MÁSTER UNIVERSITARIO EN INGENIERÍA INDUSTRIAL

TRABAJO FIN DE MÁSTER

CHARACTERISATION OF ENERGY POVERTY IN EUROPE THROUGH THE IMPLEMENTATION OF A MONITORING TOOL

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Director: José Carlos Romero Mora

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Curso 2024-2025

Madrid

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Characterisation of energy poverty in Europe through the implementation of a monitoring tool

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A mi familia, por haber hecho posible con su apoyo haber llegado hasta aquí.
A mis amigos, por haber hecho que estos años hayan sido inolvidables.
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CARACTERIZACIÓN DE LA POBREZA ENERGÉTICA EN EUROPA MEDIANTE LA IMPLEMENTACIÓN DE UNA HERRAMIENTA DE MONITORIZACIÓN

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RESUMEN DEL PROYECTO

Este trabajo desarrolla una herramienta estadística reproducible para analizar y caracterizar la pobreza energética en Europa a partir de microdatos comparables a nivel de hogar. Utilizando los ficheros armonizados de EU-SILC y HBS y siguiendo las metodologías propuestas por el Observatorio Europeo de Pobreza Energética (EPOV) y la Energy Poverty Advisory Hub (EPAH), se calculan e interpretan cuatro indicadores clave: dos de tipo objetivo (porcentaje del gasto energético respecto a los ingresos y gasto absoluto) y dos subjetivos (incapacidad de mantener el hogar adecuadamente cálido y atrasos en el pago de facturas).

Además de esta parte descriptiva, se estima un modelo de regresión logística para identificar qué factores socioeconómicos se asocian con una mayor probabilidad de experimentar pobreza energética percibida. La herramienta, construida íntegramente en lenguaje R, permite automatizar todo el proceso de importación, limpieza y análisis de los datos, lo que la convierte en una base sólida para el monitoreo periódico de este fenómeno en la Unión Europea.

Palabras clave: pobreza energética, indicadores sociales, regresión logística, EU-SILC, monitorización, energía doméstica, Europa.

1. Introducción

La pobreza energética constituye una manifestación concreta de desigualdad en Europa. Afecta a millones de personas que no pueden permitirse calentar su hogar de forma adecuada o que sufren retrasos en el pago de servicios básicos como electricidad o gas. Según datos recientes, más de 41 millones de ciudadanos europeos experimentaron este tipo de privación en 2022, y más del 7% declaró dificultades para pagar sus facturas energéticas [1]. Esta situación no solo tiene consecuencias materiales, sino también implicaciones sanitarias, sociales y emocionales, especialmente entre los colectivos más vulnerables. La transición energética que impulsa la UE no podrá ser justa si no se atiende adecuadamente a este fenómeno [2][3][4].

2. Definición del Proyecto

El objetivo del proyecto es doble. Por un lado, construir una herramienta estadística reproducible y flexible que permita monitorizar los principales indicadores de pobreza energética propuestos a nivel europeo. Por otro, caracterizar los factores sociales, laborales y residenciales que incrementan la probabilidad de que un hogar experimente esta forma de vulnerabilidad. Esta doble aproximación pretende generar evidencia útil tanto para el análisis académico como para el diseño de políticas públicas más focalizadas y efectivas.

3. Descripción del modelo/Sistema/herramienta

Se ha desarrollado un script en R que permite importar, limpiar, transformar y analizar datos procedentes de los ficheros D, H y P del EU-SILC para 22 países europeos. La herramienta calcula automáticamente los indicadores clave definidos por el EPOV: el 2M (porcentaje de hogares que gastan más del doble de la mediana en energía), el M/2 (por debajo de la mitad del gasto medio), y los dos indicadores subjetivos: incapacidad de mantener la vivienda cálida y atrasos en facturas.

Además, se realiza un análisis desagregado por variables como educación, salud, empleo, tipo de vivienda o composición familiar. Finalmente, se estima un modelo logístico que utiliza como variable dependiente la percepción de frío en el hogar, y como predictores variables categóricas transformadas en dummies. Este modelo permite calcular odds ratios y visualizar gráficamente los factores de mayor peso explicativo (véase Figura 1).

4. Resultados

Los indicadores revelan patrones geográficos claros. Países como Bulgaria, Rumanía y Grecia muestran los niveles más altos tanto en indicadores objetivos como subjetivos, lo que apunta a vulnerabilidades estructurales relacionadas con ingresos bajos, eficiencia energética deficiente y políticas sociales limitadas. Por el contrario, países como Dinamarca, Estonia o Malta presentan valores elevados en los indicadores de gasto, pero niveles bajos de malestar percibido, lo que podría reflejar un efecto mitigador de sus políticas de bienestar o de la calidad del parque inmobiliario [4][5].

El modelo de regresión logística, estimado con más de 50.000 observaciones, identifica de forma robusta los principales factores asociados a la pobreza energética percibida. Destacan especialmente el desempleo, el bajo nivel educativo, el mal estado de salud, vivir en régimen de alquiler a precio de mercado y la estructura familiar monoparental. La Figura 1 resume estos resultados mediante la representación de los *odds ratios* e intervalos de confianza. El modelo alcanza un AUC de 0.7196, lo que indica una capacidad moderada de discriminación, aunque con baja sensibilidad debido al desbalance de clases: solo un 8,9% de los hogares analizados reporta no poder mantener el hogar cálido [6].

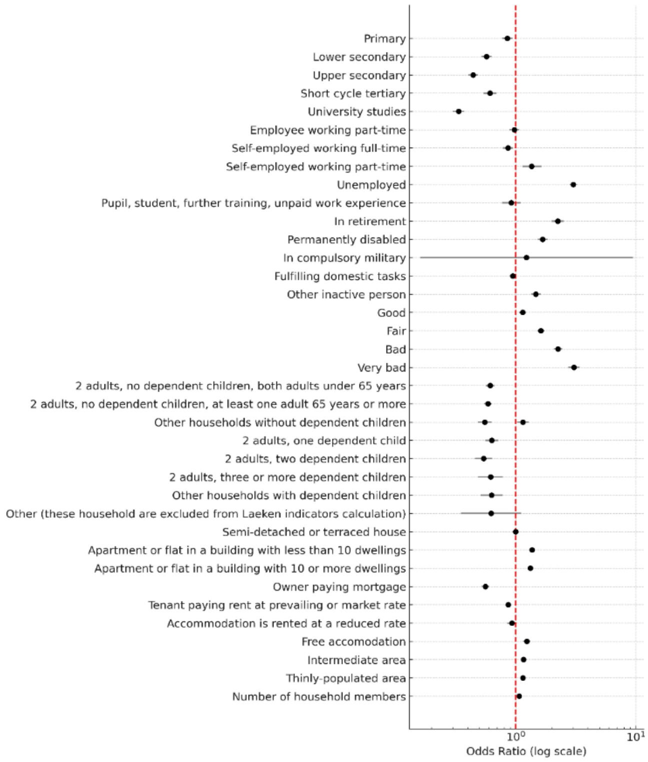

Figura 1. Representación de los odd ratios del modelo de regresión logístico.

5. Conclusiones

Este proyecto demuestra que es posible automatizar y sistematizar el análisis de la pobreza energética a escala europea, combinando diferentes fuentes de datos y adoptando un enfoque multidimensional. Lejos de ser un fenómeno homogéneo o aislado, la pobreza energética está estrechamente vinculada a otros determinantes sociales, como el empleo, la educación, la salud o la vivienda.

La herramienta desarrollada puede ser utilizada como apoyo en la toma de decisiones públicas, por ejemplo, para identificar a los beneficiarios del Social Climate Fund (SCF) aprobado por la Unión Europea [7], o para evaluar el impacto de medidas de eficiencia energética en colectivos vulnerables. Como línea de trabajo futura se propone incorporar datos longitudinales para observar la persistencia o transitoriedad del fenómeno, así como introducir nuevas variables relacionadas con el consumo energético real, los precios regionales o la calidad de la edificación [8].

6. Referencias

[1] A. Widuto, "Energy Poverty in the EU," European Parliamentary Research Service, Brussels, 2023.

[2] European Commission: Directorate-General for Energy, E3M, IEECP, Trinomics and Wuppertal Institut, "Study on optimisation of energy poverty indicators collected at EU and national level – Final report," Publications Office of the European Union, 2024.

[3] European Commission, "The Green Deal," [Online]. Available: https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/european-green-deal_es. [Accessed 8 October 2024]

[4] E. Ozdemir and G. Koukoufikis, "The persistence of energy poverty in the EU," Publications Office of the European Union, Luxembourg, 2024.

[5] J. P. Gouveia, P. Palma, S. Bessa, K. Mahoney, M. S. o. t. CENSE, N. S. o. S. a. Technology and N. U. o. Lisbon, "Energy Poverty National indicators. Insights for a more effective measuring," Energy Poverty Advisory Hub, -, 2022.

[6] S. Meyer, "Energy poverty indicators: a critical review of methods. Review of Sustainable Energy," 2018.

[7] European Union, "Regulation establishing the Social Climate Fund," 2023.

[8] R. Barrella and J. C. Romero, "Unveiling Hidden Energy Poverty in a Time of Crisis: A Methodological Approach for National Statistics," 2023.

CHARACTERISATION OF ENERGY POVERTY IN EUROPE THROUGH THE IMPLEMENTATION OF A MONITORING TOOL

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Codirector: Barella, Roberto
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ABSTRACT

This study develops a reproducible statistical tool to analyze and characterize energy poverty in Europe based on comparable microdata at the household level. Using harmonized EU-SILC and HBS files and following the methodologies proposed by the European Observatory on Energy Poverty (EPOV) and the Energy Poverty Advisory Hub (EPAH), four key indicators are calculated and interpreted: two objective indicators (percentage of energy expenditure relative to income and absolute expenditure) and two subjective indicators (inability to keep the home adequately warm and arrears in bill payments).

In addition to this descriptive part, a logistic regression model is estimated to identify which socioeconomic factors are associated with a higher probability of experiencing perceived energy poverty. The tool, built entirely in R language, automates the entire process of importing, cleaning, and analyzing data, making it a solid basis for periodic monitoring of this phenomenon in the European Union.

Keywords: energy poverty, social indicators, logistic regression, EU-SILC, monitoring, domestic energy, Europe.

1. Introduction

Energy poverty is a concrete manifestation of inequality in Europe. It affects millions of people who cannot afford to heat their homes adequately or who fall behind on payments for basic services such as electricity or gas. According to recent data, more than 41 million European citizens experienced this type of deprivation in 2022, and more than 7% reported difficulties in paying their energy bills [1]. This situation not only has material consequences, but also health, social, and emotional implications, especially among the most vulnerable groups. The energy transition promoted by the EU cannot be fair if this phenomenon is not adequately addressed [2][3][4].

2. Project Definition

The project has two objectives. On the one hand, to build a reproducible and flexible statistical tool that allows the main energy poverty indicators proposed at European level to be monitored. On the other hand, to characterize the social, labor, and residential factors that increase the likelihood of a household experiencing this form of vulnerability. This dual approach aims to generate useful evidence for both academic analysis and the design of more targeted and effective public policies.

3. Description of the model/system/tool

Se ha desarrollado un script en R que permite importar, limpiar, transformar y analizar datos procedentes de los ficheros D, H y P del EU-SILC para 22 países europeos. La herramienta calcula automáticamente los indicadores clave definidos por el EPOV: el 2M (porcentaje de hogares que gastan más del doble de la mediana en energía), el M/2 (por debajo de la mitad del gasto medio), y los dos indicadores subjetivos: incapacidad de mantener la vivienda cálida y atrasos en facturas.

Además, se realiza un análisis desagregado por variables como educación, salud, empleo, tipo de vivienda o composición familiar. Finalmente, se estima un modelo logístico que utiliza como variable dependiente la percepción de frío en el hogar, y como predictores variables categóricas transformadas en dummies. Este modelo permite calcular odds ratios y visualizar gráficamente los factores de mayor peso explicativo (véase Figura 1).

4. Results

Los indicadores revelan patrones geográficos claros. Países como Bulgaria, Rumanía y Grecia muestran los niveles más altos tanto en indicadores objetivos como subjetivos, lo que apunta a vulnerabilidades estructurales relacionadas con ingresos bajos, eficiencia energética deficiente y políticas sociales limitadas. Por el contrario, países como Dinamarca, Estonia o Malta presentan valores elevados en los indicadores de gasto, pero niveles bajos de malestar percibido, lo que podría reflejar un efecto mitigador de sus políticas de bienestar o de la calidad del parque inmobiliario [4][5].

El modelo de regresión logística, estimado con más de 50.000 observaciones, identifica de forma robusta los principales factores asociados a la pobreza energética percibida. Destacan especialmente el desempleo, el bajo nivel educativo, el mal estado de salud, vivir en régimen de alquiler a precio de mercado y la estructura familiar monoparental. La Figura 1 resume estos resultados mediante la representación de los *odds ratios* e intervalos de confianza. El modelo alcanza un AUC de 0.7196, lo que indica una capacidad moderada de discriminación, aunque con baja sensibilidad debido al desbalance de clases: solo un 8,9% de los hogares analizados reporta no poder mantener el hogar cálido [6].

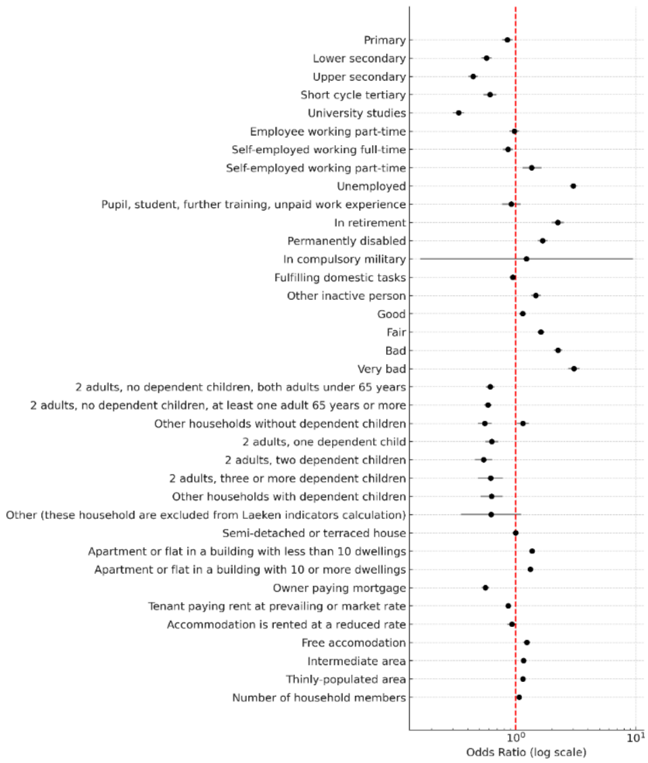

Figura 1. Representación de los odd ratios del modelo de regresión logístico.

5. Conclusions

Este proyecto demuestra que es posible automatizar y sistematizar el análisis de la pobreza energética a escala europea, combinando diferentes fuentes de datos y adoptando un enfoque multidimensional. Lejos de ser un fenómeno homogéneo o aislado, la pobreza energética está estrechamente vinculada a otros determinantes sociales, como el empleo, la educación, la salud o la vivienda.

La herramienta desarrollada puede ser utilizada como apoyo en la toma de decisiones públicas, por ejemplo, para identificar a los beneficiarios del Social Climate Fund (SCF) aprobado por la Unión Europea [7], o para evaluar el impacto de medidas de eficiencia energética en colectivos vulnerables. Como línea de trabajo futura se propone incorporar datos longitudinales para observar la persistencia o transitoriedad del fenómeno, así como introducir nuevas variables relacionadas con el consumo energético real, los precios regionales o la calidad de la edificación [8].

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1. Introduction

1.1 Context of the research work

Energy poverty, defined in the EU Energy Efficiency Directive (Directive 2023/1791) as "a situation in which a household is unable to afford to meet its essential energy needs — which ensure a basic standard of living in the relevant climatic context," [1] has emerged in recent years as one of the pressing social challenges across European countries.

This multifaceted problem arises from the combination of three main issues: low incomes, high energy prices and energy inefficient housing.

Even before the recent crises that will be discussed in this section, it was estimated that approximately 34 million Europeans were living in energy poverty, usually manifesting themself as unable to maintain their homes at a given temperature [2]. This situation has worsened in recent years, reaching 41 million people (about 9.1% of the population) unable to maintain an adequate temperature in 2022. In addition, 7% of Europeans suffered delays in paying their energy bills [3]. These figures suggest that energy poverty is a reality that affects the European Union as a whole, and is not limited to certain areas, particularly affecting people who are socially and economically vulnerable. Moreover, it is important to stress that the consequences of suffering from energy poverty go beyond mere discomfort. For instance, not being able to keep your home at an adequate temperature can have implications for health, social inclusion and personal well-being.

Recent economic and geopolitical crises have only magnified the problem. The COVID-19 pandemic and its consequences, coupled with the energy crisis caused by the Russian invasion of Ukraine, led to unprecedented volatility in the energy markets, as electricity prices are highly correlated with natural gas prices, as shown in Figure 1.

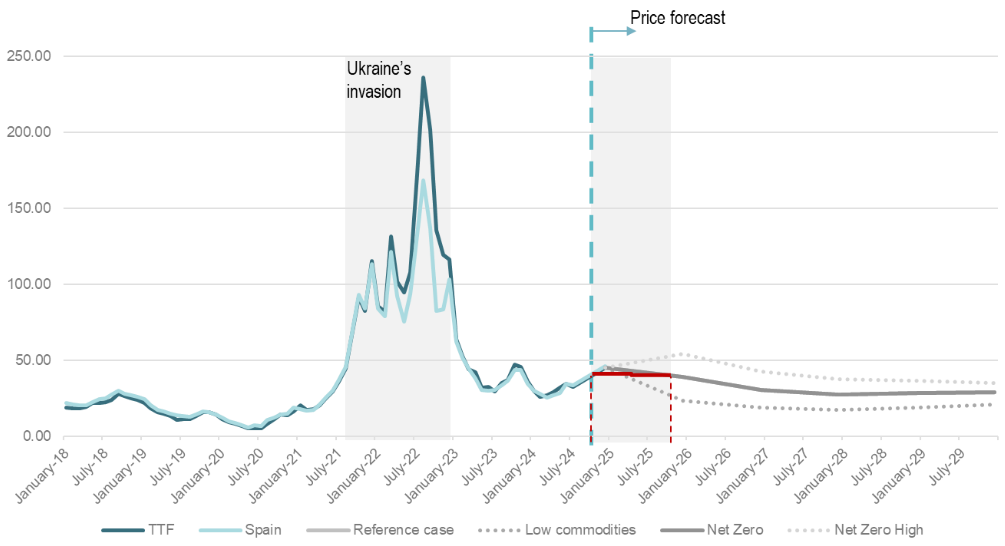

Figure 1. Historical of gas natural prices (Source: Own elaboration with historical data from TTF and MIBGAS)

As seen in the figure, in 2021, prices began surging, forcing consumers to pay much more for their energy services. Europe faced record prices and supply insecurity, which stressed the finances of millions of households, pushing new households into energy poverty. In addition, households already struggling to afford energy were hit hardest by this crisis, exacerbating their situation. This union of crises has led to energy poverty now occupying a central position in the public spotlight, prompting governments to respond with emergency measures (such as price caps, moratoria on disconnections, etc.) to protect citizens. This experience pointed out the vulnerability of the European electricity system to external pressures, reinforcing the idea of promoting domestic energy production while improving affordability [3].

At the same time, the EU energy transition strategy has highlighted energy poverty as an essential obstacle for a just energy transition. Ambitious efforts to achieve the "net zero" by 2050, which are included in regulations such as the European Green Deal and the Fit for 55 package [4], require drastic changes in terms of phasing out fossil fuels, carbon pricing and deep renovation of many buildings to achieve the energy efficiency needed to be net zero [3]. These policies, although very necessary, risk placing a heavy burden on vulnerable households if not properly managed [1]. European institutions have come to recognize that mitigating energy poverty is an essential factor in securing public support for climate policies [5] [1].

Over the last decade, energy poverty has been integrated in different ways into various initiatives, both legislative and non-legislative. For example, the EU's Electricity and Gas Market Directives oblige Member States to protect vulnerable consumers (e.g. via social tariffs) [3], while the Energy Efficiency Directive (EED) and the Energy Performance of Buildings Directive now require national plans to include measures aimed at alleviating energy poverty alongside efficiency improvements [1] [5]. Under the European Green Deal's Renovation Wave, improving building insulation and boilers is seen as an opportunity to both reduce emissions and reduce the energy bill of the home, directly benefiting people in energy poverty [3] [1].

Notably, the European Union established a new Social Climate Fund (SCF) in 2023 [6], to protect vulnerable households from the costs of the energy transition, such as fuel price increases due to carbon pricing. Although created, the SCF is linked to the implementation of the new Emissions Trading System for buildings and transport (ETS2) and is not expected to become operational until 2026. The SCF regulation explicitly identifies households in energy poverty as one of its main beneficiaries [7]. In doing so, it has become the first European legislation to enshrine an official definition of energy poverty, defining it as “a dwelling's lack of access to essential energy services that underpin a decent standard of living (such as heating, cooling, hot water, lighting and powering appliances)”.

This definition reflects the language used in the European Commission's 2020 Recommendation on energy poverty (then updated in 2023), where it urged Member States to adopt common indicators (such as the percentage of income spent on energy, or the number of households unable to maintain an adequate temperature), to properly monitor the problem [8]. To summarize, the regulatory context in the European Union reflects the general consensus that combating energy poverty is central to both social and energy policies, and reducing it is part of building a sustainable and resilient Europe [9].

1.2 Motivation

The motivation for this master's thesis stems from the growing interest in understanding what factors are driving the growth of energy poverty in Europe. This trend is particularly striking when considered alongside a growing share of renewable energies in the energy mix and ongoing improvements in energy efficiency in both housing and appliances. The coexistence of these advances with worsening energy poverty indicators suggests the presence of complex structural and socio-economic dynamics that merit in-depth exploration.

In particular, identifying the sociological profiles of those households most affected by energy poverty is essential to developing targeted and effective public policies. Understanding how certain factors, such as income level, household composition, employment status or housing characteristics influence the likelihood of vulnerability can help policymakers design interventions that directly address the needs of the most at-risk population. By emphasizing the social dimension of the problem, this thesis seeks to provide a more equitable and data-driven approach to mitigate this persistent problem in the European Union.

1.3 Objectives

This thesis aims to contribute to the understanding and analysis of energy poverty in the European Union through the use of quantitative methods and statistical programming. The specific objectives of the project are as follows:

- To assess the **current state of energy poverty** across EU Member States and review the statistical approaches and indicators commonly used to measure it.
- To examine the most recent data available from large-scale surveys, focusing on capturing the latest trends and patterns in energy poverty.
- To develop a reproducible analytical tool in **R** that allows for the extraction, cleaning, and processing of relevant data to compute the key indicators recommended by the

European Energy Poverty Observatory (EPOV) and the EU Energy Poverty Advisory Hub (EPAH).

- To construct and interpret a **logistic regression model** aimed at identifying which household-level variables are statistically significant predictors of energy poverty, thereby contributing to a deeper understanding of its sociological determinants.

2. State of the Art

2.1 Historical context and literature

The concept of energy poverty (often historically referred to as 'fuel poverty' in British studies) has evolved significantly over the years, from early definitions to the current multidimensional understanding. In early research, a distinction was made between energy poverty and fuel poverty. The former was defined as the lack of access to modern energy, while the latter related to the problem of affordability in household energy use [10]. However, the European Union uses the term *energy poverty* specifically to refer to the affordability of domestic energy, rather than access to modern energy services.

In the European context, this issue became relevant thanks to the work done by Brenda Boardman. In 1991, Boardman proposed a formal definition of fuel poverty based on household income: households with energy expenditure above 10% of their income were considered fuel poor [11]. This expenditure-based definition, usually referred to as the 10% rule, became a relevant marker in both the academic and policy worlds. For a time, it was the only fuel poverty indicator that was widely used, helping to shape early policies, especially in the UK, which sought to identify and help households with disproportionate energy expenditure.

Boardman's work emphasized that energy poverty was a relevant problem that deserved a specific policy, separating it from poverty in general, as it did not depend only on income levels but also on other factors such as energy prices or the energy efficiency of dwellings [11].

But subsequent research in the late 1990s and early 2000s began to expose the limitations of a single boundary definition. Academics and policy makers noted that the 10% rule could overlook or misclassify different household situations. For example, it could fail to capture those who keep their energy costs low at the expense of sacrificing their needs and comfort, a situation that was later termed 'hidden energy poverty' [12]. At the same time, certain households spending more than 10% could be doing so by choice, as they have more resources, and not because of a lack of income.

Already at that time, and to this day, there is no universal consensus on a single measure of energy poverty [1], so researchers have started to promote a more specific and multidimensional definition, going beyond a single number. This new perspective takes into account a range of circumstances and indicators, such as income level, comfort or household conditions, to obtain a broader picture of the problem. It also takes into account the already agreed fact that energy poverty arises from a combination of several interrelated factors (those already mentioned: low-income, high-energy costs and low energy efficiency, and others).

Recent studies argue for a more integrated view of the problem: a ‘more holistic view of energy poverty’ can identify vulnerable households that a one-dimensional measure may miss, as ‘one-dimensional measures are at risk of not reaching all households suffering from energy poverty’ [1]. Thus, indicators on the condition of dwellings, such as those with inadequate insulation, can provide additional information on the structural causes of energy poverty that income- or expenditure-based metrics are not able to capture.

Over the years, academia has also connected energy poverty with concepts such as vulnerability and energy justice. Research on energy vulnerability emphasizes dynamic risk factors that may predispose households to energy poverty, such as low income, volatile energy markets or changes in the household (such as ageing or illness). In this way, it highlights that energy poverty is not static, but a changing condition that responds to external factors [5] [13].

This has led to a distinction between persistent and transient energy poverty. Some households suffer from long-term, chronic energy poverty, while others fall into it temporarily as a result of temporary shocks, and reverse the situation when circumstances return to normal [13]. These findings have reinforced the idea that policies should be both preventives, to reduce structural vulnerability, and responsive to drastic changes, such as economic downturns or price changes.

By the 2010s, the understanding of energy poverty as the “10% rule” was outdated, moving towards a more dynamic and multidimensional definition, as discussed in this section. Policymakers began to adopt mixed approaches to defining and measuring energy poverty. In the UK, for example, the official metric was revised in 2013, shifting from the 10% indicator to a dual indicator, Low Income–High Costs (LIHC), which considered both household income and the energy expenditure required [14]. More recently, this was replaced by the Low Income–Low Energy Efficiency (LILEE) indicator, which defines a household as energy poor if it has low income and lives in a dwelling with poor energy performance. Across the EU, a variety of indicators began to be used, which can usually be classified between objective indicators (based on income and expenditure), and subjective indicators, based on household self-perception. The European Union's Statistics on Income and Living Conditions (EU-SILC) began to include questions that serve as direct indicators of energy poverty, such as a household's ability to maintain an adequate temperature, or whether they have experienced delays in paying their utilities bills [9]. These self-reported indicators have gained importance as they express the real-life impact of this situation.

At the same time, researchers such as Bouzarovski and Petrova (2015) proposed a ‘global perspective’ that bridges the gap between the concept of energy access in developing countries and that of energy poverty in developed countries [10], suggesting that, at its core, energy poverty everywhere revolves around inadequate access to energy services essential for personal well-being. This perspective has helped to unify discourses, both political and academic, and reinforced the need for common principles, despite the diversity of realities.

2.2 The EU Energy Poverty Observatory (EPOV) and Energy Poverty Advisory Hub (EPAH)

The institutional response at the European level against energy poverty gained traction with the creation, in January 2018, of the Energy Poverty Observatory (EPOV). Financed by the European Commission, EPOV's objective was to improve the visibility, data harmonization and comparability of energy poverty across Member States [14].

It provided a centralized platform that collected national and EU-wide statistics, proposed common indicators and regularly produced methodological guidelines and country reports. One of its most relevant contributions was introducing a broader set of indicators, discussed in previous sections, incorporating both objective and subjective indicators, to better address the diverse realities of energy poverty [15].

Rather than promoting a single definition or metric, EPOV encouraged the use of multiple indicators, derived primarily from the EU-SILC and Household Budget Survey (HBS), to address affordability, thermal comfort and other socio-economic drivers [16]. These efforts improved the transparency and comparability of data across the EU, allowing policymakers and researchers to identify patterns and monitor progress more effectively. In addition, EPOV served as a hub for policy learning and stakeholder engagement, publishing case studies, organizing events and promoting best practices [14].

In 2021, the European Commission created the Energy Poverty Advisory Hub (EPAH) as a successor to EPOV. While EPOV focused on measurement and knowledge sharing, EPAH is designed to support concrete actions and capacity building at the local level.

It aims to assist municipalities and regional authorities in the design, implementation and evaluation of measures that can alleviate energy poverty [17]. In addition, EPAH continues to maintain the updated Energy Poverty Indicators Dashboard, an interactive online tool that allows users to explore trends and cross-country comparisons with harmonized data [18].

In addition to the technical infrastructure, EPAH offers practical resources such as the EPAH Atlas, which enables the discovery of different projects, and an expert helpdesk through which local authorities can receive tailor-made assistance. They also provide educational materials and guidance documents that can help authorities integrate energy poverty considerations into broader social and environmental policies [18].

Both EPOV and EPAH have transformed the way the European Union approaches energy poverty. On the one hand, EPOV laid the foundations for an evidence-based approach to decision-making. On the other hand, EPAH operationalizes this data into concrete proposals at the local level, an essential activity to reduce this problem.

3. Methodology

3.1 Data

This analysis is based on micro-data from two key European-level surveys: the European Union Statistics on Income and Living Conditions (EU-SILC) and the Household Budget Survey (HBS). Both datasets are collected by national statistical institutes under a unified framework coordinated by Eurostat, and together they provide the data needed both to characterize energy poverty and to establish a sociological profile of citizens.

The EU-SILC is an annual survey that serves as the primary source of comparative statistics on income distribution, poverty, social exclusion and living conditions across the European Union [19]. It allows both cross-sectional comparisons between countries and longitudinal comparisons over time. In addition, the EU-SILC includes several self-reported indicators, which are widely used as proxies for energy poverty, such as inability to maintain an adequate temperature and late payment of utility bills, which are now standard across the EU as monitoring tools [9].

On the other hand, the HBS provides very detailed data on household consumption patterns, including spending on electricity, gas, and other fuels. At the EU-wide level, it isaggregated by Eurostat approximately every 5 years, and is originally designed to support the calculation of Consumer Price Index (CPI) weights, but it also allows for a very robust socio-economic analysis of households in energy poverty [20]. As this survey is implemented at the national level, its structure and periodicity vary between Member States, so there may be certain limitations when comparing between countries. In any case, the HBS remains one of the few suitable sources for assessing objective indicators of energy poverty related to household budgets.

The two datasets are complementary: the EU-SILC provides the household's self-perception of energy poverty, i.e. inability to keep home adequately warm, and arrears on utility bills. The HBS provides the energy burden of households, being able to calculate the 2M and M/2 indicators [21], explained in the next section. Obtaining these four indicators for the same household will build the broader picture discussed above, being able to capture different edges.

3.2 Indicators

Over the years in which the importance of energy poverty has begun to be determined, different studies have established the most relevant indicators for quantifying a situation that in real life has many facets.

The EPOV, which as mentioned above was created in 2018, began by defining energy poverty in terms of low income, excessive energy expenditure in relation to income and low energy efficiency. However, with the aim of homogenizing the surveys that each country conducts independently, in 2020 EPOV published three main types of measures, covering 28 different indicators [9], with the goal of being able to obtain reliable and replicable data from each country. These types are:

- Expenditure-based (objective): energy expenditures faced by households against established thresholds to provide the level of risk of having to limit or reduce essential energy use.
- Consensus-based or Self-reported (subjective): based on households' personal responses about the conditions of their household, and the likelihood of achieving certain living conditions.
- Direct: when obtained from a direct measure and compared to a standard. For example, measuring the ability to keep your home at a certain temperature in both winter and summer.

Among the 28 indicators, there are four that are commonly used to quantify the population living below the energy poverty line. These are detailed below, where the first two are expenditure-based, while the last two are subjective, consensus-based.

3.2.1 High share of energy expenditure in income (2M)

Indicator 2M is an objective indicator whose function is to identify households with disproportionate energy expenditure. In this case, it is considered disproportionate expenditure when such expenditure, measured in relation to the household's income, is twice the national median for the country.

$$\frac{Energy\ expenditure}{Income}[\%] > 2 \cdot Median\ (\frac{Energy\ expenditure}{Income})$$

Equation 1. Calculation of indicator 2M.

In order to normalize the income per person in houses of different sizes, the scale of modified factor is used, denominated UC2. This factor can be either taken directly from the HBS, or computed following the formula:

$$UC2 = 1 + 0.5 \cdot (N_{adults} - 1) + 0.3 \cdot N_{children}$$

Equation 2. Calculation of the scale of modified factors.

In addition, the median will be computed annually, therefore the income shown in the survey is multiplied by 12 to obtain the annual value. After these adjustments, household income is calculated as follows:

$$Annual\ income\ per\ equivalent\ person = \frac{Monthly\ income\ per\ household\ \cdot 12}{UC2}$$

Equation 3. Calculation for the annual income per equivalent person

Regarding energy expenditure, every expenditure regarding energy services is considered (e.g. electricity, natural and liquified gas, coal and other solid fuels).

For the calculation of the energy expenditure per equivalent person, the equivalence factor table proposed by Tirado-Herrero et al. [22]

Size of the household (# of members)	Equivalence factor
1 person	1.00
2 people	1.45
3 people	1.68
4 people	1.90
5+ people	1.99

Table 1. Equivalence factors for energy expenditure (Tirado-Herrero et al, 2017).

3.2.2 Low absolute energy expenditure (M/2)

The M/2 indicator is also an objective indicator whose function is complementary to the previous one, i.e. to identify those households with extremely low energy expenditure. Extremely low expenditure in this case is defined as less than half of the national median, measured in absolute terms.

$$Energy\ expenditure < \frac{(Median\ energy\ expenditure)}{2}$$

Equation 4. Calculation of indicator M/2.

3.2.3 Inability to keep home adequately warm.

This subjective indicator is obtained from the answer to a specific question in the survey: ‘Can your household afford to maintain an adequate temperature?’

The answer to this question is dichotomous, i.e. it can only be answered with Yes or No, and the results can be obtained directly from the survey itself. [5]

3.2.4 Arrears on utility bills

This subjective indicator is obtained from the question: ‘In the last 12 months, has your household experienced delays in the payment of bills (heating, electricity, gas, water, etc.) due to financial problems?’

In this case, the answer to this question is not dichotomous, as the question can be answered with ‘Yes, once’, Yes, more than once’ or ‘No’. For the purposes of the study, the first two answers are taken into account in the same way (as “Yes”). [5]

3.3 *Disaggregated Analysis*

The disaggregated analysis aims to examine in detail the socio-economic profile of the households that are already in a situation of energy poverty.

To that end, SILC surveys from the different European countries mentioned were studied, to subsequently select the variables that have been considered relevant for the purpose of understanding that profile better. Subsequently, in the logistic regression analysis (described in Section 3.4), the relevance of the selected variables is confirmed, determining the mathematical correlation that exists between the dependent variable (inability to keep home adequately warm) and the different independent variables chosen.

The selection of variables used in the analysis is based on their relevance in capturing different dimensions that are potentially associated with energy poverty. These include housing characteristics (such as dwelling type, tenure status, and degree of urbanization), socioeconomic factors (education, employment status, and type of employment), demographic composition (household structure), and health status. Their inclusion allows for a comprehensive analysis of the socioeconomic profiles potentially linked to vulnerability in this area.

The variables selected from the survey for this analysis are:

- Degree of urbanization: Households are classified into three categories, based on population density (high, medium and low density)
- Type of dwelling: Differences are analyzed among detached houses, terraced houses, and apartments in buildings of various sizes.
- Tenure status: Different tenure arrangements are examined, such as outright ownership, ownership with a mortgage, market-rate rental, subsidized rental and free accommodation.
- Health status: The self-perceived health status of household members is assessed in five categories (very good, good, fair, bad and very bad)

- Employment situation: Various employment conditions are considered, including full-time and part-time salaried employment, self-employment, unemployment, retirement, permanent disability, and other labor situations.
- Type of employment: Type of employment is also assessed, dividing households into many categories such technicians, managers, sales, agriculture, Armed Forces, etc.
- Household structure: Households are categorized based on family composition, distinguishing between single-parent households, couples without children, families with children in different combinations, and other living arrangements.
- Education: Education level is assessed, distinguishing all levels from no education to university education.

Once these variables are chosen, the dataset is filtered to have only those households that have experienced the inability to keep their house at an adequate temperature during winter. From this dataset, a function was programmed in R that is capable of obtaining the number of households for each possible answer to every question, and converting it into a percentage. The function is iterative, meaning that it obtains this information for each of the 22 states included in the EU-SILC.

Results of this study are shown in paragraph 4.2.1.

3.4 Econometric Analysis

The analysis employs a logistic regression, or logit, model to estimate the probability of the binary dependent variable that takes a value of 1 if households are not able to maintain an appropriate temperature during winter, and 0 if they do not have that problem.

Logistic regression was used because of the binary nature of the dependent variable, i.e. whether or not a household is able to maintain an adequate temperature. This method allows the probability of an outcome to be estimated based on several explanatory variables, and works well with categorical data. Unlike linear models, it does not assume normality or constant variance, and it also provides results that are easy to interpret, such as odds ratios. Although other models may offer stronger predictive capabilities, logistic regression is appropriate for explanatory uses.

Logit models are a standard technique used frequently in social sciences, medicine, or economics; and predict the risk of an event happening (dependent variable being 1) based on the interaction of different parameters (independent variables) [23].

Specifically, the model estimates the log-odds of the outcome as a linear function of the predictors, which are then transformed into probabilities via the logistic (sigmoid) function.

Mathematically, logistic regression models can be expressed as:

$$P(Y=1|X) = \frac{e^{\beta_0 + \sum \beta_i x_i}}{1 + e^{\beta_0 + \sum \beta_i x_i}}$$

Equation 5. Logistic regression's expression.

where P(Y=1|X) represents de conditional probability of the dependent variable equaling 1 given a set of explanatory variables ($X = X_1, X_2, \ldots, X_n$). This function ensures that the predicted values remain between 0 and 1 and captures the non-linear nature of the relationship between the predictors and the probability of the event. Coefficients are estimated using maximum likelihood estimation, and their exponentiated values are interpreted as odds ratios (ORs).

The model was implemented in R using the glm() function with a binomial family.

Prior to the model estimation, an extensive data pre-processing phase has been carried out. First, raw data were imported from three CSV files containing the SILC responses (file D, file H and file P) for each European country abovementioned. Then, data is filtered and merged based on household identifiers, a unique ID that ensures consistency across different datasets. In addition, variables were renamed for clarity, missing values were imputed using the mean, and categorical variables, such as employment type or education level, were transformed into numeric formats so it was compatible with the model.

Several of these variables are categorical. In such cases, R automatically converts them into dummy variables using one of the categories as the reference group. This reference category does not appear among the model coefficients; all other levels are interpreted relative to it. For instance, for the variable *Employment Status*, the category *"Employee working full-time"* was set as the reference group, and the odds ratios for other statuses (e.g., *unemployed*, *retired*) are interpreted relative to this baseline.

The model was estimated on a randomly selected training sample comprising 80% of the data, while the remaining 20% was retained for testing. Although predictive performance is discussed separately in the conclusions, this section focuses on the explanatory value of the model, interpreting the direction, magnitude, and statistical significance of each predictor.

Odds ratios above 1 indicate that the variable increases the odds of experiencing energy poverty (risk factor), whereas odds ratios below 1 imply a protective effect. Confidence intervals at the 95% level are used to assess the precision of each estimate, and z-tests are used to determine statistical significance.

This approach allows identifying key structural vulnerabilities in the population and quantifying the relative importance of each socio-economic factor in explaining differences in energy poverty risk.

4. Results

4.1 Measures of energy poverty in the EU

This section presents key indicators of energy poverty in different European Union countries, using both objective expenditure-based measures and subjective self-reported measures.

The objective indicators include the share of households with very high energy expenditure burdens, or extremely low energy expenditure, relative to the country's median. The subjective indicators capture self-perceived difficulties, in particular the share of households unable to keep their homes at an adequate temperature, as well as bill arrears.

These results are summarized in a series of figures, which highlight patterns across countries and how some results have varied over time.

High share of energy expenditure in income (2M)

Figure 2 shows the proportion of households in each EU country that spent more than twice the national median share of their income on energy in 2020, commonly known as the 2M indicator.

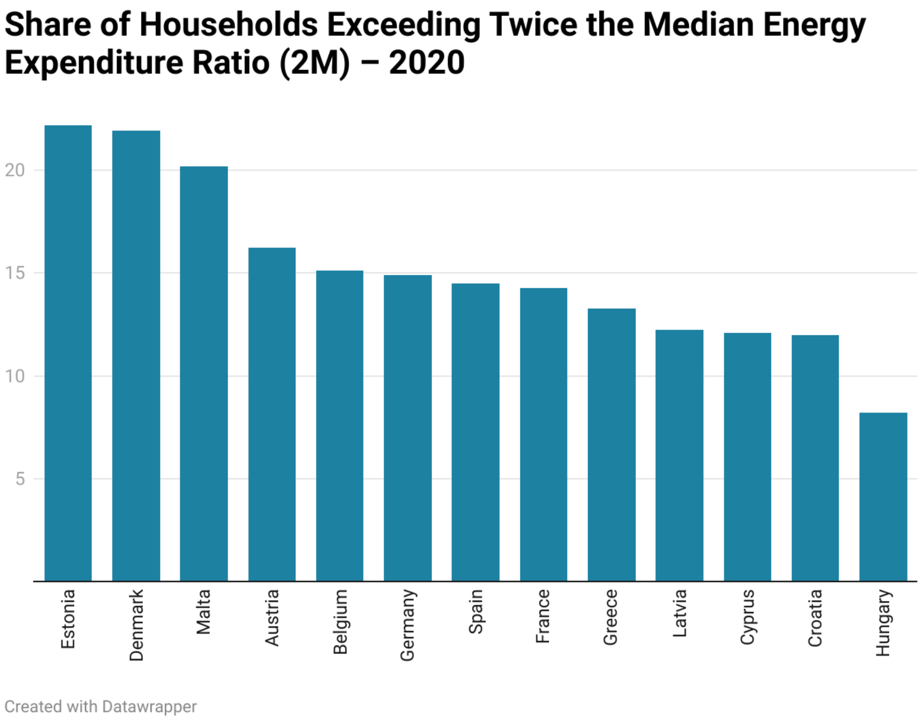

Figure 2. Share of households exceeding twice the median energy expenditure ratio (2M) in 2020

The 2M indicator reveals considerable variation between countries, without a simple East-West divide.

In 2020, the highest values were observed in countries as diverse as Estonia, Denmark and Malta, each with approximately 20-22% of households spending a high share of their income on energy.

Such high percentages in Estonia and Denmark, relatively affluent northern countries, suggest that factors beyond income alone influence this measure. For instance, very efficient housing and heating systems in these countries keep the median household's energy spending share low. As a result, even moderately high energy expenses can push some households above the 2M threshold, making them appear disproportionately burdened compared to the national median.

In contrast, Hungary and Slovakia show the lowest 2M values (less than 10%), meaning that there are few households that are exceeding twice the national median in energy expenditure.

Figure 3 illustrates the relationship between the two medians used to calculate the 2M and M/2 indicators. It shows that countries with a high median share of energy expenditure relative to income tend to have a lower percentage of households exceeding the 2M threshold. This does not necessarily reflect a lower prevalence of energy poverty, but rather a higher national median that raises the bar for what counts as "excessive" expenditure. As a result, fewer households formally exceed twice the median, even if many still face affordability issues. The inverse logic applies to M/2: a low absolute median reduces the threshold, making under-consumption harder to detect in low-income contexts.

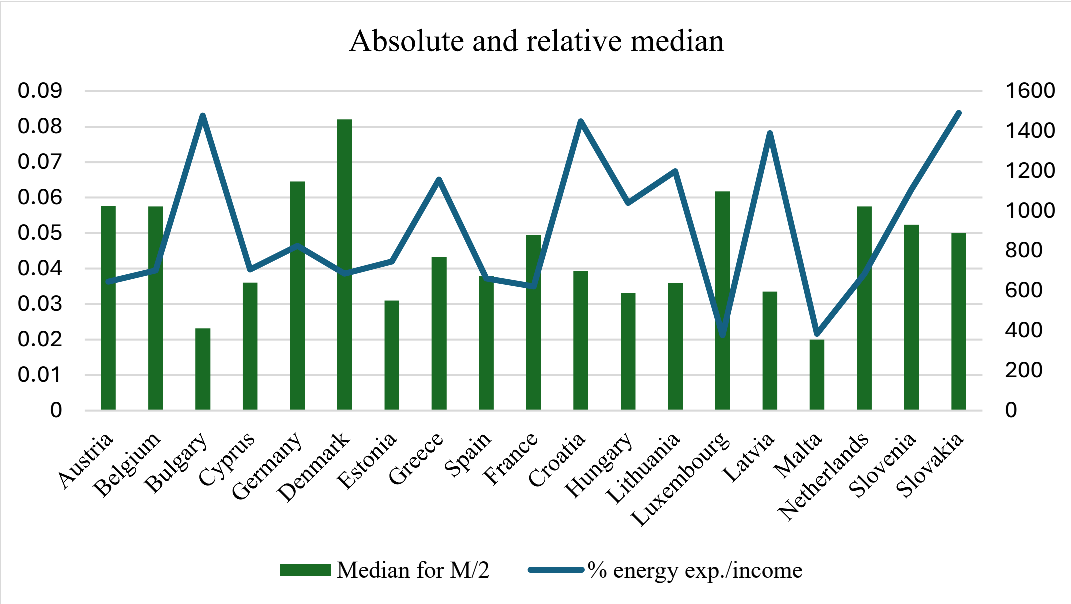

Figure 3. Absolute and relative median by country

In other words, in several Eastern European countries the "typical" household already allocates a relatively large portion of income to energy, so fewer households double that already-elevated share.

Comparing across regions, Western European countries generally cluster around mid-range 2M values (around 12–16%). For example, France, Germany, and Belgium each have about 14–15% of households above the 2M threshold. These moderate figures align with their higher average incomes and more robust welfare support, which help limit extreme energy cost burdens.

Southern Europe presents a mixed picture: Greece has a 2M rate near the sample median (~13%), and Spain indicate moderate levels as well (in the low-to-mid teens). Greece's position around the middle is notable given its severe economic difficulties since the 2010s; it suggests that by 2020, relatively few Greek households were spending twice the national median share on energy – likely because the median itself had risen during years of austerity when many cut back on energy usage.

Overall, the 2M indicator highlights where affordability stress manifests as high spending outlays: it is not exclusively the poorer EU members that top this list, but often wealthier countries with unequal energy cost distributions or very low median energy shares. Notably, some countries with high 2M rates do not always exhibit high self-reported energy poverty. For instance, Denmark's and Estonia's large 2M shares did not coincide with many people reporting inability to keep warm or bill arrears (as seen later), indicating that a high expenditure burden in those contexts may be mitigated by social support or other coping mechanisms. This discrepancy underscores that expenditure-based metrics capture a different facet of energy poverty (budget stress) than the subjective indicators.

Low absolute energy expenditure (M/2)

Figure 4 displays the share of households in 2020 whose energy expenditure were below half the national median, known as the M/2 indicator.

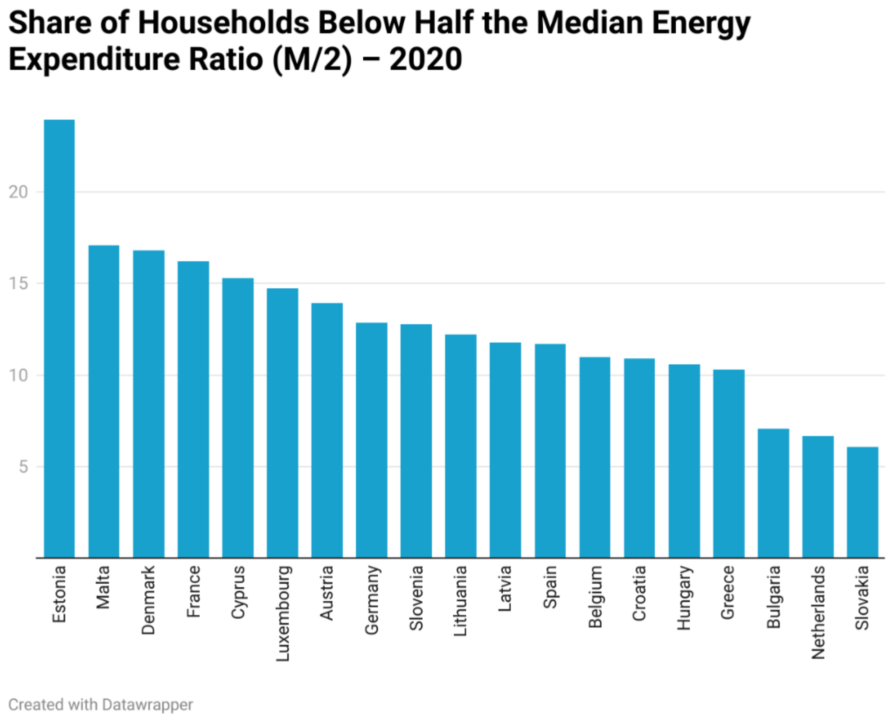

Figure 4. Share of household below half the median energy expenditure ratio (M/2) in 2020.

The M/2 indicator aims to identify households with abnormally low energy use, often interpreted (wrongly [24] [25]) as hidden energy poverty.

The 2020 data show a somewhat counter-intuitive pattern: several high-income or moderate-climate countries record the highest M/2 shares, while some lower-income Eastern countries have the lowest. The most extreme case is Estonia, where approximately 24% of the population lives in households with very low energy expenditures. Malta and Denmark also show high M/2 figures (above 17%), followed by France (~16%).

A high M/2 indicator could indicate that a significant segment of the population is consuming too little energy, potentially because they cannot afford adequate heating or air conditioning, or because of high energy efficiency standards or behavioral or climatic factors. In Malta's case, the warm climate keeps typical energy usage low (median spending is minimal, primarily for cooling), so a sizable share of households falls below half that median without necessarily suffering discomfort. In Estonia and Denmark, by contrast, winters are cold; high M/2 rates there suggest some households may be deliberately under-consuming energy, possibly to save money, despite living in a cold climate. This could reflect pockets of energy poverty where people ration heat, as well as the flip side of efficient housing, if the median household has moderate consumption thanks to good insulation, those who cannot afford proper heating stand out with very low usage. It highlights how household energy efficiency and housing quality influence this indicator: countries with advanced efficiency measures see lower overall consumption, which can unfortunately make under-consumption starker for those left behind.

At the lower end of the M/2 spectrum are countries like Slovakia, the Netherlands, and Bulgaria, each with only about 6–7% of households spending under half the median. A low value here implies that relatively few households have extremely low energy use. In the Netherlands, this could be because even more low-income households maintain a baseline level of energy consumption (due to strong social support, or standards in rental housing that ensure heating), and the median is already certainly high, making it more difficult to fall behind the middle.

In eastern countries, such as Slovakia and Bulgaria, a low M/2 indicator may indicate that the median is low, and many households cluster around that low consumption, so there are not many that use even less energy than an already modest median. For example, in Bulgaria, widespread low income levels constrain energy spending for a large portion of the population, so the median energy expenditure is very low; only a small additional fraction spends less than half of that (since that threshold is extremely low in absolute terms). Thus, ironically, Bulgaria's very low M/2 (around 7%) does not mean most households enjoy adequate energy services, rather suggesting that virtually everyone is near the low median, with few outliers using even less.

Finally, comparing 2M and M/2 results, some countries exhibit both high 2M and high M/2 shares (notably Estonia and Denmark). This points to internal inequalities: in such countries a substantial group spends very little on energy while another group spends considerably more than average. Such a dual issue could stem from heterogeneous housing conditions or income inequality, for example, modern energy-efficient homes versus old, poorly insulated homes within the same country.

In contrast, countries such as Slovakia and Hungary have both low M/2 and 2M, suggesting a more even distribution of energy expenditure (many households spend a similar proportion on energy, with fewer extreme cases). It is important to note that none of the objective indicators align perfectly with subjective experiences of energy poverty. High values of M/2 in rich countries may reflect voluntary deprivation, or a more moderate climate, while in poorer countries low absolute expenditure is simply the norm. Therefore, these expenditure-based measures must be interpreted alongside other indicators to help discern whether low consumption is by choice or constraint.

Arrears on utility bills

Figure 5 presents the share of households in arrears on utility bills across the European countries in 2008, offering a snapshot of financial vulnerability prior to the global financial crisis.

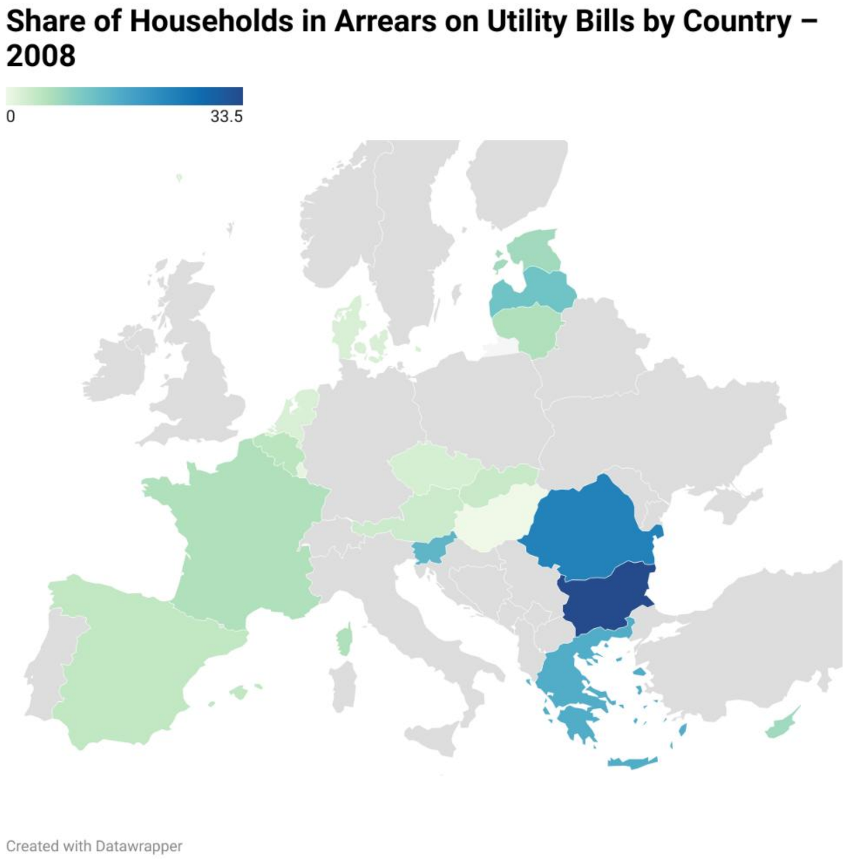

Figure 5. Share of households in arrears on utility bills, 2008

In 2008, at the start of the period examined, the share of households in arrears on utility bills (unable to pay utility bills on time due to financial difficulties) showed pronounced regional disparities. As illustrated in *Figure 5*, several Eastern European member states had alarmingly high arrears rates. In Bulgaria, just over a third of households (about 33-34%) were in arrears with their utility payments, the highest in the EU for that year. Similarly, Romania reported roughly a quarter of its households in arrears (in the mid-20s).

These figures reflect the challenging economic conditions and lower incomes in the eastern part of the Union at the time, as well as likely difficulties with energy efficiency: many households suffered when it came to keeping their homes warm, as they required higher energy inputs, strangling household budgets. Greece and some Baltic states also showed elevated arrears in 2008 (Greece around 16%, Latvia ~12%), foreshadowing potential vulnerability.

In contrast, most Western and Northern European countries had arrears rates below 5% in 2008. For instance, Austria and Denmark reported very low levels (on the order of 2–3%), and Germany and France were likewise in the low single digits. These low percentages in wealthier states point to stronger social safety nets and consumer protections that helped most households avoid utility debt, as well as higher average incomes to begin with. Even within Western Europe, there were slight differences, e.g. Portugal and Spain (not in the 21-country subset used for figures, but historically) tended to be a bit higher than the core EU average, likely because of slightly lower income levels and possibly warmer-climate households prioritizing other expenses over heating. In summary, the 2008 map shows a clear East-West divide: the new eastern members of the European Union had problems paying utility bills at a much higher rate than the established southern European countries, reflecting the real impact of the economic disparity present in the energy poverty suffered by citizens.

By 2015, the landscape of arrears on utility bills had shifted in response to economic and policy changes, most notably the aftermath of the late-2000s financial crisis and the Eurozone debt crisis. *Figure 6* reflects both improvement in some Eastern states and sharp deterioration in parts of Southern Europe.

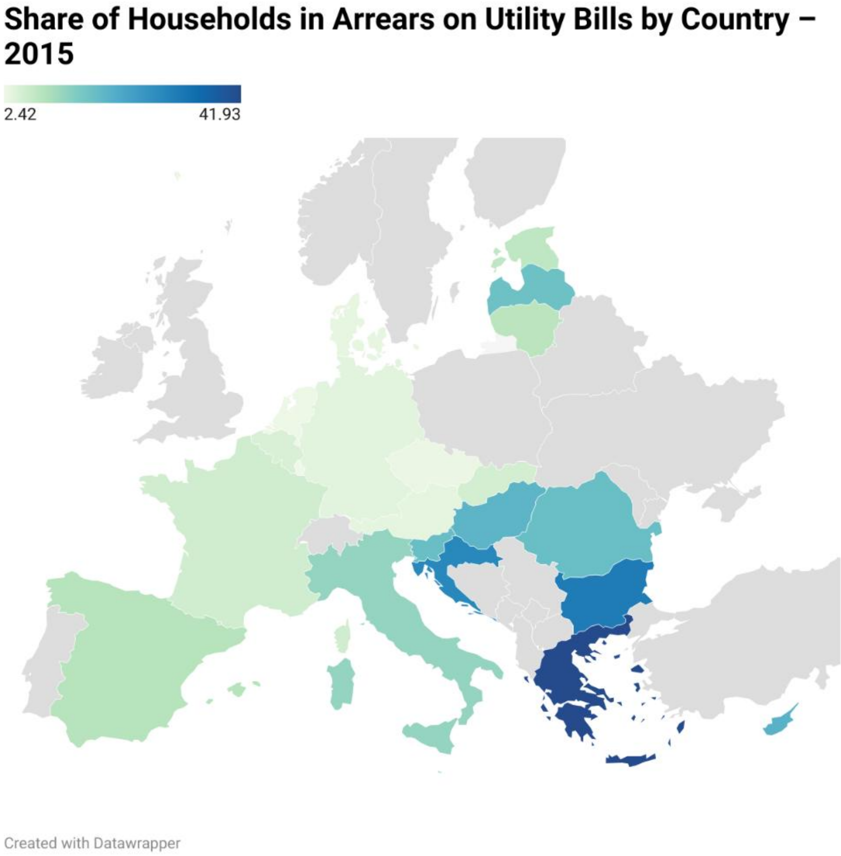

Figure 6. Share of households in arrears on utility bills, 2015.

Eastern Europe, in general, saw moderate improvements or stabilization from 2008 to 2015. For example, Bulgaria's arrears rate, while still extremely high, decreased from the mid-30s to about 31%. Romania improved even more significantly, dropping to roughly 17% by 2015 (down from ~23% in 2008), reflecting strong economic growth and possibly governmental measures like regulated energy prices or social tariffs that kept more households current on their bills.

The Baltic countries, too, experienced declines or contained levels, for instance, Latvia was around 16.8% in 2015 (up a few points from 2008, but not drastically), whereas Lithuania remained under 10%. On the other hand, Greece experienced a dramatic surge in households falling behind on utilities: by 2015, an astonishing ~42% of Greek households were in arrears, up from an already worrisome 16% in 2008. This increase made Greece the new outlier, reflecting the severe impact of the economic crisis, with unemployment, and austerity measures on Greek households to pay basic utility bills.

Other southern European countries also reported increases, with Spain almost doubling its arrears figures (from ~4.6% in 2008 to roughly 8.8% in 2015), as the recession hit incomes and unemployment rose. Italy (which did not have 2008 data in our series) had around 12–13% of households in arrears in 2015, indicating considerable stress during the post-crisis period.

In contrast, most Northwestern European countries in 2015 maintained low arrears levels, often under 5%. For instance, France and Belgium were in the 5–7% range, slightly up from 2008 but still comparatively low, possibly reflecting minor impacts of the crisis and effective consumer protection policies (such as winter disconnection moratoria or bill assistance programs). Denmark and Austria saw small upticks but remained around 3–4%. The most important regional change from 2008 to 2015, therefore, was the emergence of southern European countries, in particular Greece, as the epicenter of utility bill payment delays, overtaking even eastern European countries, which had historically led on this indicator. This underlines how macroeconomic factors can quickly spill over into energy poverty, especially where social protection or targeted energy assistance is insufficient to protect vulnerable households.

Figure 7 illustrates the share of households in arrears on utility bills in 2022, reflecting the financial impact of recent crises such as the post-pandemic recovery and the energy price surge linked to geopolitical tensions.

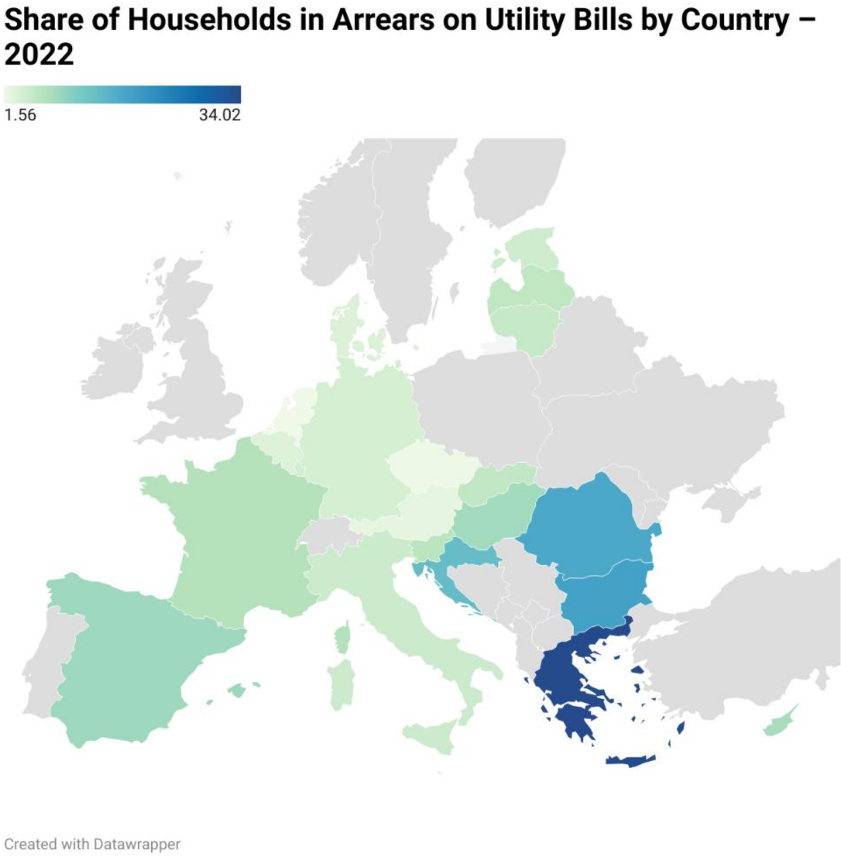

Figure 7. Share of households in arrears on utility bills, 2022.

By 2022, the situation evolved again, with many countries experiencing a recovery from the peak of the crisis in 2015, although not uniformly. Figure 7 shows how Greece remained a hotspot, but its arrears rate declined since 2015: around a third of Greek households (34%)

incurred arrears in 2022, a significant improvement from the 42% reported in 2015, though still the highest among the surveyed countries.

This reduction suggests a gradual economic recovery, as well as possible policy interventions (such as debt forgiveness programs or incentives) that helped Greek households catch up with bills.

In 2022, Eastern European countries generally continued the positive trajectory previously observed: for example, Bulgaria's arrears ratio continued to decline to around 18.8%, almost half its 2008 level (although still high relative to Western Europe). Romania more or less remained stable, at around 17.8% in 2022, similar to 2015, indicating that although initial gains had stagnated, they remained stable. Other eastern countries, such as Hungary (around 8.6% in 2022) or Latvia (~6.1%), show notable declines in 2022 compared to seven years earlier, reflecting sustained economic growth, and possibly regulations regarding electricity prices (Hungary, for example, had policies limiting its price during the 2010s).

Many Western and Northern European countries maintained low arrears in 2022, although some experienced slight increases in late 2010 and early 2020. Germany rose to around 4.1% (from ~3.9% in 2015), and Luxembourg rose to ~4.4% (from ~2.4% in 2015), small changes that may indicate growing inequality or cost-of-living pressures, even in wealthy nations.

Notably, Spain's arrears rate in 2022 (roughly 9.2%) remained elevated compared to its pre-crisis level and was slightly higher than in 2015, a unique case where a Western European country did not fully regain its pre-2008 footing. This could be attributed to persistent unemployment issues and, in the very latest data, the beginning effects of the 2021–22 energy price surge, which put new strain on households.

In summary, the 2008–2022 trend for utility bill arrears shows convergence and divergence: the extreme East–West gap of 2008 had narrowed by 2022 (Eastern rates fell significantly), but new gaps emerged during crises, with Southern Europe (Greece especially) temporarily becoming worse off. By 2022, the overall disparity is somewhat reduced relative to 2008, most countries lie in the single-digit percentages, and only a few outliers remain above 15%. Nonetheless, those outliers (Greece, and to a lesser extent Bulgaria and Romania) underscore that regional and structural factors (like economic resiliency, energy pricing, and social safety nets) result in persistent differences in households' ability to pay for energy.

Inability to keep home adequately warm.

Figure 8 shows the percentage of households in 2008 that reported being unable to keep their home adequately warm, a key subjective indicator of energy poverty.

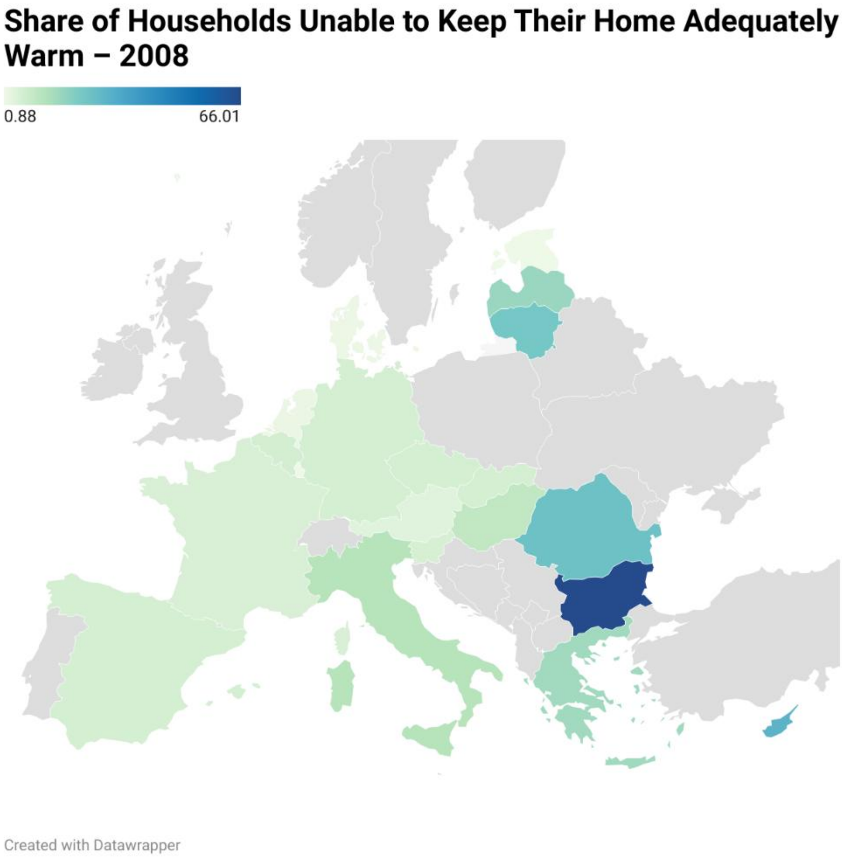

Figure 8. Share of households unable to keep their home adquately warm, 2008.

The inability to keep the home adequately warm is another core indicator of energy poverty, capturing the share of the population that reports being unable to maintain a comfortable indoor temperature during cold seasons.

In 2008, this indicator again revealed a strong regional pattern, in many ways mirroring the arrears situation but in some cases even more extreme. *Figure 8* highlights that several new EU member states had very high proportions of people unable to keep their homes warm.

Bulgaria was the most extreme case: in 2008, roughly 66% of Bulgarians reported inability to adequately heat their home, effectively two out of every three households suffered from thermal discomfort due to economic or material constraints. This extraordinary figure reflects the combined effect of low incomes, high relative energy costs, and poor housing insulation in Bulgaria at that time. Other Eastern countries also faced severe levels: about 24–25% in Romania and the Baltic states. Among the surveyed set, Latvia and Lithuania had approximately 16.8% and 22.6% respectively in 2008, indicating significant challenges in the Baltic region.

Meanwhile, Southern Europe presented a mixed scenario in 2008: Greece had around 15.4% of its population cold at home, which is notable given its milder climate, a sign that even in warmer countries, inadequate heating infrastructure or fuel affordability can cause hardship (in Greece's case, many homes might not have efficient heating systems, and poverty was already an issue for a segment of the population).

Western Europe and Scandinavia (e.g. France, Germany, the Netherlands, Denmark) reported much lower rates in 2008, typically under 10%. For instance, France was around 5–6%, Austria

~4%, and Denmark exceptionally low at about 1.7%. That Denmark's rate was so low despite a cold climate speaks to its excellent housing insulation, high incomes, and strong social support, factors that ensured almost all Danes could keep warm.

The stark East–West divide in 2008's heating adequacy indicator underscores how housing quality and energy efficiency (often lower in post-socialist housing stock) and household resources determined whether families could stay warm in winter.

By 2015, the inability-to-keep-warm indicator showed both significant improvement in some Eastern countries and a worrying backslide in parts of Southern Europe. *Figure 9* demonstrates these contrasting trends.

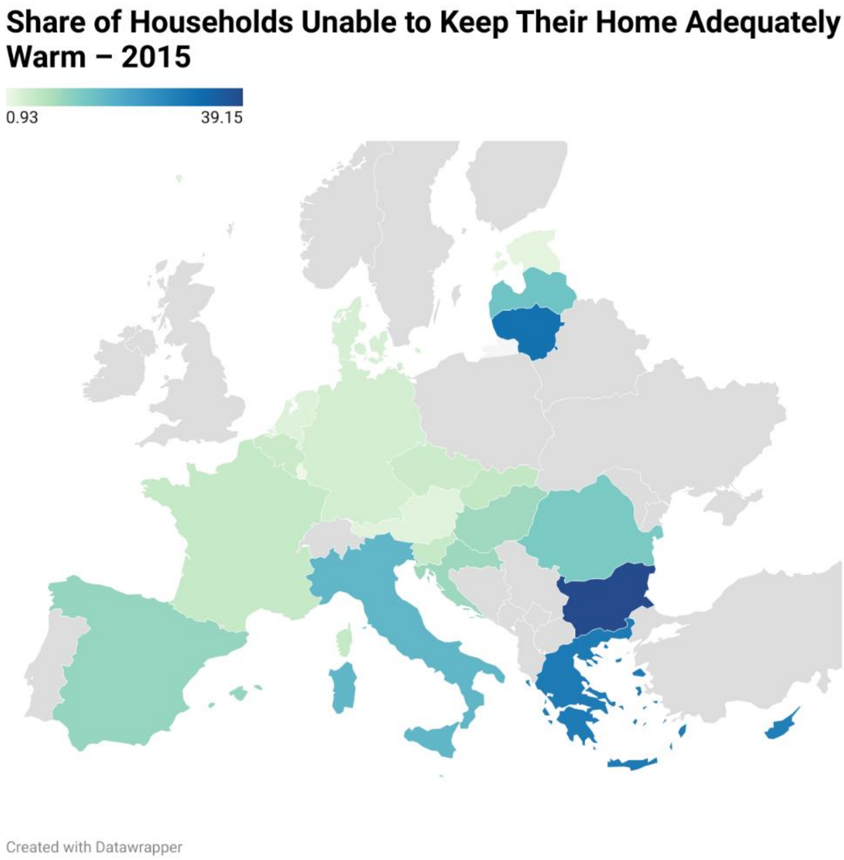

Figure 9. Share of households unable to keep their home adequately warm, 2015.

In Eastern Europe, several countries saw a dramatic drop in this indicator between 2008 and 2015, thanks to economic growth and likely investments in housing energy efficiency (often supported by EU funds for renovation). For example, Bulgaria's rate fell from 66% to roughly 39% in 2015, still very high, but a substantial improvement in people's living conditions. Romania achieved an even steeper reduction, from about 24.6% down to nearly 13.2% by 2015. This halving of Romania's rate may reflect rising incomes as well as extensive use of subsidies for heating and building upgrades. Similarly, Latvia modestly reduced its rate to about 14.5% by 2015, and Hungary and Poland (though Poland not plotted) also saw declines, indicating a general trend of Eastern Europe slowly closing the gap in basic thermal comfort. However, not all Eastern countries improved: Lithuania experienced an increase, with its inability-to-keep-warm share climbing to around 31% in 2015 (up from ~22% in 2008). Lithuania's spike might be related to economic volatility or energy price hikes in the early 2010s that disproportionately affected its population, illustrating that progress can be uneven.

The most noteworthy changes by 2015 occurred in Southern Europe, where the fallout of the economic crisis severely impacted households' ability to afford heating. Greece again stands out: the percentage of Greeks unable to keep their home warm nearly doubled, soaring from ~15% in 2008 to about 29% in 2015. This mirrors the surge in utility bill arrears and reflects how deeply the Greek population was affected by income loss and fuel price increases (e.g., higher taxes on heating fuel were introduced during the crisis). Italy also saw a rise: from roughly 11% in 2008 (based on available data) to around 17% in 2015, indicating that more Italian households struggled with heating post-recession (especially in poorer regions of Italy or among vulnerable groups like the elderly in inefficient homes). Spain, despite its relatively mild winters, increased from about 6% to 10.6% over the same period, a significant jump that likely owes to the economic strain of the Great Recession, combined with the fact that Spanish homes are often not designed for heating (many lack central heating, so when temperatures do drop, low-income families find it hard to stay warm).

Meanwhile, Western and Northern Europe mostly maintained low levels in 2015. Some countries even improved slightly: for instance, Germany went down to ~4.1% (from ~5.9% in 2008), possibly due to policy efforts and continued efficiency improvements. France hovered around 5%, relatively unchanged, and the Nordic and Western countries remained in the low single digits (Denmark did rise slightly to ~3.7% by 2015, but still very low).

The year 2015 thus marked a peak of divergence in the EU: Eastern Europe was starting to catch up on this indicator (with notable improvements), while parts of Western Europe were steady, but Southern Europe had sharply worsened, reflecting how macroeconomic crises coupled with energy price and housing issues translated into real household-level heating difficulties.

Finally, by 2022, many of these trends had partially reversed or moderated. *Figure 10* shows that most countries improved in their ability to keep homes warm compared to 2015, thanks to economic recovery and possibly policy measures, although new challenges were emerging by the early 2020s.

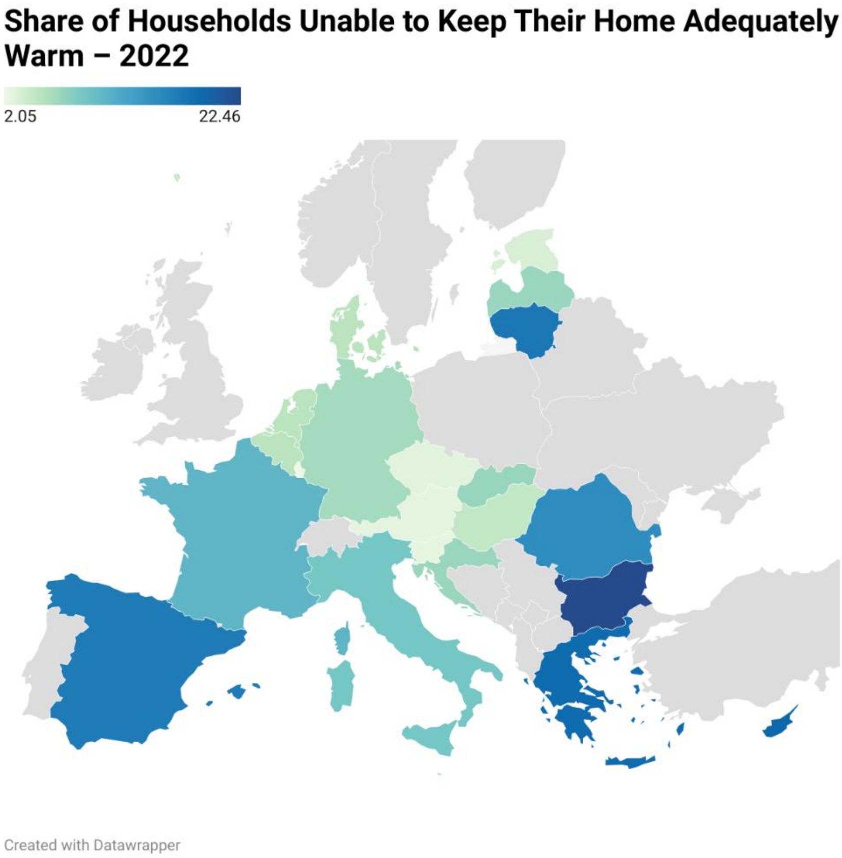

Figure 10. Share of households unable to keep their home adequately warm, 2022.

In Greece, for example, its indicator fell from 29% in 2015 to 18.7% in 2022. This remarkable improvement, in line with the gradual exit from the economic crisis, as well as targeted interventions (e.g. social tariffs for electricity), helped households to warm up again. Still, at nearly 19%, Greece remained one of the worst in the EU in 2022, second only to a few Eastern countries, indicating that a large minority of Greeks continued to live in energy poverty conditions.

Eastern Europe mostly continued its positive trajectory: Bulgaria brought its inability-to-keep-warm indicator to 22.5%, almost a third of its 2008 level, an impressive long-term improvement, although still a fifth of Bulgarians are still unable to heat their homes adequately. Lithuania, which saw an increase in this indicator, improved substantially in 2022, falling to 17.5%, suggesting that the factors that led to the worsening in 2015 were corrected in the following years. Latvia and Romania remained relatively low for the region (above 7% and 15% respectively in 2022), sustaining the improvements they made earlier.

Some Central European countries, such as Hungary, achieved really low figures (~4.7% in 2022, down from 9.6% in 2008), approaching Western levels, probably due to a combination of energy price controls and improved insulation, making heating more affordable for households.

A few countries did worsen their figures compared to 2015, possibly reflecting new stresses. Notably, the Spanish figure rose to around 17.1% in 2022, a notable increase from 10.6% in 2015, matching the Italian figure in 2008. This increase made Spain one of the worst countries on this indicator in 2022, despite its friendly climate. Its timing suggests that new stresses, such as rising energy prices and stagnating household incomes, were affecting Spain. Italy, by contrast, saw a significant improvement in 2022: its indicator dropped to around 8.8%, almost half of what was reported in 2015, indicating a strong recovery.

Among Western countries, most remained low; however, Germany's rate rose slightly back to 6.4% in 2022 (from 4.1% in 2015), and Denmark's increased to 5.1% (from 3.7% in 2015). Although these levels are still comparatively low, the upward creep in some wealthy nations might hint at the early impact of the 2021–2022 energy price crisis, which made heating noticeably more expensive even for higher-income countries toward the end of our observation period.

In summary, between 2008 and 2022 the inability to keep homes warm in the EU generally declined, and the worst-off Eastern countries made the most substantial gains, vastly reducing (though not eliminating) the East–West gap. Yet, vulnerabilities persist: Greece in the south and Bulgaria in the east still reported double-digit shares of population living in inadequately heated homes in 2022. The data also show that fortunes can change, a country like Spain, traditionally having low reported thermal discomfort, can see a surge in this indicator, underlining that energy poverty is a moving target influenced by economic conditions and energy prices.

4.2 Socio-economic profile of energy poverty

4.2.1 Disaggregated Analysis

In order to better understand the causes and forms in which energy poverty manifests itself, this section analyzes in a disaggregated manner the socioeconomic profile of the households that reported not being able to maintain their homes at an adequate temperature, as detailed in the Methodology section.

Through the study of variables such as type of housing tenure, employment status, educational level, household composition or degree of urbanization, it is possible to identify which profiles are more exposed to this problem. This analysis also makes it possible to better target public policies and design more specific interventions. Each of the following sections focuses on one of these variables and presents how the responses are distributed within the group of households affected by energy poverty. However, the percentage of households in each cluster should be borne in mind when analysing these figures.

Degree of urbanization.

Figure 11 shows the distribution of households that report not being able to maintain their homes at an adequate temperature according to the degree of urbanization. The data indicate that energy poverty is not a problem exclusive to cities or rural areas.

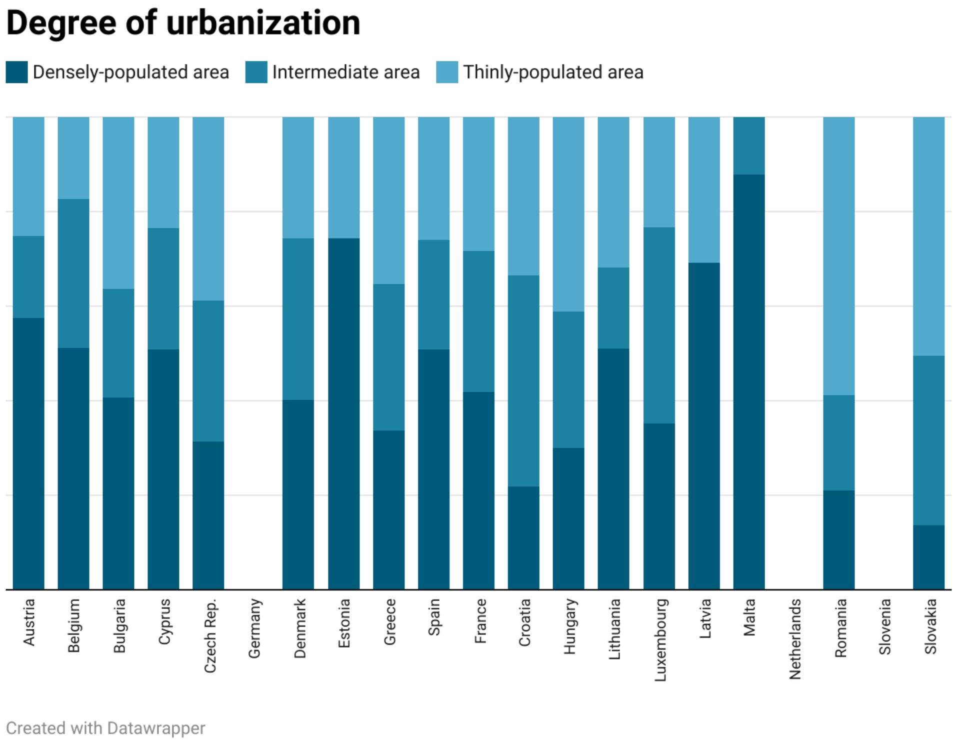

Figure 11. Disaggregated analysis by degree of urbanization, 2020.

A significant proportion of affected households live in densely populated urban areas, although this partly reflects the fact that most of the population is urban. Likewise, in many regions, sparsely populated rural areas also account for a considerable share, however, the relative size of these clusters should be considered when interpreting their weight in the overall results. Notably, some Eastern EU Member States exhibit a pronounced rural profile, for example, in Romania and Slovakia, a majority of households struggling to keep warm are in thinly populated areas, indicating that rural poverty and poor housing conditions contribute markedly to energy poverty.

In contrast, in highly urbanized or small countries, such as Malta, virtually all households in energy poverty are concentrated in urban settings. Overall, the pattern at the EU level shows a slight tilt towards urban areas, although with important exceptions depending on the country. This highlights that both urban and rural households face difficulties in maintaining an adequate temperature in their dwellings.

Type of dwelling

Figure 12 shows the breakdown of households unable to keep warm by type of dwelling. Multi-unit dwellings (apartments) constitute a large segment of energy-poor households at the EU level.

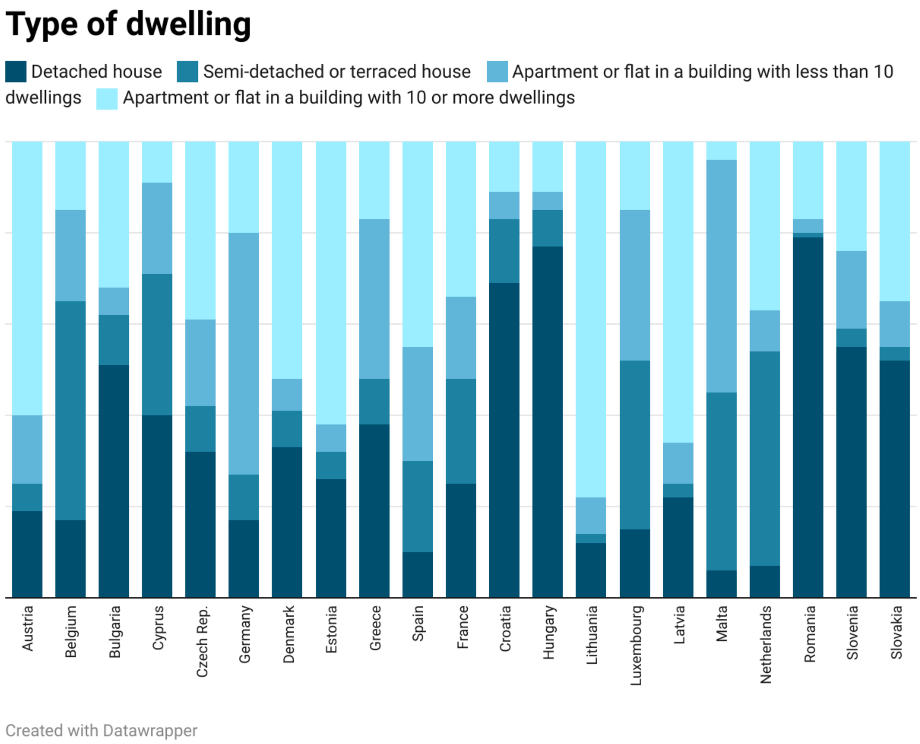

Figure 12. Disaggregated analysis by type of dwelling, 2020.

In many countries, a majority of those struggling with indoor warmth live in apartment buildings, often large complexes with ten or more flats, although this may reflect the overall housing structure in those countries, where apartments dominate. This suggests caution when interpreting the prevalence of energy poverty solely by dwelling type. This pattern may be related to low-income families living in older or energy-inefficient apartment blocks, including social housing, that are difficult to heat.

However, the type of housing in which households in energy poverty reside varies considerably between European countries. In several countries in Eastern Europe and the Baltic region, for example, the majority of affected households live in single-family houses, suggesting that many of these vulnerable families are rural homeowners living in insulated dwellings with poor insulation or inefficient heating systems.

In contrast, in some Western European countries, such as Belgium, a significant proportion of affected households reside in terraced or semi-detached houses, highlighting the diversity of residential contexts in which energy poverty manifests itself. Overall, the difficulty of maintaining a household at an adequate temperature occurs in all types of dwellings, although apartments and older single-family houses appear more frequently as scenarios for this form of deprivation.

Tenure status

Figure 13 illustrates the tenure status of households reporting inadequate warmth.

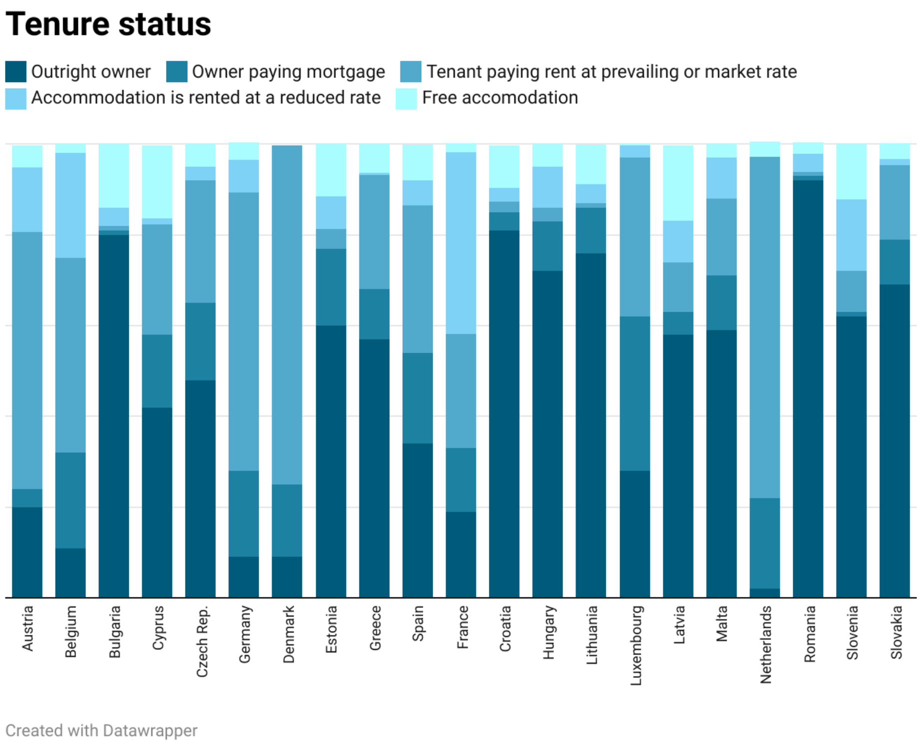

Figure 13. Disaggregated analysis by tenure status, 2020.

Across the EU, renters are disproportionately represented among those struggling to heat their homes. Households renting at market rates form a particularly large share of the energy poor in many Member States, for instance, in countries like Germany and Austria, well over half of energy-poor households are tenants paying full rent. This underscores the vulnerability of renters, who often have lower incomes and less capacity to improve the energy efficiency of their homes.

In some countries, tenants of social housing (with reduced rent) represent a significant part of the affected population. This is the case, for example, in France, where a considerable proportion of households in energy poverty live in subsidized rentals. This indicates that, even with rental support, many low-income households cannot afford adequate heating.

On the other hand, in Eastern and Southern Europe, where home ownership rates are high, the majority of affected households are homeowners. Many of them are elderly or low-income families who live in older housing and have limited resources to make improvements. This situation reflects another face of energy poverty, associated not with access to housing, but with the ability to maintain it in adequate conditions.

By contrast, households paying off mortgages are relatively underrepresented in the energy-poor group, suggesting that those in the process of buying homes tend to have higher incomes or newer dwellings. These tenure-related patterns highlight that renters (and to some extent economically vulnerable homeowners) face the greatest difficulties in keeping homes warm.

Employment status

Figure 14 presents the employment status of individuals in households unable to keep their home warm. The profile is characterized by an overrepresentation of economically inactive and unemployed groups.

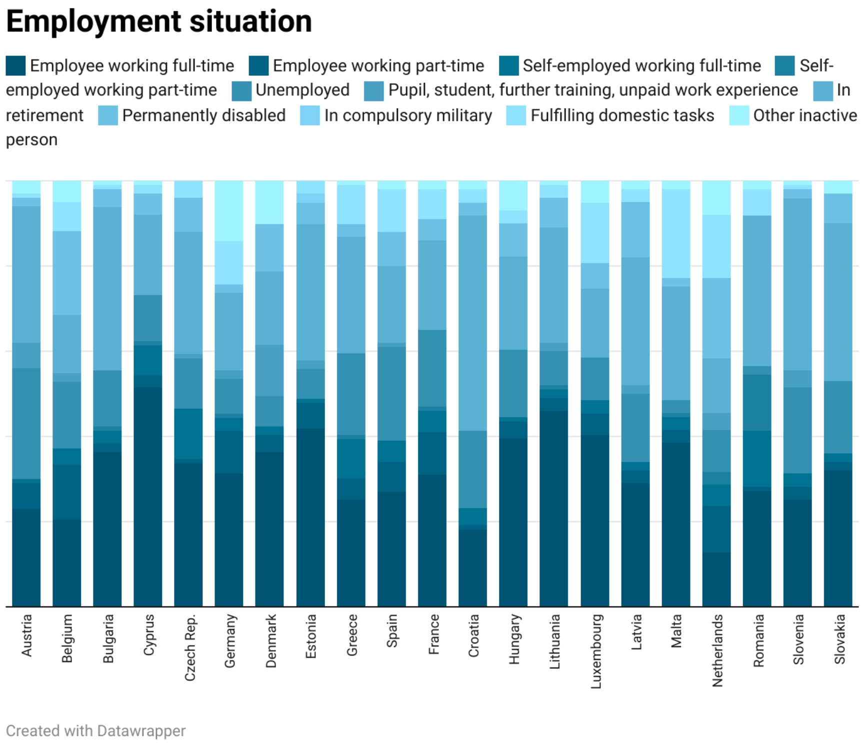

Figure 14.Disaggregated analysis by employment situation, 2020.

Unemployed persons consistently make up a significant share of the energy-poor population across Europe, aligning with the expectation that lack of paid work (and the resulting low income) heightens vulnerability to energy poverty. Likewise, retirees on fixed incomes form a large portion of these households in many countries, in several cases, pensioners constitute around one-third (or more) of those living in inadequately heated homes. This indicates that older adults, especially those living alone on modest pensions, often struggle with heating costs.

Other inactive groups are prominent as well: for example, in some Western European countries a notable segment of energy-poor households includes people classified as permanently disabled or those fulfilling domestic care duties, reflecting how health issues and caregiving responsibilities can limit income and coincide with energy hardship.

Importantly, a considerable fraction of energy-poor households are also headed by working individuals. In particular, many countries report a non-trivial share of full-time or part-time employees among the energy poor, a phenomenon highlighting the "working poor" who, despite employment, have wages too low or energy costs too high to ensure adequate warmth at home. In summary, while non-working populations (unemployed, pensioners, disabled) are most strongly associated with inability to keep homes warm, having a job is not always sufficient protection against energy poverty.

Type of employment

Figure 15 displays the distribution of energy-poor households by type of employment (occupation) of the household head or main earner.

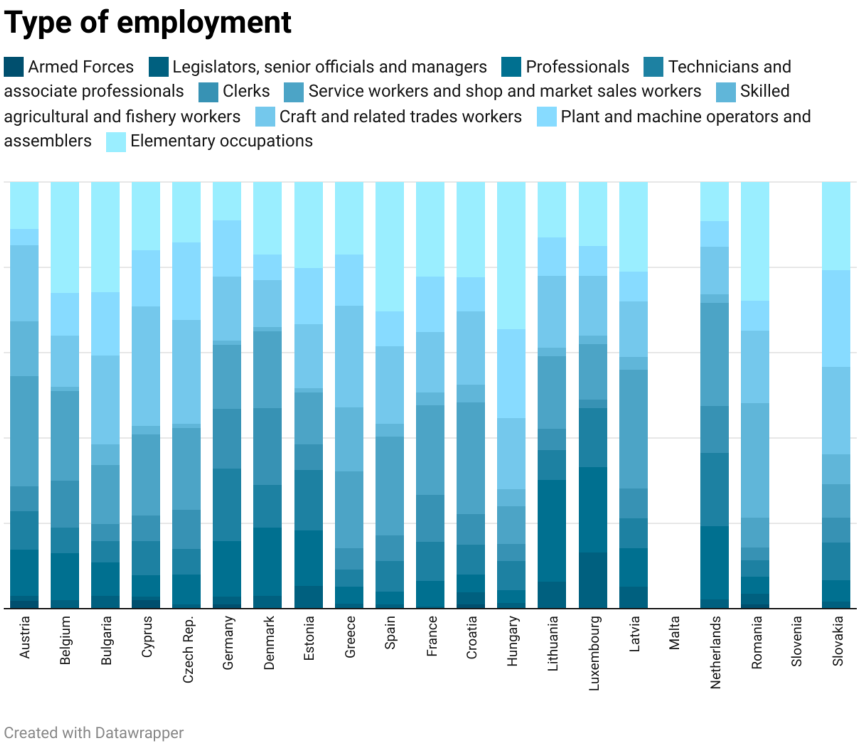

Figure 15. Disaggregated analysis by type of employment, 2020.

Lower-skilled occupations are clearly prevalent among this vulnerable group. In many EU countries, the largest shares of households unable to keep warm are headed by individuals working in elementary occupations, craft and trade work, or as plant and machine operators, jobs typically associated with lower earnings. For example, workers in elementary (unskilled) roles often represent one of the single biggest occupational categories among households in energy poverty (reaching 20–30% of this group in some countries such as Spain or Bulgaria).

Service and sales workers are another common component of the households in energy poverty profile, reflecting the inclusion of many low-paid service employees.

In contrast, high-skilled professionals and managers are only a small minority within this group, underlining the link between low-paying job sectors and energy affordability issues. There are occasional exceptions to this general pattern (for instance, a few countries see a somewhat higher share of households in energy poverty with professional or technical workers, possibly due to unique labor market or housing situations), but overall the data confirm that energy poverty in 2020 was concentrated among households engaged in lower-tier occupations.

Health status

Figure 16 examines self-reported health status among individuals in households that could not keep their home adequately warm. The data suggest a correlation between poor health and energy poverty.

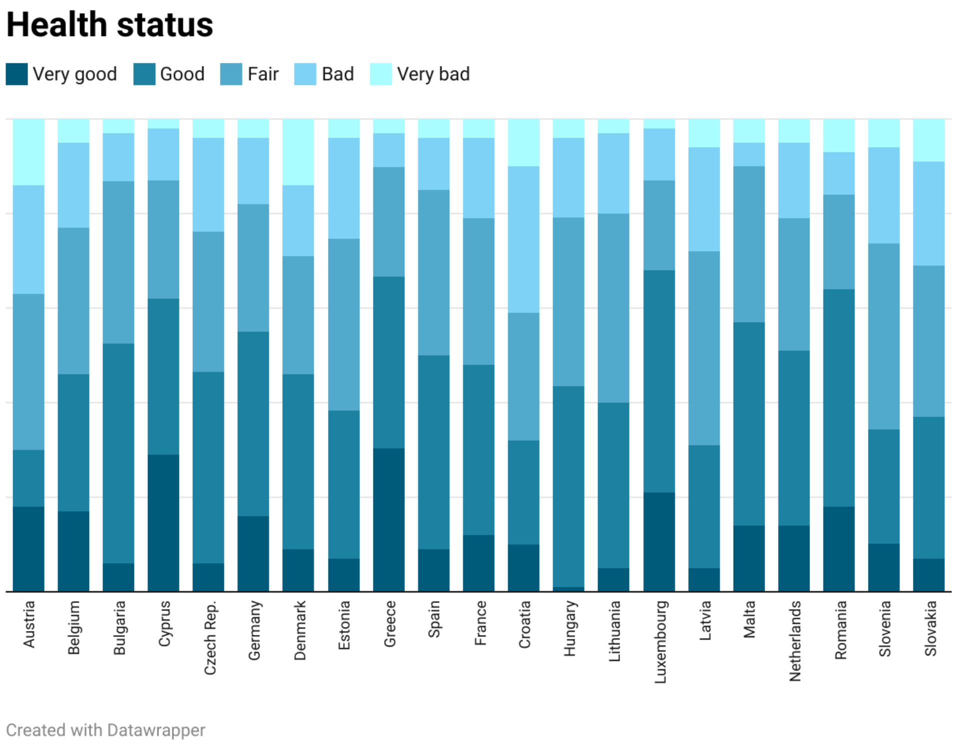

Figure 16. Disaggregated analysis by health status, 2020.

EU-wide, a large portion of people in households in energy poverty report less-than-good health. Notably, "fair" health is a common rating in this group, and a considerable share report bad or very bad health. For example, in several countries over half of the population in energy poverty describes their health as fair or poor, indicating that households facing energy poverty often include members with health problems or disabilities. This may imply that chronic illness or limited physical capacity (which can reduce earning ability and increase vulnerability) is associated with difficulty in maintaining adequate home heating.

However, the relationship is not uniform across all countries. In some member states, a significant fraction of those unable to keep warm still report good or very good health, suggesting that energy poverty also affects many otherwise healthy working-age individuals (likely due to economic factors alone). Overall, health status data highlight that while energy poverty frequently overlaps with health vulnerabilities, it is a multifaceted issue impacting both healthy and less healthy populations, with the causality possibly running both ways (poor health can be both a cause and a consequence of living in a cold home).

Household structure

Figure 17 shows the household structure of those who reported being unable to keep their home warm. Certain household types are clearly more susceptible to energy poverty.

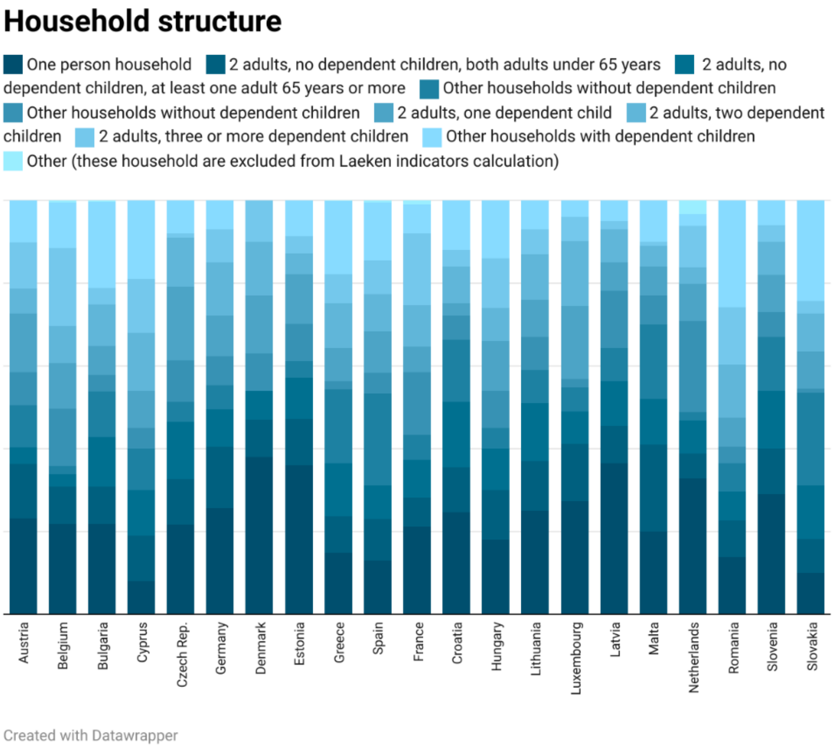

Figure 17. Disaggregated analysis by household structure, 2020.

One-person households comprise a substantial share of the affected group across the EU. However, since these households are also common in the overall population, their prominence in the energy-poor segment should be considered in relative, not absolute, terms.

Single-parent families and other households with dependent children are another important component, many countries see a high proportion of households in energy poverty that include children, indicating the strain of heating costs on families (particularly those with one breadwinner or many dependents).

In some countries, large families, e.g., two adults with three or more children, are overrepresented among households in energy poverty. This highlights how the presence of multiple dependents can increase vulnerability by raising energy consumption needs and putting greater pressure on household budgets.

In contrast, households consisting of two adults without children, especially when both are of working age, tend to be underrepresented among the affected population. The existence of two incomes or the possibility of sharing expenses helps to alleviate the economic burden associated with household heating. In sum, the EU-wide profile in 2020 suggests that both ends of the household-size spectrum, single occupants and larger families, as well as single parents are particularly prone to inadequate warmth at home, whereas middle-sized households with multiple working adults are relatively less affected.

Education

Figure 18 shows the distribution of educational levels among people living in households that reported not being able to keep their dwelling at an adequate temperature in 2020. The data reveal a relationship between lower educational attainment and greater vulnerability to energy poverty across the European Union as a whole.

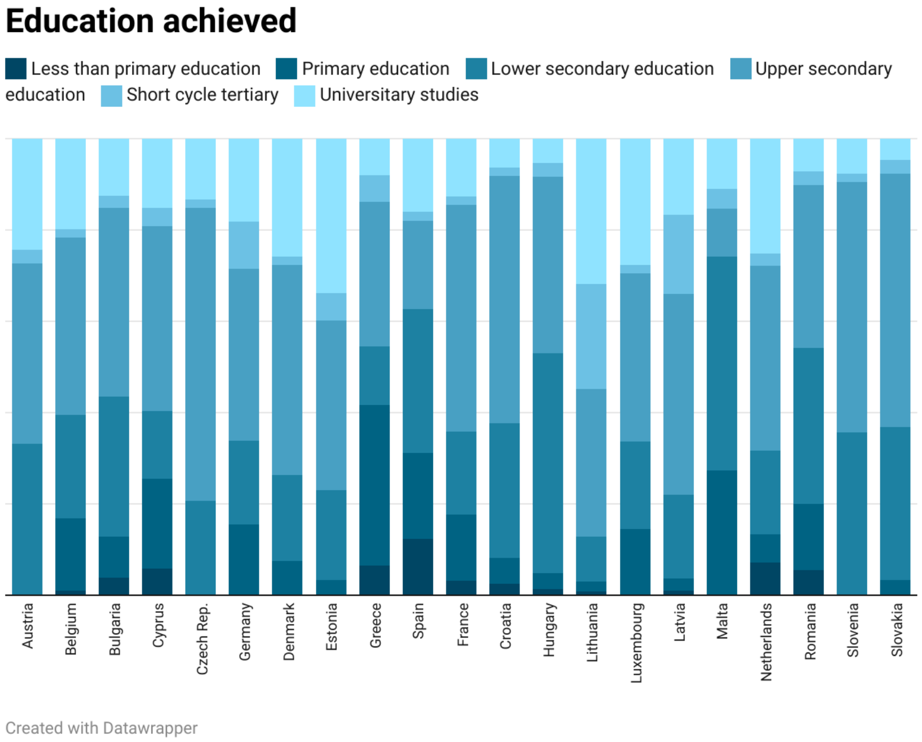

Figure 18. Disaggregated analysis by education level achieved, 2020.

Households headed by individuals with no formal education or with only primary or lower secondary education represent the majority of those affected in almost all EU Member States. This pattern is particularly pronounced in Southern and Eastern European countries, such as Bulgaria, Romania or Greece, where the share of individuals in energy poverty with only basic education exceeds half of the total in some cases.

In contrast, the proportion of people with tertiary education (either short cycle or university) among those experiencing energy poverty is consistently low, indicating that a higher level of education acts as a protective factor against this problem. This trend is in line with broader socioeconomic patterns, as educational level is closely related to job opportunities, earning capacity and access to (or knowledge of) energy efficiency measures. Countries such as the Netherlands or Luxembourg, where a relatively high proportion of the population has completed tertiary education, also have a lower presence of people with this level of education among those who report not being able to keep their homes adequately warm.

However, a considerable proportion of people suffering from energy poverty have higher secondary education or vocational training. This shows that education, although important, is not always enough on its own to avoid this situation of vulnerability, especially when combined with other factors such as unemployment, high housing costs or the poor quality of the housing stock.

In short, the data suggest that a low level of education is one of the structural factors behind energy poverty in Europe. It is therefore essential to move towards integrated policies that jointly address education, employment and access to decent housing.

4.2.2 Logistic regression model

To better understand the drivers of energy poverty, a regression model has been developed, using the binary indicator of the inability to maintain the home at an adequate temperature as the dependent variable. The model includes the socioeconomic variables mentioned in the disaggregated analysis, allowing for the association of these variables with a higher probability of experiencing this type of problem.

The results, presented in Figure 19, and broken down in more detail in Annex II, show a clear pattern of associations.

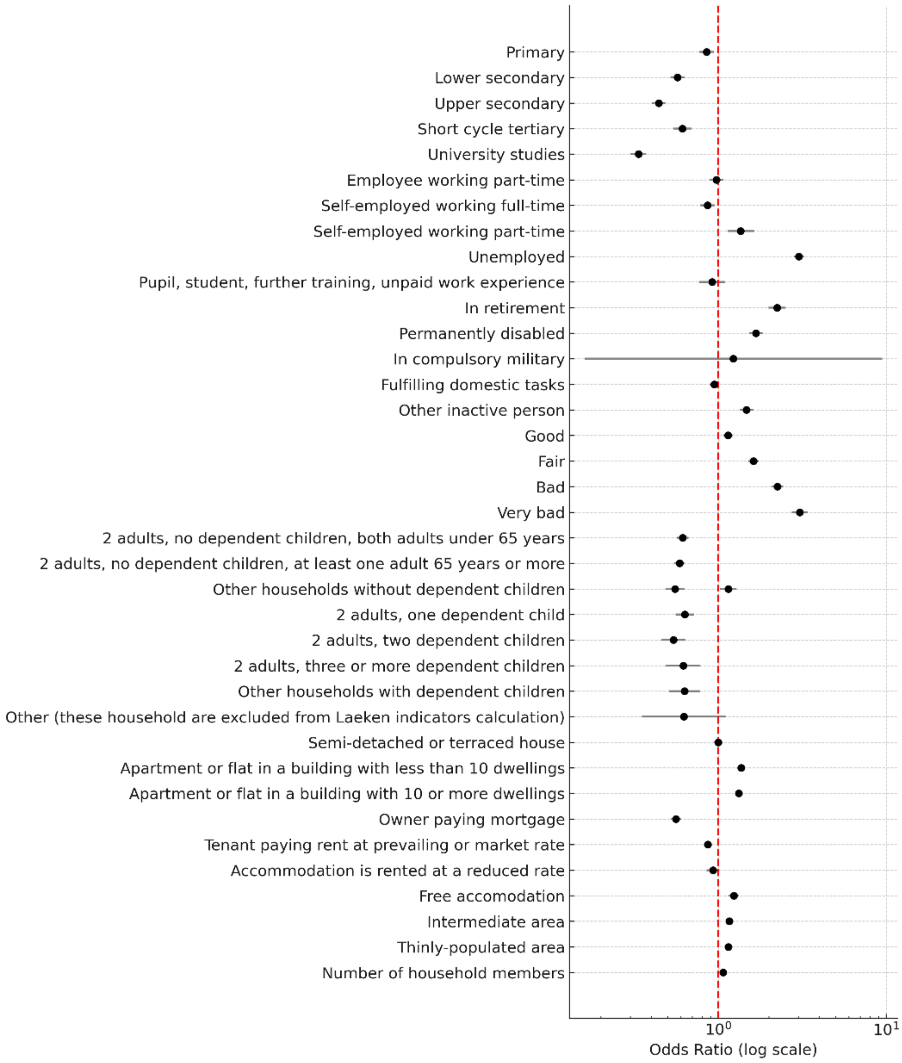

Figure 19. Odds ratio with 95% confidence intervals.

Several variables are strongly and significantly linked to energy poverty, even when controlling for the influence of others. For ease of interpretation, estimated coefficients are expressed as odds ratios (OR). Values greater than one indicate a higher probability of reporting an inability to keep the home at an adequate temperature, while values less than one suggest a protective effect.

One of the most consistent results is in relation to employment status. Unemployed people face much higher probabilities of living in energy poverty compared to those in full-time employment. This is confirmed by a large and highly significant odds ratio, reinforcing the role that job insecurity and lack of income play in a household's ability to maintain comfortable indoor conditions. Similarly, households in which the main earner reports permanent disability also show significantly elevated risks. By contrast, retired or self-employed individuals do not differ significantly from the employed reference group once other factors are accounted for.

Household composition also plays an important role. Single-parent households, and to a lesser extent single-person households, are among the most exposed profiles. These results are consistent with the disaggregated analysis presented earlier, and point to the financial problems that come with limited income, or lack of sharing household costs. In contrast, households with two adults, particularly those without children, show a lower probability of experiencing energy poverty.

Education appears as a protective factor. Households where the reference person has only completed primary education or less are considerably more likely to suffer from energy poverty compared to those with university-level education. A clear gradient is observed: the lower the educational attainment, the higher the odds of experiencing inadequate warmth. This is in line with the idea that education improves access to better employment and income opportunities, and possibly to more energy-efficient living conditions.

Health status is another strong predictor. Respondents who report bad or very bad health conditions are significantly more likely to live in energy poverty. This may reflect both reduced earning capacity and increased heating needs in households where health issues are present. The gradient is again clear: the worse the reported health, the higher the probability of energy vulnerability.

In terms of housing, tenure status proves to be one of the most relevant factors. Households renting at market prices show significantly higher odds of experiencing energy poverty compared to outright homeowners. Even subsidized rental is associated with higher risk, though to a lesser degree. In contrast, owning a home with a mortgage does not show a statistically significant difference from outright ownership.

The type of housing also matters. Living in a detached or semi-detached house is associated with a higher likelihood of energy poverty compared to those living in apartments. This is likely to reflect structural differences in energy demand, as the larger or older things are, the more energy they typically require to heat adequately, and many may have poor insulation.

The number of household members is positively associated with energy poverty, although its effect is moderate.

Finally, the degree of urbanization does not appear to be a significant predictor once the rest of the variables are included in the model, suggesting that the differences between rural and urban are sufficiently explained by differences in housing characteristics, and by income-related variables.

Taken together, these results provide a detailed picture of the socio-economic and housing-related factors that explain variation in energy poverty risk. In particular, unemployment, low education, poor health, tenancy, and vulnerable family structures consistently emerge as key factors. These results will be discussed in the next section, with a focus on the implications for policymakers.

5. Conclusions

5.1 Key findings

The regression model shows the following trends with statistically significant results. The analysis shows that the households most affected tend to be unemployed or with a permanent disability, have low educational attainment, report poor health, or live alone or as single parents. Renting, especially at market rates, is associated with a higher probability of energy poverty, as is living in detached houses, which are often older and require more energy to heat. In contrast, dual-adult households without children, university-educated individuals, and owner-occupiers (particularly those with mortgages) are less likely to face this issue.

Unemployment, low education levels, and poor health are strongly associated with a higher likelihood of being unable to keep the home warm. Household composition also matters: single-parent families, in particular, are among the most vulnerable groups, while couples without children show the lowest levels of risk. Housing characteristics, especially tenure type and dwelling structure, further contribute to shaping these outcomes.

Although the model was built primarily to understand the relevant factors behind energy poverty, it has also shown some predictive capability. It performs well in identifying those households that are not energy poor, but does rather worse in identifying the small proportion of households that are. This is probably a reflection of both the imbalance in the dataset and the complication of this phenomenon. Still, the model manages to detect key patterns, and its predictive accuracy could be improved by adding more variables or by further fine-tuning the method.

In addition to the regression results, the indicator-based analysis across countries reveals consistent regional patterns. Eastern and Southeastern European countries consistently show high levels across both objective (2M, M/2) and subjective (thermal discomfort, arrears) indicators, pointing to structural vulnerabilities rooted in income constraints, housing inefficiencies, and limited support mechanisms. Conversely, countries like Denmark, Estonia, and Malta score high on expenditure-based indicators but report low subjective hardship, suggesting that high energy costs are mitigated by better housing conditions or stronger welfare systems. Most Western and Northern countries, including France, Germany, and Austria, report moderate levels of objective burden and low subjective energy poverty. These variations highlight the value of a multidimensional approach: no single indicator fully captures energy poverty, and national context plays a critical role in shaping its expression.

5.2 Next steps and final recommendations

The results of this research show that energy poverty is linked to several economic and social vulnerabilities. It does not affect the population randomly, but tends to focus on households facing many disadvantages, particularly unemployment, low education, poor health and poor housing conditions. These findings suggest several practical and research-oriented next steps and some policy recommendations.

From a policy point of view, it would make sense to focus efforts on the most exposed groups: unemployed individuals, single-parent families, elderly people living alone, and renters. These are the profiles that appear most consistently in the data. Measures could include financial support during winter, such as heating allowances or targeted subsidies, as well as longer-term actions to improve housing conditions, especially in the rental sector. Improving the energy efficiency of older buildings or offering support for heating system upgrades could be particularly helpful for reducing structural exposure.

It would also be worth paying special attention to the link between energy poverty and health. Households where someone is in poor or very poor health are much more likely to report difficulties keeping the home warm. Coordinating energy assistance with health or social care services could help reach these cases more effectively.

On the research side, the model developed in this thesis shows that it is possible to identify clear risk patterns, but also reveals some limitations. Its ability to correctly predict cases of energy poverty is modest, partly because the number of affected households in the sample is relatively small. This limitation is confirmed by additional validation metrics. The area under the ROC curve (AUC) for the model is 0.7196, indicating moderate discriminative power. Furthermore, the target variable is highly imbalanced, with only 8.9% of the observations representing households affected by energy poverty. The confusion matrix reinforces this issue: although the model correctly classifies most non-affected households (16,134 true negatives), it identifies only 7 true positives out of 1,499 actual cases. This very low sensitivity suggests that the model struggles to detect the minority class, a challenge commonly associated with imbalanced datasets.

Future lines of research could explore alternative modeling techniques to the one used, or the possibility of incorporating new variables that could be relevant, and even better explain the problem, such as more detailed data on the price of electricity in each region, or the level of energy efficiency of households. Using longitudinal data could help to understand how energy poverty evolves over time, and whether affected households remain in that state consistently.

Finally, although this study has focused on a single indicator, the inability to maintain the home at an adequate temperature, future research could focus on other dimensions of energy poverty, such as the delay in the payment of utility bills, in order to understand the problem from another angle, and compare the results, obtaining a clearer picture of the situation.

In conclusion, this research contributes to identifying who is most exposed to energy poverty, and why. The results can be used to create targeted responses to the vulnerable beneficiaries, as well as opening the door to further iterations of the model, which can be refined to increase its predictive capability.

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Annex I: Alignment with UN's Sustainable Development Goals

SDG 1: End poverty in all its forms everywhere.

The lack of access to energy sources aggravates the situation of vulnerability of many families. In this sense, addressing energy poverty is key to reducing poverty as a whole, as it improves the quality of life of the people involved.

SDG 7: Ensure access to affordable, reliable, sustainable and modern energy for all.

Ensuring an affordable energy supply is essential to combat energy poverty, as many families cannot afford to pay for their energy consumption. In addition, ensuring clean energy also helps to mitigate climate change, improving the overall well-being of society.

SDG 10: Reduce inequality within and among countries.

Energy poverty affects the most vulnerable households, aggravating the economic gap with the rest of the population. In addition, being in this situation makes them more exposed to unhealthy living conditions and social exclusion, aggravating the inequality suffered.

Annex II: Logistic regression model results

Theme	Variable	Estimate	Std. Error	OR	Lower CI	Upper CI
Education	Primary	-0.1583	0.0496	0.8537	0.7759	0.9393
	Lower secondary	-0.5586	0.0492	0.5719	0.5214	0.6274
	Upper secondary	-0.8143	0.0488	0.4428	0.4044	0.4847
	Short cycle tertiary	-0.4903	0.0629	0.6127	0.5411	0.6939
	University studies	-1.0932	0.0545	0.3347	0.3003	0.3729
Employment status	Employee working part-time	-0.0249	0.0486	0.9754	0.8841	1.0758
	Self-employed working full-time	-0.1447	0.0510	0.8652	0.7784	0.9617
	Self-employed working part-time	0.3077	0.0934	1.3604	1.1261	1.6422
	Unemployed	1.1063	0.0357	3.0236	2.8302	3.2275
	Pupil, student, further training, unpaid work experience	-0.0848	0.0906	0.9187	0.7706	1.0955
	In retirement	0.8085	0.0603	2.2444	1.9880	2.5325
	Permanently disabled	0.5169	0.0490	1.6769	1.5201	1.8494
	In compulsory military	0.2083	1.0417	1.2313	0.1632	9.2886
	Fulfilling domestic tasks	-0.0557	0.0294	0.9458	0.8902	1.0052
	Other inactive person	0.3877	0.0469	1.4734	1.3391	1.6201
Health status	Good	0.1355	0.0329	1.1451	1.0715	1.2234
	Fair	0.4854	0.0351	1.6251	1.5205	1.7367
	Bad	0.8130	0.0402	2.2548	2.0865	2.4365
	Very bad	1.1167	0.0545	3.0545	2.7472	3.3996
Type of household	2 adults, no dependent children, both adults under 65 years	-0.4863	0.0406	0.6151	0.5682	0.6656
	2 adults, no dependent children, at least one adult 65 years or more	-0.5301	0.0361	0.5886	0.5471	0.6335
	Other households without dependent children	-0.5921	0.0661	0.5529	0.4838	0.6315
	Other households without dependent children	0.1375	0.0597	1.1474	1.0214	1.2888
	2 adults, one dependent child	-0.4574	0.0640	0.6328	0.5573	0.7190
	2 adults, two dependent children	-0.6117	0.0850	0.5425	0.4563	0.6448
	2 adults, three or more dependent children	-0.4794	0.1215	0.6190	0.4903	0.7813
	Other households with dependent children	-0.4620	0.1070	0.6302	0.5117	0.7766
	Other (these household are excluded from Laeken indicators calculation)	-0.4696	0.2943	0.6253	0.3528	1.1083
	Semi-detached or terraced house	-0.0014	0.0304	0.9986	0.9404	1.0607

Type of dwelling	Apartment or flat in a building with less than 10 dwellings	0.3136	0.0287	1.3684	1.2922	1.4491
	Apartment or flat in a building with 10 or more dwellings	0.2807	0.0261	1.3240	1.2551	1.3969
Tenure status	Owner paying mortgage	-0.5785	0.0338	0.5609	0.5216	0.6030
	Tenant paying rent at prevailing or market rate	-0.1424	0.0276	0.8674	0.8215	0.9161
	Accommodation is rented at a reduced rate	-0.0711	0.0457	0.9314	0.8517	1.0186
	Free accommodation	0.2139	0.0358	1.2385	1.1515	1.3322
Degree of urbanization	Intermediate area	0.1503	0.0246	1.1621	1.1044	1.2222
	Thinly populated area	0.1409	0.0252	1.1514	1.0907	1.2155
Number of members	-	0.0689	0.0238	1.0713	1.0226	1.1225

Annex III: R Script

Logistic regression model

```r
# Librerías necesarias
library(dplyr)
library(purrr)
library(DescTools)
library(reshape2)
library(statar)
library(Amelia)
library(pROC)
library(car)

# Directorio con los archivos
data_dir <- "C:/Users/alvar/Documents/ECV/ECV/TODO/"

# Listar todos los archivos CSV
files <- list.files(data_dir, pattern = "\\.csv$", full.names = TRUE)

# Lista de países
countries <- c("AT", "BE", "BG", "CY", "CZ", "DE", "DK", "EE", "EL", "ES", "FR",
"HR", "HU", "LT", "LU", "LV", "MT", "NL", "RO", "SI", "SK")

# Función para procesar cada país
process_country <- function(country) {
  country_files <- files[grepl(paste0("^", country, "20"), basename(files))]
  file_D <- grep("D\\.csv$", country_files, value = TRUE)
  file_H <- grep("H\\.csv$", country_files, value = TRUE)
  file_P <- grep("P\\.csv$", country_files, value = TRUE)

  df_D <- read.csv(file_D)
  df_H <- read.csv(file_H)
  df_P <- read.csv(file_P)
```

```
  tablaD1 <- select(df_H, "HB030", "HH010", "HH021", "HX060", "HX040", "HH050")
  names(tablaD1)  <-  c("Code",  "Tipo_Viv",  "Tenencia",  "Tipo_Fam",  "Nmiemb",
"Temperatura")
  tablaD2 <- select(df_D, "DB030", "DB100", "DB090")
  names(tablaD2) <- c("Code", "Urbanizacion", "Factor")
  tablaD3 <- select(df_P, "PB030", "PL031", "PE040", "PL051", "PH010")
  names(tablaD3) <- c("Code", "Sit_Lab", "Educacion", "Tipo_Empl", "Salud")

  tablaD3_primario <- tablaD3 %>%
    mutate(Hogar = substr(Code, 1, nchar(Code)-2)) %>%
    group_by(Hogar) %>%
    slice_min(Code, with_ties = FALSE) %>%
    ungroup() %>%
    select(-Hogar)

  tablaD3_primario$Code        <-        substr(tablaD3_primario$Code,        1,
nchar(tablaD3_primario$Code)-2)

  merge1 <- merge(tablaD1, tablaD2, by = "Code")
  desagregado <- merge(merge1, tablaD3_primario, by = "Code")

  desagregado$Educacion <- substr(desagregado$Educacion, 1, 1)
  desagregado$Tipo_Empl <- substr(desagregado$Tipo_Empl, 1, 1)

  return(desagregado)
}

# Procesar países
all_results <- list()
for (country in countries) {
  message(paste("Procesando país:", country))
  result <- process_country(country)
  all_results[[country]] <- result
}
```

```r
final_results <- do.call(rbind, all_results)


# Preparar datos
training.data.raw <- final_results
training.data.raw$Temperatura <- ifelse(training.data.raw$Temperatura == 2, 1, 0)


# Selección y limpieza
data <- subset(training.data.raw, select = c("Tipo_Viv", "Tenencia", "Tipo_Fam",
"Nmiemb", "Urbanizacion", "Sit_Lab", "Educacion", "Tipo_Empl", "Salud",
"Temperatura"))



# Conversión de variables
data$Tipo_Viv <- as.factor(data$Tipo_Viv)
data$Tenencia <- as.factor(data$Tenencia)
data$Tipo_Fam <- as.factor(data$Tipo_Fam)
data$Urbanizacion <- as.factor(data$Urbanizacion)
data$Sit_Lab <- as.factor(data$Sit_Lab)
data$Tipo_Empl <- as.factor(data$Tipo_Empl)
data$Educacion <- as.factor(data$Educacion)
data$Salud <- as.factor(data$Salud)  # ordinal
data$Temperatura <- as.factor(data$Temperatura)


#moda


moda <- function(x){
  ux <- unique(x[!is.na(x)])
  ux[which.max(tabulate(match(x,ux)))]
}


for (col in names(data)) {
  if (any(is.na(data[[col]]))) {
    if (is.factor(data[[col]])) {
      data[[col]][is.na(data[[col]])] <- moda(data[[col]])
```

```
    } else {
      data[[col]][is.na(data[[col]])] <- mean(data[[col]], na.rm = TRUE)
    }
  }
}

# División train/test aleatorio
set.seed(123)
indexes <- sample(1:nrow(data), size = 0.9 * nrow(data))
train <- data[indexes, ]
test <- data[-indexes, ]

# Modelo logístico
model <- glm(Temperatura ~ ., family = binomial(link = "logit"), data = train)
summary(model)

# Colinealidad
vif(model)

# Como predice de bien?
fitted.results <- predict(model, newdata = test, type = 'response')
fitted.results.bin <- ifelse(fitted.results > 0.5, 1, 0)

# Matriz de confusión
confusion <- table(Predicted = fitted.results.bin, Actual = test$Temperatura)
print(confusion)

# Precisión
error <- mean(fitted.results.bin != as.numeric(as.character(test$Temperatura)))
print(paste('Accuracy:', round(1 - error, 4)))

# AUC
roc_obj <- roc(as.numeric(as.character(test$Temperatura)), fitted.results)
print(paste("AUC:", round(auc(roc_obj), 4)))
```

Disaggregated Analysis

```
# Librerías necesarias
library(dplyr)
library(purrr)
library(DescTools)
library(reshape2)
library(statar)

# Directorio con los archivos
data_dir <- "C:/Users/alvar/Documents/ECV/ECV/TODO/"

# Listar todos los archivos CSV
files <- list.files(data_dir, pattern = "\\.csv$", full.names = TRUE)

# Obtener la lista de países a partir de los nombres de archivos
countries <- unique(substr(basename(files), 1, 2))

# Función para calcular distribuciones ponderadas y proporciones

elempty <- list()
compute_props <- function(df, var, flag=NULL) {
  data <- df
  if (!is.null(flag) && flag %in% names(df)) {
    data <- data %>% filter(.data[[flag]] == 1)
  }
  data %>%
    filter(!is.na(.data[[var]])) %>%
    mutate(wt = as.numeric(Factor) * as.numeric(Nmiemb)) %>%
    group_by(value = .data[[var]]) %>%
    summarise(weight = sum(wt, na.rm = TRUE), .groups = "drop") %>%
    mutate(prop = weight / sum(weight))
}
```

```
# Función para procesar cada país
process_country <- function(country) {
  country_files <- files[grepl(paste0("^", country, "20"), basename(files))]
  file_D <- grep("D\\.csv$", country_files, value = TRUE)
  file_H <- grep("H\\.csv$", country_files, value = TRUE)
  file_P <- grep("P\\.csv$", country_files, value = TRUE)

  df_D <- read.csv(file_D, stringsAsFactors = FALSE)
  df_H <- read.csv(file_H, stringsAsFactors = FALSE)
  df_P <- read.csv(file_P, stringsAsFactors = FALSE)

  tablaA2 <- df_H %>%
    select(HB030, HH050, HH050_F, HS021, HS021_F, HX040, HY020, HY020_F) %>%
    rename(Code=HB030, Temperature=HH050, Temperature_f=HH050_F,
           Retrasos=HS021, Retrasos_f=HS021_F, Nmiemb=HX040,
           Renta=HY020, Renta_f=HY020_F) %>%
    mutate(Code = as.character(Code))
  tablaB <- df_D %>%
    select(DB030, DB090, DB040) %>%
    rename(Code=DB030, Factor=DB090, CCAA=DB040) %>%
    mutate(Code = as.character(Code))
  totecv2 <- inner_join(tablaA2, tablaB, by="Code")

  totpop <- sum(as.numeric(totecv2$Factor) * as.numeric(totecv2$Nmiemb), na.rm =
TRUE)

  # Deciles de renta
  totecv2$DECILEQ <- xtile(
    x = as.numeric(totecv2$Renta) / as.numeric(totecv2$Nmiemb),
    n = 10,
    wt = as.numeric(totecv2$Factor) * as.numeric(totecv2$Nmiemb)
  )

  # Retrasos y temperatura inadecuada
```

```
  perret2          <-    totecv2    %>%    filter(Retrasos    !=    3)             %>%
summarise(sum(as.numeric(Factor)*as.numeric(Nmiemb))/totpop) %>% pull()

  pertempe2     <-     totecv2     %>%     filter(Temperature     ==     2)     %>%
summarise(sum(as.numeric(Factor)*as.numeric(Nmiemb))/totpop) %>% pull()


  # Preparación tablas desagregado

  tablaD1 <- df_H %>%

    select(HB030, HH010, HH010_F, HH021, HH021_F, HX060, HX040) %>%

    rename(Code=HB030, Tipo_Viv=HH010, Tipo_Viv_F=HH010_F,

           Tenencia=HH021, Tenencia_F=HH021_F, Tipo_Fam=HX060, Nmiemb=HX040) %>%

    mutate(Code = as.character(Code))

  tablaD2 <- df_D %>%

    select(DB030, DB100, DB100_F, DB090) %>%

    rename(Code=DB030,  Urbanizacion=DB100,  Urbanizacion_F=DB100_F,  Factor=DB090)
%>%

    mutate(Code = as.character(Code))

  tablaD3 <- df_P %>%

    select(PB030, PL031, PL031_F, PE040, PE040_F, PL051, PL051_F, PH010, PH010_F)
%>%

    rename(Code=PB030, Sit_Lab=PL031, Sit_Lab_F=PL031_F,

           Educacion=PE040, Educacion_F=PE040_F,

           Tipo_Empl=PL051, Tipo_Empl_F=PL051_F,

           Salud=PH010, Salud_F=PH010_F) %>%

    mutate(Code = as.character(Code))

  tablaD3_primario <- tablaD3 %>%

    mutate(Hogar = substr(Code,1,nchar(Code)-2)) %>%

    group_by(Hogar) %>% slice_min(Code, with_ties=FALSE) %>% ungroup() %>%

    mutate(Code = substr(Code,1,nchar(Code)-2)) %>% select(-Hogar)


  desagregado <- tablaD1 %>%

    inner_join(tablaD2, by="Code") %>%

    inner_join(tablaD3_primario, by="Code")


  # Filtrar hogares con temperatura inadecuada

  codes_bad <- totecv2 %>% filter(Temperature == 2) %>% pull(Code)
```

```r
  desag_temp <- desagregado %>% filter(Code %in% codes_bad)
  tottemp    <- sum(as.numeric(desag_temp$Factor) * as.numeric(desag_temp$Nmiemb),
na.rm = TRUE)

  # Función auxiliar para listas nombradas
  mklist <- function(dist, prefix) {
    props <- as.list(dist$prop)
    nm    <- paste0(prefix, dist$value)
    if (length(props) != length(nm)) {
      nm <- nm[seq_along(props)]
    }
    names(props) <- nm
    props
  }

  # Listas distribuciones variables
  urb_list  <-  mklist(compute_props(desag_temp,  "Urbanizacion","Urbanizacion_F"),
"perurb")
  viv_list  <-  mklist(compute_props(desag_temp,  "Tipo_Viv",        "Tipo_Viv_F"),
"perviv")
  ten_list  <-  mklist(compute_props(desag_temp,  "Tenencia",        "Tenencia_F"),
"perten")
  sal_list  <-  mklist(compute_props(desag_temp,  "Salud",              "Salud_F"),
"persal")
  lab_list  <-  mklist(compute_props(desag_temp,  "Sit_Lab",          "Sit_Lab_F"),
"perlab")
  fam_list <- mklist(compute_props(desag_temp, "Tipo_Fam", NULL), "perfam")
  edu_list  <-  mklist(compute_props(desag_temp,  "Educacion",      "Educacion_F"),
"peredu")
  emp_list         <-         mklist(compute_props(desag_temp,         "Tipo_Empl",
"Tipo_Empl_F"),"peremp")

  # juntar resultado
  results <- c(
    list(country = country, perret2 = perret2, pertempe2 = pertempe2),
    urb_list, viv_list, ten_list, sal_list, lab_list, fam_list, edu_list, emp_list
  )
```

```
  as.data.frame(results, stringsAsFactors = FALSE)
}

# exportar a csv
todos <- lapply(countries, process_country)
all_results <- bind_rows(todos)
write.csv(all_results, "resultados_por_pais.csv", row.names = FALSE)

print(all_results)
```

2M and M/2 calculation

```
# Paquetes necesarios
library(readxl)
library(dplyr)

#Carga de datos
df <- read_excel("HBS_HH_SI.xlsx")
df <- df %>% rename(
  WEIGHT    = HA10,      # peso muestral
  EQ_INC    = HB062,     # unidades de consumo (UC2)
  NH        = HB05       # nº de miembros
)

#GASTO_ENERGÍA total
df <- df %>% mutate(
  ENERGY_EXP = rowSums(across(c(
    EUR_HE0451,  # electricidad
    EUR_HE0452,  # gas natural
    EUR_HE0453,  # GPL
    EUR_HE0454,  # fuel-oil
    EUR_HE0455   # combustibles sólidos + biomasa
  )), na.rm = TRUE)
)
```

```
#Cálculo de per cápita equivalente
df <- df %>% mutate(
  INCPER = EUR_HH099 / EQ_INC,
  EQ_CONS = case_when(
    NH == 1 ~ 1,
    NH == 2 ~ 1.45,
    NH == 3 ~ 1.68,
    NH == 4 ~ 1.90,
    NH > 4  ~ 1.99,
    TRUE    ~ NA_real_
  ),
  EXPPER = ENERGY_EXP / EQ_CONS
)

#Filtrar casos válidos y % gasto
df <- df %>%
  filter(
    INCPER > 0,
    !is.na(EXPPER),
    EXPPER <= INCPER
  ) %>%
  mutate(
    PCTG = EXPPER / INCPER
  )

#Calcular mediana ponderada de PCTG
wm <- df %>%
  arrange(PCTG) %>%
  mutate(
    cumw   = cumsum(WEIGHT),
    totw   = sum(WEIGHT)
  )
medp <- wm$PCTG[ which(wm$cumw >= wm$totw/2)[1] ]
```

```
#Umbral 2M usando esa mediana ponderada y clasificación 2M
th2M <- 2 * medp

df <- df %>%
  mutate(
    is2M = as.integer(PCTG > th2M),
    w2M  = WEIGHT * is2M
  )

#cálculo indicador final 2m
IND2M <- sum(df$w2M, na.rm = TRUE) / sum(df$WEIGHT, na.rm = TRUE)

# umbral m/2 con mediana no ponderada
M_exp    <- median(df$EXPPER, na.rm = TRUE)
umbral_M2 <- M_exp / 2

# clasificar hogares en m/2 y ponderación
df <- df %>%
  mutate(
    is_M2 = as.integer(EXPPER < umbral_M2),
    w_M2  = WEIGHT * is_M2
  )

#cálculo indicador final m/2
IND_M2 <- sum(df$w_M2, na.rm = TRUE) / sum(df$WEIGHT, na.rm = TRUE)

cat("Indicador 2M (hogares):", round(IND2M * 100, 2), "%\n")
cat("IndicadoR M/2:", round(IND_M2 * 100, 2), "%\n")
```

This study is based on data from Eurostat, EU-SILC 2008,2015, 2020, 2022. The responsibility for all conclusions drawn from the data lies entirely with the author(s).