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Analysis of the multidimensional energy poverty in Italy using the partially ordered set

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ABSTRACT

Adequate warmth, cooling, lighting, and electrical device use are indispensable in upholding suitable living standards, health, and social inclusion. The energy crisis that followed the COVID-19 pandemic and exacerbated by rising energy prices due to the Russian-Ukrainian war has pushed energy poverty to the forefront of the EU political agenda. Although it is largely contingent upon the availability and affordability of energy services, the predominant energy expenditure approach only emphasizes the latter. Recognizing the phenomenon's multidimensionality and accurately assessing its incidence and severity are crucial for effective mitigation. However, compensation and dichotomisation of energy dimensions involved in the standard dual cut-off identification procedure may result in a loss of information. This limitation becomes more pronounced when using ordinal data, which is increasingly common in measuring multidimensional deprivation. Analyzing order relations in discrete mathematics, this paper adopts the non-compensative partially ordered set approach for the first time to examine multidimensional energy poverty in Italy using panel data for 2004–2018 from the EU_SILC database. Results show that severe energy poverty has affected at least 4.75 % of Italian households, progressively decreasing to 2.56 % in 2018, suggesting the need for the official adoption of new multidimensional measurement tools for more precise targeted policies.

1. Introduction

Energy is a crucial driver of economic development, and ending energy poverty is a central political process to the 2030 Agenda for Sustainable Development (Sy and Mokaddem, 2022). In recent years, reliable energy access has become crucial for mitigating poverty and promoting sustainable economic growth, leading to growing interest in energy poverty among policymakers, political institutions, and academics (Belaïd, 2022; Djeunankan et al., 2023; Sy and Mokaddem, 2022). In line with the United Nations (UN), the EU Energy Poverty Observatory, 2020 "Clean Energy for all Europeans" package reiterated that ensuring citizens' well-being is inextricably linked to energy services. Adequate warmth, cooling, lighting, and electricity are indispensable factors in upholding suitable living standards and health, realising individuals' capabilities, and fostering social inclusion (Hesselman et al., 2021). Before the COVID-19 pandemic, more than 124 million European citizens - mainly in Central, Eastern, and Southern Member States - were experiencing energy poverty (Bienvenido-Huertas, 2021). This condition is driven by a combination of low income, high energy prices and low energy efficiency of housing, which can trap households in the vicious circle of energy poverty (Bonatz et al., 2019). Lockdown measures intensified the energy vulnerability of many families, as they have experienced a reduction in essential energy services due to job loss or higher energy costs (Carfora et al., 2022). The war in Ukraine further exacerbated the situation, with oil prices rising by 80 % and European gas prices by 600 % in early 2022, resulting in unprecedented energy expenditure for households, especially in Italy, Spain, Poland, France, and the United Kingdom (Faiella et al., 2022). Therefore, price spikes and the reassessment of energy strategies across Europe have elevated energy poverty on the EU policy agenda (Belaïd, 2022).

Despite robust quantification is crucial for understanding the issue (Vurro et al., 2022), policymakers face challenges in identifying the extent and intensity of energy poverty (Belaïd, 2022). At the European level, three main methods have been employed for its evaluation (Faiella et al., 2022): direct measurement, the consensual approach, and the expenditure one. While direct measurement is infrequently utilised due to the scarcity of national datasets on indoor temperatures, the expenditure approach is the predominant method for national evaluation (Thomson Bouzarovski and

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Snell, 2017). Although it is criticized for its complexity,[1] it offers objectivity and quantifiability (Kashour and Jaber, 2024). Particularly through the use of the LIHC indicator (Hills, 2012), this methodology can capture the distinct nature of energy poverty with respect to the monetary one, enabling direct comparison - something not fully achievable through multidimensional approaches (Castaño-Rosa et al., 2020). The widely used 10 % percentage rule proposed by Boardman (2010) is valued for its simplicity and adaptability, so that its results can be easily understandable and communicable, facilitating the establishment of an effective policy trajectory (Castaño-Rosa et al., 2019). However, focusing only on energy affordability and household energy burdens, it constrains its nature to a unidimensional concern (Aristondo and Onaindia, 2018). Moreover, when measuring the impact of energy expenditure on household income, the energy expenditure indices may not provide information on the causes of energy poverty (Thema and Vondung, 2020).

It is essential to recognise that while energy consumption constitutes a fundamental element, it alone does not ensure well-being and human development (Frigo et al., 2021). When evaluating social phenomena, such as human development, well-being and poverty, Sen (1999) contends that income-based metrics inadequately account for the challenges faced by the most economically disadvantaged segments within societies, economic and environmental disparities, and other crucial determinants of quality of life, such as healthcare and education (Samarakoon, 2019). Energy poverty extends beyond household disposable income, so that conventional expenditure indices can overlook important material energy deprivation and social exclusion caused by energy poverty (Halkos and Aslanidis, 2023; Pereira et al., 2017). To address this disadvantage, Healy and Clinch (2002) proposed the use of a consensual approach that estimates energy poverty through household self-evaluation of energy affordability, thermal comfort, dwelling's energy efficiency, and the perceived difficulties in ensuring adequate domestic energy services (Bollino and Botti, 2017). This methodology is simpler than the expenditure approach and facilitates cross-country comparisons due to the availability of standardized data on housing conditions and the accessibility of energy services through the EU_SILC survey (Rademaekers et al., 2016). While it allows the collection of information about the real experiences of the energy poor and their perceived burdens (Thomson Bouzarovski and Snell, 2017), it risks possible misclassification due to the misperception[2] of low-income families (Herrero, 2017).

By focusing on the opportunities for individuals to lead a good life rather than solely on their material well-being, the Capability Approach provides a more comprehensive understanding of the effects of energy systems on human life, as well as the interactions between energy poverty and well-being (Bartiaux et al., 2019). From this perspective, energy poverty evaluation demands more complex computational tools to recognise the multifaceted nature of the deprivations. Within the academic debate, two distinct methods of synthesis can be identified: the compensative and the non-compensative approaches (Maggino, 2017). The prevailing method for assessing multidimensional energy precariousness is the dual cut-off identification procedure developed by Alkire and Foster (2007). This methodology has several advantages for computing energy poverty. First, it allows for the recognition of the multidimensional nature of energy poverty by focusing directly on energy deprivation and thus overcoming the division between energy unaffordability and inaccessibility. Indeed, it enumerates the dimensions in which households experience energy deprivation through unidimensional thresholds that dichotomize each energy variable and a multidimensional one that allows to synthesize the individual deprivations by giving them an average deprivation score. Since the evaluation of material deprivation and well-being is progressively shifting towards multidimensional frameworks of ordinal variables rather than numerical ones (Fattore et al., 2011), alternative synthesis procedures have emerged in recent years (Alaimo et al., 2022a). In particular, Fattore et al. (2011) proposed the partially ordered set (posetic) approach as a non-compensative framework. It can be well-suited for evaluating deprivations using discrete data and indicators measured on diverse scales (Fattore and Arcagni, 2018), allowing for an accurate examination of multidimensional deprivation. In particular, Comim and Hirai (2022) highlight how it provides a more robust conceptual utilization of the capability approach.

The Italian case is particularly interesting for the multidimensional examination of energy poverty. This phenomenon has affected an average of 8 % of Italian households in the last twenty years, increasing the incidence from 8.6 % in 2016 to 8.8 % in 2018 (ENEA, 2020). Italy is particularly exposed to the energy crisis, potential disruption of gas supply from Russia and price volatility (Frilingou et al., 2023; Ruggieri et al., 2023), which, combined with political instability, steadily increasing poverty, unemployment, and net income inequality, makes this country particularly vulnerable to energy poverty. Additionally, rising temperatures and more frequent heatwaves since the 1970s have increased the demand for summer cooling, a challenge exacerbated by the low energy efficiency and ageing condition[3] of the residential building stock (Faiella and Lavecchia, 2021). Indeed, Italy ranks fifth worst in the European Energy Poverty Index (EEPI) produced by OpenExp in 2019 (OpenExp, 2019). Only 29.4 % of Italian households have air conditioning, and 37 % of the poorest population live in houses that are not adequately cool in the summer. Moreover, the Italian Statistical Institute (ISTAT) estimates that only 3 % of them have a dryer and one in four a freezer, while almost all own at least a refrigerator, a washing machine and a dishwasher (Ungaro, 2014). Therefore, the percentage of energy-poor households is projected to rise beyond 9.7 % due to the recent dramatic increase in energy prices.

The Italian government adopted a definition and an official indicator only in the 2017 National Energy Strategy (SEN), based on the unidimensional energy expenditure approach developed by Faiella and

[1] According to Rademaekers et al. (2016), this approach can capture the severity of energy poverty by use of different thresholds. However, this aspect may represent a limit because it can be affected by the arbitrary choices of the researcher and by sensitivity to fluctuations in energy prices (Hills, 2012), and it may vary from country to country. At the same time, the use of a relative threshold, as such the twice the national median income, could make it difficult to classify the energy-poor households with consequent policy implications when the income/expenditure distribution shifts in the population as a whole (Charlier and Legendre, 2021). In addition, as the only source of harmonised energy expenditure data is the Household budget survey, the absence of standardized data on energy expenditure limits the possibility of comparative evaluations between European countries (Thomson, Bouzarovski, et al., 2017). On the contrary, a main advantage can be the fact that the application of this methodology would require the use of the required energy consumption. However, its modelling requires a thorough understanding of the energy efficiency characteristics of the housing stock and the socio-demographic characteristics of households, which needs a lot of data that is currently almost exclusively the preserve of the UK (Herrero, 2017). In addition, the complexity of the methodology below makes it difficult to transfer to other countries, so many countries are forced to resort to actual energy expenditure, which is considered a poor proxy for energy poverty due to the influence of specific needs and preferences of households (Moore, 2012; Papada and Kaliampakos, 2018).

[2] Household self-assessments can underestimate the phenomenon because the subjective nature of the responses can expose estimates to possible exclusion errors and the difficulty of comparing culturally specific perceptions, so households may not self-identify as energy-poor (Herrero, 2017).

[3] Over 60 % of the Italian building stock is outdated, having been constructed before 1976 (Federesco, 2017). Law No 373/1976 is the first Italian legislation on energy efficiency, issued following the oil crisis of 1973 that had generated a rapid increase in oil prices. It contained the first provisions on the containment of energy consumption for thermal purposes in buildings; in particular, it established the first constraints for the design, installation, start-up and management of thermal installations, and the first measures on thermal insulation.

Lavecchia (2015). Paradoxically, despite the absence of an official measure of energy vulnerability, there have been specific tools to sustain household energy expenditure for over five years (Faiella and Lavecchia, 2015). The primary instrument employed to alleviate the impact of energy costs on low-income households has been the provision of economic aid, particularly *Bonus elettrico* and *Bonus gas.*[4] However, this approach does not offer a sustainable solution for energy-poor households because it merely mitigates the immediate risk of poverty, providing only short-term relief (Pereira and Marques, 2023). The underlying structural causes of energy insecurity can be addressed through energy retrofit policies (Atanasiu et al., 2014). Enhancing energy performance diminishes energy consumption, improves thermal comfort with and the physical and mental health of the occupants, promotes social inclusion, and stimulates job creation with positive effects on the whole economy (Santamouris, 2018). As emphasized within the 2019 National Integrated Energy and Climate Plan (PNIEC), these programs stand as imperatives to counter the growing prevalence of energy poverty exacerbated by the significant upsurge in energy prices caused by the Russian-Ukrainian conflict (Guan et al., 2023). To encourage the energy retrofit of the Italian residential housing stock, *ecobonus,*[5] has been in place since 2007. Although the National Energy Poverty Observatory was established in 2019 to assess the temporal evolution of the phenomenon and support policymakers (EU Energy Poverty Observatory, 2020), the effectiveness of these tools is still little examined (Koengkan et al., 2023).

To the author's knowledge, the posetic approach has been employed in prior research for the multidimensional measurement of deprivation and well-being. Still, it has not yet been applied to studying energy poverty. Adopting a multifaceted framework informed by the Capability Approach, this paper wants to contribute to the literature by using the posetic approach to evaluate energy poverty in Italy for the first time to assess the incidence and the severity of the phenomenon. This paper investigates the multidimensional energy poverty in Italy using panel data from 2004 to 2018 from the Italian European Union Statistics on Income and Living Conditions (EU_SILC) survey, whose variables are categorical or dichotomous. Comparing the posetic approach with the unidimensional expenditure indicator and the dual cut-off identification procedure, this paper highlights how the former could be a valid methodology for computing the incidence and intensity of energy poverty by using the EU_SILC ordinal variables. Considering the multidimensional and fuzzy nature of this phenomenon, it could provide policymakers with a valuable tool to support the design of tailored policies.

The remainder of the paper is organized as follows. Section 2 introduces the conceptual framework and, in particular, the relationship between the Capability Approach and energy poverty. Section 3 describes the data and the methodological strategy. Section 4 discusses the results and policy implications, and Section 5 presents the concluding remarks.

2. Energy poverty in the capability approach

Energy poverty is an independent form of deprivation extending beyond income poverty because a household having stable employment and an income slightly above the poverty threshold might not be able to keep the dwelling adequately warm, even if it cannot be classified at risk of poverty (Bouzarovski Thomson et al., 2020). Energy poverty is characterised by heterogeneous elements, such as the difficulties in keeping the home adequately warm, arrears in utility bills, and the presence of leaks, dampness, and rot in the dwelling, which necessitates simultaneous consideration to delineate the energy poverty construct accurately (Halkos and Gkampoura, 2021). The prevailing conceptual frameworks for understanding and measuring energy poverty are hampered, on the one hand, by the terminological confusion between fuel poverty and energy poverty and, on the other hand, the excessive use of expenditure unidimensional indicators. Indeed, for a long time, the terminology confusion between energy poverty and fuel poverty has influenced the primary conceptual paradigms (Boemi et al., 2017), mainly depending on whether the focus was on developing or developed countries. Research endeavours pertaining to the latter typically employ the former term to denote energy availability. At the same time, fuel poverty is preferred to describe energy unaffordability in the context of developed countries assuming energy availability as already established (Thomson and Bouzarovski, 2018). However, its multidimensional nature requires a more complex conceptualisation (Sareen et al., 2020). In parallel with the search for a common definition, a significant line of literature is dedicated to developing methodologies to measure the magnitude of energy poverty (Belaïd, 2022). As mentioned in the introduction, assessing only the relationship between household income and energy expenditure, the prevailing expenditure approach constraining energy poverty to a unidimensional concern primarily focused on energy affordability (Aristondo and Onaindia, 2018). Since this phenomenon transcends mere income insufficiency, it is essential to move beyond simply identifying individuals experiencing energy poverty and instead focus on understanding the underlying causes, mechanisms, and impacts of energy poverty on people's lives (Rafi et al., 2021).

Sen (2014) emphasizes the critical importance of extending access to environmentally sustainable energy sources in enhancing the overall quality of human life (Samarakoon, 2019). Energy poverty leads to "*the absence of sufficient choice in accessing adequate, affordable, reliable, high-quality, safe and environmentally benign energy services to support economic and human development*" (Reddy, 2000, p.44). Berry (2018) contends that relying solely on energy expenditure inadequately captures households' challenges in accessing essential energy services. Globally, consumers advocate for the provision of standardized energy services that offer them the real opportunity to do and be what they value, enhancing human capabilities (Shortall and Mengolini, 2023). The absence of materially and socially sufficient energy services at home justifies adopting a multidimensional framework that incorporates all forms of domestic energy deprivation, emphasizing the instrumental role of energy services in well-being (Bouzarovski and Petrova, 2015). Therefore, "*understanding the role that energy services play within people's lives' calling for a 'people-centered approach, reaching beyond the technical issues, to deliver energy services that meet peoples' needs and priorities*" (Bouzarovski and Petrova, 2015, p. 5). Within this perspective, Pereira et al. (2011) state that energy poverty can be more comprehensively understood through a more accurate multidimensional framework aligning with Amartya Sen's capability approach (Sadath and Acharya, 2017). Proposed as an alternative to the mainstream neoclassical model of human progress, the capability approach posits that economic development should focus beyond material wealth on factors that facilitate human flourishing, expanding people's capabilities - their freedom to promote and achieve what they value doing and being (their functioning) (Samarakoon, 2019). Deprivation denotes a state of disadvantage, failing to realise essential functionings to human life and fully participating in society, often linked to insufficient resources. This approach highlights the intrinsic importance of non-monetary deprivations to capture the poverty experience and gain a deeper understanding of what it truly means to be impoverished (Alkire et al., 2015).

[4] Introduced in 2009, the *elettrico* and *gas* bonuses are two cumulative social subsidies, granted through direct discounts in energy bills, for a maximum of twelve months, aimed at limiting the impact of energy expenditure on the income of households in energy poverty (Faiella and Lavecchia, 2021). The eligibility is linked to the household income and wealth, in particular to the Indicator of the Equivalent Economic Situation (ISEE) which does not take into account any energy aspect.

[5] The Ecobonus is a energy retrofitting tax credit which enables the recuperation of up from 50 % to 85 % of the upfront investment in energy efficiency improvements in 10 years (Faiella and Lavecchia, 2021).

Therefore, this approach offers a new conceptual framework for building a more holistic image of the energy-poor experiences, moving beyond unidimensional energy expenditure indices (Crentsil et al., 2019).

Within the economic facilities,[6] the availability and affordability of energy services represent a precondition to realising valuable functionings such as being healthy or well-fed, thereby augmenting individuals' capabilities (Bouzarovski and Petrova, 2015). Conversely, energy poverty represents the deprivation of this crucial infrastructure, hindering the achievement of essential capabilities (Crentsil et al., 2019). Day et al. (2016) provide a new conceptualisation of energy poverty within the Capability Approach by observing a sequential relationship between energy carriers, energy services and capabilities: the realization of basic capabilities depends on secondary capabilities, which necessitate one or more energy services, themselves reliant on the availability of energy supply and fuels. The relationship between each of the phases is dynamic and context-specific because different persons or households may require a different amount of energy services to be able to achieve an adequate level of secondary capabilities, which depend on the household size, the specific needs and circumstances of the components and the local environment (Middlemiss et al., 2019). Therefore, energy poverty represents "*an inability to realise essential capabilities as a direct or indirect result of insufficient access to affordable, reliable and safe energy services, and taking into account available reasonable alternative means of realising these capabilities*" (Day et al., 2016, p. 260). By highlighting the instrumental role of energy services for human -wellbeing, this characterization extends energy poverty beyond a simple material deprivation and acknowledges its multidimensional nature, combining economic and physical inaccessibility in a single conceptual framework easily adaptable to various geographic and climatic contexts. This approach offers a more comprehensive understanding of what constitutes it, its determinants and its consequences. Finally, one of the strengths of Sen's vision is the recognition of human diversity: assuming that energy poverty can have different forms and effects, this approach facilitates the consideration that not all individuals are equipped in the same way in the face of the phenomenon, and also highlights the inequalities between energy-poor households and the other social groups (Grazini, 2023).

3. Data and method

In the absence of dedicated surveys, the only national data sources at the European level are the Household Budget Survey (HBS) and the European Union Statistics on Income and Living Conditions (EU_SILC). While the former focuses on households' expenditure on goods and services, including expenses related to energy uses, the latter provides information on income distribution, poverty, and social exclusion. However, since neither survey is specifically designed to measure energy poverty, each exhibits advantages and limitations. HBS is commonly used for analyzing energy expenditure burdens at the national[7] level, but it fails to capture broader socio-economic determinants of energy vulnerability and critical contextual factors such as household income stability and regional disparities in energy access (Bouzarovski et al., 2016; Robinson et al., 2019). As a result, while HBS is useful for assessing financial strain from energy costs, it does not fully reflect the lived experiences of energy-poor households.

Currently, available data on energy poverty are largely limited to qualitative or dichotomous variables, such as those provided by the EU-SILC survey (Thomson Bouzarovski and Snell, 2017). While this survey provides harmonised data on monetary poverty and material deprivation and serves as one of the primary data sources for formulating consensual energy poverty indicators (Bouzarovski and Tirado Herrero, 2017), it has limitations. Thomson Snell and Bouzarovski (2017) point out that the EU-SILC survey relies on a narrow conceptualisation of energy poverty, risking oversimplifying the issue's complexity. Moreover, household energy expenditure is aggregated with rent/mortgage payments and other housing costs to form a composite 'total housing cost' variable, preventing a direct comparison between energy expenditure and consensual measures at the micro level. Disaggregating these variables, as suggested by Thomson Bouzarovski and Snell (2017), would allow the complementation of qualitative data on energy deprivation with quantitative data related to energy consumption. Survey methodologies, such as long completion times (Cong et al., 2022), may introduce biases, leading to unreliable data. While the longitudinal EU-SILC data facilitate monitoring the persistence of energy poverty, it may inadequately capture regional disparities (Karpinska and Śmiech, 2020). Finally, although the standardized methodology enables cross-country analyses, it risks overlooking important local factors influencing energy access and affordability.

Despite the weaknesses mentioned above, the subjective indicators included in the EU_SILC survey can be a crucial tool for understanding households' perceptions of the lived experiences of energy deprivation and associated challenges (Phimister et al., 2015). Since many of the EU_SILC variables are categorical or dichotomous, standard compensative methods and, in particular, the dual cut-off identification procedure has been criticized as inappropriate and often inconsistent with ordinal data (Alaimo et al., 2022b). This approach presents several advantages that enhance the accuracy and comprehensiveness of energy poverty evaluation. Focusing on the deprivation of energy services, the dual cut-off identification procedure allows a direct assessment of multidimensional energy poverty without deriving indirect information through correlated variables, such as energy expenditure (Nussbaumer et al., 2012; Olang et al., 2018). Moreover, the dual cut-off identification procedure is a versatile methodology that supports both cross-regional comparative studies and geographical context-specific national analyses (Olang et al., 2018). In particular, unlike expenditure-based methods, this approach quantifies not only the incidence but also the severity of deprivation through two distinct thresholds that offer two different levels of analysis (Dotter and Klasen, 2020). In fact, besides assessing them in the reference population, it is possible to decompose the analysis by focusing on the magnitude and intensity of deprivation in individual dimensions or breaking down results by specific subpopulations.

By clearly defining thresholds for deprivation, policymakers can better target interventions that address the specific dimensions and magnitude of household vulnerabilities (Nguyen and Nasir, 2021). While the use of unidimensional thresholds enables differentiation between energy poverty dimensions, the resulting dichotomization - classifying households simply as poor or non-poor – leads to a substantial loss of nuanced information (Freudenberg, 2003) and deflects "*in anti-poverty policy by ignoring the greater misery of the poorer among the poor*" (Guarini, 2017). This limitation is particularly important given the primary challenge of limited comprehensive qualitative and quantitative data in measuring energy poverty (Certomà et al., 2023). Furthermore, the dual cut-off identification procedure involves a multidimensional threshold for aggregating energy deprivations into synthetic indicators. However, the method's complexity and reliance on multiple indicators complicate communication and policy design for energy poverty (Siksnelyte-Butkiene, 2021). As a compensative method, it requires researchers to choose the weights attributed to the different

[6] Personal freedoms also serve an instrumental role in advancing human development. Sen (1999) identifies five categories of instrumental freedoms: (1) political freedoms, encompassing the ability to choose leaders, express opinions, and participate in voting; (2) economic facilities, referring to access to and use of economic resources; (3) social opportunities, which include access to education and healthcare; (4) transparency guarantees, ensuring openness and accountability; and (5) protective security, which involves social safety nets and institutional measures to prevent extreme deprivation.

[7] HBS datasets lack EU-wide harmonization, leading to disparities in sampling methods, variable definitions, and survey frequency among Member States.

dimensions (Decancq and Lugo, 2013), which introduces arbitrariness that can significantly affect results as well as indicate the absence of specific relevance of the individual dimensions (Chiappero-Martinetti et al., 2015; Guarini, 2017). On the contrary, the non-aggregative methodologies, such as the posetic approach, do not involve normalizing or aggregating the basic indicators (Alaimo, 2022; Ibáñez-Forés et al., 2023). Therefore, the significance of the theory of partially ordered set within socio-economic investigations is growing thanks to the extensive reservoir of non-quantitative information accessible across diverse domains, such as inequality and poverty, economic and political sciences or sustainable development (Maranzano et al., 2021).

3.1. EU_SILC database and energy poverty dimensions

The capability approach views energy poverty as a persistent lack of energy-related dimensions that hinders essential functionings like education and health, negatively affecting individuals' abilities to achieve well-being and live a meaningful life (Villalobos et al., 2021). The EU-SILC survey, with its comprehensive dataset on housing and living conditions, provides detailed information on household living conditions that allows for a nuanced understanding of how energy services impact overall well-being and poverty levels (Valverde et al., 2021). Therefore, the Italian EU_SILC survey carried out by the ISTAT was utilised to evaluate the incidence and severity of energy poverty in Italy from 2004 to 2018. Since energy poverty negatively affects the well-being of the entire household, the characteristics of the householder are often used in the literature as a proxy for those of his householder (Xiao et al., 2021). The householder data has been extracted from the personal dataset implementing the procedure[8] proposed by Marino et al. (2021), resulting in two databases comprising 206,055 observations from 2004 to 2015 and 64,724 units from 2016 to 2018.

Following the existing literature on multidimensional energy poverty and, in particular, the theoretical framework of the capability approach described in Section 2, this paper considers the direct impact of energy services on human capabilities for the selection of energy dimensions. The European Union defines energy poverty as a condition in which households lack access to essential energy services necessary to maintain "*a normal life*" and health, including adequate heating, cooling, lighting, and energy for powering appliances (Lee and Malerba, 2017). Limiting the scope of analysis to the European context, the examination of energy poverty has predominantly revolved around the consideration of heating needs, ignoring the fundamental role of other energy services in determining the household's well-being (Thomson Simcock et al., 2019). Frequently resulting from poor insulation and high energy costs, living in cold homes is associated with increased hospital admissions and a higher prevalence of respiratory diseases, particularly among vulnerable populations such as the elderly and those with chronic conditions (Simcock et al., 2016). Two other dimensions are commonly examined: energy burden and thermal efficiency of dwellings. European Commission has adopted these three dimensions as criteria for measuring energy poverty by using the following three variables from the EU_SILC survey (Kashour and Jaber, 2024): the inability to keep the home adequately warm, the arrears on the utility bills, and the presence of problems with a leaking roof and/or damp ceilings, dampness in the walls, floors or foundation and/or rot in window frames and door.

In addition to health, energy access is intricately linked with a broader spectrum of fundamental human capabilities, such as the cultivation of intellectual faculties and social connections. According to Löfquist (2020), the provision of electricity is predominantly an instrumental human right, essential for the realization and protection of fundamental rights related to health, housing, and education. Indeed, the possession of electrical appliances can be used as a proxy for electricity availability and affordability, as well as energy deprivations (Deller, 2018). Access to hot water, washing machines, and dryers facilitates personal and clothing care and fosters individuals' active participation in their community's social life and interactions with others (Walker et al., 2016). Similarly, owning television, computers, internet connection, and the possibility of charging and using mobile phones allows people to realise important capabilities, such as maintaining social relationships, keeping informed and seeking employment (Bartiaux et al., 2021). Many energy-poor often report sacrificing phone usage to pay energy bills, which can isolate them from relatives and friends (Middlemiss et al., 2019). Refrigeration and freezers are crucial to preserving food and ensuring adequate nutrition, which in turn allow people to have optimal health (Bartiaux et al., 2021). Finally, the connection between car ownership and energy poverty is evident in the tendency of low-income households to forgo vehicle ownership due to financial limitations, thereby restricting their mobility, employment opportunities and access to improved energy services. Conversely, households that do own cars may face an increased energy burden, further straining their financial resources for other energy needs and potentially contributing to energy poverty (Klein and Smart, 2019; Simcock et al., 2021).

Although it is one of the main European data sources for studying energy poverty, the EU_SILC survey does not investigate certain essential domestic energy services. With rising temperatures and more frequent heatwaves due to climate change, the demand for cooling has gained prominence at the European level and, in particular, in the Mediterranean countries (Fabbri, 2015; Faiella et al., 2020). Exposure to elevated indoor temperatures can raise the risk of respiratory, cardiovascular, and circulatory diseases, thrombosis and thermoregulatory disorders with a possible increase in hospital admissions, especially among vulnerable social groups such as children, the elderly, individuals with chronic illnesses, and low-income households (Li et al., 2022; Randazzo et al., 2020). Despite the European Commission launching the Heating and Cooling Strategy in 2016, the disproportionate attention to heating has consequently resulted in a deficiency of comprehensive and adequate cooling data (Bouzarovski Thomson et al., 2020). Indeed, cooling-related data[9] were only included in specific EU-SILC modules in 2007 and 2012, limiting the ability to examine the longitudinal contribution of this dimension to household energy vulnerability.

Similarly, the EU_SILC survey does not examine cooking and lighting services, despite their critical role in safeguarding health, mitigating mental health disorders (e.g., stress, depression) and reducing domestic accidents (Ouedraogo, 2013). Lighting extends productive work hours beyond daylight, heightens economic returns, enhances academic performance through extended study periods, and fosters social relations (Ochoa and Graizbord, 2016; Simcock et al., 2016). Since there is no other longitudinal survey at the European and Italian levels that allows the examination of these energy deprivations during the selected period, a limitation of this study is the absence of cooling, cooking, and lighting, but it uses the EU_SILC dataset as it is a crucial primary source for examining the experience of energy-poor households. Therefore, taking as a reference the theoretical framework mentioned above, as well as the limits of the chosen national survey, this paper has selected the 9 EU_SILC energy dimensions in Table 1, reporting the level of single domestic energy services and related material deprivation with the related response categories. All these energy deprivations affected the Italian population in the period 2004–2018, as shown in Table A.1 of

[8] According to Marino et al. (2021), the person responsible for the accommodation shall be identified firstly. Secondly, if two members have been selected, the individual earning the highest income is considered. Finally, if the previous criteria have not yet been met, the eldest individual is identified as the householder.

[9] In 2020, Eurostat decided not to investigate cooling again, which will result in a significant loss of harmonised data at the European level with the risk that individual national statistical institutes will no longer examine it (Thomson et al., 2019).

Table 1
Energy poverty dimensions extracted from the EU_SILC dataset.

EU_SILC Variable	Modes
Arrears on utility bills	Yes / No
Do you have a telephone (including a mobile phone)?	Yes No, cannot afford No, other reason
Do you have a colour TV?	Yes No, cannot afford No, other reason
Do you have a computer?	Yes No, cannot afford No, other reason
Do you have a washing machine?	Yes No, cannot afford No, other reason
Do you have a car?	Yes No, cannot afford No, other reason
Ability to keep home adequately warm	Yes / No
Bath or shower in the dwelling	Yes / No
Leaking roof, damp walls/floors/foundation, or rot in window frames or floor	Yes / No

Appendix A, displaying the percentage frequencies of each energy vulnerability. In particular, the two correlation matrices (see Table A.2 and A.3 in Appendix A) do not show significant correlations between the variables, supporting the hypothesis that each of them represents a different dimension of energy poverty.

3.2. *The partially ordered set methodology*

This section aims to present the main aspects of the posetic approach, but the reader can see Fattore and Arcagni (2018) for a detailed mathematical exposition. Drawing upon Sen's notion of "partial ordering", which recognises the impossibility of directly comparing individual well-being, Fattore et al. (2015) employ the posetic approach as an innovative method for quantifying multidimensional material deprivation, quality of life, and holistic well-being. Fattore (2016) sustains that "*a preliminary and fundamental step, in social evaluation, is the identification of the evaluation space associated to the data, i.e. of the mathematical entity that best reproduces the structure of the data and defines how they can be formally treated. For multidimensional deprivation, the natural evaluation space is a partially ordered set*". As a non-compensative approach, the posetic approach respects the nature of data by avoiding dimensions' aggregation or the use of weighting schemes when constructing synthetic indicators (Alaimo et al., 2022a; Guarini, 2017). Sen (1995) argues that the interdependence among various dimensions of a phenomenon is often insufficient for effective compensation. Therefore, the posetic approach does not result in information loss as it does not involve any form of trade-off between energy dimensions, nor does it assign relative importance to them when assessing household energy poverty. Instead, it synthesizes data through multidimensional comparisons of the statistical units, assessing the degree to which they exhibit dominance over one another rather than consolidating the units' scores on the input variable system into numerical values for ranking purposes (Fattore and Alaimo, 2023).

This multidimensional comparison juxtaposes achievement configurations against reference benchmarks used as thresholds for deprivation or well-being. Unlike the monetary or counting approaches, the introduction of thresholds does not give a binary perspective on poverty because the posetic approach attributes a deprivation degree, which provides a gradual distribution of the phenomenon across the reference population. Capturing the various nuances and aspects of energy poverty from the relational structure of the data, the posetic procedure leads to a fuzzy depiction of this phenomenon and a more accurate evaluation of its prevalence (Arcagni et al., 2019). This framework's capacity to measure the incidence and severity, as well as recognise the level and structure of energy poverty, makes it a valuable tool for formulating targeted policies. Still, it can also take into account the distribution of energy poverty so that direct policies can also be formulated to address "soft" forms of energy poverty, which, although less serious, still require attention (Fattore and Arcagni, 2018). However, the posetic approach also has some significant weaknesses. First, it involves substantial computational requirements, with "*the computation complexity and time*" that grow significantly with a high number of observations or variables, as in this paper (Alaimo et al., 2022a). Furthermore, Fattore and Brüggemann (2017) suggest that the current posetic literature has inadequately addressed two critical issues for policymakers: the complexity of its theory and results and the difficulty of being understood by non-expert readers, as well as the need for temporal evaluation of policy effects. These disadvantages, as well as those of the dual cut-off identification procedures (see Section 3), suggest that no approach is perfect or the best method; each has strengths and weaknesses. However, the posetic approach can represent valid alternatives for analyzing well-being and deprivation cases, preserving specific cases' potential incomparability (Alaimo et al., 2022a) and enhancing the evaluation process's realism and robustness.

As proposed by Fattore (2016), given a set $v_1, v_2, \ldots, v_k$ of k ordinal attributes related to deprivations with an ordinal scale of possibly different numbers of degrees $m_1, m_2, \ldots, m_k$, sequences of score in each deprivation dimension are defined as achievement profiles[10] such as $p = (p_1, p_2, \ldots, p_k)$ and $q = (q_1, q_2, \ldots, q_k)$. All combinations of possible profiles generate the "*achievement space*". The posetic approach aims to order these profiles by identifying superior combinations in relation to others. Within the framework of deprivation assessment, it engages in a comparative analysis of profiles to identify those characterised by higher levels of deprivation than the others. The set Π is transformed into a partially ordered set $(\Pi, \trianglelefteq)$ known as the "*achievement poset*" by introducing the following "*partial order relation* $(\trianglelefteq)$":

$$q \trianglelefteq p \Longleftrightarrow q_i \leq p_i \forall i = 1, 2, \ldots, k \tag{1}$$

According to the previous equation, profile q is equal to or more deprived than profile p if and only if achievements of profile q in $v_1, v_2, \ldots, v_k$ are equal to or worse than those of p. Therefore, this approach aims to examine the information coming from the order relation set on the data organized into "*a component-wise partially ordered set*", which is assumed as the basic data structure for the scoring and ranking process. Posets have both a "vertical" dimension (comparability/dominance between elements) as well as a "horizontal" one (incomparability) (Fattore and Alaimo, 2023). Two deprivation profiles p and q can be ranked in terms of deprivation only if all scores of q are not greater than those of p, or vice versa; in such cases, they are termed comparable. Conversely, if q and p contain conflicting scores, they are considered incomparable (Arcagni et al., 2019). So, a profile p component-wise dominates profile q if and only if all the scores of p are not lower than those of q and at least one of them is higher. Therefore, the main strength of the posetic approach is the ability to incorporate incomparabilities, which are fundamental to the complexity of deprivation, naturally

[10] The achievement profiles "*are the combinations of scores of each statistical units in the basic indicators considered, describing the status of units*" (Alaimo, Fiore, et al., 2022, p. 4).

leading to a fuzzy portrayal of poverty, as mentioned before (Arcagni et al., 2019).

The achievement poset serves as the evaluation space of deprivation and the primary input to derive individual measurements of and synthetic indices of deprivation. The poverty evaluation extends beyond the mere composition of a deprivation score and the measurement against an objective deprivation scale, as in the dual cut-off identification procedure. Consequently, evaluating deprivation presents a challenge that entails multidimensional comparisons between deprivation profiles and specific benchmark profiles, representing a multidimensional threshold exogenously identified by experts (Fattore and Arcagni, 2018). Considering a partially ordered set, if any two elements of it are comparable, the partial order is defined as a linear order, a complete order, or a *chain*. Conversely, it is called *antichain* if all pairs of elements in the partially ordered set are incomparable. As suggested by Fattore (2016), the deprivation threshold (τ) should be selected through the antichain of achievement poset, implying that it should comprise only fully deprived and incomparable profiles. Consequently, profiles that fall below it are categorized as entirely impoverished. In contrast, those that are above or incomparable with the benchmark profile could be partially deprived or not deprived at all.

Operationally, the methodology consists of the following steps (Arcagni et al., 2019). First, a partial ordering of deprivation profiles is established, wherein one profile is assessed as having greater deprivation than another if, and only if, all scores within the former are not superior to those of the latter, with at least one score being significantly lower. Second, a deprivation threshold is imposed by selecting a set of benchmark profiles based on experts' judgments. Profiles falling below this cut-off are classified as poor. Third, the degree and the severity of deprivation of each partially deprived profile are computed by comparing them to the thresholds, computing the so-called identification and severity scores.

To identify deprived profiles in the achievement posets, an identification function defined as *idn(.)* assigns to each statistical unit an identification score, that is, a degree of deprivation between 0 and 1, as follows:

$$idn(.) : \Pi \mapsto [0, 1] \tag{2}$$

$$: \boldsymbol{p} \mapsto idn(\boldsymbol{p}) \tag{3}$$

Fattore (2016) sustains "*each deprivation attribute v_i can be seen as a linear order on the set V_i of its degrees. The achievement poset is then the so-called product order of the linear orders associated to the attributes,* i.e. *the cartesian product of $V_1, V_2, \ldots, V_k$ partially ordered*" by the eq. 1. According to Fattore and Arcagni (2018), Π is one possibility for partially ordering achievement profiles. For instance, prioritizing certain attributes creates a different partial order on the profile set, resulting in an extended poset, thereby converting some incomparabilities into comparabilities. Moreover, we can define it as a linear extension of Π when all the profiles are comparable, so it represents a complete order obtained extending the initial poset. The set of linear extensions of the achievement poset Π is defined as $\Omega(\Pi)$. Conversely, we can see Π of the intersection of $\Omega(\Pi)$. Each linear extension functions as a binary classifier, definitively categorizing profiles into either deprivation or non-deprivation by assessing the position relative to the threshold. Various linear extensions may categorize profiles differently, as the ordering of profiles varies between extensions and related classifiers.

During the identification stage, a counting procedure is still applied to the linear extensions of profiles rather than directly to the profiles themselves. As said before, "*the value of the identification function on a profile p is computed counting the fraction of linear extensions of the achievement poset*" (Fattore and Arcagni, 2018, p. 1056). Considering an element ℓ of $\Omega(\Pi)$, the deprivation threshold τ and τ_ℓ is the maximum element of τ in ℓ $idn_\ell(p)$ is the deprivation classifier associated with linear extension ℓ. Since τ_ℓ is a deprived profile, in the linear order ($\trianglelefteq_\ell$) of ℓ, all profiles ordered below it are deprived so that the function attributes them a value of 1 and 0 otherwise as follows:

$$idn_\ell(\boldsymbol{p}) = 1 \leftrightarrow \boldsymbol{p} \trianglelefteq_\ell \tau_\ell; \text{otherwise}; idn_\ell(\boldsymbol{p}) = 0 \tag{4}$$

So, the identification function can be written as follows:

$$idn(\boldsymbol{p}) = \frac{1}{|\Omega(\Pi)|} \sum_{\ell \in \Omega(\Pi)} idn_\ell(\boldsymbol{p}) \tag{5}$$

Some profiles can obtain one from all the linear extensions; other ones can receive one only from some classifiers, while others may not be deprived of all linear extensions. The fraction of binary classifiers scoring a profile to one is assumed as its identification score. Therefore, one of the properties of the function is to divide achievement into three groups: completely deprived, partially deprived and non-deprived units.

Then, the posetic approach computes the intensity of deprivation using a severity function *svr* (.). In this case, deprivation severity can be calculated only on a subset of completely or partly deprived profiles ($D \cup A$) as follows:

$$svr : D \cup A \mapsto \mathrm{R}^+ \tag{6}$$

$$: \boldsymbol{p} \mapsto svr(\boldsymbol{p}) \tag{7}$$

From an operational point of view, deprivation severity is calculated as the "*distance of deprived profiles from non-deprivation, computed by averaging distances in the linear extensions of Π*" (Fattore, 2016, p. 10), by using the following formula, where $svr_\ell(\boldsymbol{p})$ is the distance of the profile p from the highest element of the threshold (Fattore and Arcagni, 2018):

$$svr(\boldsymbol{p}) = \frac{1}{|\Omega(\Pi)|} \sum\nolimits_{\ell \in \Omega(\Pi)} svr_\ell(\boldsymbol{p}) \tag{8}$$

The obtained values are assigned to each statistical unit according to its deprivation profile to reconstruct the distribution of the phenomenon within the referred population. Ultimately, findings are aggregated at the population level by calculating the headcount ratio, which highlights the percentage of energy-poor households, and the poverty gap, which measures the severity of their condition. In the posetic approach, the classic headcount ratio corresponds to the average of the deprivation identification function (Arcagni et al., 2019), so this paper computed a weighted mean of it to take into account the sample design. Then, the incidence and severity of multidimensional energy poverty of the posetic approach are assessed in relation to the unidimensional estimates obtained by the Italian government using the energy expenditure approach and the Multidimensional Energy Poverty Index (MEPI) developed by Nussbaumer et al. (2012). As better explained in Appendix C,[11] the latter was built using the dual cut-off identification procedure of Alkire and Foster (2011) for the aggregation phase. Since the posetic approach does not impose different importance on the energy dimensions, an equal weight has been imposed on the individuals attributed for applying the dual cut-off identification procedure. Next, Appendix C presents a sensitivity analysis conducted by calculating the MEPI and the posetic approach using the same multidimensional cut-off in order to test the versatility of the two methods when using ordinal data from the EU_SILC survey, which was placed in the 90th percentile of the annual distribution of energy deprivation scores of Italian households, following the work of Brau and Delugas (2019). Finally, Appendix E reports a sensitivity analysis for evaluating the relevance of each energy attribute. The study involved a sequential removal of each energy dimension, followed by a recalculation of the incidence and poverty gap, effectively replicating the initial evaluation. Subsequently, the indicators were broken down based on the tenure status of the dwelling to identify specific

[11] See Appendix C for the mathematical details of the dual cut-off identification procedure, the subjective choice of energy poverty thresholds and the construction of the Multidimensional Energy Poverty Index.

Table 2
Description of profiles of energy deprivations used as poverty threshold.

222222222		222222221		222222212		222222122	
Profile	Dimensions	Profile	Dimensions	Profile	Dimensions	Profile	Dimensions
2	No arrears on utility bills	2	No arrears on utility bills	2	No arrears on utility bills	2	No arrears on utility bills
2	No mobile phone for other reasons	2	No mobile phone for other reasons	2	No mobile phone for other reasons	2	No mobile phone for other reasons
2	No TV for other reasons	2	No TV for other reasons	2	No TV for other reasons	2	No TV for other reasons
2	No PC for other reasons	2	No PC for other reasons	2	No PC for other reasons	2	No PC for other reasons
2	No washing machine for other reasons	2	No washing machine for other reasons	2	No washing machine for other reasons	2	No washing machine for other reasons
2	No car for other reasons	2	No car for other reasons	2	No car for other reasons	2	No car for other reasons
2	No damp and mould problems	2	No damp and mould problems	2	No damp and mould problems	1	Presence of damp and mould problems
2	Ability to keep adequately warm	2	Ability to keep adequately warm	1	Inability to keep adequately warm	2	Ability to keep adequately warm
2	Presence of bath or shower	1	No bath or shower	2	Presence of bath or shower	2	Presence of bath or shower

222222112		222222211		222222121	
Profile	Dimensions	Profile	Dimensions	Profile	Dimensions
2	No arrears on utility bills	2	No arrears on utility bills	2	No arrears on utility bills
2	No mobile phone for other reasons	2	No mobile phone for other reasons	2	No mobile phone for other reasons
2	No TV for other reasons	2	No TV for other reasons	2	No TV for other reasons
2	No PC for other reasons	2	No PC for other reasons	2	No PC for other reasons
2	No washing machine for other reasons	2	No washing machine for other reasons	2	No washing machine for other reasons
2	No car for other reasons	2	No car for other reasons	2	No car for other reasons
1	Presence of damp and mould problems	2	No damp and mould problems	1	Presence of damp and mould problems
1	Inability to keep adequately warm	1	Inability to keep adequately warm	2	Ability to keep adequately warm
2	Presence of bath or shower	1	No bath or shower	1	No bath or shower

social groups that are disproportionately affected by energy poverty.

3.2.1. The identification of energy poverty threshold

The posetic approach is a non-compensative method used to construct indices that capture both the incidence and intensity of energy poverty by incorporating combinations of ordinal variables related to energy deprivation (Maranzano et al., 2021). Then, it compares these profiles with benchmark ones, which are defined subjectively by the researcher by evaluating deprivation in individual dimensions and adopting possible theoretical combinations as poverty thresholds (Arcagni et al., 2019). Since the variables extracted from the EU_SILC database are categorical or dichotomous, this paper conducts a preliminary recording of questionnaire responses to render them orderly and select the energy deprivation benchmark profiles. Concerning the dichotomous variables, a value of 1 was assigned to the absence of the attribute, service inability, or inefficiency, while a value of 2 was allocated to the possession or efficient provision of the service. For the other dimensions, the responses were recorded by assigning the following increasing values:

- 1, if the household declares that they cannot afford the attribute,
- 2, if the household states that they do not have the attribute for reasons other than a lack of economic resources,
- 3, if it declares not to be deprived.

Regarding variables with three modes, the recoding mentioned above allows for distinguishing between those who lack an attribute due to financial constraints and are unequivocally experiencing deprivation in that dimension and those who face deprivation for reasons unrelated to financial limitations, such as habits, behaviours, and culture. While recognizing that energy deprivation may also be related to factors other than those related to household income, such as culture, behaviour or special needs, EU_SILC and, in particular, the response category "2" do not provide detailed subclasses. Therefore, it was decided not to consider this category as energy deprivation due to the extreme heterogeneity of underlying motivations that can generate misleading results. Lastly, individuals with the attribute in question certainly do not experience poverty. To establish the deprivation threshold, this study selects all the combinations presenting the mode "*no, other reasons*" (see Table 2) to identify clearly energy-poor households, initially distinguishing them from those without energy deprivations, as follows: *"222222222", "222222221", "222222212", "222222122", "222222112", "222222211", "222222121"*.

Observing some socio-demographic characteristics of the households corresponding to the selected profiles reported in Table D.1 in Appendix D, these are mostly composed of a single female component, and more than half of these households are not classified as income-poor. However, householders are mostly retired or inactive and have low levels of education. Finally, in line with Section 3.2, this study employs the deprivation profile "*222222222*" as a threshold because it is an antichain[12] and dominates all other profiles, which have not been included for respecting the "non-redundancy" requirement (Fattore, 2016, p. 841). Classifying all households below this threshold as energy-poor allows us to focus on the most severe energy deprivation. The group that is thus formed will be composed of these households who report arrears in the utility bills, the absence of one or more electrical appliances due to financial constraints, challenges in adequately heating their homes during winter, residing in dwellings plagued by dampness and mould problems, or, in the most extreme situations, declaring a lack of domestic hot water. These criteria definitively classify them as experiencing energy poverty.

[12] The "POSetR" package and the function "incomparability" of the package PARSEC have been implemented to select and test the antichain.

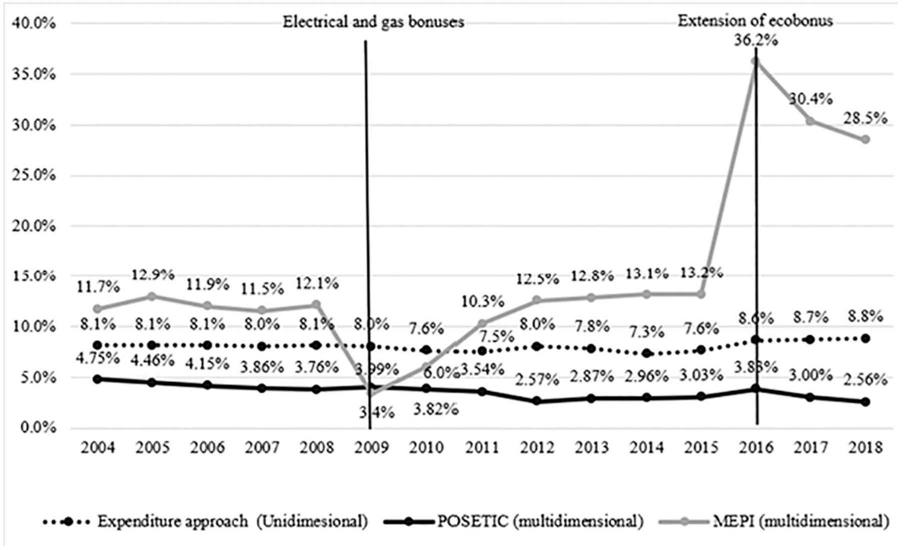

Fig. 1. The comparison of the energy poverty incidence obtained by unidimensional and multidimensional approaches.

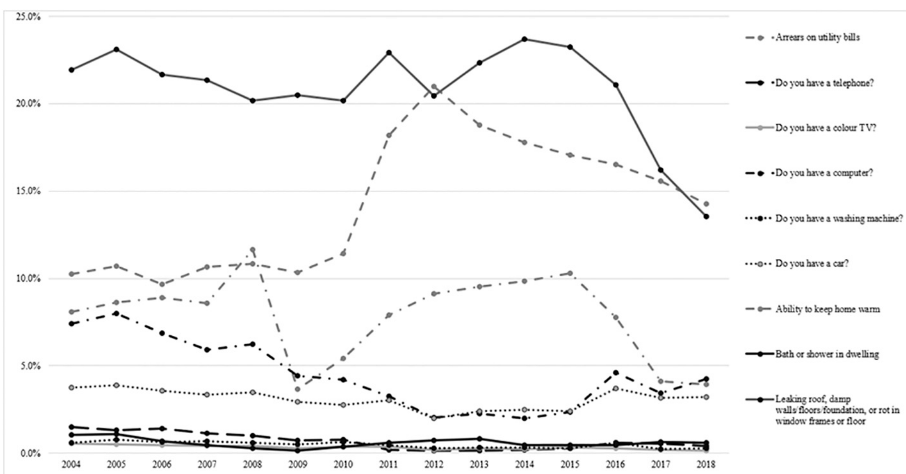

Fig. 2. The trend of energy deprivations in the period 2004–2018.

4. Results and policy implications

This section elucidates the evolution of multidimensional energy poverty from 2004 to 2018 by applying the posetic[13] approach to the EU_SILC data and, then discusses its potential influence by comparing it with more commonly used methodologies in academic and political contexts to compute the spread and intensity of energy poverty. As mentioned in Section 3.1, the weighted average of the identification scores represents the headcount ratio (see Appendix B for the summary statistics of the identification function); Fig. 1 shows a progressive decrease in the incidence of energy poverty from 2004 to 2018. After the peak of 2005, the percentage of energy-poor households remained relatively stable at around 4 % of the Italian population until 2011. Starting from 2012, the energy poverty incidence decreased modestly by oscillating around 2.50 % of Italian households, which is attributed both to general lifestyle advancements between 2000 and 2016 (Manduzio et al., 2018), including the electrical equipment in homes (Fig. 2 demonstrates a reduction in all energy deprivations), and to the decrease in the residential demand for natural gas for heating due to milder winter (Faiella et al., 2017). This trend continued until 2018, when energy poverty affected about 2.6 % of Italian households.

Even if Fig. 1 compares two measures that are not perfectly overlapping, the percentage of Italian energy-poor households resulting from the posetic approach consistently remains below the values estimated by the Italian government using unidimensional energy expenditure indicators, which ranges between 8.1 % and 8.8 % of Italian households in the period 2004–2018. These results may indicate that some income-poor households could be classified as energy-poor ones by the unidimensional indicator even if they do not suffer from severe energy deprivation. Due to the lack of direct energy expenditure data, this study adopts the variable "arrears on utility bills" as a proxy of energy affordability, the same dimension measured by the unidimensional index. As shown in Table A.1 of Appendix A, this variable assumes values similar to the national indicator until 2016. Therefore, the lower incidence of energy poverty obtained by the posetic approach could result from the inclusion of other dimensions of material deprivation,

[13] To compute the identification and severity functions, the PARSEC package is used in Rstudio software. It is based on the implementation of the Bubley-Dyer (1999) algorithm, which allows for the generation of uniform sampling of the linear extensions of the partially ordered set. For a more technical explanation of the procedure, see Bubley and Dyer (1999) and Arcagni (2017). Further clarifications can be included at request.

which could mitigate the negative effect of energy burden in some cases. Given that the number of households reporting energy bill arrears and the energy expenditure index appears to remain stable at around 8–9 %, this result could indicate that both of these measures may not be able to capture the positive effect of the *elettrico* and *gas* bonuses (supporting households only in paying energy bills, as described in footnote 4) or that these subsidies could only be partially effective[14] in mitigating energy poverty if policymakers focus only on affordability dimension (Miniaci et al., 2014). However, this analysis would require a comparison between the energy expenditure index, income poverty, and the posetic approach at the household level. Since the EU_SILC survey does not provide household energy expenditure, this paper is limited to national-level comparisons. On the contrary, data allows us to verify the overlap between multidimensional energy poverty and income poverty at the individual household level. The posetic approach seems to support the hypothesis that these are correlated but distinct phenomena (Marchand et al., 2019). Indeed, as shown in Table 3, while income poverty appears to affect about 20 % of Italian households, energy-poor families range from 4.75 % to 2.56 %, with less than 1 % of them also suffering from income poverty.

Furthermore, the energy expenditure index has grown since 2016, when the 2017 Budget Act extended the ecobonus eligibility to the incipient families, authorizing them to transfer tax credits to suppliers and financial institutions (Manduzio et al., 2018), represented by the second line in Fig. 1. A substantial number of energy-poor households are forced to reside in rental housing, whose landlords are often reluctant to invest in energy upgrading since they cannot benefit from the immediate energy savings in the energy bill produced by the intervention and are not sure of recovering costs by potential rent increases (ENEA, 2020; Ugarte et al., 2016). Moreover, these interventions require an initial upfront investment that low-income households cannot sustain due to their constrained financial resources and limited credit access (Faiella Lavecchia et al., 2019). Finally, ecobonus primarily targets the improvement of energy efficiency rather than helping energy-poor households get out of energy precariousness (Martini, 2021). For these reasons, many of them remained excluded from the pool of potential eligible beneficiaries. Focusing on the English Warm Front program, Boardman (2010) contends that energy retrofit policies can effectively counter this phenomenon only when explicitly tailored to address the needs of the energy poor.

In the period 2000–2016, the slowdown in the rate of improvement of energy efficiency (10.7 %), compared to the 90s of the last century, was not able to compensate for the recovery in domestic energy consumption caused by demographic effects, the growth of the housing stock, and a further increase in energy prices (ENEA, 2018; Faiella and Lavecchia, 2021), These circumstances may elucidate the slight rise in the incidence of energy poverty between 2013 and 2016, computed throughout the expenditure index. Conversely, the posetic incidence, which includes aspects relating to the energy efficiency of housing, has been decreasing progressively since 2015 and seems to capture a possible effect of improvement of energy efficiency produced by ecobonus and other incentives. According to the energy poverty literature (see, e.g., Aristondo and Onaindia, 2018), this result seems to confirm the need for a multidimensional approach to measuring energy poverty that looks at both energy affordability and material energy deprivation.

Then, this paper compares the incidence and severity obtained through the posetic approach with those obtained by applying the dual cut-off identification procedure and MEPI, which is widely regarded as the standard methodology for multidimensional energy poverty assessment (Sokołowski et al., 2020). Despite both highlighting its multidimensional nature, the two methodologies return very different results in terms of the incidence and intensity of this phenomenon in Italy. Taking into consideration the former, the MEPI always classifies a greater number of households as multidimensionally energy-poor, while the posetic approach identifies fewer families because the threshold focuses only on those households suffering from severe forms of energy deprivation. This result seems to highlight a possible error in the classification of MEPI, potentially due to a less stringent multidimensional threshold that considers as energy-poor even when they are deprived only in relation to electrical equipment for reasons other than financial constraints, but rather related to consumption preferences. Although they also represent energy deprivation, their combinations cannot indicate a serious energy poverty condition. Therefore, the MEPI could risk overestimating the incidence of energy poverty, which increased from 11.69 % (2′724’264 households) in 2004 to 28.48 % (7′374’739 households) of Italian households in 2018 (Fig. 1). Indeed, the sensitivity analysis in Appendix C highlights that the posetic approach also identifies more households as energy poor when we use the deprivation profiles corresponding to the same multidimensional threshold of the dual cut-off identification procedure. This result seems to support the hypothesis that MEPI's criteria may represent a relatively lenient threshold, potentially leading to an overestimation of the phenomenon's prevalence. As demonstrated in Table C.4., the posetic approach not only classifies more households as energy-poor compared to the MEPI, but also reveals a limited overlap between the two samples. Moreover, the average identification score of the posetic approach shows a more stable trend, probably due to the fact that it does not require any compensation between energy dimensions. On the contrary, MEPI seems more sensitive to the choice of the number and weights of poverty dimensions, which directly influence the calculation of the deprivation score attributed to individual households (Sadath and Acharya, 2017), being a weighted average of the hardships suffered by households in each dimension.

Recently, several European Member States have focused on assessing the severity of energy poverty, whose knowledge is fundamental to assisting the most impacted individuals (Maxim et al., 2016). A significant drawback of the prevailing energy expenditure approach is their exclusive focus on quantifying the incidence, overlooking the intensity of energy deprivation. Multidimensional approaches, instead, allow to compute the severity, comparing the poverty gap of the posetic approach with the average of the censored weighted deprivation score of MEPI, as shown in Fig. 3. As for incidence, the two methodologies return different intensities of the phenomenon between Italian households, even if the difference in value is smaller than in the previous case. MEPI showed a greater degree of deprivation compared to the poverty gap of the posetic method until 2015, a year in which a turnaround was observed. In the first case, the average intensity of the deprivations decreased progressively from 0.30 in 2004 to 0.16 in 2018. In the second case, Italian households experienced deprivation in at least two energy dimensions, with the poverty gap ranging between 0.26 in 2006 and 0.19 in 2015. Overall, the reduction in deprivation across all energy dimensions indicates a general improvement in quality of life in the Italian context (see Fig. 2). Therefore, many energy services, in particular the provision of electrical appliances, have become less accessible to energy-poor households due to poor financial availability, thus exacerbating the severity of their condition. This aspect may not be grasped through the MEPI, which implies the implicit compensation between energy dimensions and gives them equal weight, underestimating the relevance of individual attributes (Guarini, 2017).

The lack of overlap between the two multidimensional indices between the two severity indices could depend on the fact that the posetic approach performs a counting procedure not simply on the number of deprivations but on the linear extensions of the profiles, as indicated in Section 3.2. Deprivation is no longer considered as a sum of individual

[14] The Italian Regulatory Authority for Energy, Networks, and Environment reported that less than one-third of eligible recipients formally applied for the social bonuses primarily due to the eligibility criteria being linked to the economic situation of households expressed through the Equivalent Economic Conditions Indicator (ISEE) rather than to energy vulnerability indicators (Federesco, 2017).

Table 3
Overlap between income poverty and energy poverty from the posetic approach in the period 2004–2018.

	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Poor households															
Poor households in the sample	1128	2146	3144	4024	3935	1162	1898	2956	3874	3583	3814	2603	4363	4430	4109
Absolute value in the population	4,638,409	9,505,980	14,325,232	19,588,711	18,947,388	5,378,373	10,311,968	15,607,893	20,580,740	20,112,134	21,333,844	17,185,687	6,143,591	5,973,178	5,937,167
% on population	19.90 %	20.23 %	20.19 %	20.59 %	19.57 %	20.99 %	20.55 %	21.64 %	21.24 %	21.08 %	21.41 %	22.41 %	23.79 %	23.14 %	22.93 %
Energy-poor households															
Energy-poor households in the sample	259	417	589	702	695	183	334	434	445	448	490	301	629	524	437
Absolute value in the population	999,007	2,186,163	2,997,170	3,596,068	3,881,423	912,986	1,762,891	2,449,025	3,070,473	3,112,791	3,031,648	1,855,750	789,843	611,264	531,796
% on population	4.75 %	4.46 %	4.15 %	3.86 %	3.76 %	3.99 %	3.82 %	3.54 %	2.57 %	2.87 %	2.96 %	3.03 %	3.83 %	3.00 %	2.56 %
Income and energy-poor households															
Income and energy-poor households in the sample	31	57	87	101	143	54	64	85	92	93	87	51	126	97	87
Absolute value in the population	118,296	307,544	476,594	599,648	734,640	282,488	375,558	560,108	660,993	662,100	589,983	352,412	180,581	135,656	120,579
% on population	0.51 %	0.65 %	0.67 %	0.63 %	0.76 %	1.10 %	0.75 %	0.78 %	0.68 %	0.69 %	0.59 %	0.46 %	0.70 %	0.53 %	0.47 %

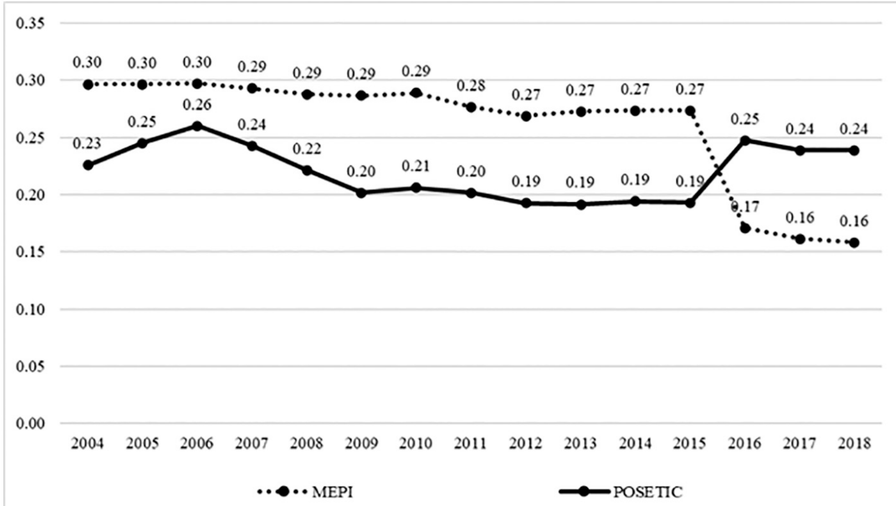

Fig. 3. The comparison of the intensity of energy poverty between 2004 and 2018 in Italy, according to the two multidimensional approaches.

unidimensional deprivations but as a "global property" of the profiles, eliminating the indeterminacy of poverty (Fattore, 2016). While the poverty gap is computed by keeping count of the distance between the deprived and not deprived profiles, MEPI measures the intensity of energy poverty simply as the mean of the deprivation score assigned only to the energy-poor households, which depends significantly on the importance assigned to each energy dimension through the weights and the multidimensional threshold imposed by the researcher (Freudenberg, 2003). In contradistinction to the counting methodology that implements a unique discrete value as the multidimensional threshold, the posetic framework permits the selection of an array of profiles to establish its threshold, reflecting the understanding that energy poverty does not have a singular expression, but rather, it is multifaceted and fuzzy. Therefore, the posetic approach seems to generate more reliable and robust results related to the incidence and the severity of this phenomenon when only discrete data such as those of EU_SILC are available. Moreover, selecting a threshold of deprivation profiles that focus mainly on the most serious forms of energy deprivation by identifying with greater certainty the energy poor, it can provide policymakers with a broader and more realistic assessment of the energy poor's experience for designing appropriate tailoring policies.

The sensitivity analysis delineates two distinct degrees of significance pertaining to energy dimensions, as outlined in Tables E.1. and E.2. in Appendix E. These are a strong influence and a mitigating impact on the energy vulnerability experienced by Italian households. First, all selected energy dimensions have an impact on findings of the posetic approach, which, however, do not change significantly with the removal of the variable "Bath or shower in the dwelling". This result may be due to the fact that less than 1 % of the Italian population has reported a deprivation in this dimension, although it is crucial for well-being because its presence allows the achievement of essential skills such as being in good health, being presentable in public and participating in community life. Secondly, the energy variables have a strong influence on reducing the incidence of energy poverty and increasing the poverty gap. This group includes arrears on utility bills, PC ownership, the ability to keep the home adequately warm, and problems with leaking roofs, damp walls/floors/foundations, or rot in window frames or floors. It is important to know that these variables are a proxy of the three main drivers of household energy poverty: aligned with Thomson Bouzarovski and Snell (2017), energy vulnerability depends on high energy costs and low income, captured by arrears on utility bills, as well as on energy performance of buildings and appliances, represented by the presence of damp and mould problems, and the specific energy needs of households, as in this case represented by the need to keep the house adequately heated. Conversely, the ownership of telephones, TVs, washing machines, and cars seems to have a mitigation effect on energy vulnerability because their elimination produces an increase in the incidence of energy poverty and, at the same time, a reduction in the poverty gap.

As previously noted, a substantial share of households experiencing energy poverty are renters (Boardman, 2010), particularly those paying market rents who have limited financial resources for energy expenses. Indeed, the decomposition of poset by the tenure status (see Tables E.3 and E.4 of Appendix E) highlights a greater incidence and severity of energy poverty among tenant households in the private rental sector, especially up to 2012. Social housing is also highly vulnerable due to the energy obsolescence of building stock and the precarious households' socio-economic condition, with an incidence ranging from 9.05 % in 2004 to 8.92 % in 2018, confirming the need to intervene with a specific energy retrofit program of social housing stock as indicated by the 2019 PNIEC. This measure should, however, also be extended to the private rental sector, which has the highest severity of energy deprivation with a poverty gap that fluctuates between 0.3418 in 2004 and 0.2347 in 2018. In the period 2004–2018, the number of energy-poor households in free accommodation progressively decreased, while the incidence and severity are significantly lower among homeowners because they may be more willing to undertake energy renovation of buildings being able to benefit directly from the benefits, such as the potential for a warmer, more comfortable home, lower energy bills and other private benefits (Kerr and Winskel, 2020).

5. Concluding remarks

Recent surges in energy prices in Europe pose a significant risk to the post-pandemic economic recovery, household incomes, and the nascent ecological transition (Belaïd, 2022). This escalation in energy prices and domestic energy consumption is heightening the energy vulnerability of numerous European households, undermining the efficacy of European policies to attain the UN Sustainable Development Goals (Carfora et al., 2022). Addressing energy poverty is an essential prerequisite for advancing a fair and just transition to carbon-neutral Europe by 2050, pursued by the *European Green Deal Strategy*, thereby guaranteeing the inclusion of all individuals and preventing any form of exclusion (Rodriguez-Alvarez et al., 2021). In Italy, concern regarding energy poverty has garnered heightened significance within the energy policy framework in light of the recent sharp rises in natural gas and electricity prices (IEA, 2023). However, government interventions during 2021–2022 to address rising energy prices were less effective for the poorest households, who experienced a higher relative increase in energy expenditure on the total one compared to the average household (Faiella and Lavecchia, 2022).

Framing energy poverty within the capability approach provides a more suitable theoretical foundation for analyzing energy poverty and assessing the deprivations faced by energy-poor individuals in Italy. This perspective emphasizes its multidimensional nature, encompassing energy access, well-being, and the quality and energy efficiency of both dwellings and appliances. Within this framework, this paper employs the posetic approach to compute the incidence and severity of multidimensional energy poverty in Italy between 2004 and 2018 using EU_SILC qualitative data. Requiring discrete values for analyzing multidimensional systems of ordinal attributes (Carlsen and Bruggemann, 2022), the findings reveal a progressive decrease in the diffusion of this phenomenon among Italian families (from 4.75 % in 2004 to 2.56 % of Italian households in 2018), while also highlighting the intensity of energy deprivation among energy-poor households increased from 0.23 in 2004 to 0.26 in 2006, declined to a low of 0.19 between 2012 and 2015, and subsequently rose to 0.24 in 2018.

Methodologies for gauging energy poverty are experiencing a consistent expansion in both volume and intricacy. To assess its robustness, the posetic approach was compared with the energy expenditure index employed by the Italian government and the dual cut-off identification procedure, widely used today to evaluate income poverty and multidimensional energy poverty. Considering only the energy affordability and measuring the energy burden, the unidimensional indicator may overestimate the magnitude of energy poverty by including households not necessarily deprived of essential energy services, superimposing energy poverty onto income poverty. However, as the EU_SILC survey does not provide any detailed information on household energy expenditure, the incidence of Italian energy expenditure is exogenous to the model, and it is only available at the national level. Therefore, the level of income poverty cannot be compared with this indicator at an aggregate level to check for possible overlap between income poverty and energy unaffordability, as well as it is not possible to verify the overlap between the posetic approach and the expenditure indicator. Further research will try to integrate the EU_SILC survey with data from the HBS survey to assess the intersection between income poverty and energy poverty, as well as between the posetic approach and the national energy expenditure index. Considering that the proportion of households reporting energy bill arrears and the energy expenditure index have remained stable at approximately 8–9 %, this outcome may suggest that these indicators are insufficient in capturing the positive impact of the electricity and gas subsidies. Moreover, further research will be needed to integrate the EU_SILC database with energy prices and energy bill data for Italian households to verify the effectiveness of social bonuses.

The lower incidence of energy poverty computed by the posetic approach may result from the incorporation of additional dimensions of material deprivation, which, in certain cases, could alleviate the negative impact of the energy burden. Moreover, its decreasing trend seems to capture a possible effect of improvement of energy efficiency produced by ecobonus and other incentives, highlighting the importance of considering multiple dimensions beyond mere energy expenditure for providing a nuanced understanding of energy poverty. Considering the results, policymakers should consider a multidimensional framework when designing interventions to combat energy poverty because it allows the assessment of both the incidence and severity of the phenomenon, a characteristic neglected by the unidimensional expenditure index. Understanding both the breadth and depth of deprivation is essential for designing targeted and effective interventions, particularly in Italy, where policy approach remain fragmented and lack a long-term vision (Federesco, 2017). Comparison between the posetic approach and the dual cut-off identification procedure yields very different results in terms of the incidence and intensity of energy poverty. In particular, the latter seems to overestimate the incidence because the former also yields an even higher magnitude when using the same multidimensional threshold of MEPI. Instead, the posetic approach allows the identification of fewer families as multidimensionally energy-poor, focusing on more severe energy deprivations. This difference is attributable to the fact that the dual cut-off identification procedure and MEPI are constrained by the implicit compensation between dimensions and dichotomization of variables (Freudenberg, 2003), while the posetic approach does not require the choice of a weight vector and considers ordinal relationships instead of weighted averages. Therefore, it can provide policymakers with a broader and more realistic assessment of energy poors' experience for designing appropriate tailoring policies. Moreover, the posetic approach and the MEPI reveals minimal overlap between the two energy-poor groups at the national level. Future research could usefully compare households classified as poor by the counting approach with their corresponding identification scores under the posetic method, providing deeper insight into the distinctions between these assessment frameworks at the individual level. However, the posetic approach is characterised by increasing computational complexity as a function of the number of dimensions, which may have influenced the fact that the threshold adopted in this study clearly divides the population into two groups. Therefore, future research will focus on the detailed analysis of deprivation profiles in order to identify a threshold that returns a gradual distribution of the phenomenon in the population.

Both multidimensional methodologies reveal significant severity of energy deprivation among Italian households. However, while the MEPI reflects the relevance of individual attributes only if the researcher imposes different subjective weights on dimensions, the posetic approach incorporates the varying attribute values to achieve identical functioning through the utilization of linear extensions. Indeed, the reversal trend of the poverty gap seems to capture the increased inaccessibility for energy-poor households to many energy services, which are increasingly considered essential due to the improvement in the quality of life that has affected the Italian context. To conclude, the results seem to confirm the need for a multidimensional approach to measuring energy poverty, which considers both energy accessibility and material deprivation. As Boardman (2010) suggested, existing policy instruments should be strengthened, and new policies should be explicitly tailored to the needs of energy-poor households. Focusing on the most severe forms of energy deprivations, the posetic approach can identify with greater certainty energy poor and facilitate more targeted policy measures, especially today, when the few data available to policymakers are categorical, ordinal, and dichotomous. Since it explicitly considers a dimension linked to the energy performance of housing stock, the posetic method could represent a key element in advancing the energy retrofit program imposed by the 2019 PNIEC, particularly especially in the social housing and private rental sector, which sensitivity analysis identified as the most vulnerable. Similarly, it can be a valuable tool to invest the substantial resources provided by the Italian National Recovery and Resilience Plan effectively. These funds will significantly stimulate economic growth and job creation, promote social resilience by improving the population's living conditions, and, most importantly, represent an unprecedented opportunity to eradicate energy poverty.

CRediT authorship contribution statement

Chiara Grazini: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The author declares that she has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The author states that no financial assistance was received for the work. The author declares that there are no patents or copyrights to be asserted that are relevant to the work in the manuscript.

Appendix A. The percentage frequencies of energy deprivations in the Italian population in the period 2004–2018

Table A.1
The percentage frequencies of energy dimensions across Italian households in the period 2004–2018.

EU_SILC Variables and modes	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Arrears on utility bills															
Yes	8.1 %	8.6 %	8.9 %	8.6 %	11.6 %	3.7 %	5.4 %	7.9 %	9.1 %	9.5 %	9.8 %	10.3 %	7.8 %	4.1 %	4.0 %
No	91.9 %	91.4 %	91.1 %	91.4 %	88.4 %	22.5 %	45.1 %	65.9 %	90.9 %	90.5 %	90.2 %	89.7 %	92.2 %	95.9 %	96.0 %
Do you have a telephone?															
No, cannot afford	1.5 %	1.3 %	1.4 %	1.2 %	1.0 %	0.7 %	0.8 %	0.2 %	0.1 %	0.2 %	0.2 %	0.3 %	0.6 %	0.6 %	0.4 %
No, other reason	3.0 %	3.0 %	3.1 %	2.7 %	2.5 %	2.5 %	2.6 %	3.1 %	2.6 %	2.8 %	2.7 %	2.7 %	1.8 %	1.1 %	1.0 %
Yes	91.5 %	94.5 %	94.3 %	95.0 %	95.7 %	96.2 %	96.3 %	97.0 %	97.1 %	97.4 %	97.0 %	96.9 %	96.7 %	96.7 %	97.5 %
Do you have a colour TV?															
No, cannot afford	0.6 %	0.5 %	0.5 %	0.4 %	0.4 %	0.3 %	0.3 %	0.4 %	0.2 %	0.3 %	0.3 %	0.3 %	0.3 %	0.2 %	0.1 %
No, other reason	3.0 %	3.0 %	3.1 %	2.7 %	2.5 %	2.5 %	2.6 %	3.1 %	2.6 %	2.8 %	2.7 %	2.7 %	1.8 %	1.1 %	1.0 %
Yes	96.5 %	96.4 %	96.5 %	96.8 %	97.0 %	97.2 %	97.1 %	96.5 %	97.2 %	96.9 %	97.0 %	97.0 %	97.9 %	98.7 %	98.8 %
Do you have a computer?															
No, cannot afford	7.4 %	8.0 %	6.9 %	5.9 %	6.2 %	4.4 %	4.2 %	3.3 %	2.1 %	2.3 %	2.0 %	2.3 %	4.6 %	3.5 %	4.2 %
No, other reason	53.3 %	50.6 %	49.3 %	48.1 %	45.3 %	43.8 %	42.1 %	38.2 %	36.3 %	34.8 %	34.6 %	34.2 %	33.1 %	33.0 %	32.7 %
Yes	39.3 %	41.4 %	43.9 %	45.9 %	48.4 %	51.8 %	53.7 %	58.5 %	61.7 %	62.9 %	63.4 %	63.5 %	62.3 %	63.6 %	63.1 %
Do you have a washing machine?															
No, cannot afford	0.6 %	0.8 %	0.6 %	0.7 %	0.6 %	0.5 %	0.7 %	0.5 %	0.3 %	0.3 %	0.3 %	0.3 %	0.6 %	0.2 %	0.3 %
No, other reason	2.6 %	2.5 %	2.5 %	2.1 %	2.2 %	2.1 %	2.1 %	2.8 %	1.9 %	2.0 %	1.8 %	1.8 %	1.1 %	0.9 %	1.0 %
Yes	96.8 %	96.7 %	96.9 %	97.2 %	97.3 %	97.4 %	97.2 %	96.7 %	97.8 %	97.7 %	97.9 %	97.9 %	98.3 %	98.9 %	98.7 %
Do you have a car?															
No, cannot afford	3.8 %	3.9 %	3.6 %	3.3 %	3.5 %	2.9 %	2.8 %	3.0 %	2.0 %	2.4 %	2.5 %	2.4 %	3.7 %	3.2 %	3.2 %
No, other reason	18.6 %	17.9 %	17.7 %	17.9 %	17.5 %	18.1 %	18.3 %	18.1 %	18.8 %	18.4 %	18.2 %	18.7 %	15.6 %	18.2 %	15.8 %
Yes	77.6 %	78.2 %	78.7 %	78.8 %	79.0 %	78.9 %	79.0 %	78.8 %	79.2 %	79.2 %	79.3 %	78.9 %	80.7 %	78.7 %	81.0 %
Ability to keep home adequately warm															
No	10.3 %	10.7 %	9.7 %	10.7 %	10.8 %	10.4 %	11.4 %	18.2 %	21.0 %	18.8 %	17.8 %	17.1 %	16.5 %	15.6 %	14.2 %
Yes	89.7 %	89.3 %	90.3 %	89.3 %	89.2 %	89.6 %	88.6 %	81.8 %	79.0 %	81.2 %	82.2 %	82.9 %	83.5 %	84.4 %	85.8 %
Bath or shower in the dwelling															
No	1.0 %	1.1 %	0.7 %	0.5 %	0.3 %	0.2 %	0.3 %	0.6 %	0.7 %	0.8 %	0.5 %	0.5 %	0.5 %	0.6 %	0.6 %
Yes	99.0 %	98.9 %	99.3 %	99.5 %	99.7 %	99.3 %	99.3 %	99.2 %	99.3 %	99.2 %	99.5 %	99.5 %	99.5 %	99.4 %	99.4 %
Leaking roof, damp walls/floors/foundation, or rot in window frames or floor															
Yes	21.9 %	23.1 %	21.6 %	21.4 %	20.2 %	20.5 %	20.2 %	23.0 %	20.4 %	22.3 %	23.7 %	23.3 %	21.1 %	16.2 %	13.5 %
No	78.1 %	76.9 %	78.4 %	78.6 %	79.8 %	79.5 %	79.8 %	77.0 %	79.6 %	77.7 %	76.3 %	76.7 %	78.9 %	83.8 %	86.5 %

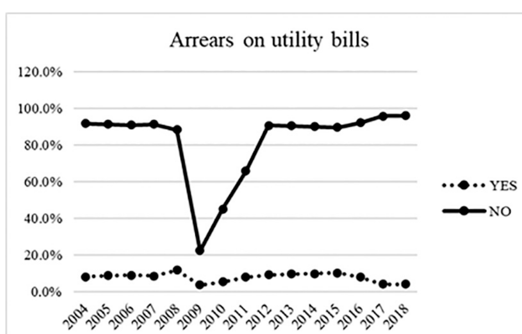

Fig. A.1. The evolution of Arrears on utility bills in the period 2004–2018.

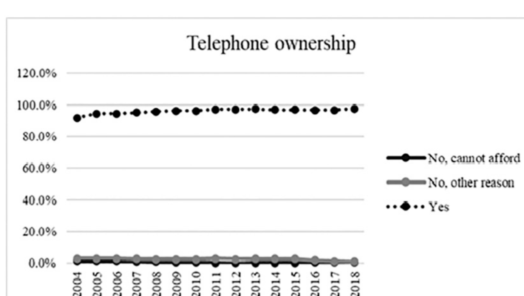

Fig. A.2. The trend of telephone ownership in Italy between 2004 and 2018.

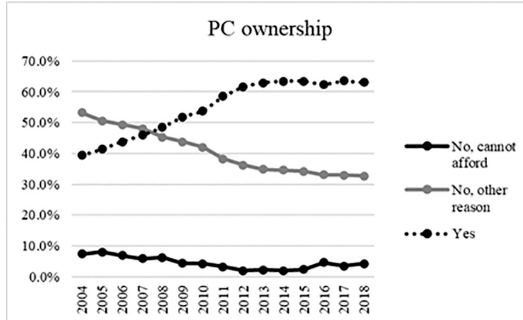

Fig. A.3. The evolution of percentage frequencies of PC ownership in the period 2004–2018.

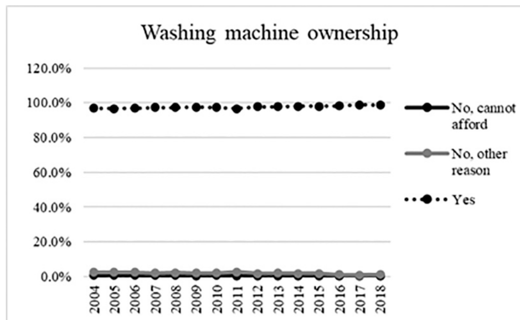

Fig. A.4. The washing machine ownership across Italian households in the period 2004-2018.

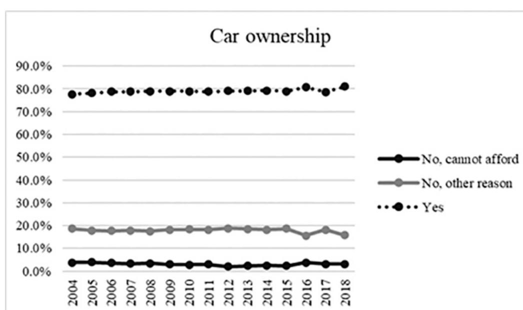

Fig. A.5. The percentage frequencies of car ownership in the period 2004–2018.

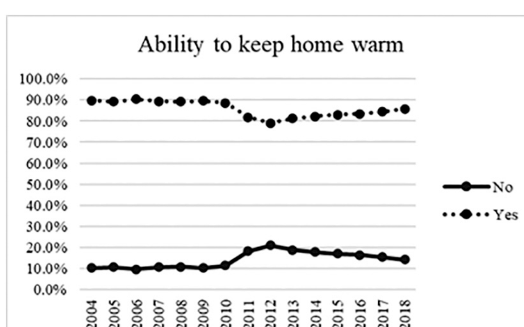

Fig. A.6. The trend of the ability to keep warm in the period 2004–2018.

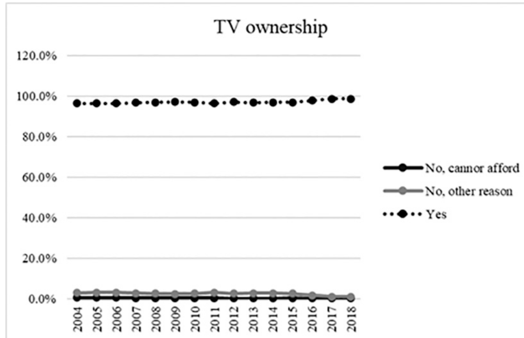

Fig. A.7. The percentage frequencies of TV ownership in the period 2004–2018.

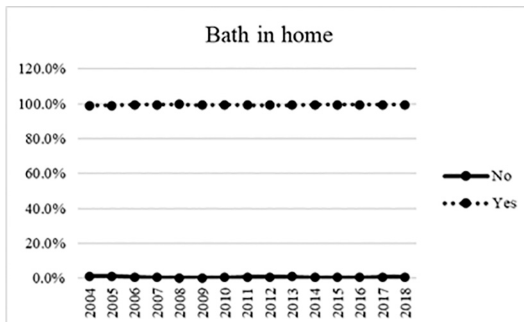

Fig. A.8. The evolution of bath presence in the period 2004–2018.

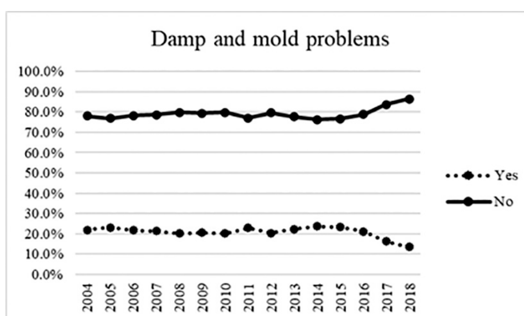

Fig. A.9. The percentage frequencies of damp and mould problems in the period 2004–2018.

Table A.2
Correlation matrix for the period 2004–2015.

	Arrears on utility bills	Do you have a telephone (including a mobile phone)?	Do you have a colour TV?	Do you have a computer?	Do you have a washing machine?	Do you have a car?	Ability to keep home adequately warm	Bath or shower in the dwelling	Leaking roof, damp walls/floors/ foundation, or rot in window frames or floor
Arrears on utility bills	1								
Do you have a telephone (including a mobile phone)?	0.056	1							
Do you have a colour TV?	0.037	0.102	1						
Do you have a computer?	0.078	0.207	0.065	1					
Do you have a washing machine?	0.041	0.167	0.234	0.118	1				
Do you have a car?	0.076	0.242	0.080	0.383	0.149	1			
Ability to keep home adequately warm	0.162	0.045	0.047	0.098	0.049	0.076	1		
Bath or shower in the dwelling	0.228	0.123	0.0651	0.172	0.086	0.171	0.175	1	

(*continued on next page*)

Table A.2 (*continued*)

	Arrears on utility bills	Do you have a telephone (including a mobile phone)?	Do you have a colour TV?	Do you have a computer?	Do you have a washing machine?	Do you have a car?	Ability to keep home adequately warm	Bath or shower in the dwelling	Leaking roof, damp walls/floors/ foundation, or rot in window frames or floor
Leaking roof, damp walls/floors/ foundation, or rot in window frames or floor	0.024	0.093	0.065	0.059	0.128	0.084	0.057	0.063	1

Table A.3
Correlation matrix for the period 2016–2018.

	Arrears on utility bills	Do you have a telephone (including a mobile phone)?	Do you have a colour TV?	Do you have a computer?	Do you have a washing machine?	Do you have a car?	Ability to keep home adequately warm	Bath or shower in the dwelling	Leaking roof, damp walls/floors/ foundation, or rot in window frames or floor
Arrears on utility bills	1.000								
Do you have a telephone (including a mobile phone)?	0.032	1.000							
Do you have a colour TV?	0.045	0.080	1.000						
Do you have a computer?	0.113	0.243	0.076	1.000					
Do you have a washing machine?	0.060	0.094	0.285	0.120	1.000				
Do you have a car?	0.114	0.294	0.106	0.484	0.157	1.000			
Ability to keep home adequately warm	0.136	0.038	0.045	0.095	0.059	0.097	1.000		
Bath or shower in the dwelling	0.201	0.151	0.062	0.213	0.090	0.207	0.120	1.000	
Leaking roof, damp walls/floors/ foundation, or rot in window frames or floor	0.008	0.067	0.041	0.036	0.037	0.046	0.017	0.054	1.000

Appendix B. Summary statistics of the posetic approach

Table B.1
Mean and median values of identification and severity function.

Year	Frequencies	Identification function		Severity function	
		Mean	Median	Mean	Median
2004	1 = 259 0 = 6000	0.455	0.000	0.136	0.000
2005	1 = 417 0 = 11,138	0.504	1.000	0.140	0.001
2006	1 = 589 0 = 15,973	0.540	1.000	0.186	0.023
2007	1 = 702 0 = 20,233	0.572	1.000	0.195	0.037
2008	1 = 695 0 = 20,177	0.535	1.000	0.165	0.018
2009	1 = 183 0 = 5819	0.423	0.000	0.108	0.000
2010	1 = 334 0 = 9744	0.457	0.000	0.126	0.000
2011	1 = 434 0 = 14,579	0.482	0.000	0.141	0.000
2012	1 = 445 0 = 19,074	0.445	0.000	0.118	0.000
2013	1 = 448 0 = 18,012	0.475	0.000	0.134	0.000

(continued on next page)

Table B.1 (*continued*)

Year	Frequencies	Identification function		Severity function	
		Mean	Median	Mean	Median
2014	1 = 490 0 = 19,164	0.487	0.000	0.137	0.000
2015	1 = 301 0 = 13,039	0.411	0.000	0.110	0.000
2016	1 = 629 0 = 20,696	0.494	0.000	0.150	0.000
2017	1 = 524 0 = 21,702	0.443	0.000	0.138	0.000
2018	1 = 437 0 = 20,736	0.457	0.000	0.135	0.000

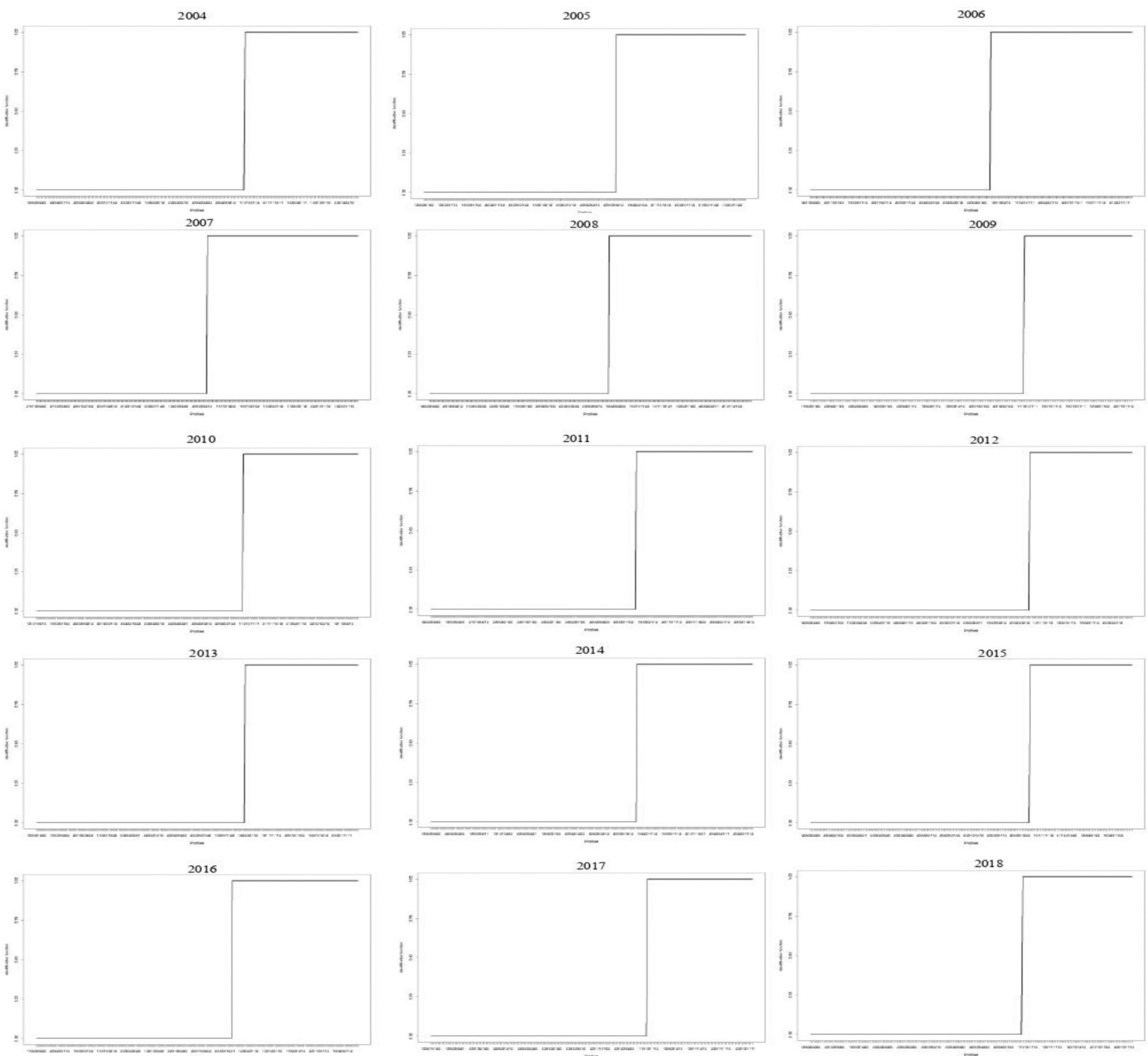

Fig. B.2. Annual distribution of the identification function.

Appendix C. The dual cut-off identification procedure and the Multidimensional Energy Poverty Index (MEPI)

According to Sen (1976), multidimensional poverty evaluation consists of an identification method and an aggregation measure. Following this approach, this paper adopted the dual cut-off identification procedure to identify multidimensional Italian energy-poor households. This appendix does not delve into an exhaustive mathematical exploration of the dual cut-off identification procedure but rather elucidates the fundamental components of this method. Introduced by Gordon et al. (2003) as the "Bristol Approach" and later adopted by Chakravarty and D'Ambrosio (2006) to build a multidimensional measure of social exclusion, the counting approach has only been officially formalized in the dual cut-off identification procedure by Alkire and Foster, 2007 under the Oxford Poverty and Human Development Initiative. After choosing the reference population ($n \geq 2$)

and identifying d energy poverty dimensions, this method counts the number of dimensions in which individuals are deprived (Atkinson, 2003). Defining x_{ij} as the achievement of the household i in the dimension j, its attainments across all poverty dimensions could be represented through the following matrix $n \times d$:

$$X = [x_{ij}] \tag{C.1}$$

The dual cut-off identification requires two different thresholds for identifying people experiencing multidimensional poverty. The former is called "deprivation cut-off". It is a unidimensional threshold, which is used to verify whether an individual is deprived or not in each dimension. Representing it by z_j, it indicates the baseline level of accomplishment necessary to avoid conditions of deprivation in dimension j. Comparing the achievement of households with z_j, the dual cut-off identification procedure classifies them as deprived if their achievement falls below the unidimensional deprivation cut-off, assigning a value of 1 and 0 otherwise, as follows:

$$g_{ij} = \begin{cases} 1, & x_{ij} < z_j \\ 0, & x_{ij} \geq z_j \end{cases} \tag{C.2}$$

To differentiate between deprived and not-deprived households in each energy dimension, this paper used the unidimensional thresholds reported in Table C.1.

Table C.1
Unidimensional thresholds of energy poverty dimensions.

EU_SILC Variable	Unidimensional cut-off
Arrears on utility bills	Yes
Do you have a telephone (including a mobile phone)?	No, cannot afford + No, other reason
Do you have a colour TV?	No, cannot afford + No, other reason
Do you have a computer?	No, cannot afford + No, other reason
Do you have a washing machine?	No, cannot afford + No, other reason
Do you have a car?	No, cannot afford + No, other reason
Ability to keep home adequately warm	No
Bath or shower in the dwelling	No
Leaking roof, damp walls/floors/foundation, or rot in window frames or floor	Yes

According to Decancq and Lugo (2013), one of the fundamental problems when building a multidimensional indicator of poverty is the choice of weights that determine the trade-off between different dimensions. The compensative nature of the dual cut-off identification procedure requires the researcher to choose a vector of weights to be assigned to energy dimensions, which indicate the relative importance of deprivation in each attribute (Alkire et al., 2015):

$$W = (w_1, w_2, \ldots, w_d) \tag{C.3}$$

If w_j is the generic weight assigned to the energy dimension j $(w_j > 0)$, their sum must equal to 1:

$$\sum_{j=1}^{d} w_j = 1 \tag{C.4}$$

In multidimensional poverty research, it is a common practice to define dimensions' weights in a normative way based on the researcher's value assessments and, in particular, assign equal weights to each dimension, thereby not prioritizing any particular dimension over others, as exemplified in the work of Alkire and Apablaza (2016). Since poset does not impose any trade-off between the selected dimensions, I have imposed weights equal to the nine examined energy dimensions.

After selecting the vector of the weights and recording privations in each energy dimension, statistical units obtain a *deprivation score* (c_i), which is a weighted sum of the deprivations they suffered in each attribute, as expressed by the following equation:

$$c_i = \sum_{j=1}^{d} w_j g_{ij} \tag{C.5}$$

Finally, the dual cut-off identification procedure incorporates a second "*poverty threshold*" (k), which establishes the minimum number of deprivations an individual must experience to be classified as multidimensional energy poor. According to Alkire et al. (2015), it corresponds to the minimum deprivation score a household needs to exhibit in order to be identified as multidimensional poor. From an operational perspective, this method implies an identification function (p_k), which gives households the value of 1 if their deprivation score falls below the threshold k, or 0 otherwise, as in Eq. (C.6):

$$p_k(x_{ij}, z) = \begin{cases} 1, & c_i < k \\ 0, & c_i \geq k \end{cases} \tag{C.6}$$

The common criteria for setting up the multidimensional threshold are the union and intersection ones. Although these criteria have the advantage of not being influenced by the weighting method of variables, they may be subject to classification errors and lack the precision required for effective policy implementation (Alkire et al., 2015). By classifying all households that are deprived in at least one dimension as poor, the former risks producing an excessively large sample by including no poor households. The latter, instead, could create a sample that is too small by selecting only households that are lacking in all attributes. Therefore, Alkire and Foster (2007) suggest the use of an intermediate cut-off. Following the work of Brau and Delugas (2019), which examines the incidence of energy poverty in Italy by applying the dual cut-off identification procedure to the EU_SILC survey, this paper sets the multidimensional threshold at the 90th percentile of the distribution of deprivation score attributed to families. Like the threshold chosen for the posetic approach, this value theoretically allows all those families trapped in severe energy poverty to be classified as energy poor.

For the aggregation stage, this paper selected the Multidimensional Energy Poverty Index (MEPI) developed by Nussbaumer et al. (2012) based on the dual cut-off identification procedure. This composite index allows us to encapsulate the incidence and the severity of energy poverty in a single composite index of easy reading and interpretation. as it is the product of the *headcount ratio* (H) and the *average of the censored weighted deprivation score* (A):

$$MEPI = H^{*}A \tag{C.7}$$

According to Crentsil et al. (2019). the headcount ratio measures the ratio of households experiencing multidimensional energy poverty (q) to the total population (n), as represented in the following equation:

$$H = q/n \tag{C.8}$$

The intensity of multidimensional energy poverty is calculated as the average of the censored weighted deprivation scores of households identified as energy poor, as follows:

$$A = \frac{\sum_{i=1}^{n} c_i(k)}{q} \tag{C.9}$$

Despite, as mentioned in Section 3, all evaluation methods have strengths and weaknesses so that one method cannot be defined better than another; this sensitivity analysis compares the incidence and intensity of energy poverty computed through the posetic approach and the MEPI by using the same multidimensional threshold (see Tables C.2 and C.3). In particular, the deprivation profiles corresponding to the 90th percentile of the deprivation score distribution obtained by the dual cut-off identification procedure were set as a threshold, obtaining different results in terms of incidence (see Table C.2) and intensity (see Table C.3). From an operational point of view, the 90th percentile of the deprivation distribution scores obtained with formula (C.4) and using the maximal function was taken as a reference, the following deprivation profiles were selected for the new estimation of the posetic approach based on dual cut-off identification procedures:

- 2004–2015: "211333222","213133222","213212222","213222221","213231222","213333122","213333212","231133222","231313222","231331222", "231333122","231333212","233113222","233131222","233133122","233133212","233133221","233231221","233311222","233313122", "233313212","233313221","233331122","233331212","233333112","233333121","233333211"
- 2016-2018: "213333222","231333222","233133222","233313222","233331222","233333122","233333212","233333221"

When using ordinal data from the EU_SILC survey, the posetic approach could be a better method for assessing multidimensional energy poverty because Fattore and Arcagni (2018) observe that it allows for taking into account the order relations between energy attributes and avoiding scaling ordinal data into numerical or binary one, so that energy poverty is examined as an overall feature of the deprivation profile of the statistical unit. Let's examine the multidimensional thresholds of the two approaches. We can see how the single point value of the dual cut-off identification procedure, equal to 0.22, actually corresponds to several very different energy deprivation profiles. Consider, for example, two theoretical profiles, "233333221" and "233333212", which are characterised by being privates in a single but different dimension. By assigning equal weight to all dimensions and using a single value as a multidimensional cut-off, the dual cut-off identification procedure would assign the same deprivation score to both profiles, considering them equivalent (Fattore and Maggino, 2018). This means that incomparabilities are removed, transforming the original achievement partially ordered set into a linear order of equivalence classes of profiles when we have ordinal attributes. By examining their ordinal relations, the two profiles could be characterised by different degrees of deprivation with respect to their position relative to one or more benchmark profiles, which could enlarge the sample of energy-poor households considering various combinations of deprivation. Indeed, the posetic approach returns a higher number of energy-poor households, leading to the assumption that the profiles of deprivation corresponding to the 90th percentile may represent a low-restrictive threshold, risking overestimating the incidence of the phenomenon. Table C.4 shows that the posetic approach not only could classify too many households as energy-poor compared to the MEPI, but also, there is a limited overlap between the two samples. On the contrary, MEPI returns a higher average intensity of deprivation, which is to be calculated as the average deprivation scores of energy-poor households, as expressed by the eq. (C.9). So, this sensitivity analysis seems to indicate a greater adaptability of the posetic approach to discrete and ordinal data.

Table C.2
The incidence of energy poverty measured by using the same multidimensional threshold in MEPI and the posetic approach.

Year	MEPI	Posetic Approach
2004	11.69 %	20.31 %
2005	12.93 %	19.82 %
2006	11.95 %	18.34 %
2007	11.51 %	17.86 %
2008	12.10 %	17.98 %
2009	3.38 %	18.21 %
2010	5.98 %	16.96 %
2011	10.27 %	19.13 %
2012	12.54 %	17.63 %
2013	12.82 %	17.08 %
2014	13.12 %	17.23 %
2015	13,16 %	17.26 %
2016	36.22 %	42.81 %
2017	30.36 %	38.94 %
2018	28.48 %	36.59 %

Table C.3
The intensity of energy deprivation calculated by using the same multidimensional threshold in MEPI and the posetic approach.

Year	MEPI	Posetic approach
2004	0.30	0.0995
2005	0.30	0.1011
2006	0.30	0.1036
2007	0.29	0.0973
2008	0.29	0.0909
2009	0.29	0.0897
2010	0.29	0.0929
2011	0.28	0.0819
2012	0.27	0.0704
2013	0.27	0.0758
2014	0.27	0.0759
2015	0.27	0.0788
2016	0.17	0.0451
2017	0.16	0.0393
2018	0.16	0.0361

Table C.4
Overlap between the two samples of multidimensional energy-poor families.

MEPI (headcount ratio)	Posetic approach (90th percentile)	Overlap
693	1183	81
1354	2077	198
1826	2793	271
2198	3395	351
2332	3430	333
679	955	161
1101	1598	208
1861	2553	322
2260	3106	377
2194	2878	327
2316	3090	348
1544	1950	189
7028	8486	2793
6331	8419	2377
5488	7456	1903

Appendix D. Some socio-demographic characteristics of households corresponding to the threshold energy deprivation profiles

Table D.1
Socio-demographic features of benchmark deprivation profiles.

	222222222	222222221	222222212	222222122	222222112	222222211	222222121
Poverty index (yes)	35.60 %	28.60 %	51.40 %	35.50 %	37.50 %	42.90 %	40.00 %
Tenure status							
Owner	51.70 %	66.70 %	52.90 %	67.70 %	56.20 %	57.10 %	70.00 %
Tenant_market_price	13.80 %	–	5.90 %	6.50 %	12.50 %	–	
Tenant_reduced_price	–	–	2.90 %	–	–	–	20.00 %
Free_accomodation	34.50 %	33.30 %	38.20 %	25.80 %	31.20 %	42.90 %	10.00 %
Number of members	1	1	1	1	1	1	1
Gender householder							
Female	57.50 %	71.40 %	42.90 %	64.50 %	37.50 %	71.40 %	60.00 %
Male	42.50 %	28.60 %	57.10 %	35.50 %	62.50 %	28.60 %	40.00 %
Educational level householder							
Pre_primary	13.60 %	14.30 %	9.10 %	28.00 %	26.70 %	33.30 %	42.90 %
Primary	44.40 %	57.10 %	54.50 %	36.00 %	20.00 %	16.70 %	42.90 %
Lower_secondary	13.60 %	14.30 %	24.20 %	16.00 %	26.70 %	33.30 %	–
Upper_secondary	18.50 %	14.30 %	9.10 %	12.00 %	20.00 %	16.70 %	–
Post_secondary	1.20 %	–	–	–	–	–	–
First_stage_tertiary	8.60 %	–	3.00 %	8.00 %	6.70 %	–	14.30 %
Employment status householder							
Retired	46.20 %	50.00 %	35.70 %	51.70 %	43.80 %	42.90 %	50.00 %
Unemployed	1.20 %	–	7.10 %	–	6.20 %	–	–
Working_parttime	–	–	17.90 %	–	–	–	–
Working_fulltime	31.20 %	33.30 %	14.30 %	20.70 %	18.80 %	28.60 %	12.50 %
Student	1.20 %	–	3.60 %	–	–	–	–

(*continued on next page*)

Table D.1 (*continued*)

	222222222	222222221	222222212	222222122	222222112	222222211	222222121
Military_community_service	–	–	–	–	–	–	–
Inactive_person	11.20 %	–	3.60 %	17.20 %	25.00 %	–	25.00 %
Domestic_tasks	2.50 %	–	14.30 %	6.90 %	6.20 %	14.30 %	12.50 %
Disabled	–	16.70 %	3.60 %	3.40 %	–	14.30 %	–
Urbanization degree							
Densely_populated	23.00 %	42.90 %	28.60 %	22.60 %	25.00 %	57.10 %	10.00 %
Intermediate	43.70 %	28.60 %	42.90 %	35.50 %	37.50 %	14.30 %	30.00 %
Thinly_populated	33.30 %	28.60 %	28.60 %	41.90 %	37.50 %	28.60 %	60.00 %

Appendix E. Sensitivity analysis

Table E.1
The impact of single energy dimensions on the average identification score.

Energy poverty dimensions	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
All variables	4.75 %	4.46 %	4.15 %	3.86 %	3.76 %	3.99 %	3.82 %	3.54 %	2.57 %	2.87 %	2.96 %	3.03 %	3.83 %	3.00 %	2.56 %
No “Arrears on utility bills”	3.97 %	3.76 %	3.43 %	3.14 %	2.91 %	2.83 %	2.81 %	2.49 %	1.86 %	2.01 %	2.04 %	1.91 %	3.11 %	2.49 %	2.23 %
No “Do you have a telephone (including a mobile phone)?”	7.62 %	8.02 %	7.20 %	6.92 %	6.94 %	7.26 %	6.88 %	7.02 %	5.60 %	5.85 %	5.83 %	6.28 %	6.37 %	5.05 %	4.64 %
No “Do you have a colour TV?”	8.84 %	8.50 %	7.74 %	7.55 %	7.44 %	7.46 %	7.22 %	7.47 %	6.35 %	6.26 %	6.10 %	6.88 %	7.09 %	5.49 %	5.24 %
No “Do you have a computer?”	3.62 %	3.58 %	3.51 %	3.20 %	3.16 %	3.29 %	3.31 %	3.37 %	2.64 %	2.90 %	3.07 %	3.11 %	3.33 %	2.56 %	2.07 %
No “Do you have a washing machine?”	8.83 %	8.48 %	7.78 %	7.44 %	7.29 %	7.31 %	7.05 %	7.42 %	6.23 %	6.35 %	6.14 %	6.87 %	7.12 %	5.60 %	5.11 %
No “Do you have a car?”	5.39 %	5.52 %	4.93 %	4.74 %	4.41 %	4.88 %	4.38 %	4.05 %	3.19 %	3.37 %	3.45 %	3.68 %	4.26 %	2.71 %	2.62 %
No “Ability to keep home adequately warm”	3.38 %	3.21 %	2.93 %	2.58 %	2.56 %	2.43 %	2.40 %	1.95 %	1.27 %	1.39 %	1.56 %	1.74 %	2.47 %	1.97 %	1.67 %
No “Bath or shower in the dwelling”	4.60 %	4.31 %	4.08 %	3.76 %	3.71 %	3.96 %	3.79 %	3.44 %	2.45 %	2.71 %	2.89 %	2.97 %	3.81 %	2.95 %	2.52 %
No “Leaking roof, damp walls/ floors/foundation, or rot in window frames or floor”	3.05 %	3.14 %	2.79 %	2.65 %	2.53 %	2.54 %	2.48 %	2.16 %	1.41 %	1.70 %	1.60 %	1.70 %	2.74 %	2.31 %	2.03 %

Table E.2
The impact of each energy attribute on the poverty gap.

Energy poverty dimensions	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
All variables	0.225	0.245	0.260	0.243	0.221	0.201	0.206	0.202	0.193	0.192	0.194	0.193	0.247	0.239	0.223
No “Arrears on utility bills”	0.245	0.260	0.282	0.266	0.238	0.235	0.236	0.251	0.233	0.240	0.234	0.244	0.270	0.274	0.248
No “Do you have a telephone (including a mobile phone)?”	0.195	0.198	0.203	0.193	0.185	0.176	0.184	0.185	0.170	0.181	0.184	0.174	0.226	0.209	0.194
No “Do you have a colour TV?”	0.207	0.220	0.226	0.207	0.199	0.198	0.198	0.179	0.162	0.174	0.182	0.170	0.235	0.232	0.203
No “Do you have a computer?”	0.223	0.229	0.241	0.228	0.191	0.190	0.193	0.183	0.169	0.165	0.171	0.160	0.204	0.201	0.176
No “Do you have a washing machine?”	0.204	0.209	0.218	0.203	0.195	0.186	0.193	0.171	0.162	0.171	0.180	0.171	0.221	0.228	0.199
No “Do you have a car?”	0.200	0.196	0.214	0.195	0.181	0.196	0.181	0.176	0.157	0.160	0.156	0.147	0.180	0.186	0.157
No “Ability to keep home adequately warm”	0.236	0.256	0.286	0.272	0.231	0.210	0.220	0.225	0.214	0.223	0.203	0.201	0.248	0.232	0.204
No “Bath or shower in the dwelling”	0.289	0.312	0.328	0.322	0.305	0.279	0.276	0.271	0.267	0.270	0.283	0.274	0.340	0.325	0.314
No “Leaking roof, damp walls/ floors/foundation, or rot in window frames or floor”	0.288	0.274	0.300	0.262	0.241	0.211	0.231	0.239	0.231	0.223	0.229	0.237	0.273	0.257	0.243

Table E.3
The incidence of multidimensional energy poverty according to tenure status of dwelling.

Tenure status	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Owner	2.82 %	2.40 %	2.18 %	1.99 %	2.17 %	2.66 %	1.77 %	2.19 %	1.80 %	1.71 %	1.60 %	1.68 %	1.66 %	1.36 %	1.24 %
Tenant at market price	10.74 %	10.74 %	10.53 %	10.18 %	9.37 %	9.39 %	10.70 %	7.30 %	5.71 %	6.84 %	6.89 %	6.88 %	10.13 %	8.27 %	6.34 %
Tenant at a reduced price	9.05 %	10.22 %	9.04 %	8.77 %	8.19 %	4.97 %	11.06 %	11.13 %	4.30 %	6.50 %	8.68 %	8.33 %	12.14 %	7.17 %	8.92 %
Free accommodation	8.39 %	8.14 %	7.61 %	6.93 %	5.60 %	5.74 %	5.67 %	6.11 %	3.60 %	5.33 %	5.69 %	6.17 %	6.61 %	4.60 %	3.94 %

Table E.4
The severity of multidimensional energy poverty according to tenure status of dwelling.

Tenure status	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Owner	0.1490	0.1991	0.2278	0.2108	0.1772	0.1772	0.1780	0.2146	0.1855	0.1811	0.1689	0.1582	0.1787	0.2064	0.1926
Tenant at market price	0.3418	0.3194	0.2864	0.2687	0.2579	0.2709	0.2057	0.2930	0.2031	0.1840	0.1983	0.2480	0.2895	0.2761	0.2347
Tenant at a reduced price	0.2345	0.2051	0.3268	0.2518	0.2495	0.1470	0.1743	0.1551	0.1880	0.1780	0.1890	0.1824	0.2826	0.2158	0.3002
Free accommodation	0.2058	0.2429	0.2352	0.2554	0.2450	0.1679	0.3015	0.2606	0.2382	0.2322	0.2475	0.1814	0.2423	0.1819	0.2275

Data availability

The data that has been used is confidential.

References

Alaimo, L.S., 2022. Complexity of Social Phenomena: Measurements, Analysis, Representations and Synthesis, vol. 127. Sapienza Università Editrice.

Alaimo, L.S., Fiore, M., Galati, A., 2022a. Measuring consumers' level of satisfaction for online food shopping during COVID-19 in Italy using POSETs. Socio Econ. Plan. Sci. 82, 101064.

Alaimo, L.S., Ivaldi, E., Landi, S., Maggino, F., 2022b. Measuring and evaluating socio-economic inequality in small areas: an application to the urban units of the municipality of Genoa. Socio Econ. Plan. Sci. 83, 101170.

Alkire, S., Apablaza, M., 2016. Multidimensional Poverty in Europe 2006–2012: Illustrating a Methodology. Oxford Poverty and Human Development Initiative Working Papers.

Alkire, S., Foster, J., 2007. Counting and multidimensional poverty. OPHI Work. Pap. 95 (7), 476–487.

Alkire, S., Foster, J., 2011. Counting and multidimensional poverty measurement. J. Public Econ. 95 (7–8), 476–487.

Alkire, S., Foster, J.E., Seth, S., Santos, M.E., Roche, J., Ballon, P., 2015. Multidimensional Poverty Measurement and Analysis: Chapter 5–the Alkire-Foster Counting Methodology.

Arcagni, A., 2017. PARSEC: An R package for partial orders in socio-economics. In: Partial Order Concepts in Applied Sciences. Springer, pp. 275–289.

Arcagni, A., di Belgiojoso, E.B., Fattore, M., Rimoldi, S.M.L., 2019. Multidimensional analysis of deprivation and fragility patterns of migrants in Lombardy, using partially ordered sets and self-organizing maps. Soc. Indic. Res. 141 (2), 551–579.

Aristondo, O., Onaindia, E., 2018. Counting energy poverty in Spain between 2004 and 2015. Energy Policy 113, 420–429.

Atanasiu, B., Kontonasiou, E., Mariottini, F., 2014. Alleviating fuel poverty in the EU: Investing in home renovation, a sustainable and inclusive solution. In: Buildings Performance Institute Europe (BPIE), Brussels.

Atkinson, A.B., 2003. Multidimensional deprivation: contrasting social welfare and counting approaches. J. Econ. Inequal. 1 (1), 51–65.

Bartiaux, F., Maretti, M., Cartone, A., Biermann, P., Krasteva, V., 2019. Sustainable energy transitions and social inequalities in energy access: a relational comparison of capabilities in three European countries. Global Trans. 1, 226–240.

Bartiaux, F., Day, R., Lahaye, W., 2021. Energy poverty as a restriction of multiple capabilities: a systemic approach for Belgium. J. Hum. Dev. Capabilities 22 (2), 270–291.

Belaïd, F., 2022. Implications of poorly designed climate policy on energy poverty: global reflections on the current surge in energy prices. Energy Res. Soc. Sci. 92, 102790.

Berry, A., 2018. Measuring Energy Poverty: Uncovering the Multiple Dimensions of Energy Poverty.

Bienvenido-Huertas, D., 2021. Do unemployment benefits and economic aids to pay electricity bills remove the energy poverty risk of Spanish family units during lockdown? A study of COVID-19-induced lockdown. Energy Policy 150, 112117.

Boardman, B., 2010. Fixing Fuel Poverty: Challenges and Solutions. Routledge.

Boemi, S.-N., Avdimiotis, S., Papadopoulos, A.M., 2017. Domestic energy deprivation in Greece: a field study. Energ. Build. 144, 167–174.

Bollino, C.A., Botti, F., 2017. Energy poverty in Europe: a multidimensional approach. PSL Q. Rev. 70 (283), 473–507.

Bonatz, N., Guo, R., Wu, W., Liu, L., 2019. A comparative study of the interlinkages between energy poverty and low carbon development in China and Germany by developing an energy poverty index. Energ. Build. 183, 817–831.

Bouzarovski, S., Petrova, S., 2015. A global perspective on domestic energy deprivation: overcoming the energy poverty–fuel poverty binary. Energy Res. Soc. Sci. 10, 31–40.

Bouzarovski Thomson, H., Cornelis, M., Varo, A., Guyet, R., 2020. Towards an Inclusive Energy Transition in the European Union: Confronting Energy Poverty Amidst a Global Crisis. European Commission, Brussels, Belgium.

Bouzarovski, S., Tirado Herrero, S., 2017. The energy divide: integrating energy transitions, regional inequalities and poverty trends in the European Union. Eur. Urban Reg. Stud. 24 (1), 69–86.

Bouzarovski, S., Tirado Herrero, S., Petrova, S., Ürge-Vorsatz, D., 2016. Unpacking the spaces and politics of energy poverty: path-dependencies, deprivation and fuel switching in post-communist Hungary. Local Environ. 21 (9), 1151–1170.

Brau, R., Delugas, E., 2019. Subjective well-being and Energy Poverty: new insights from the combination of objective and subjective indicators. In: Energy Challenges for the Next Decade, 16th IAEE European Conference, August 25-28, 2019.

Bubley, R., Dyer, M., 1999. Faster random generation of linear extensions. Discret. Math. 201 (1–3), 81–88.

Carfora, A., Scandurra, G., Thomas, A., 2022. Forecasting the COVID-19 effects on energy poverty across EU member states. Energy Policy 161, 112597.

Carlsen, L., Bruggemann, R., 2022. Partial order as decision support between statistics and multicriteria decision analyses. Standards 2 (3), 306–328.

Castaño-Rosa, R., Solís-Guzmán, J., Rubio-Bellido, C., Marrero, M., 2019. Towards a multiple-indicator approach to energy poverty in the European Union: a review. Energ. Build. 193, 36–48.

Castaño-Rosa, R., Solís-Guzmán, J., Marrero, M., 2020. Energy poverty goes south? Understanding the costs of energy poverty with the index of vulnerable homes in Spain. Energy Res. Soc. Sci. 60, 101325.

Certomà, C., Corsini, F., Di Giacomo, M., Guerrazzi, M., 2023. Beyond income and inequality: the role of socio-political factors for Alleviating Energy Poverty in Europe. Soc. Indic. Res. 1–42.

Chakravarty, S.R., D'Ambrosio, C., 2006. The measurement of social exclusion. Rev. Income Wealth 52 (3), 377–398.

Charlier, D., Legendre, B., 2021. Fuel poverty in industrialized countries: definition, measures and policy implications a review. Energy 236, 121557.

Chiappero-Martinetti, E., Egdell, V., Hollywood, E., McQuaid, R., 2015. Operationalisation of the capability approach. In: Facing Trajectories from School to Work. Springer, pp. 115–139.

Comim, F., Hirai, T., 2022. Sustainability and human development indicators: a poset analysis. Ecol. Econ. 198, 107470.

Cong, S., Nock, D., Qiu, Y.L., Xing, B., 2022. Unveiling hidden energy poverty using the energy equity gap. Nat. Commun. 13 (1), 2456.

Crentsil, A.O., Asuman, D., Fenny, A.P., 2019. Assessing the determinants and drivers of multidimensional energy poverty in Ghana. Energy Policy 133, 110884.

Day, R., Walker, G., Simcock, N., 2016. Conceptualising energy use and energy poverty using a capabilities framework. Energy Policy 93, 255–264.

Decancq, K., Lugo, M.A., 2013. Weights in multidimensional indices of wellbeing: an overview. Econ. Rev. 32 (1), 7–34.

Deller, D., 2018. Energy affordability in the EU: the risks of metric driven policies. Energy Policy 119, 168–182.
Djeunankan, R., Njangang, H., Tadadjeu, S., Kamguia, B., 2023. Remittances and energy poverty: fresh evidence from developing countries. Util. Policy 81, 101516.
Dotter, C., Klasen, S., 2020. An absolute multidimensional poverty measure in the functioning space (and relative measure in the resource space): an illustration using Indian data. In: Dimensions of Poverty: Measurement, Epistemic Injustices, Activism, pp. 225–261.
ENEA, 2018. Energy Efficiency Trends and Policies in ITALY. ENEA. https://www.odyssee-mure.eu/publications/national-reports/energy-efficiency-italy.pdf.
ENEA, 2020. Rapporto Annuale Efficienza Energetica, p. 2020.
EU Energy Poverty Observatory, 2020. Member State Reports on Energy Poverty, p. 2019. https://doi.org/10.2833/81567.
Fabbri, K., 2015. Building and fuel poverty, an index to measure fuel poverty: an Italian case study. Energy 89, 244–258.
Faiella, I., Lavecchia, L., 2015. La povertà energetica in Italia. Polit. Econ. 31 (1), 27–76.
Faiella, Lavecchia, L., 2021. Energy poverty. How can you fight it, if you can't measure it? Energ. Build. 233, 110692.
Faiella, I., Lavecchia, L., 2022. Contenimento dei prezzi dell'energia e spesa delle famiglie. Energia 36–39.
Faiella Lavecchia, L., Miniaci, R., Valbonesi, P., 2019. Primo Rapporto Sullo Stato Della Povertà Energetica in Italia. Osservatorio Italiano Sulla Povertà Energetica (OIPE).
Faiella, I., Lavecchia, L., Borgarello, M., 2017. Una Nuova Misura Della Povertà Energetica Delle Famiglie (A new measure of households' Energy Poverty). Bank of Italy Occasional Paper, 404.
Faiella, I., Lavecchia, L., Miniaci, R., V. P, 2020. La povertà energetica in Italia Secondo rapporto dell'Osservatorio Italiano sulla Povertà Energetica (OIPE).
Faiella, I., Lavecchia, L., Miniaci, R., Valbonesi, P., 2022. Household energy poverty and the "Just Transition.". In: Handbook of Labor, Human Resources and Population Economics. Springer, pp. 1–16.
Fattore, M., 2016. Partially ordered sets and the measurement of multidimensional ordinal deprivation. Soc. Indic. Res. 128 (2), 835–858.
Fattore, M., Alaimo, L.S., 2023. A partial order toolbox for building synthetic indicators of sustainability with ordinal data. Socio-Economic Planning Sciences 88, 101623.
Fattore, M., Arcagni, A., 2018. A reduced posetic approach to the measurement of multidimensional ordinal deprivation. Soc. Indic. Res. 136 (3), 1053–1070.
Fattore, M., Brüggemann, R., 2017. Partial Order Concepts in Applied Sciences. Springer.
Fattore, M., Maggino, F., 2018. Some considerations on well-being evaluation procedures, taking the cue from "exploring multidimensional well-being in switzerland: Comparing three synthesizing approaches.". Soc. Indic. Res. 137 (1), 83–91.
Fattore, M., Maggino, F., Greselin, F., 2011. Socio-economic evaluation with ordinal variables: integrating counting and poset approaches. Stat. Appl. 1 (2011), 31–42.
Fattore, M., Maggino, F., Arcagni, A., 2015. Exploiting ordinal data for subjective well-being evaluation. Stat. Trans. New Ser. 3 (16), 409–428.
Federesco, 2017. Fuel Poverty ed Efficienza Energetica: Strumenti e Misure di Contrasto Alla Precarietà Energetica in Italia.
Freudenberg, M., 2003. Composite Indicators of Country Performance: A Critical Assessment.
Frigo, G., Baumann, M., Hillerbrand, R., 2021. Energy and the good life: capabilities as the Foundation of the Right to access Energy services. J. Hum. Dev. Capabilities 1–31.
Frilingou, N., Xexakis, G., Koasidis, K., Nikas, A., Campagnolo, L., Delpiazzo, E., Chiodi, A., Gargiulo, M., McWilliams, B., Koutsellis, T., 2023. Navigating through an energy crisis: challenges and progress towards electricity decarbonisation, reliability, and affordability in Italy. Energy Res. Soc. Sci. 96, 102934.
Gordon, D., Nandy, S., Pantazis, C., Pemberton, S., Townsend, P., 2003. The Distribution of Child Poverty in the Developing World. Centre for International Poverty Research, Bristol.
Grazini, C., 2023. La povertà energetica come privazione delle capacità. Mon. e Cred. 76 (301).
Guan, Y., Yan, J., Shan, Y., Zhou, Y., Hang, Y., Li, R., Liu, Y., Liu, B., Nie, Q., Bruckner, B., 2023. Burden of the global energy price crisis on households. Nat. Energy 8 (3), 304–316.
Guarini, G., 2017. Partially ordered set theory and Sen's capability approach: A fruitful relationship. In: Partial Order Concepts in Applied Sciences. Springer, pp. 177–189.
Halkos, G.E., Aslanidis, P.-S.C., 2023. Addressing multidimensional energy poverty implications on achieving sustainable development. Energies 16 (9), 3805.
Halkos, G.E., Gkampoura, E.-C., 2021. Evaluating the effect of economic crisis on energy poverty in Europe. Renew. Sust. Energ. Rev. 144, 110981.
Healy, J.D., Clinch, J.P., 2002. Fuel Poverty in Europe: A Cross Country Analysis Using A New Composite Measurement. Environmental Studies Research Series Working Papers.
Herrero, S.T., 2017. Energy poverty indicators: a critical review of methods. Indoor Built Environ. 26 (7), 1018–1031.
Hesselman, M., Varo, A., Guyet, R., Thomson, H., 2021. Energy poverty in the COVID-19 era: mapping global responses in light of momentum for the right to energy. Energy Res. Soc. Sci. 81, 102246.
Hills, J., 2012. Getting the Measure of Fuel Poverty: Final Report of the Fuel Poverty Review. Centre for Analysis of Social Exclusion, London School of Economics and Political Science, London, UK.
Ibáñez-Forés, V., Alejandrino, C., Bovea, M.D., Mercante, I., 2023. Prioritising organisational circular economy strategies by applying the partial order set theory: tool and case study. J. Clean. Prod. 406, 136727.
IEA, 2023. Italy, p. 2023. https://www.iea.org/reports/italy-2023.
Karpinska, L., Śmiech, S., 2020. On the persistence of energy poverty in Europe: how hard is it for the poor to escape? Energy Res. Lett. 1 (3).
Kashour, M., Jaber, M.M., 2024. Revisiting energy poverty measurement for the European Union. Energy Res. Soc. Sci. 109, 103420.
Kerr, N., Winskel, M., 2020. Household investment in home energy retrofit: a review of the evidence on effective public policy design for privately owned homes. Renew. Sust. Energ. Rev. 123, 109778.
Klein, N.J., Smart, M.J., 2019. Life events, poverty, and car ownership in the United States. J. Transp. Land Use 12 (1), 395–418.
Koengkan, M., Fuinhas, J.A., Auza, A., Ursavaş, U., 2023. The impact of Energy efficiency regulations on Energy Poverty in residential dwellings in the Lisbon metropolitan area: an empirical investigation. Sustainability 15 (5), 4214.
Lee, K., Malerba, F., 2017. Catch-up cycles and changes in industrial leadership: windows of opportunity and responses of firms and countries in the evolution of sectoral systems. Res. Policy 46 (2), 338–351.
Li, Y., Ning, X., Wang, Z., Cheng, J., Li, F., Hao, Y., 2022. Would energy poverty affect the wellbeing of senior citizens? Evidence from China. Ecol. Econ. 200, 107515.
Löfquist, L., 2020. Is there a universal human right to electricity? Int. J. Hum. Rights 24 (6), 711–723.
Maggino, F., 2017. Developing indicators and managing the complexity. In: Complexity in Society: From Indicators Construction to Their Synthesis, pp. 87–114.
Manduzio, L., Federici, A., Bertini, I., Moneta, R., 2018. Rapporto Annuale Efficienza Energetica 2018. Analisi e Risultati Delle Policy di Efficienza Energetica del Nostro Paese.
Maranzano, P., Ascari, R., Chiodini, P.M., Manzi, G., 2021. Analysis of sustainability propensity of bike-sharing customers using partially ordered sets methodology. Soc. Indic. Res. 157, 123–138.
Marchand, R., Genovese, A., Koh, S.C.L., Brennan, A., 2019. Examining the relationship between energy poverty and measures of deprivation. Energy Policy 130, 206–217.
Marino, M., Rocchi, B., Severini, S., 2021. Conditional income disparity between farm and non-farm households in the European Union: a longitudinal analysis. J. Agric. Econ. 72 (2), 589–606.
Martini, C., 2021. The Ecobonus incentive scheme and Energy Poverty: is Energy efficiency for all? Smart Sustain. Plan. Cities Reg. 2019 (3), 497–510.
Maxim, A., Mihai, C., Apostoaie, C.-M., Popescu, C., Istrate, C., Bostan, I., 2016. Implications and measurement of energy poverty across the European Union. Sustainability 8 (5), 483.
Middlemiss, L., Ambrosio-Albalá, P., Emmel, N., Gillard, R., Gilbertson, J., Hargreaves, T., Mullen, C., Ryan, T., Snell, C., Tod, A., 2019. Energy poverty and social relations: A capabilities approach. Energy Res. Soc. Sci. 55, 227–235.
Miniaci, R., Scarpa, C., Valbonesi, P., 2014. Energy affordability and the benefits system in Italy. Energy Policy 75, 289–300.
Moore, R., 2012. Definitions of fuel poverty: implications for policy. Energy Policy 49, 19–26.
Nguyen, C.P., Nasir, M.A., 2021. An inquiry into the nexus between energy poverty and income inequality in the light of global evidence. Energy Econ. 99, 105289.
Nussbaumer, P., Bazilian, M., Modi, V., 2012. Measuring energy poverty: focusing on what matters. Renew. Sust. Energ. Rev. 16 (1), 231–243.
Ochoa, R.G., Graizbord, B., 2016. Privation of energy services in Mexican households: an alternative measure of energy poverty. Energy Res. Soc. Sci. 18, 36–49.
Olang, T.A., Esteban, M., Gasparatos, A., 2018. Lighting and cooking fuel choices of households in Kisumu City, Kenya: A multidimensional energy poverty perspective. Energy Sustain. Dev. 42, 1–13.
OpenExp, 2019. European Energy Poverty Index (Eepi): Assessing Member States' Progress in Alleviating the Domestic and Transport Energy Poverty Nexus.
Ouedraogo, N.S., 2013. Energy consumption and human development: evidence from a panel cointegration and error correction model. Energy 63, 28–41.
Papada, L., Kaliampakos, D., 2018. A stochastic model for energy poverty analysis. Energy Policy 116, 153–164. https://doi.org/10.1016/j.enpol.2018.02.004.
Pereira, D.S., Marques, A.C., 2023. How do energy forms impact energy poverty? An analysis of European degrees of urbanisation. Energy Policy 173, 113346.
Pereira, M.G., Freitas, M.A.V., da Silva, N.F., 2011. The challenge of energy poverty: Brazilian case study. Energy Policy 39 (1), 167–175.
Pereira, R.H.M., Schwanen, T., Banister, D., 2017. Distributive justice and equity in transportation. Transp. Rev. 37 (2), 170–191.
Phimister, E., Vera-Toscano, E., Roberts, D., 2015. The dynamics of energy poverty: evidence from Spain. Econ. Energy Environ. Policy 4 (1), 153–166.
Rademaekers, K., Yearwood, J., Ferreira, A., Pye, S., Hamilton, I., Agnolucci, P., Grover, D., Karásek, J., Anisimova, N., 2016. Selecting Indicators to Measure Energy Poverty. Trinomics, Rotterdam, The Netherlands.
Rafi, M., Naseef, M., Prasad, S., 2021. Multidimensional energy poverty and human capital development: empirical evidence from India. Energy Econ. 101, 105427.
Randazzo, T., De Cian, E., Mistry, M.N., 2020. Air conditioning and electricity expenditure: the role of climate in temperate countries. Econ. Model. 90, 273–287.
Reddy, A.K.N., 2000. Energy and Social Issues, in "World Energy Assessment". UNPD, New York.
Robinson, C., Lindley, S., Bouzarovski, S., 2019. The spatially varying components of vulnerability to energy poverty. Ann. Am. Assoc. Geogr. 109 (4), 1188–1207.
Rodriguez-Alvarez, A., Llorca, M., Jamasb, T., 2021. Alleviating energy poverty in Europe: front-runners and laggards. Energy Econ. 103, 105575.
Ruggieri, G., Andreolli, F., Zangheri, P., 2023. A policy roadmap for the energy renovation of the residential and educational building stock in Italy. Energies 16 (3), 1319.
Sadath, A.C., Acharya, R.H., 2017. Assessing the extent and intensity of energy poverty using multidimensional Energy Poverty index: empirical evidence from households in India. Energy Policy 102, 540–550.

Samarakoon, S., 2019. A justice and wellbeing centered framework for analysing energy poverty in the global south. Ecol. Econ. 165, 106385.
Santamouris, M., 2018. Minimizing Energy Consumption, Energy Poverty and Global and Local Climate Change in the Built Environment: Innovating to Zero. Elsevier.
Sareen, S., Thomson, H., Herrero, S.T., Gouveia, J.P., Lippert, I., Lis, A., 2020. European energy poverty metrics: scales, prospects and limits. Global Trans. 2, 26–36.
Sen, A., 1976. Poverty: an ordinal approach to measurement. Econometrica: Journal of the Econometric Society 219–231.
Sen, A., 2014. Global warming is just one of many environmental threats that demand our attention New Republic. newrepublic.com/article/118969/environmentalists-obsess-about-global-warmingignore-poor countries.
Sen, A., 1995. Inequality Reexamined. Harvard University Press.
Sen, A., 1999. Lo sviluppo è libertà. Perché non c'è crescita senza democrazia. Mondadori, Cles op. or. Development as Freedom.
Shortall, R., Mengolini, A., 2023. Assessing energy justice in EU-funded energy poverty alleviation projects. In: 2023 19th International Conference on the European Energy Market (EEM), pp. 1–13.
Siksnelyte-Butkiene, I., 2021. A systematic literature review of indices for energy poverty assessment: a household perspective. Sustainability 13 (19), 10900.
Simcock, N., Walker, G., Day, R., 2016. Fuel poverty in the UK: beyond heating. People Place Policy 10 (1), 25–41.
Simcock, N., Jenkins, K.E.H., Lacey-Barnacle, M., Martiskainen, M., Mattioli, G., Hopkins, D., 2021. Identifying double energy vulnerability: a systematic and narrative review of groups at-risk of energy and transport poverty in the global north. Energy Res. Soc. Sci. 82, 102351.
Sokołowski, J., Lewandowski, P., Kiełczewska, A., Bouzarovski, S., 2020. A multidimensional index to measure energy poverty: the Polish case. In: Energy Sources, Part B: Economics, Planning, and Policy, pp. 1–20.
Sy, S.A., Mokaddem, L., 2022. Energy poverty in developing countries: a review of the concept and its measurements. Energy Res. Soc. Sci. 89, 102562.
Thema, J., Vondung, F., 2020. Expenditure-based indicators of energy poverty—an analysis of income and expenditure elasticities. Energies 14 (1), 8.
Thomson, H., Bouzarovski, S., 2018. Addressing Energy Poverty in the European Union: State of Play and Action. EU Energy Poverty Observatory, Manchester.
Thomson Bouzarovski, S., Snell, C., 2017. Rethinking the measurement of energy poverty in Europe: a critical analysis of indicators and data. Indoor Built Environ. 26 (7), 879–901.
Thomson Simcock, N., Bouzarovski, S., Petrova, S., 2019. Energy poverty and indoor cooling: an overlooked issue in Europe. Energ. Build. 196, 21–29.
Thomson Snell, C., Bouzarovski, S., 2017. Health, well-being and energy poverty in Europe: a comparative study of 32 European countries. Int. J. Environ. Res. Public Health 14 (6), 584.
Ugarte, S., van der Ree, B., Voogt, M., Eichhammer, W., Ordoñez, J.A., Reuter, M., Schlomann, B., Lloret Gallego, P., Villafafila Robles, R., 2016. Energy Efficiency for Low-Income Households.
Ungaro, P., 2014. L'indagine Istat sui consumi energetici delle famiglie: principali risultati. ISTAT, Roma.
Valverde, J.R.R., Mackenbach, J.P., Nusselder, W.J., 2021. Trends in inequalities in disability in Europe between 2002 and 2017. J. Epidemiol. Community Health 75 (8), 712–720.
Villalobos, C., Chávez, C., Uribe, A., 2021. Energy poverty measures and the identification of the energy poor: A comparison between the utilitarian and capability-based approaches in Chile. Energy Policy 152, 112146.
Vurro, G., Santamaria, V., Chiarantoni, C., Fiorito, F., 2022. Climate change impact on Energy Poverty and Energy efficiency in the public housing building stock of Bari, Italy. Climate 10 (4), 55.
Walker, G., Simcock, N., Day, R., 2016. Necessary energy uses and a minimum standard of living in the United Kingdom: Energy justice or escalating expectations? Energy Res. Soc. Sci. 18, 129–138.
Xiao, Y., Wu, H., Wang, G., Wang, S., 2021. The relationship between energy poverty and individual development: exploring the serial mediating effects of learning behavior and health condition. Int. J. Environ. Res. Public Health 18 (16), 8888.