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A new distributional based indicator to measure energy poverty in Italy☆

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ABSTRACT

Energy poverty refers to a situation where households struggle to access or afford essential energy services needed for daily living-such as heating, cooling, lighting, and cooking. Traditionally, this issue is evaluated using a fixed lower bound for the energy expenditure, commonly set at 10% of household income. In response to these concerns, the current study questions the effectiveness of fixed thresholds and introduces an alternative, data-driven methodology. This technique enables the identification of endogenous threshold points that accurately reflect the heterogeneity in household energy spending distributions. Furthermore, we enhance the estimation of energy poverty by combining these endogenous thresholds with a measure of economic vulnerability. This statistical framework enables the definition of a new energy poverty indicator defined as the joint probability that energy expenditure exceeds the endogenous threshold and non-energy expenditure falls below 60% of the national median. This offers a probabilistic assessment of energy poverty. Using data from the Italian National Institute of Statistics (ISTAT), specifically the Household Budget Survey (HBS), for the years 2019-2023, the analysis of energy indicator reveals that energy poverty is prevalent mainly in Southern regions of Italy. Furthermore, a spatial analysis covering the period 2019-2022 is conducted to explore the regional drivers of energy poverty.

1. Introduction

Energy poverty is becoming a priority concern in the twenty-first century, due to its crucial connection with energy security, social justice, and sustainable development. This complex issue impacts families in both emerging and industrialized countries alike, crossing conventional economic divides and underscoring the widespread character of energy accessibility problems in modern times.

Energy poverty can be characterized as the inability to obtain economically viable, dependable, and sufficient energy services necessary for human welfare and socioeconomic advancement [1,2]. This characterization includes not merely the complete lack of energy availability but also circumstances where families encounter excessive energy expenses compared to their earnings, insufficient energy provisions that cannot satisfy fundamental requirements, or unstable energy delivery that interrupts routine activities and economic prospects.

The worldwide extent of energy poverty is overwhelming. Based on International Energy Agency data [3], more than a billion individuals globally experience energy poverty today, predominantly located in Sub-Saharan Africa and emerging Asian regions. Nevertheless, this predicament extends beyond the Global South. Across Europe, the share of residents incapable of properly warming their dwellings increased substantially from 6.9% in 2021 to 10.6% in 2023 [4], primarily due to the energy emergency resulting from geopolitical conflicts and supply network failures. Likewise, within the United States, one-third of families indicate facing energy difficulties [5], demonstrating that energy poverty endures including in advanced economies.

Italy offers an especially instructive example for analyzing energy poverty patterns within industrialized nations. By the end of 2023, approximately 2.36 million Italian families (9% of all residents) were living in energy poverty. This rate is among the highest incidence levels recorded since methodical data gathering started in 1997 [6].

This surge has been especially pronounced within families in the bottom two income brackets, as 293,000 more households fell into energy poverty. This distribution highlights energy poverty's regressive character, whereby the most financially disadvantaged groups shoulder an excessive load and frequently adopt management approaches that might include cutting back on vital energy services. The phenomenon shows a pronounced concentration in Southern regions and Islands,

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where economic vulnerabilities intersect with climatic needs and infrastructure challenges. The social dimensions of energy poverty in Italy reveal patterns of inequality. Particularly concerning is the growth of "hidden energy poverty" – households reporting zero heating expenditure – indicating that many low-income families are forced to give up essential energy services [7]. Perhaps most troubling is the intergenerational dimension of energy poverty in Italy. Approximately 10.6% of households with minors – affecting 1.15 million children – live in energy-poor conditions, with these families often characterized by multiple overlapping vulnerabilities including low educational attainment of household heads, precarious employment, and inadequate housing conditions. The persistence of such conditions, despite the allocation of more than 2.2 billion euros in social bonuses in 2023 that reached only 18% of energy-poor households, highlights the challenge of identifying and reaching the most vulnerable populations, suggesting the need for more comprehensive approaches that address the multidimensional nature of energy vulnerability in contemporary Italy [8].

Energy poverty's intricacy goes past basic availability measures to include various aspects such as cost-effectiveness, dependability, standards, and environmental viability of energy provisions. This complex character carries major consequences for assessment methods, since conventional single-metric approaches frequently miss the complete range of energy poverty realities [9]. Additionally, how energy poverty appears differs substantially between various settings, shaped by elements including weather patterns, building quality features, energy system maturity, policy structures, and socioeconomic circumstances [10].

Energy poverty's impacts are extensive and interrelated, influencing health results, academic achievement, work efficiency, and community participation. Families in energy poverty frequently encounter challenging choices between energy spending and additional vital requirements including nutrition, medical care, and schooling, generating deprivation patterns that may continue through successive generations [11,12]. Furthermore, insufficient energy availability can worsen current disparities, especially in at-risk groups such as seniors, young people, economically disadvantaged households, and excluded populations [13].

Considering energy poverty's critical nature and intricacy, there exists an essential requirement for solid, thorough, and setting-appropriate assessment methods capable of guiding successful policy measures and monitoring advancement toward energy fairness objectives. Precise energy poverty assessment remains vital for recognizing impacted groups, comprehending root causes, assessing intervention success, and guaranteeing that energy transition strategies do not unintentionally worsen current disparities. This research tackles this analytical issue through developing an innovative conceptual structure that goes further than conventional energy poverty assessment methods. We define a novel energy poverty indicator that captures both energy-specific deprivation and financial vulnerability. This is achieved by combining endogenous region-specific expenditure thresholds derived through an iterative stratification procedure-with a relative measure of economic constraints. The present approach departs from income-based indicators in favor of an expenditure-based framework, for several interconnected reasons. Consumption expenditure is widely regarded as a better measure of material living standards than income, particularly toward the bottom of the distribution, as it smooths short-term fluctuations and is less subject to underreporting as noted by [14,15].

The methodological innovation is twofold. First, we define region-specific energy expenditure thresholds that reflect different socio-economic contexts, thereby overcoming the limitations of fixed-threshold approaches [16]. Second, we model household expenditures as Gamma-distributed random variables, which allow us to represent the typical right-skewed nature of spending behavior. This statistical framework enables the computation of the indicator as a joint probability-that is, the likelihood that a household simultaneously faces both energy-related and economic constraints-offering a more probabilistic assessment of energy poverty.

Furthermore, this paper extends the analysis to investigate the determinants and spatial dynamics of the energy poverty indicator at the regional level in Italy. Using a comprehensive panel dataset spanning 2019–2022, we examine how socioeconomic factors, energy infrastructure, housing conditions, and demographic characteristics influence energy poverty patterns across Italian regions. Our empirical investigation employs multiple econometric specifications, including fixed effects, dynamic panel models, and spatial autoregressive approaches, to capture both temporal persistence and geographical spillover effects. This multi-method approach allows us to identify not only the direct determinants of regional energy poverty but also the spatial interdependencies that characterize its distribution, revealing how energy vulnerability in one region can influence neighboring territories through contagion mechanisms and shared structural factors.

This combined methodology constitutes an analytical improvement in energy poverty studies, providing a more factually based and situationally appropriate assessment instrument. Through removing dependence on preset limits while preserving methodological precision, and by incorporating spatial dimensions and regional heterogeneity, our structure delivers improved accuracy in recognizing energy-disadvantaged groups and advances the development of fact-driven policy formulation in this essential field of social investigation.

The remainder of the paper is structured as follows. Section 2 presents the formulation of the energy poverty indicator. Section 3 describes the dataset used in this study and discusses the results of the energy poverty analysis across Italian regions. In particular, the proposed model is validated using the HBS dataset, which captures household spending habits from 2019 to 2023. Section 4 examines the regional determinants of the energy poverty indicator through static, dynamic, and spatial panel models for the period 2019–2022. Finally, Section 5 concludes the paper. The Appendix contains the proofs of the main results.

2. Definition of the new energy poverty indicator

2.1. Approach overview

Energy poverty describes a condition in which households face significant difficulties in accessing or affording the energy services necessary to meet basic needs, such as heating, cooling, lighting, and cooking. Traditionally, this phenomenon has been assessed using a fixed-threshold approach – most notably, the 10% rule – which considers a household to be energy poor if its energy expenditures exceed 10% of its total income or overall consumption budget [16]. While straightforward, such threshold-based methods have been widely criticized for their arbitrary nature and limited ability to account for variations across different socio-economic contexts or household characteristics [17,18].

To address these concerns, the current study moves away from fixed thresholds by introducing an alternative, data-driven methodology. Our approach uses an iterative stratification procedure based on two-component log-normal mixture models. We apply this model to the ratio of expenditure net of energy to total expenditure, noting that energy costs can be negative when households sell excess electricity. This negative cost primarily involves solar adopters whose post-PV electricity bill is negative, resulting in savings greater than 100% [19]. This happens, for example, when excess generation is sent back to the grid through net metering, resulting in large credits that exceed the household's electricity consumption costs [19,20].

This technique enables the identification of endogenous thresholds that more accurately reflect the underlying heterogeneity in household energy spending behaviors, rather than imposing a uniform standard across all households.

Furthermore, we enhance the estimation of energy poverty by integrating these endogenous thresholds with a relative measure of economic vulnerability — namely, whether a household's net of energy to total expenditure falls below 60% of the national median [21]. This joint condition allows for a more refined and regionally sensitive analysis of energy poverty, with particular attention to the Italian context.

To capture the typically right-skewed nature of consumption data, we employ the Gamma distribution and restrict the analysis to households with positive energy expenditure. This modeling choice allows for a more accurate representation of effective expenditure patterns, leading to more reliable and context-specific assessments of energy poverty.

2.2. Theoretical model: Assumptions

Let $-\infty < X_1 < \infty$ be the energy costs and $Y > 0$ be other expenses. Note that, energy expenditure X_1 may be negative in cases where households generate income by selling electricity back to the grid. However, to take into account only the effective energy expenditure we restrict attention to the case $X = X_1 | X_1 > 0$. This reflects typical expenditure behavior for the majority of households, where energy consumption represents a positive cost. Therefore, by assuming

$$X \sim \text{Gamma}(\alpha_1, \beta), \quad \text{and} \quad \frac{Y}{k} \sim \text{Gamma}(\alpha_2, \beta), \tag{1}$$

be independent Gamma-distributed random variables, the total adjusted expenditure, U:

$$U = X + \frac{Y}{k}, \tag{2}$$

follows a Gamma distribution $U \sim \text{Gamma}(\alpha_1 + \alpha_2, \beta)$.

Note that, we set the unit-specific scaling factor, k, in order to make X and Y comparable (i.e., they share the same scale parameter β). More in details, k is defined as the ratio of the rate parameters β and β_2 obtained from the Gamma distributions fitted to the variables X and Y, respectively, that is $k = \frac{\beta}{\beta_2}$. In other words, the constant k is introduced to rescale Y such that its support aligns with that of X, ensuring comparability between the two distributions.

The use of the Gamma distribution reflects its flexibility in capturing skewness, kurtosis, and heavy tails, which are common in expenditure data, especially due to the presence of large or atypical consumption values. The distributional properties of the Gamma have been shown to approximate income distributions more accurately than the Log-normal alternative, particularly in the upper tail [22], and given the well-documented analogies between income and expenditure distributions in the household economics literature, this evidence lends indirect support to its application in expenditure modeling. More directly, [23] demonstrated that a Generalised Linear Model (GLM) with a Gamma family and log link is the preferred estimator for strictly positive, right-skewed outcomes such as health expenditures, as it avoids the retransformation bias introduced when log-transforming the dependent variable under OLS. Further supporting this approach, [24] found that the Gamma GLM with log link consistently outperformed alternative specifications in predictive accuracy across a range of expenditure distributions.

We define the expenditure ratio as:

$$\varphi = \frac{X}{X+Y} \in (0,1), \tag{3}$$

and introduce the *adjusted* (or transformed) expenditure ratio defined as:

$$\bar{\varphi} = \frac{X}{X + \frac{Y}{k}} \in (0,1). \tag{4}$$

As shown in the following Section, U and $\bar{\varphi}$ are analytically tractable and they are related to φ according to Eq. (5) (see Appendix 6.2 for further details):

$$\varphi = \frac{\bar{\varphi}}{k(1-\bar{\varphi}) + \bar{\varphi}}. \tag{5}$$

Under the Gamma assumptions above, $\bar{\varphi}$ follows a Beta distribution where the parameters α_1 and α_2 are those of Eq. (1), that is:

$$\bar{\varphi} \sim \text{Beta}(\alpha_1, \alpha_2).$$

This result leverages a standard identity: if $X \sim \text{Gamma}(\alpha_1, \beta)$ and $Z \sim \text{Gamma}(\alpha_2, \beta)$ are independent, then the ratio

$$\frac{X}{X+Z} \sim \text{Beta}(\alpha_1, \alpha_2).$$

In our case, $Z = Y/k$, and the Beta distribution arises naturally as the distribution of the proportion of total adjusted expenditure attributable to energy.

2.3. Theoretical model: Joint distribution and estimation

In our framework, the probability of a household being energy poor is determined by assessing whether a combined situation occurs, which captures both the relative energy spending effort (high costs) and the overall economic hardship (low expenditures). This approach represents an adaptation of the Low Expenditure High Costs (LEHC) framework introduced by [21], which incorporates both economic vulnerability and higher energy expenditure conditions to identify households facing energy poverty.

Accordingly, the energy poverty indicator (*EP*) is defined as the probability of a given household being classified as energy poor:

$$EP = P\left(\frac{X}{X+Y} > \bar{a},\ Y < \bar{m}\right), \tag{6}$$

where $\bar{a}$ represents a unit-specific threshold and $\bar{m}$ the 60% of the national median of total expenses net of energy Y. Therefore, Eq. (6) identifies households in energy poverty if:

- Their energy expenditure ratio exceeds a specific threshold (High Costs condition);
- Their net total expenditure is below the poverty threshold (Low Expenditures condition).

Differently from [16,21], we set the value of $\bar{a}$ endogenously by taking into account the distribution of the expenditure components, X and Y.

The joint probability in Eq. (6) can be rewritten (see Appendix 6.1) as follows:

$$P\left(\frac{X}{X+Y} > \bar{a},\ Y < \bar{m}\right) = P\left(\bar{\varphi} > \frac{k\bar{a}}{1+(k-1)\bar{a}},\ U < \frac{\bar{m}}{k(1-\bar{\varphi})}\right). \tag{7}$$

Since $U = X + \frac{Y}{k}$ and $\bar{\varphi} = \frac{X}{X+\frac{Y}{k}}$ are independent (see Appendix 6.2), the joint density function is:

$$f_{U,\bar{\varphi}}(U,\bar{\varphi}) = \frac{\beta^{\alpha_1+\alpha_2}}{\Gamma(\alpha_1)\Gamma(\alpha_2)}(U\bar{\varphi})^{\alpha_1-1}(U(1-\bar{\varphi}))^{\alpha_2-1}e^{-\beta U\bar{\varphi}}e^{-\beta U(1-\bar{\varphi})}|J|, \tag{8}$$

where $|J|$ represents the absolute value of the determinant of the Jacobian matrix J:

$$J = \begin{bmatrix} \bar{\varphi} & U \\ (1-\bar{\varphi}) & -U \end{bmatrix}. \tag{9}$$

Hence, the joint probability in Eq. (6) can be written as:

$$P\left(\bar{\varphi} > \frac{k\bar{a}}{1+(k-1)\bar{a}},\ U < \frac{\bar{m}}{k(1-\bar{\varphi})},\right) = \int_{\frac{k\bar{a}}{1+(k-1)\bar{a}}}^{1}\int_{0}^{\frac{\bar{m}}{k(1-\bar{\varphi})}} f_{U,\bar{\varphi}}(U,\bar{\varphi})\,dU\,d\bar{\varphi}. \tag{10}$$

Substituting Eq. (8) into Eq. (10) and integrating, the expression in Eq. (10), that is the energy poverty indicator EP, simplifies to (see Appendix 6.2):

$$EP = \int_{\frac{k\bar{a}}{1+(k-1)\bar{a}}}^{1} \frac{\gamma\left(\alpha_1+\alpha_2, \frac{\beta\bar{m}}{k(1-\bar{\varphi})}\right)}{\Gamma(\alpha_1)\Gamma(\alpha_2)}\bar{\varphi}^{\alpha_1-1}(1-\bar{\varphi})^{\alpha_2-1}\,d\bar{\varphi}. \tag{11}$$

Here, $\gamma(\alpha_1+\alpha_2, \frac{\beta\bar{m}}{k(1-\bar{\varphi})})$ denotes the lower incomplete Gamma function, which corresponds to the cumulative distribution function of a

Gamma random variable with shape $\alpha_1 + \alpha_2$ and rate 1 , evaluated at $x = \frac{\beta \bar{m}}{k(1-\bar{\varphi})}$. We observe that the lower incomplete Gamma function with parameter s and upper limit x is defined as:

$$\gamma(s,x) = \int_0^x t^{s-1} e^{-t}\, dt.$$

Notably, α_1, α_2 and β in Eq. (11) are estimated via maximum likelihood at the unit level, while the endogenous threshold $\bar{a}$ is also unit-specific but obtained through the iterative procedure developed by [25].

2.4. Rethinking energy poverty threshold

The method to determine the thresholds adapts the stratification algorithm developed by [25], originally applied to income distributions, to endogenously determine the threshold $\bar{a}$ in Eq. (6). Here, it is applied to the ratio $\frac{Y}{X_1+Y} \in (0,+\infty)$ since the EP indicator in Eq. (6) can be rewritten as follows:

$$EP = P\left(\frac{Y}{X+Y} < 1-\bar{a},\ Y < \bar{m}\right)$$
$$= P\left(\frac{Y}{X_1+Y} < 1-\bar{a},\ Y < \bar{m} \,\middle|\, X_1 > 0\right). \tag{12}$$

Specifically, the adaptive algorithm identifies sub-groups of households at each iteration by approximating the distribution of variable $\frac{Y}{X_1+Y}$ using a sequence of two-component log-normal mixtures. When a significant change in the distribution is detected, a change point is identified. The procedure continues until no further change points are observed. These change points, derived from the structure of the data, are used as thresholds in place of a fixed benchmark.

We denote n the number of units and ψ_i the value of the variable $\frac{Y}{X_1+Y}$ for each unit $i = 1,\dots,n$. In the initial step, the procedure detects the first change point a^1, which partitions the full set of ratios $\mathcal{S}_n = \{\psi_1,\psi_2,\dots,\psi_n\}$ into two non-overlapping subsets: a left group $\mathcal{K}_1 = \{\psi \in \mathcal{S}_n \mid \psi \in (0,a^1]\}$, containing all ratios less than or equal to the threshold a^1, and a right group $\mathcal{R}_1 = \mathcal{S}_n \setminus \mathcal{K}_1$, which includes ratios greater than a^1.

In the second step, the algorithm focuses on $\mathcal{R}_1$, the subset obtained from the previous iteration. Specifically, it determines a new threshold $a^2 > a^1$, dividing $\mathcal{R}_1$ into two disjoint parts: the left group $\mathcal{K}_2 = \{\psi \in \mathcal{S}_n \mid \psi \in (a^1,a^2]\}$, and the right group $\mathcal{R}_2 = \{\psi \in \mathcal{S}_n \mid \psi \in (a^2,+\infty)\}$.

This process continues in the kth iteration, where the algorithm identifies a threshold a^k and splits the current subset $\mathcal{R}_{k-1}$ into two groups: $\mathcal{K}_k = \{\psi \in \mathcal{S}_n \mid \psi \in (a^{k-1},a^k]\}$, and $\mathcal{R}_k = \{\psi \in \mathcal{S}_n \mid \psi \in (a^k,+\infty)\}$. The change point a^k of the mixture is determined using the following rule[1]:

$$a^k = \min\{\psi \in \mathcal{R}_{k-1} \ \wedge\ \pi_k f_{1,k}(\psi - a^{k-1}) = (1-\pi_k) f_{2,k}(\psi - a^{k-1})\}, \tag{13}$$

where $f_{1,k}(x)$ and $f_{2,k}(x)$, $x \in \mathbb{R}_+$, are the log-normal densities of parameters $\mu_{1,k}$, $\mu_{2,k}$, $\sigma_{1,k}$, $\sigma_{2,k} \in \mathbb{R}$ associated with the two mixture components.

An explicit formula for the change points is

$$a^k = \exp\left\{\min\{\log(a^k_+), \log(a^k_-)\}\right\}, \tag{14}$$

where $\log(a^k_+)$, $\log(a^k_-)$ are given by

$$\log(a^k_\pm) = \frac{\sigma^2_{1,k}\sigma^2_{2,k}}{\sigma^2_{2,k} - \sigma^2_{1,k}} \left[\left(\frac{\mu_{1,k}}{\sigma^2_{1,k}} - \frac{\mu_{2,k}}{\sigma^2_{2,k}}\right) \pm \sqrt{\Delta_k}\right],$$

with Δ_k defined as

$$\Delta_k = \left(2\log\left(\frac{\sigma_{2,k}\pi_k}{\sigma_{1,k}(1-\pi_k)}\right) - \left(\frac{\mu_{1,k}}{\sigma_{1,k}}\right)^2 + \left(\frac{\mu_{2,k}}{\sigma_{2,k}}\right)^2\right) \frac{(\sigma^2_{2,k} - \sigma^2_{1,k})}{\sigma^2_{1,k}\sigma^2_{2,k}}$$
$$+ \left(\frac{\mu_{1,k}}{\sigma^2_{1,k}} - \frac{\mu_{2,k}}{\sigma^2_{2,k}}\right)^2.$$

In the kth iteration, the change point a^k serves as the boundary between the two groups $\mathcal{K}_k$ and $\mathcal{R}_k$, effectively splitting the sample into two subsets with different distributions. The procedure ends when no further a^k can be identified, i.e. when Eq. (13) has no solution.

The endogenous threshold $\bar{a}$ appearing in our energy poverty indicator is obtained by considering only the first iteration ($k = 1$) for each unit.

3. Energy poverty indicator across Italian regions

This study explores energy poverty among Italian households at the regional level, using data from the HBS conducted by the ISTAT between 2019 and 2023.[2] The HBS offers comprehensive insights into household spending habits across Italy, reflecting changes in both the amount and structure of expenditures. It includes essential social, economic, and geographic indicators, enabling an in-depth examination of household behavior. The survey is a key tool for generating official statistics on both relative and absolute poverty, as well as for compiling inflation measures based on spending categories. By integrating consumption patterns with socio-demographic information, the HBS provides a critical foundation for analyzing economic conditions and guiding policymaking and market decisions.

Here, we present results for the EP indicator obtained as the joint probability defined in Eq. (6), separately for the five years considered. First, following Eq. (14), we compute the endogenous thresholds at the regional level. Then, we illustrate the values of the headcount ratio by highlighting differences between pre and post COVID-19 (Table 1) and its geographical distribution across regions (Fig. 1).

Table 1 reports the proportion of households experiencing energy poverty, as measured by the EP indicator defined in Eq. (6). The endogenous thresholds $\bar{a}$ are shown in parentheses, while the corresponding median values $\bar{m}$ (in thousands of euros) are 2043.53, 1976.97, 2061.51, 2206.81, and 2263.53 for the years 2019 to 2023, respectively. A clear regional pattern emerges: Southern Italian regions generally report higher rates of energy poverty compared to the Central and Northern regions, as well as the national average. However, there are a few notable exceptions to this trend, which are further detailed in Fig. 2. On the whole, the incidence of energy poverty has worsened over time, with the national average increasing from 12.60% in 2019 to 13.80% in 2023. This upward trend points to deepening regional inequalities, which were already present before the COVID-19 pandemic and have since been exacerbated in its aftermath.

These findings align with the most recent estimates provided by the Italian Energy Poverty Observatory (OIPE) which show a similar increase in the share of energy-poor households — rising from 8.5% in 2019 to 9.0% in 2023 [26]. For completeness, Table 11 in Appendix 6.3 reports the share of households experiencing energy poverty according to OIPE estimates at the regional level for the available period 2021–2023. While the gap in absolute values between OIPE estimates and those derived here reflects the use of different measurement approaches, both analyses consistently point to a growing incidence of energy poverty over the period under consideration and concur in highlighting a marked divide between Northern and Southern regions.

The year 2022 is particularly noteworthy due to the sharp increase in energy prices triggered by the Russia–Ukraine conflict and the Italian government's countermeasure: the substantial expansion of the Bonus Sociale per l'Energia Elettrica e il Gas. The bonus was extended in scope and value throughout 2022, temporarily cushioning households from the full burden of rising energy bills. The effect of this policy is

[1] Hereafter we assume $a^0 = 0$.

[2] HBS data is available at the following link https://www.istat.it/en/microdata/household-budget-survey.

Table 1
Values of the EP indicator according to Eq. (6) for each region by year, with endogenous thresholds $\bar{a}$ shown in round brackets. Values are expressed as percentages.

Region	2019	2020	2021	2022	2023
Piedmont	11.90	11.50	13.00	11.40	10.90
	(11.709)	(13.383)	(12.048)	(15.658)	(14.815)
Aosta Valley	12.30	11.40	12.00	14.20	11.20
	(10.588)	(13.535)	(10.588)	(12.262)	(9.814)
Lombardy	9.90	11.00	10.60	11.80	12.50
	(8.016)	(9.230)	(8.622)	(8.701)	(10.006)
Trentino-South Tyrol	10.00	7.80	8.80	9.70	10.40
	(7.010)	(9.416)	(8.033)	(11.164)	(10.684)
Veneto	12.00	11.80	14.80	12.90	9.70
	(12.189)	(9.438)	(8.271)	(11.154)	(11.460)
Friuli-Venezia Giulia	9.10	12.40	12.70	13.00	12.00
	(12.218)	(8.036)	(8.640)	(9.302)	(8.027)
Liguria	15.20	13.40	14.50	14.30	13.50
	(6.261)	(7.789)	(7.726)	(6.934)	(7.481)
Emilia-Romagna	9.70	11.30	12.20	11.80	13.20
	(7.778)	(9.102)	(8.606)	(11.946)	(8.506)
Tuscany	9.30	12.20	12.30	11.80	10.70
	(7.985)	(8.245)	(8.193)	(9.157)	(9.471)
Umbria	14.40	15.70	13.60	15.40	11.20
	(8.498)	(9.238)	(9.992)	(10.322)	(10.436)
Marche	13.50	13.30	11.50	12.50	11.50
	(9.306)	(7.989)	(9.753)	(11.914)	(12.621)
Lazio	10.70	9.60	10.50	9.80	9.80
	(9.166)	(9.768)	(9.254)	(10.263)	(9.987)
Abruzzo	15.40	14.40	15.00	14.40	14.90
	(10.422)	(11.102)	(11.105)	(13.569)	(10.569)
Molise	12.00	19.60	20.30	9.70	20.10
	(12.677)	(11.180)	(9.774)	(22.333)	(11.491)
Campania	16.50	17.90	17.40	18.60	19.20
	(8.922)	(8.265)	(8.948)	(10.164)	(8.946)
Apulia	18.00	18.30	17.70	21.20	24.60
	(10.169)	(10.886)	(12.446)	(11.562)	(9.009)
Basilicata	14.60	16.30	22.80	18.10	22.50
	(12.811)	(15.381)	(9.520)	(13.883)	(7.556)
Calabria	19.40	20.90	16.50	18.30	20.20
	(9.825)	(9.908)	(12.067)	(15.731)	(11.515)
Sicily	17.90	15.70	12.60	15.80	14.90
	(10.354)	(9.994)	(10.960)	(11.358)	(10.488)
Sardinia	8.00	22.30	19.60	17.00	18.30
	(13.458)	(7.197)	(9.347)	(10.889)	(9.288)
Italy	**12.60**	**13.40**	**13.40**	**13.70**	**13.80**

visible in Table 1. At the national level, the EP rate increased only modestly from 13.40% in 2021 to 13.70% in 2022, a much smaller jump than might have been expected given the severity of the energy price shock. Similar conclusions are reached by [27], who find, through microsimulation, that fiscal mitigation measures successfully reduced both inequality and energy poverty incidence over the 2021–2023 period. Importantly, the endogenous threshold for 2022 tends to be higher in several regions – reflecting that the reference distribution of energy expenditure shifted upward – which means that the model is implicitly detecting that even households spending more on energy were partially shielded by transfers, compressing the tail. The OIPE data support this interpretation: the rate actually fell from 8.5% in 2021 to 7.7% in 2022 (Table 11), the lowest value in the observed window, consistent with the hypothesis that direct household transfers temporarily reduced measured energy poverty incidence even amid record energy prices.

Moreover, two regions stand out for their marked volatility: Sardegna and Molise. In both cases, the small regional HBS sample size makes the estimated expenditure distribution – and hence the endogenous threshold – particularly sensitive to year-specific sampling variation, which drives large swings in the EP rate across years.

A visual overview of these disparities is provided in Fig. 1, which maps the geographical distribution of the energy poverty indicator across Italian regions for the years 2019 to 2023. The map employs a red color scale, where darker shades indicate higher levels of energy poverty. This visualization reinforces the pronounced divide between the Northern and Southern parts of Italy, underscoring the urgency of implementing regionally tailored policy interventions.

Table 2
Gini index values based on the EP indicator in Eq. (6), calculated using the fixed Boardman threshold ($\bar{a} = 0.1$) and the endogenous threshold ($\bar{a} = a^1$), respectively.

	2019	2020	2021	2022	2023
EP ($\bar{a} = 0.1$)	0.158	0.15	0.126	0.139	0.173
EP ($\bar{a} = a^1$)	0.194	0.164	0.181	0.189	0.16

The development and application of a localized, area-level indicator – as illustrated in this analysis – represents a foundational step toward establishing a comprehensive national dashboard on energy poverty. Such a tool could play a crucial role in informing and guiding targeted strategies to alleviate energy poverty, particularly among the most vulnerable populations, as emphasized in recent policy discussions [21].

For the sake of analytical robustness, we compute the Gini inequality index for the poverty index (EP) in Eq. (6) using both endogenous and the fixed Boardman thresholds (i.e., 10%). By varying spending thresholds at regional level, indicator captures inequality more effectively, showing higher Gini index values (see Table 2) for the years 2019–2023.

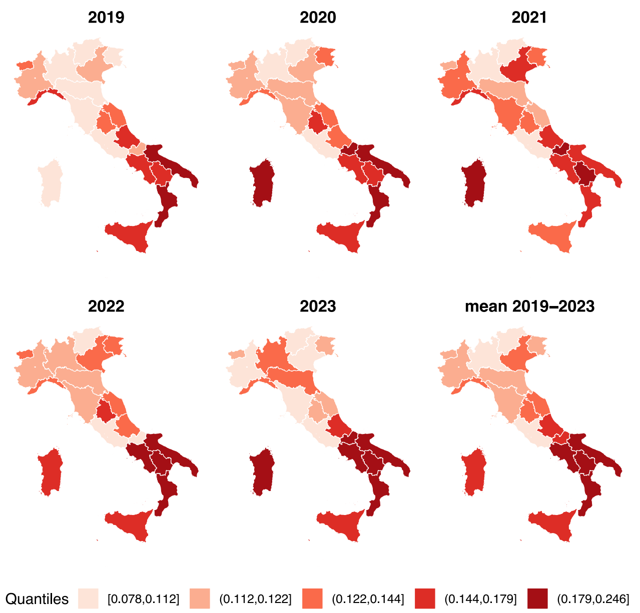

Fig. 1. Spatial distribution of households in energy poverty for the years 2019–2023. Darker colors indicate higher level of energy poverty.

4. Factors affecting regional energy poverty

This section investigates the determinants of regional energy poverty in Italy using a comprehensive panel dataset spanning the period 2019–2022. Two preliminary clarifications are in order. First, while the construction of the energy poverty indicator draws on the full five-year window through 2023, the econometric regressions are necessarily constrained to the period 2019–2022, owing to the unavailability of regional-level data for several key explanatory variables in the most recent year. Second, the unit of observation varies depending on the analytical context: in the microdata analyses, which draw on household-level survey records, it refers to the individual household, whereas in the following aggregate econometric framework it refers to the region. On this basis, the empirical strategy aims to identify the key socioeconomic, demographic, and housing factors driving energy poverty patterns across Italian regions. To this end, we employ multiple econometric specifications – fixed effects, dynamic panel, and spatial autoregressive models – designed to capture both temporal dynamics and spatial interdependencies. This multi-method approach seeks to provide robust evidence on the mechanisms underlying regional energy vulnerability, offering essential insights for the design of territorially differentiated policy interventions.

4.1. Regional contextual data

This section presents the regional panel dataset constructed for the period 2019–2022, encompassing key socioeconomic and energy-related variables across Italian regions. The analysis employs a comprehensive set of regressors selected to capture the multidimensional nature of energy poverty, building upon the theoretical framework and regional energy poverty indicators established in previous sections. Following the methodological approach of Bertoldi and Mosconi [28], we implement panel econometric techniques to examine the determinants and spatial patterns of the EP indicator at the regional level.

The selection of explanatory variables is grounded in established literature on energy poverty and reflects the complex interplay between household characteristics, energy market conditions, and housing quality. Our empirical framework incorporates variables that capture both direct energy-related factors and broader socioeconomic determinants that influence household energy vulnerability (see Tables 3 and 4). Regional per capita residential electricity consumption (ELC, measured in kWh) serves as a fundamental indicator of energy usage patterns, consistent with recent studies examining the relationship between electricity consumption and energy hardship [29,30]. This variable captures regional variations in energy demand while accounting for demographic differences across territories.

The inclusion of photovoltaic production systems (PVS, measured in millions of kWh) reflects Italy's commitment to renewable energy transition and the role of distributed generation in alleviating energy costs. Recent empirical evidence demonstrates that residential solar installations, particularly those benefiting from Italy's tax exemption schemes, contribute significantly to reducing household energy expenditure and promoting energy independence [31,32]. The adoption of

Fig. 2. Distribution of households in energy poverty for the years 2019–2023. Red (light blue) bars indicate regions where energy poverty is higher (lower) than the national average, represented by the red dashed line.

Table 3
Variables description.

ID	Description	Unit of measurement	Source
ELC	Per capita energy consumption	kWh	Italian Regulatory Authority for Energy, Networks and Environment
PVS	Photovoltaic production	Millions of kWh	
INC	Per capita declared income	Thousand euros	Italian Ministry of Finance
PRI	Energy prices index	Percentage (%)	Italian National Statistical Institute
HDR	Households declaring high housing deprivations	Percentage (%)	
OVR	Overcrowding rates	Percentage (%)	
AGE	Average regional ages	Numeric	
EDU	Regional graduates	Percentage (%)	

Table 4
Descriptive statistics.

Variable	Mean	Sd	Min	Max	Median
ELC	3292.21	2815.04	158.42	11 355.75	2156.78
PVS	0.1	0.06	0	0.23	0.09
INC	21.24	3.13	16.17	26.41	22.05
PRI	103.73	1.22	101.55	105.72	103.97
HDR	10.79	2.55	7	17.55	10.8
OVR	2.52	0.2	2.17	3.15	2.5
AGE	46.31	1.44	43.15	49.2	46.51
EDU	0.15	0.02	0.11	0.21	0.15

self-generation technologies represents a crucial pathway for households to mitigate energy poverty, particularly in regions with favorable climatic conditions and supportive policy frameworks.

The national energy price index for blue and white collar households (PRI) captures the impact of energy cost fluctuations on different socioeconomic groups, recognizing that price volatility disproportionately affects vulnerable populations [33]. Energy prices constitute a critical determinant of energy affordability, with sudden increases potentially pushing borderline households into energy poverty. Regional per capita declared income (INC, measured in thousands of euros) controls for economic disparities across territories, acknowledging income as a primary driver of energy transitions and household energy security [34]. Lower income levels have been consistently associated with increased reliance on inefficient energy sources and reduced capacity to invest in energy-efficient technologies [35].

The percentage of households reporting severe housing deprivation (HDR) functions as a proxy for the inability to maintain adequate housing conditions, including proper heating and cooling [36]. This indicator captures the intersection between housing quality and energy poverty, recognizing that substandard accommodation often correlates with energy inefficiency and higher vulnerability to energy hardship. Overcrowding rates (OVR) represent a critical housing dimension linked to energy poverty through multiple pathways. Financial constraints that force households into overcrowded accommodations typically coincide with limited resources for adequate energy services [37]. These households often occupy older buildings with poor thermal performance, creating a scenario where increased occupancy generates higher energy demands while inefficient building characteristics exacerbate energy waste and costs. This dynamic establishes a reinforcing cycle where economically vulnerable populations experience both spatial deprivation and energy hardship simultaneously.

Family demographic profiles significantly influence energy poverty risk through their effects on income generation capacity and energy consumption requirements. This analysis focuses on two pivotal demographic indicators: regional average age (AGE) and educational attainment proxied by the percentage of regional graduates (EDU). Age represents a crucial vulnerability factor, as elderly populations typically face fixed pension incomes while experiencing elevated heating and cooling needs due to health considerations and extended home occupancy. In addition, older households often reside in legacy housing stock characterized by poor energy efficiency, compounding their energy cost burden. Educational attainment, measured through regional graduation rates, serves as an indicator of human capital endowment and economic opportunity access. Higher educational levels correlate with improved employment prospects, enhanced earning potential, and greater awareness of energy efficiency programs and support mechanisms [38]. Educated populations demonstrate superior capacity to navigate complex energy markets and policy instruments, potentially reducing their exposure to energy poverty.

4.2. Empirical models

To address the several econometric issues arising when estimating the impact of regional contextual factors and unobserved heterogeneity on energy poverty, we use various empirical models and estimators. We first estimate the following (static) panel model:

$$EP_{i,t} = \mu_i + \sum_{z=1}^{k} \theta_z x_{i,t}^z + \delta_t + \upsilon_{i,t} \tag{15}$$

with $i = 1, 2, \dots, 20$, $z = 1, 2, \dots, 8$ and $t = 1, 2, \dots, 5$.

$EP_{i,t}$ is the energy poverty indicator of region i computed according to Eq. (6); δ_t are time fixed effects; μ_i denotes region-specific fixed effects; and $\upsilon_{i,t}$ is the idiosyncratic error term. The covariates $x_{i,t}^z$, $z = 1, \dots, 8$, correspond to the regional variables described in Tables 3 and 4: per capita residential electricity consumption ($ELC_{i,t}$), photovoltaic production ($PVS_{i,t}$), per capita declared income ($INC_{i,t}$), national energy price index ($PRI_{i,t}$), housing deprivation rate ($HDR_{i,t}$), overcrowding rate ($OVR_{i,t}$), average regional age ($AGE_{i,t}$), and share of regional graduates ($EDU_{i,t}$). The corresponding coefficients θ_z, $z = 1, \dots, 8$, measure the marginal effect of each covariate on the energy poverty indicator.

We first estimate Eq. (15) by using a fixed effect estimator. In this case, it is assumed that the idiosyncratic error $\upsilon_{i,t}$ is independent of the regressors and the individual component (time-invariant unit). The results of the model estimates (15) are reported in Table 5.

The estimates of the coefficients are mostly not significant even though of time and cross-sectional problems in the residuals do not arise, as revealed by the results of the Breusch–Godfrey and Pesaran CD tests, that led us to accept the null hypothesis of time and cross-sectional independence of residuals.

To control for endogeneity problems, we add a time-lagged-dependent variable and estimate a set of dynamic panel specifications with the generalized method of moments (GMM) estimator. Our dynamic model is the following:

$$EP_{i,t} = \mu_i + \lambda EP_{i,t-1} + \sum_{z=1}^{k} \theta_z x_{i,t}^z + \upsilon_{i,t} \tag{16}$$

where λ is the autoregressive coefficient capturing temporal persistence in energy poverty, $EP_{i,t-1}$ is the one-period lag of the dependent

Table 5
Fixed effect specification results. Estimated coefficients $\hat{\theta}_z$ correspond to the covariates defined after Eq. (15).

Parameter	Variable	Estimate	Std. error	p-value	
$\hat{\theta}_1$	ELC	0.001	0.000	0.147	
$\hat{\theta}_2$	PVS	0.024	0.068	0.728	
$\hat{\theta}_3$	INC	−0.006	0.002	0.004	**
$\hat{\theta}_4$	PRI	0.000	0.002	0.930	
$\hat{\theta}_5$	HDR	0.002	0.001	0.214	
$\hat{\theta}_6$	OVR	0.022	0.019	0.253	
$\hat{\theta}_7$	AGE	0.007	0.003	0.018	*
$\hat{\theta}_8$	EDU	−0.369	0.207	0.079	.
	Diagnostic		**Statistic**	**p-value**	
	Serial correlation		3.513	0.476	
	Pesaran CD		0.580	0.562	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

Table 6
Dynamic specification results. $\hat{\lambda}$ is the autoregressive coefficient from Eq. (16); $\hat{\theta}_z$ are defined after Eq. (15).

Parameter	Variable	Estimate	Std. error	p-value	
$\hat{\lambda}$	$EP_{i,t-1}$	−0.592	0.133	0.000	***
$\hat{\theta}_1$	ELC	0.000	0.000	0.032	*
$\hat{\theta}_2$	PVS	1.093	0.397	0.006	**
$\hat{\theta}_3$	INC	0.031	0.013	0.012	*
$\hat{\theta}_4$	PRI	−0.002	0.005	0.700	
$\hat{\theta}_5$	HDR	0.000	0.001	0.941	
$\hat{\theta}_6$	OVR	−0.045	0.039	0.249	
$\hat{\theta}_7$	AGE	0.034	0.029	0.237	
$\hat{\theta}_8$	EDU	−2.419	1.632	0.138	
	Diagnostic		**Statistic**	**p-value**	
	Sargan test		5.311	0.150	
	Autocorrelation test		−1.165	0.244	
	Pesaran CD		−0.821	0.412	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

variable, and all other terms are defined as in Eq. (15). Results of the dynamic estimations are reported in Table 6. In this specification, we instrumented our measurement of energy poverty with its lags.

The dynamic model introduces an element of time persistence that does not present endogeneity problems (the absence of the serial correlation in disturbances is not rejected). Consequently, the GMM estimator proves to be consistent. However, many coefficients continue to be insignificant.

Building upon the econometric evidence from our fixed effects and dynamic panel specifications, we extend our investigation to examine spatial interdependencies in energy poverty distribution across Italian regions. The geographical pattern exhibited in Fig. 1 reveals pronounced spatial clustering of energy poverty levels, with clear regional concentration particularly evident in the Southern regions, warranting formal investigation of spatial autocorrelation mechanisms.

Our computation of Moran's I statistic for the regional energy poverty distribution yields compelling evidence of spatial dependence ($I = 0.641$, p-value < 0.001). This highly significant positive spatial autocorrelation confirms that regional energy poverty exhibits systematic clustering, where high-poverty regions are contiguous to similarly affected territories. The substantial magnitude of Moran's I indicates strong spatial correlation that cannot be adequately captured by conventional aspatial panel estimators.

These findings necessitate the implementation of spatial econometric specifications to avoid model misspecification and parameter bias. The presence of significant spatial autocorrelation violates the independence assumption underlying standard panel models, potentially leading to inconsistent estimates and invalid statistical inference.

Table 7
SAR specification results. $\hat{\lambda}$ is the spatial autoregressive coefficient from Eq. (17); $\hat{\theta}_z$ are defined after Eq. (15).

Parameter	Variable	Estimate	Std. error	p-value	
$\hat{\lambda}$	Spatial lag ($W \cdot EP$)	0.372	0.113	0.000	***
$\hat{\theta}_1$	ELC	0.001	0.001	0.018	**
$\hat{\theta}_2$	PVS	0.069	0.058	0.231	
$\hat{\theta}_3$	INC	−0.004	0.002	0.017	**
$\hat{\theta}_4$	PRI	−0.003	0.002	0.232	
$\hat{\theta}_5$	HDR	0.002	0.001	0.090	.
$\hat{\theta}_6$	OVR	0.032	0.016	0.050	*
$\hat{\theta}_7$	AGE	0.007	0.002	0.001	**
$\hat{\theta}_8$	EDU	−0.550	0.177	0.002	**
	Diagnostic		**Statistic**	**p-value**	
	Serial correlation		−2.452	0.117	
	Pesaran CD		−0.431	0.666	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

Consequently, we employ spatial methodology to explicitly model both direct determinant effects and spatial spillover mechanisms operating through the regional connectivity matrix.

Hence, to investigate spatial interactions across regions and over time we use a spatial lag model proposed by [39].

The extent of cross-sectional correlation is measured using a "spatial matrix" W, a non-negative $n \times n$ matrix (where n is the number of regions) of known constants. W describes the spatial arrangement of the units in the sample and its non-zero element w_{ij} specifies the strength of the relationship between unit i and unit j. Moreover, w_{ij} indicates whether two regions can be considered as neighbors. The diagonal elements w_{ii} are all set equal to 0 to exclude self-neighbors by convention. Such a weighted spatial matrix is not symmetric, since it is generally used in a row-standardized form.The choice of a contiguity-based spatial weight matrix is motivated by the administrative and institutional nature of the phenomena under investigation. Energy poverty in Italy is strongly shaped by regional policy frameworks, energy infrastructure networks, and housing regulations that operate along administrative boundaries and tend to generate spillovers primarily among contiguous territories. In this context, contiguity weights more faithfully capture the relevant channels of spatial interaction than distance-based alternatives such as k-nearest neighbors, which may link regions that share little institutional or infrastructural commonality despite geographical proximity — a concern especially relevant given Italy's pronounced north-south heterogeneity. Moreover, Sicily and Sardinia are linked to each other in the spatial weight matrix to prevent their isolation from the network, which would otherwise bias spatial dependence measures.

We hence estimate the following spatial autoregressive (SAR) model:

$$EP_{i,t} = \mu_i + \lambda \sum_{i \neq j} w_{ij,t} EP_{j,t} + \sum_{z=1}^{k} \theta_z x_{i,t}^z + \delta_t + v_{i,t} \tag{17}$$

where λ is the spatial autoregressive coefficient measuring spillover effects across neighboring regions, $\sum_{i \neq j} w_{ij,t} EP_{j,t}$ is the spatially weighted average of energy poverty in neighboring regions (the spatial lag), and all remaining terms retain the same interpretation as in Eq. (15). Region i's dependent variable thus depends on that of its neighbors, and the strength of these spatial interactions is captured by λ.

The results of the maximum likelihood estimates are reported in Table 7. The positive and significant spatial lag coefficient confirms our hypothesis of spill-over effects.

As noted by [40], coefficients in spatial lag models do not correspond to marginal effects due to the feedback structure embedded in the spatial multiplier $(I_n - \lambda W)^{-1}$. Following [41], we decompose the estimated coefficients into direct, indirect, and total effects (Table 8).

Table 8
Direct, indirect, and total impact estimates from the SAR model.

Parameter	Variable	Direct	Indirect	Total
$\hat{\theta}_1$	ELC	0.000003	−0.000001	0.000002
$\hat{\theta}_2$	PVS	0.070	−0.021	0.050
$\hat{\theta}_3$	INC	−0.004	0.001	−0.003
$\hat{\theta}_4$	PRI	−0.003	0.001	−0.002
$\hat{\theta}_5$	HDR	0.002	−0.001	0.001
$\hat{\theta}_6$	OVR	0.032	−0.010	0.023
$\hat{\theta}_7$	AGE	0.008	−0.002	0.005
$\hat{\theta}_8$	EDU	−0.559	0.166	−0.393

Table 9
SDM results. $\hat{\lambda}$ is the spatial autoregressive coefficient from Eq. (18); $\hat{\theta}_z$ are the direct covariate effects; $\hat{\gamma}_z$ are the spatially lagged covariate effects.

Parameter	Variable	Estimate	Std. error	p-value	
$\hat{\lambda}$	Spatial lag ($W \cdot EP$)	−0.493	0.115	0.000	***
Direct effects ($\hat{\theta}_z$)					
$\hat{\theta}_1$	ELC	0.000	0.000	0.128	
$\hat{\theta}_2$	PVS	0.083	0.062	0.178	
$\hat{\theta}_3$	INC	−0.005	0.003	0.187	
$\hat{\theta}_4$	PRI	0.000	0.003	0.958	
$\hat{\theta}_5$	HDR	0.002	0.001	0.076	.
$\hat{\theta}_6$	OVR	0.038	0.020	0.055	.
$\hat{\theta}_7$	AGE	0.009	0.004	0.009	**
$\hat{\theta}_8$	EDU	−0.232	0.327	0.477	
Spatial lag effects ($\hat{\gamma}_z$)					
$\hat{\gamma}_1$	$W \cdot$ ELC	−0.000	0.000	0.457	
$\hat{\gamma}_2$	$W \cdot$ PVS	−0.372	0.187	0.047	*
$\hat{\gamma}_3$	$W \cdot$ INC	−0.002	0.005	0.646	
$\hat{\gamma}_4$	$W \cdot$ PRI	−0.009	0.005	0.055	.
$\hat{\gamma}_5$	$W \cdot$ HDR	0.001	0.002	0.774	
$\hat{\gamma}_6$	$W \cdot$ OVR	−0.033	0.044	0.445	
$\hat{\gamma}_7$	$W \cdot$ AGE	−0.002	0.005	0.734	
$\hat{\gamma}_8$	$W \cdot$ EDU	−0.633	0.667	0.343	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

The direct effect captures the impact of a change in a covariate within the same region, while the indirect effect measures the spillover on neighboring regions. The total effect is the sum of the two. The decomposition confirms that income and education exert the largest total effects on energy poverty, while the indirect (spillover) component, though consistently signed, remains modest in magnitude relative to the direct effect.

Coefficients are mostly significant. Specifically, we fail to reject the null hypotheses of the Baltagi, Song, Jung, and Koh conditional LM test and the Pesaran CD test, respectively, confirming the absence of time and spatial dependence in the model's residuals.

As noted by [40], coefficients in spatial lag models do not correspond to marginal effects due to the feedback structure embedded in the spatial multiplier $(I_n - \lambda W)^{-1}$. Following [41], we decompose the estimated coefficients into direct, indirect, and total effects (Table 8). The direct effect captures the impact of a change in a covariate within the same region, while the indirect effect measures the spillover on neighboring regions. The total effect is the sum of the two. The decomposition confirms that income and education exert the largest total effects on energy poverty, while the indirect (spillover) component, though consistently signed, remains modest in magnitude relative to the direct effect, reflecting a partial spatial attenuation of the overall impact.

We also considered the Spatial Durbin Model (SDM), which extends the SAR specification by including spatial lags of the explanatory variables (WX), thereby allowing for spatial spillovers in both the dependent and independent variables. The SDM is specified as:

$$EP_{i,t} = \mu_i + \lambda \sum_{i \neq j} w_{ij,t} EP_{j,t} + \sum_{z=1}^{k} \theta_z x_{i,t}^z + \sum_{z=1}^{k} \gamma_z \sum_{i \neq j} w_{ij,t} x_{j,t}^z + \delta_t + v_{i,t} \quad (18)$$

Table 10
Moran's I test for spatial autocorrelation of SAR residuals by year.

Year	Moran's I	Expectation	Std. deviate	p-value	
2019	0.230	−0.053	1.849	0.032	*
2020	−0.251	−0.053	−1.269	0.898	
2021	0.063	−0.053	0.768	0.221	
2022	0.036	−0.053	0.554	0.290	

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1.

where the additional coefficients γ_z capture the indirect spatial effects of the neighboring regions' characteristics on local energy poverty.

The estimation results of the SDM are reported in Table 9. While the spatial autoregressive coefficient $\hat{\lambda}$ remains significant, the spatially lagged regressors are largely insignificant, and a Likelihood Ratio test for $H_0 : \gamma_1 = \cdots = \gamma_8 = 0$ yields $LR = 11.333$ ($df = 8$, p-value $= 0.184$), supporting the SAR as the preferred specification. From a substantive standpoint, the insignificance of the WX terms suggests that regional energy poverty is primarily driven by local socioeconomic conditions, while spatial dependence operates through the outcome variable itself – i.e., through contagion or common unobserved shocks affecting neighboring regions – rather than through cross-regional spillovers of specific covariates.

We assess whether the SAR model adequately captures spatial dependence by computing Moran's I statistic on the model residuals for each year (Table 10). The null hypothesis of no spatial autocorrelation in the residuals is not rejected for three out of four years (2020–2022), while the 2019 residuals exhibit borderline significance at the 5% level. Overall, these results confirm that spatial autocorrelation has been adequately addressed by the SAR specification.

4.3. Discussion of results

Although all econometric specifications demonstrate robustness and pass relevant diagnostic tests, the spatial autoregressive (SAR) model yields the most comprehensive and statistically significant results. Given the superior performance of spatial specification in capturing both regional heterogeneity and cross-sectional spillover effects, we focus our discussion on the SAR estimates presented in Table 7.

The spatial lag coefficient (λ) shows strong evidence of significant spillover effects of energy poverty across Italian regions. Aligning with recent results [42], this suggests that energy poverty is increasingly spatially concentrated, possibly due to contagion mechanisms or common unobserved factors that disregard administrative borders.

Energy poverty is also found to be spatially clustered and closely linked to socioeconomic determinants such as household income, educational attainment, and nutrition levels. These results underscore the necessity of developing geographically-targeted and socioeconomically-aware policy strategies [43].

Among the energy-related variables, per capita electricity consumption (ELC) exhibits a positive and significant coefficient, indicating that higher regional electricity consumption is associated with increased energy poverty levels. This counterintuitive result may reflect the presence of inefficient energy usage patterns or inadequate heating and cooling systems that require excessive energy input to maintain basic comfort levels [44]. Alternatively, this relationship could capture regions where high consumption coincides with poor energy affordability [45], suggesting that consumption levels alone do not guarantee energy security. Photovoltaic production (PVS) shows no significant impact on regional energy poverty, which may indicate that the benefits of distributed solar generation have not yet reached sufficient scale or penetration to affect aggregate regional indicators.

The income variable (INC) demonstrates a negative and significant relationship with energy poverty confirming the fundamental role of economic capacity in determining energy vulnerability [46]. This result aligns with theoretical expectations that higher income levels provide households with greater resources to afford adequate energy services and invest in energy-efficient technologies. The magnitude suggests that each additional thousand euros of per capita income is associated with a measurable reduction in regional energy poverty levels.

Housing conditions show mixed but important effects. The overcrowding rate (OVR) exhibits a positive and significant coefficient, supporting our theoretical framework that spatial constraints and financial limitations create reinforcing cycles of deprivation. Households living in overcrowded conditions are particularly vulnerable to energy poverty and overcrowded housing typically indicates both economic stress and suboptimal living conditions that exacerbate energy inefficiency [37]. The housing deprivation indicator (HDR) shows marginal significance suggesting a weaker but potentially relevant relationship between general housing quality and energy poverty.

Demographic characteristics reveal significant patterns. Regional average age (AGE) demonstrates a positive and significant effect confirming that areas with older populations face elevated energy poverty risks [47]. This relationship likely reflects the combination of fixed pension incomes, higher heating requirements, and residence in older, less energy-efficient housing stock characteristic of elderly households. Educational attainment (EDU) shows a strong negative, indicating that regions with higher graduation rates experience substantially lower energy poverty levels. This finding, in line with some recent studies [48], supports the human capital hypothesis, where education facilitates access to better employment opportunities, higher incomes, and greater awareness of energy efficiency programs and support mechanisms.

The energy price index (PRI) lacks statistical significance, which may reflect the national nature of this variable that provides insufficient regional variation for identification in our model. This result suggests that local and regional factors may be more influential than national price movements in determining energy poverty patterns across Italian regions.

5. Conclusions

This study aimed to propose an alternative tool for measuring energy poverty using an innovative methodological approach that combines data-based threshold identification. The indicators obtained were then used in a spatial analysis of the regional determinants and endogenous factors that can cause the phenomenon. Our results reveal that energy poverty in Italy has significant spatial concentration with effects that transcend administrative boundaries—a pattern that conventional analyses often overlook. Our empirical results show that energy poverty is fundamentally determined by the interaction of structural factors operating at different scales. While income levels and housing quality emerge as primary determinants, the significant spatial lag coefficient indicates that local energy poverty cannot be analyzed in isolation. This spatial interdependence suggests that energy poverty in one region amplifies vulnerability in neighboring territories, creating clusters of disadvantage that require coordinated policy responses. In Italy, the problem has become particularly significant and topical, with energy poverty affecting around 9% of Italian households at the end of 2023, marking one of the highest levels since the phenomenon began to be measured. This escalation has had a disproportionate impact, especially on lower-income households—a trend that has forced many vulnerable families to compromise their access to basic energy services. Furthermore, current social protection mechanisms have significant coverage gaps, with government energy support programs reaching less than one-fifth of affected households in 2023, thus revealing fundamental weaknesses in current identification and distribution systems that require comprehensive methodological improvements [6]. These findings highlight the need to launch coordinated initiatives at the national level that nonetheless take into account local peculiarities, ensuring that the interconnected nature of energy poverty is recognized. Isolated interventions may prove insufficient when neighboring areas continue to experience high levels of poverty, as spatial contagion mechanisms can undermine localized efforts. The findings of this paper have other fundamental policy implications. First, the strong negative relationship between education levels and energy poverty highlights the importance of human capital development as a long-term strategy for reducing energy poverty. Regions with higher graduation rates show substantially lower levels of energy poverty, suggesting that investments in education can produce indirect but substantial benefits. Second, the role of housing conditions needs to be addressed with more effective tools. The evidence regarding the positive association between overcrowding rates and energy poverty points to the need for integrated housing policies. While policy interventions to improve housing quality are essential and necessary, they should be targeted at households that suffer most from energy inefficiency and, consequently, high consumption. Additionally, energy support mechanisms should take greater account of demographic patterns. As our analysis reveals, greater vulnerability is found in regions with older populations, which face both fixed incomes and potentially higher heating needs due to health considerations. In this context, our data-driven methodology offers a more precise targeting tool for policymakers, effectively minimizing Type I errors (inefficient resource allocation due to misidentification of non-poor households as energy-poor) and Type II errors (exclusion of those in need, whereby truly energy-poor households fail to receive the support they require) in the identification of energy-poor households. This increased accuracy is essential for efficient resource allocation, particularly given fiscal constraints and the urgency of the energy transition. Moreover, the approach can be adapted to other national contexts, providing a replicable framework for evidence-based energy poverty assessment. Some limitations of this work must be acknowledged, however. First, our reliance on expenditure data rather than actual energy consumption could lead to an underestimation of poverty among households that consume less or do not consume at all for various reasons (for example, because their expenditure is entirely subsidized). Second, although the regional analysis reveals important spatial patterns, it could be further refined at the provincial level to understand the dynamics of energy poverty in contexts with more specific characteristics. These limitations will be the starting point for our future research agenda, which will focus on integrating data on household spending behavior with income data and on developing behavioral microsimulation models that can improve our understanding of the dynamics of energy poverty. By overcoming these strategic and operational challenges, we will pave the way for crafting more robust, fair, and long-term solutions to address energy poverty and improve household economic conditions, prioritizing support for groups disproportionately affected by energy affordability constraints.

CRediT authorship contribution statement

Alfonso Carfora: Writing – review & editing, Writing – original draft, Software, Methodology. **Gloria Polinesi:** Writing – review & editing, Writing – original draft, Software, Methodology. **Maria Cristina Recchioni:** Writing – review & editing, Writing – original draft, Software, Methodology. **Francesca Mariani:** Writing – review & editing, Writing – original draft, Software, Methodology. **Mariateresa Ciommi:** Writing – review & editing, Writing – original draft, Software, Methodology.

Appendix 6

6.1. Appendix A

In this appendix, we prove the following identity:

$$P\left(\frac{X}{X+Y} > \bar{a},\ Y < \bar{m}\right) = P\left(\bar{\varphi} > \frac{k\bar{a}}{1+(k-1)\bar{a}},\ U < \frac{\bar{m}}{k(1-\bar{\varphi})}\right). \tag{19}$$

According to Eqs. (2) and (4), we have :

$$X = \bar{\varphi}U, \tag{20}$$

$$\frac{Y}{k} = U - \bar{\varphi}U = (1-\bar{\varphi})U, \tag{21}$$

$$Y = k(U - X) = k(U - \bar{\varphi}U) = k(1-\bar{\varphi})U. \tag{22}$$

By substituting Eq. (22), the condition $Y < \bar{m}$ becomes:

$$k(1-\bar{\varphi})U < \bar{m}, \tag{23}$$

which implies:

$$U < \frac{\bar{m}}{k(1-\bar{\varphi})}. \tag{24}$$

Using Eqs. (20) and (22), we rewrite the ratio as:

$$\frac{X}{X+Y} = \frac{\bar{\varphi}U}{\bar{\varphi}U + k(1-\bar{\varphi})U} = \frac{\bar{\varphi}U}{[k(1-\bar{\varphi})+\bar{\varphi}]\,U} = \frac{\bar{\varphi}}{k(1-\bar{\varphi})+\bar{\varphi}}. \tag{25}$$

Thus, the inequality $\frac{X}{X+Y} > \bar{a}$ becomes:

$$\frac{\bar{\varphi}}{k(1-\bar{\varphi})+\bar{\varphi}} > \bar{a}. \tag{26}$$

Multiplying both sides by the denominator yields:

$$\bar{\varphi} > \bar{a}\,[k(1-\bar{\varphi})+\bar{\varphi}]. \tag{27}$$

Expanding and simplifying the right-hand side:

$$\bar{\varphi} > \bar{a}k(1-\bar{\varphi}) + \bar{a}\bar{\varphi}. \tag{28}$$

Bringing all terms involving $\bar{\varphi}$ to one side, we obtain:

$$\bar{\varphi} - \bar{a}\bar{\varphi} + \bar{a}k\bar{\varphi} > \bar{a}k, \quad \bar{\varphi}\,[1+(k-1)\bar{a}] > \bar{a}k, \tag{29}$$

which leads to the final condition:

$$\bar{\varphi} > \frac{\bar{a}k}{1+(k-1)\bar{a}}. \tag{30}$$

6.2. Appendix B

In this Appendix we prove the following identity:

$$P\left(\bar{\varphi} > \frac{k\bar{a}}{1+(k-1)\bar{a}},\ U < \frac{\bar{m}}{k(1-\bar{\varphi})}\right) = \int_{\frac{k\bar{a}}{1+(k-1)\bar{a}}}^{1} \frac{\Gamma(\alpha_1+\alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)}\bar{\varphi}^{\alpha_1-1}(1-\bar{\varphi})^{\alpha_2-1}\frac{\gamma\left(\alpha_1+\alpha_2, \frac{\beta\bar{m}}{k(1-\bar{\varphi})}\right)}{\Gamma(\alpha_1+\alpha_2)}\,d\bar{\varphi}. \tag{31}$$

We assume that the random variables X and $\frac{Y}{k}$ are independent. Therefore, their joint density function is given by:

$$f_{X,Y/k}(x, y/k) = \frac{\beta^{\alpha_1+\alpha_2}}{\Gamma(\alpha_1)\Gamma(\alpha_2)}x^{\alpha_1-1}\left(\frac{y}{k}\right)^{\alpha_2-1}e^{-\beta x}e^{-\beta(y/k)}, \quad x>0, y>0. \tag{32}$$

Using the variable transformations according to Eqs. (20) and (21), we can express Eq. (32) in terms of U and $\bar{\varphi}$ as follows:

$$f_{U,\bar{\varphi}}(U,\bar{\varphi}) = f_{X,Y/k}(U\bar{\varphi}, U(1-\bar{\varphi}))|U| = \frac{\beta^{\alpha_1+\alpha_2}}{\Gamma(\alpha_1)\Gamma(\alpha_2)}(U\bar{\varphi})^{\alpha_1-1}(U(1-\bar{\varphi}))^{\alpha_2-1}e^{-\beta(U\bar{\varphi})}e^{-\beta(U(1-\bar{\varphi}))}|J|, \tag{33}$$

where $|J|$ represents the absolute value of the determinant of the Jacobian J:

$$J = \begin{bmatrix} \bar{\varphi} & U \\ (1-\bar{\varphi}) & -U \end{bmatrix}. \tag{34}$$

Substituting $|J| = |-\bar{\varphi}U - (1-\bar{\varphi})U| = |-U| = U$ in Eq. (33) and multiplying and dividing by $\Gamma(\alpha_1+\alpha_2)$, we obtain:

$$f_{U,\bar{\varphi}}(U,\bar{\varphi}) = \underbrace{\frac{\Gamma(\alpha_1+\alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)}\bar{\varphi}^{\alpha_1-1}(1-\bar{\varphi})^{\alpha_2-1}}_{\bar{\varphi}\sim Beta(\alpha_1,\alpha_2)}\underbrace{\frac{\beta^{\alpha_1+\alpha_2}}{\Gamma(\alpha_1+\alpha_2)}U^{\alpha_1+\alpha_2-1}e^{-\beta U}}_{U\sim Gamma(\alpha_1+\alpha_2,\beta)}. \tag{35}$$

Table 11
Proportion of households experiencing energy poverty according to OIPE estimations for each region by year.

Region	2021	2022	2023
Piedmont	8.1	7.0	7.7
Aosta Valley	6.8	8.7	7.7
Lombardy	5.3	5.1	7.2
Trentino-South Tyrol	8.6	8.6	11.4
Veneto	5.6	5.2	6.3
Friuli-Venezia Giulia	6.3	5.7	5.6
Liguria	4.8	4.7	7.0
Emilia-Romagna	6.1	6.5	7.1
Tuscany	5.5	4.5	6.2
Umbria	6.7	6.8	4.9
Marche	4.6	4.5	4.9
Lazio	6.1	5.0	5.8
Abruzzo	12.2	8.4	8.4
Molise	16.0	16.7	17.6
Campania	11.3	9.3	9.6
Apulia	16.4	13.7	17.4
Basilicata	15.0	13.4	17.8
Calabria	16.7	22.4	19.1
Sicily	14.6	12.0	14.2
Sardinia	11.8	8.9	12.5
Italy	**8.5**	**7.7**	**9.0**

Eq. (35) implies that the two variables U and $\bar{\varphi}$ are independent. We now compute the joint probability:

$$P\left(\bar{\varphi} > \frac{k\bar{a}}{1+(k-1)\bar{a}},\ U < \frac{\bar{m}}{k(1-\bar{\varphi})}\right) = \int_{\frac{k\bar{a}}{1+(k-1)\bar{a}}}^{1} \frac{\Gamma(\alpha_1+\alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)}\bar{\varphi}^{\alpha_1-1}(1-\bar{\varphi})^{\alpha_2-1}d\bar{\varphi}\int_0^{\frac{\bar{m}}{k(1-\bar{\varphi})}}\frac{\beta^{\alpha_1+\alpha_2}}{\Gamma(\alpha_1+\alpha_2)}U^{\alpha_1+\alpha_2-1}e^{-\beta U}dU. \tag{36}$$

Since:

$$\int_0^{\frac{\bar{m}}{k(1-\bar{\varphi})}}\frac{\beta^{\alpha_1+\alpha_2}}{\Gamma(\alpha_1+\alpha_2)}U^{\alpha_1+\alpha_2-1}e^{-\beta U}dU = \frac{\gamma\left(\alpha_1+\alpha_2, \frac{\beta\bar{m}}{k(1-\bar{\varphi})}\right)}{\Gamma(\alpha_1+\alpha_2)}, \tag{37}$$

where $\frac{\gamma\left(\alpha_1+\alpha_2, \frac{\beta\bar{m}}{k(1-\bar{\varphi})}\right)}{\Gamma(\alpha_1+\alpha_2)}$ is the regularized lower incomplete gamma function, which is exactly the cumulative distribution function of a Gamma distributed random variable with parameters $\alpha_1+\alpha_2$ and rate parameter β, evaluated at $x = \frac{\bar{m}}{k(1-\bar{\varphi})}$.

Hence, we obtain the final expression:

$$P\left(\bar{\varphi} > \frac{k\bar{a}}{1+(k-1)\bar{a}}\ U < \frac{\bar{m}}{k(1-\bar{\varphi})}\right) = \int_{\frac{k\bar{a}}{1+(k-1)\bar{a}}}^{1} \frac{\Gamma(\alpha_1+\alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)}\bar{\varphi}^{\alpha_1-1}(1-\bar{\varphi})^{\alpha_2-1}\frac{\gamma\left(\alpha_1+\alpha_2, \frac{\beta\bar{m}}{k(1-\bar{\varphi})}\right)}{\Gamma(\alpha_1+\alpha_2)}\,d\bar{\varphi}. \tag{38}$$

6.3. Appendix C

See Table 11.

Data availability

Data will be made available on request.

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