems among Greek households.

Nonetheless, except for the level of energy poverty across time, it is also important to report the rates of energy poverty by income deciles according to the energy poverty indicators we account for in our empirical analysis (Table 3).

As can be seen, income plays a crucial role in energy poverty, as lower-income households are more likely to face it than higher-income households. More specifically, we can observe that households belonging to the first income decile are around 2–3 times more likely to suffer from energy poverty than households belonging to the ninth decile of annual income and double likely than median income households. In relative numbers, more than 40% of the households in the lowest 10% of the income distribution indicate that they cannot keep their houses warm and delay paying their utility bills. In addition, more than 44% of the households indicate that arrears are an issue for the same category, while around one out of four confirm leakages problems in their homes. Concerning material deprivation, the path seems to be the same. Around 20% of the households in the first decile of income distribution declare at least one deprivation issue, more than doubled that of the households in the tenth decile. As far as the 2-item deprivation is concerned, the situation is precisely the same but with lower percentages (6.6% against 1.4%). In contrast, the 3- and 4-item material deprivation issues seem not to be an issue for these specific investigated households.

Thereupon, we present dynamic Probit model estimations and average marginal effects of the models for consensual energy poverty metrics in Table 4. Columns (1), (5), and (9) display the results of dynamic models before estimating marginal effects. More specifically, these models present dynamic Probit specifications considering that the outcome variable's initial condition is exogenous. At the same time, columns (3), (7), and (11) show the empirical results when implementing the Wooldridge Conditional Maximum Likelihood estimator that addresses the initial condition problem in our data.

Columns (2), (4), (6), (8), (10), and (12) show the average marginal effects (AVE) for each estimated

Table 4 Dynamic probit and WCLM regression results on energy poverty persistence, 2017–2020

Variables	Inability to keep warm home				Arrears to utility bills				Leak, damp, etc.			
	(1) PROBIT	(2) MFX	(3) WCML	(4) MFX	(5) PROBIT	(6) MFX	(7) WCML	(8) MFX	(9) PROBIT	(10) MFX	(11) WCML	(12) MFX
Lag of energy poverty	1.733*** (0.0483)	0.312*** (0.008)	0.790*** (0.0695)	0.128*** (0.014)	1.303*** (0.0501)	0.319*** (0.013)	0.486*** (0.0583)	0.105*** (0.016)	4.369*** (0.569)	0.149*** (0.008)	4.273** (0.123)	0.091*** (0.012)
Ln of age	0.333*** (0.066)	0.060*** (0.012)	−0.085 (0.493)	−0.011 (0.066)	−0.167*** (0.055)	−0.041*** (0.013)	0.074 (0.421)	0.014 (0.082)	0.111 (0.148)	0.004 (0.005)	2.433** (1.135)	0.080** (0.037)
Ln of real income per capita	−0.363*** (0.036)	−0.065*** (0.006)	−0.299*** (0.081)	−0.040*** (0.011)	−0.417*** (0.035)	−0.102*** (0.008)	−0.347*** (0.067)	−0.068*** (0.013)	−0.405*** (0.079)	−0.014*** (0.002)	−0.389* (0.211)	−0.013* (0.007)
Tertiary education	−0.218*** (0.052)	−0.039*** (0.009)	−0.285*** (0.087)	−0.038*** (0.012)	−0.142*** (0.042)	−0.035*** (0.010)	−0.141** (0.061)	−0.028** (0.012)	−0.153 (0.133)	−0.005 (0.004)	−0.145 (0.126)	−0.005 (0.004)
Married	−0.289*** (0.0360)	−0.052*** (0.006)	−0.438*** (0.062)	−0.059*** (0.008)	−0.107*** (0.031)	−0.026*** (0.008)	−0.156*** (0.047)	−0.030*** (0.009)	−0.502*** (0.093)	−0.017*** (0.003)	−0.476*** (0.093)	−0.016*** (0.003)
Unemployed	0.345*** (0.0705)	0.062*** (0.013)	0.441*** (0.101)	0.059*** (0.014)	0.262*** (0.0615)	0.064*** (0.015)	0.333*** (0.0821)	0.065*** (0.016)	0.207 (0.145)	0.007 (0.005)	0.203 (0.157)	0.007 (0.005)
Migration	0.281*** (0.0795)	0.051*** (0.014)	0.304** (0.133)	0.041** (0.018)	0.130* (0.0712)	0.032* (0.017)	0.179* (0.104)	0.035* (0.020)	0.230 (0.164)	0.008 (0.006)	0.202 (0.187)	0.007 (0.006)
Detached house	0.173*** (0.0477)	0.031*** (0.009)	0.236*** (0.079)	0.032*** (0.011)	0.0501 (0.039)	0.012 (0.009)	0.0637 (0.0590)	0.012 (0.012)	0.109 (0.937)	0.004 (0.003)	0.069 (0.118)	0.002 (0.004)
Dark rooms	0.278*** (0.0640)	0.050*** (0.011)	0.471*** (0.101)	0.063*** (0.013)	0.292*** (0.0583)	0.071*** (0.014)	0.420*** (0.0797)	0.082*** (0.015)	0.731*** (0.174)	0.025*** (0.004)	0.713*** (0.121)	0.024*** (0.004)
Number of rooms	−0.0626*** (0.0201)	−0.011*** (0.004)	−0.0811** (0.0338)	−0.011** (0.005)	−0.0114 (0.0163)	−0.003 (0.004)	−0.0173 (0.0250)	−0.003 (0.005)	−0.153*** (0.048)	−0.005*** (0.001)	−0.155*** (0.051)	−0.005*** (0.002)
Rural areas	−0.171*** (0.0482)	−0.031*** (0.009)	−0.288*** (0.0814)	−0.039*** (0.011)	−0.128*** (0.040)	−0.031*** (0.010)	−0.189*** (0.0605)	−0.037*** (0.056)	−0.087 (0.094)	−0.003 (0.003)	−0.074 (0.120)	−0.002 (0.004)
Island	−0.178*** (0.0495)	−0.032*** (0.009)	−0.242*** (0.0871)	−0.033*** (0.012)	−0.0486 (0.0410)	−0.012 (0.010)	−0.0437 (0.0656)	−0.009 (0.013)	0.189* (0.105)	0.006** (0.003)	0.318 (0.122)	0.010** (0.004)
Ln of energy price	1.213*** (0.195)	0.218*** (0.035)	1.163*** (0.346)	0.156*** (0.047)	−0.213 (0.180)	−0.052 (0.044)	−0.756*** (0.291)	−0.148*** (0.057)	6.008*** (1.122)	0.206 (0.200)	6.235*** (1.000)	0.206*** (0.035)
Ln of CDD	−0.128*** (0.0486)	−0.023*** (0.009)	−0.374** (0.148)	−0.050** (0.020)	−0.116*** (0.043)	−0.028*** (0.010)	−0.208* (0.120)	−0.041* (0.023)	−0.074 (0.158)	−0.002 (0.005)	−1.148* (0.629)	−0.038* (0.020)
Ln of HDD	−0.420*** (0.071)	−0.075*** (0.013)	−0.198 (0.406)	−0.027 (0.054)	−0.247*** (0.061)	−0.060*** (0.015)	−0.019 (0.335)	−0.004 (0.065)	−0.080 (0.182)	−0.003 (0.006)	−5.994** (2.750)	−0.198** (0.091)

Table 4 (continued)

Variables	Inability to keep warm home				Arrears to utility bills				Leak, damp, etc.			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	PROBIT	MFX	WCML	MFX	PROBIT	MFX	WCML	MFX	PROBIT	MFX	WCML	MFX
Constant	6.578***		9.625*		5.373***		8.859**		12.367***		22.428***	
	(1.015)		(4.999)		(0.918)		(3.987)		(2.976)		(8.475)	
Observations	11,888	11,888	11,888	11,888	11,790	11,790	11,790	11,790	11,888	11,888	11,888	11,888
Number of groups	4,080	4,080	4,080	4,080	4,076	4,076	4,076	4,076	4,088	4,088	4,088	4,088

***1% significance level, **5% significance level, and *10% significance level. Robust standard errors are shown in parentheses. WCML refers to Wooldridge Conditional Maximum Likelihood estimator; MFX denotes the average marginal effects

model. Generally, empirical findings present strong evidence for genuine energy poverty state dependence among Greek households. This finding indicates that if a household faces energy poverty in one period, the likelihood of remaining energy poor in the next period is higher. Without addressing the issue of the initial condition, findings point out that the chances of indicating an inability to keep the house adequately warm are higher by 31.2% if the household had reported the same living conditions in the previous period. Regarding reporting arrears to utility bills and building issues such as leaks and dampness, the probabilities are 31.9% and 14.9%, respectively. Once controlled for the initial condition problem, the positive coefficient of the lag of the dependent variable validates the existence of significant dynamics of genuine state dependence. However, as expected (Drescher & Janzen, 2021), persistence coefficients are likely upward biased without reflecting the actual state dependencies within households (Hechman, 1981). Results of our analysis employing the WCML estimator confirm evidence of genuine state dependence in consensual-based energy poverty indices, but poverty persistence is now 12.8%, 10.5%, and 9.1%, respectively.

Most empirical results align with prior expectations regarding the relationship between energy poverty and independent variables. Firstly, socio-economic and demographic characteristics are significant predictors of energy poverty. In particular, higher income status is negatively related to energy poverty. In other words, as households' real income increases, the probability of facing energy poverty decreases. We also find that being more educated significantly decreases the household's chance of suffering from energy poverty. It is confirmed that higher education affects individuals' and households' energy efficiency-related decisions that can keep households out of energy poverty (Awan et al., 2022; Legendre & Ricci, 2015). Our regression results also support the assumption that married people, possibly due to the high dependency ratio in Greek families, are negatively associated with consensual-based energy poverty. On the contrary, older people, unemployment status, and migration background are positively related to energy poverty.

Regarding dwelling characteristics, living in urban areas, in mainland Greece, in small houses with dark rooms, and detached houses experience a higher

Table 5 Chronic energy-poor households per year, 2017–2020

Variables		Starting year	Chronic energy-poor households		
		2017	2018	2019	2020
Inability to keep warm home	Total number (% of households)	1086 (24.3)	669 (15.0)	497 (11.1)	444 (9.9)
Arrears to utility bills	Total number (% of households)	1364 (31.1)	849 (19.0)	589 (13.2)	443 (9.8)
Leak, damp, etc.	Total number (% of households)	574 (12.9)	418 (9.4)	409 (9.2)	403 (9.0)

probability of facing energy poverty. Homeownership is large in levels in Greece. So, the positive effect of detached houses on energy poverty might be correlated with the high level of home ownership confirming previous studies (Awan et al., 2022). Regarding the region of living, empirical results reveal unobserved regional heterogeneity (Kostakis, 2020; Pereira & Marques, 2023). More specifically, findings show that households in urban areas are more energy poor which may be due to the limited access to alternative fuels that can be used to cover energy needs.

On the contrary, rural dwellers can be at low risk of affordability issues than urban ones. Besides urban and rural, we used another local dummy variable (islands/mainland). Marginal effects show that compared to households in mainland Greece, households from islands are relatively less energy poor. This heterogeneity across Greece may be due to these provinces' high population and lifestyle differences (Kostakis & Lolos, 2022). Big houses are negatively related to energy poverty, meaning households living in large properties are less likely to be energy poor. Families living in big houses may have a higher socioeconomic status, and their homes are designed and equipped with energy-efficient features. That means they can install more energy-efficient appliances, reducing energy consumption and cost. Moreover, while big houses may require more heating and/or cooling energy than smaller homes, they may also have the potential to benefit from economies of scale and decrease their energy dependence.

As for energy cost, a higher energy cost increases the chances of facing the inability to keep a warm home and dwelling issues within the house. However, the higher energy cost seems to decrease the probability of being in arrears on utility bills. This result, even if unexpectant, can be explained due to several

different channels. Firstly, we talk about a brief period in which the increase in energy cost is marginal. At the same time and based on previous studies (Dagoumas & Kitsios, 2014), there exists a delay in the effect of the economic cost on energy demand as consumers need more time to respond to different financial figures and change their lifestyle habits. Moreover, as energy is essential for families, several households might have moderated other essentials in favor of energy needs.

Finally, regarding climatic conditions, households that need more energy to cover either cooling or heating days have lower chances of facing consensual-based energy poverty. Households that need more energy to cover their needs live mainly in regions with more unusual temperatures. That has led them to require more energy to maintain a comfortable indoor temperature. Still, these homes may also have heating and cooling systems designed to be more energy-efficient, which can help reduce energy bills and lower the risk of energy poverty. These households may also have access to government energy assistance programs that can help improve their home's energy efficiency and financial stability and reduce the risk of energy poverty.

Even though we confirm genuine energy poverty state dependence effects in consensual-based metrics, estimating the identification function of energy poverty between households is of high interest. Thus we estimate the successive periods facing energy poverty by classifying the households as chronic energy poor (they were poor all previous years). More specifically, our analysis is based on a specific period of four years, while we have intentionally restricted our investigation to the same set of households throughout this period. By maintaining a consistent sample, we aim to avoid potential biases that could arise from

Table 6 Transition, state dependence, and projected steady-state probability of poverty

		Tertiary education (lower education)	Married (unmarried)	Unemployed (employed)	Migrated (Greek)	Detached (apartment)	Dark rooms (light rooms)	Rural (urban)	Island (continental)
Inability to keep warm home	Entry pr	0.12 (0.84)	0.09 (0.15)	0.17 (0.11)	0.15 (0.11)	0.13 (0.10)	0.17 (0.11)	0.10 (0.13)	0.09 (0.12)
	Exit pr	0.81 (0.75)	0.79 (0.70)	0.67 (0.77)	0.70 (0.76)	0.74 (0.22)	0.66 (0.77)	0.79 (0.73)	0.80 (0.75)
	Persistence pr	0.19 (0.25)	0.21 (0.30)	0.33 (0.23)	0.30 (0.24)	0.26 (0.22)	0.34 (0.23)	0.21 (0.27)	0.20 (0.25)
	St.-state pr	0.09 (0.13)	0.10 (0.17)	0.20 (0.12)	0.18 (0.13)	0.15 (0.11)	0.21 (0.12)	0.11 (0.15)	0.10 (0.14)
Arrears bills	Entry pr	0.16 (0.19)	0.18 (0.21)	0.25 (0.18)	0.22 (0.18)	0.19 (0.18)	0.27 (0.18)	0.17 (0.21)	0.18 (0.19)
	Exit pr	0.73 (0.70)	0.72 (0.67)	0.61 (0.71)	0.66 (0.70)	0.69 (0.71)	0.59 (0.71)	0.73 (0.68)	0.71 (0.70)
	Persistence pr	0.27 (0.30)	0.28 (0.33)	0.39 (0.29)	0.35 (0.30)	0.31 (0.29)	0.41 (0.29)	0.27 (0.32)	0.29 (0.30)
	St.-state pr	0.18 (0.22)	0.20 (0.23)	0.29 (0.20)	0.25 (0.21)	0.22 (0.20)	0.32 (0.20)	0.19 (0.23)	0.20 (0.21)
Leakages, damp, etc	Entry pr	0.01 (0.02)	0.01 (0.03)	0.03 (0.02)	0.03 (0.02)	0.02 (0.01)	0.05 (0.01)	0.02 (0.02)	0.03 (0.02)
	Exit pr	0.08 (0.07)	0.09 (0.04)	0.05 (0.07)	0.05 (0.07)	0.07 (0.08)	0.02 (0.07)	0.08 (0.07)	0.04 (0.08)
	Persistence pr	0.91 (0.93)	0.91 (0.96)	0.95 (0.93)	0.94 (0.93)	0.93 (0.92)	0.98 (0.93)	0.92 (0.93)	0.96 (0.92)
	St.-state pr	0.14 (0.21)	0.11 (0.43)	0.33 (0.19)	0.34 (0.19)	0.22 (0.19)	0.74 (0.15)	0.18 (0.22)	0.39 (0.17)

All presented values refer to probabilities

including larger datasets with varying household compositions. Alternatively, we could say that using precisely identical households could make the different years more comparable. Table 5 highlights these results.

Table 5 provides a picture of households' successive years of energy poverty. 2017 is the base year (starting point), and findings refer to the following years. All indicators show a decline in households that remain energy poor. However, it is highly worrying that around 9–10% of the households experience permanent energy poverty, irrelevant to the indicator chosen. This issue is more stressful for households unable to keep their house warm. Alternatively, it can be said that irrelevant the starting point of facing energy poverty based on different indicators, a long-run equilibrium of about 9–10% of the households facing it is present. Nevertheless, it should be mentioned that the equilibrium point is based on a short period. Also, a more extended dataset would likely reveal a slowing decline in chronic energy poverty, and transitionary energy-poor issues can mainly determine the total energy poverty level. After that, we provide further descriptive evidence on the dynamic function of energy poverty by household socioeconomic and dwelling characteristics in Table 6.

More specifically, we measure steady-state expected dynamics, adding transition rates and associated statistics at different levels of the time-constant covariates (Grotti & Cutuli, 2018). Exit probability (*Exit pr*) indicates the probability of not facing energy poverty at time t conditional of having been in the status at previous time. On the other hand, entry probability (*Entry pr*) indicates the probability of facing energy poverty at time t conditional of not having been in this status at the previous time. Persistence probability (*Persistence pr*)

indicates the probability of facing energy poverty in the status at time *t* conditional on having been in the status at the last time. These estimates help to reveal how the outcome's dynamics differ between households with different characteristics. They may also indicate possible accumulation over time of short-run effects for any given profile once time-constant individual unobservables have been accounted for (Grotti & Cutuli, 2018).

In our case, we compute the statistics for different educational levels, family, labor and migration status, area of living, and dwelling characteristics. As expected, regarding the indicator of inability to keep a warm home, it is evident that of other compositional factors, education stratifies poverty dynamics over time, reducing entry risks (8.4 versus 11.5) and increasing the exit chances (80.9 versus 75.4). State dependence and the projected steady-state probability of poverty are consistently significantly higher among those with lower educational degrees. Similarly, married people, employed and without migration background present lower entry risks (9.1 versus 14.7, 10.6 versus 16.8, 11.0 versus 15.1) and higher exit chances (79.4 versus 70.1, 76.8 versus 66.8, 76.4 versus 69.7) while presenting higher metrics of state dependence and the projected steady-state probability of poverty respectively.

Regarding dwelling characteristics, households living in detached houses, in urban areas, inland, and with existing dark rooms present a higher probability of entry and facing energy poverty and a lower probability of exit from this issue. We find similar results based on the rest of the consensual-based energy poverty indicators. Generally, we can notice that a higher educational level significantly decreases the chances of facing energy poverty and increases the probability of escaping from this issue. Being single or unemployed significantly increases the likelihood of suffering from energy poverty and the probability of chronically remaining energy poor. Migration background also has a higher probability of facing energy poverty and remaining chronically energy poor across time. Based on dwelling characteristics and households' living areas, detached houses and house problems are less likely to escape energy poverty. On the other hand, living in rural areas and islands significantly drops the chances of entering into energy poverty while increasing the probability of escaping from this issue if it is present.

Conclusions, policy implications, and limitations

Energy poverty is linked with SDGs, so it is crucial to investigate its state and dynamic feature in a developed European economy. Although energy poverty has been widely studied by previous research, we fill a research gap by examining state dependence on energy persistence and transition by relying on consensual-based indicators in Greece. To achieve these goals, the present paper employs data from four surveys of EU-SILC that are nationally representative and covers a period between 2017 and 2020. The analysis period was selected due to data limits as we precisely took identical households, estimating their energy poverty behavior over time.

The main highlights of this research are as follows. First, we probe genuine energy poverty state dependence effects among Greek households. Once controlled for the initial condition, empirical results show that an energy-poor household today is up to 10–12% more likely to face energy poverty tomorrow, confirming poverty persistence. Second, energy poverty is associated with socioeconomic and demographic determinants, dwelling characteristics, market information, and climatic conditions. Furthermore, it is highly interesting that around 9–10% of the sample can be chronically energy-poor households. Education, marital and labor status, migration background, dwelling characteristics, and living area can affect probabilities and chances to enter, stay in, and escape energy poverty.

More specifically, using two different dynamic approaches, a dynamic random effects Probit model and the Wooldridge Conditional Maximum Likelihood (WCML) estimator, we investigate (a) how several household-level factors affect energy poverty, (b) the extent to which energy poverty persists, and (c) the likelihood of being a household experiencing chronic or temporary energy poverty. Although we have utilized both econometric specifications, most of our results are primarily grounded on the WCML estimator.

The dynamic relationship underlines that a trap of persistent energy poverty in Greece will be challenging to overcome without any policy interventions. Figure 1 presents the estimated relationships between the relevant variables.

Evidence suggests that household composition and socioeconomic characteristics such as educational
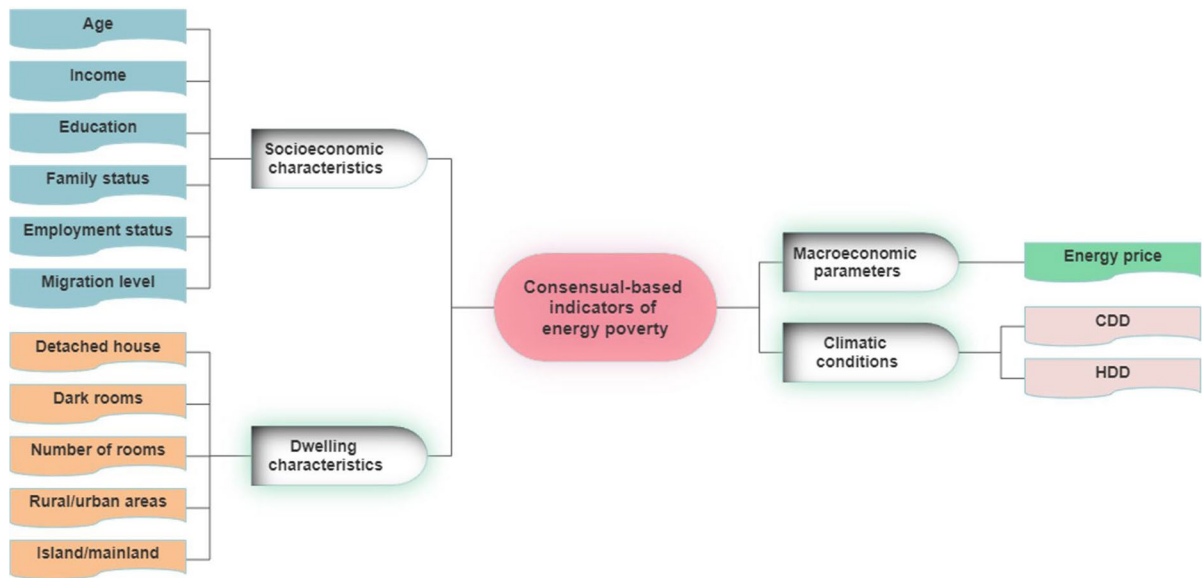
Fig. 1 Relationships between the variables of interest

attainment, income level, being-working, ethnicity, and marital status are related to energy poverty in Greece. Also, dwelling characteristics, including the number of rooms, dark rooms, and the type of house, affect the likelihood of facing energy poverty. In addition, area of living, energy cost, and climatic conditions can affect households' energy poverty rates in the country. Finally, we find that different household compositions have differentiated probabilities of being energy poor over time.

Subsequently, we perform dynamic regression analyses that can provide significant policy suggestions and assist policymakers in making decisions. Our empirical findings demonstrate that socioeconomic and dwelling characteristics are substantial factors in dealing with energy poverty. Therefore, policymakers and governments should prioritize addressing energy poverty among households. First, empirical results show that several dwelling characteristics can affect household energy poverty. Thus, policies to improve the energy efficiency of buildings (for example, insulation and use of renewable energy sources) should be implemented. This strategy could help reduce household energy costs and decrease the likelihood of facing household energy poverty.

Also, area of living and socioeconomic status seem to matter for energy poverty. Therefore, authorities could offer financial assistance to households

struggling with energy poverty through subsidies or tax credits for clean energy generation. For instance, more generous and specific energy-saving programs incentivizing "renovation and energy saving in dwellings" will bring several benefits.

Simultaneously, decision-makers could prioritize addressing energy poverty in policy-making and ensure that assistance policies must consider the needs of low-income households and households which live in areas with extreme and unusual climatic conditions. Third, education is a strategic parameter that can improve consuming energy behavior. Thus, governments could invest in energy education programs to increase knowledge and awareness about energy use and conservation. This policy would help households understand how to use energy more efficiently and reduce energy costs. Also, systematically disseminating information to households about the efficient use of electrical appliances and IT equipment and educational school programs focused on energy saving can increase energy efficiency and reduce household energy poverty.

Nevertheless, the energy cost (price) can also be decreased in its generation status. So, the energy interconnection of South Greek islands with the mainland energy grid will allow the replacement of fossil fuel energy generation with renewable energy ones to achieve significant cost efficiency and reduce

environmental degradation. At the same time, this policy could create a more affordable and diverse energy market, benefiting households struggling with energy poverty.

However, we should also acknowledge that our study has some potential shortcomings that can be addressed by future research. First, households are not incentivized to tell the truth for all self-reported data and may be subject to errors. So, it would be more informative to note that our households are identified as energy-poor based on some consensual-based indicators. Also, having more data and richer longitudinal data sets would allow for a more sophisticated empirical analysis that can give more robust consensual-based results around energy poverty persistence and transition among households. More specifically, as multiple previous periods are considered, the numbers for different years might be incomparable, and any observed downward trend should be interpreted cautiously. Also, a more extended dataset could reveal a (hopefully) slowing decline in chronic energy poverty. Thus, all these empirical findings must be justified using more data and extended periods. Moreover, introducing expenditure-based energy poverty indicators will allow comparisons and reveal more general results that can be easily generalized around the national energy poverty issue. Lastly, it is central to mention the complexity of the energy poverty issue that single indicators cannot fully capture. Therefore, future research could inflate research by using multiple indicators to understand the issue comprehensively. European indicators, which refer to several material deprivation rates, are promising for unfolding energy poverty issues for households in developed and developing countries.

Author contributions   Both authors contributed equally.

Data availability   Data are available upon request with the permission of Hellenic Statistical Observatory.

Declarations

Competing interests   The authors declare no competing interests.

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