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An Unaffordable Burden to Consumers? Energy Poverty in Portugal, 2019-2021

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Abstract

Energy poverty is a multifaceted societal and environmental issue that disproportionately affects poor households. In Portugal, energy poverty rates are among the highest in Europe, with 20.08% of households affected in 2023. To inform targeted policy design aimed at combating energy poverty among those disproportionately affected, this study explores energy poverty in Portugal and analyzes the socio-economic, dwelling, and regional characteristics that influence the likelihood of households below the poverty line to experience energy poverty. The main findings indicate that tenure status, educational attainment, poor housing conditions, and regional disparities all influence the likelihood of energy poverty.

Keywords: Energy Poverty, Household Characteristics, Income Inequality, Financial Deprivation, Public Policy

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1 Introduction

Energy poverty is gaining prominence and recognition. In the European Union energy poverty rates increased by almost 4 percentage points from 6.9% in 2021 to 10.6% in 2023 (Eurostat, 2024a). The problem is officially defined by the European Parliament (2023) as ”a household’s lack of access to essential energy services, where such services provide basic levels and decent standards of living and health, including adequate heating, hot water, cooling, lighting, and energy to power appliances, [...]”

The recent increase in energy poverty rates is likely to persist, as climate change makes securing energy at affordable prices increasingly challenging (International Energy Agency, 2022). Ongoing climate change has contributed to disruptions in energy markets both on the demand and supply sides. On the supply side, extreme events such as heatwaves, cyclones, and floods damage production facilities and transportation infrastructure. (International Energy Agency, 2022; IPCC, 2023) On the demand side, rising average temperatures lead to increasing energy needs, particularly for cooling. These disruptions affect energy prices, as observed in Europe during the 2022 heatwave, when an increased demand for cooling caused a spike in electricity prices. (International Energy Agency, 2022) As a result, households need to allocate a larger share of their expenditures to energy expenses, with low-income households disproportionately affected due to limited financial resources (Heller, Schittekatte, and Batlle, 2024). It is therefore essential to consider the concept of energy poverty and its consequences when addressing the broader goals of sustainable development and a just transition.

Portugal is, unfortunately, a good example of the severity of energy poverty, making it a critical case to study. In 2023, energy poverty rates in Portugal were significantly above the European average (20.8% vs 10.6% in 2023). Alongside Spain, Portugal reported the highest share of the population living in energy poverty within the European Union, with 20.8% of households affected (Eurostat, 2024a). Despite the recent increase in research on energy poverty, this study complements previous work by analyzing the characteristics of households that are disproportionately affected, specifically, those below the poverty line.

Energy poverty has severe adverse impacts on health, well-being, general life quality, and social attainment, underlining the need for targeted, effective policy intervention (Bouzarovski, 2018). Designing such policies requires understanding the characteristics that influence a household's likelihood to be energy poor. This is the goal of this study. Given that low-income households are disproportionately affected by energy poverty, the Portuguese households below the poverty line will be the focus of this study. Therefore, the research question guiding this study is: *How do socio-economic, dwelling, and regional characteristics influence the likelihood of Portuguese households below the poverty line to experience energy poverty?* To address this research question, a logit regression is conducted using panel survey data from the Portuguese Survey on Income and Living Conditions (ICOR). The main findings indicate that tenure status, educational attainment, poor housing conditions, and regional disparities all influence the conditional probability of being energy poor.

This paper is structured as follows. The next section reviews the literature on energy poverty, with a particular focus on Portugal. Section 3 describes the data used followed by an explanation of the methodology in section 4. The main results are then presented and interpreted in section 5. In section 6 the main results are discussed and an outlook on how to incorporate the results for future research is provided. Section 7 offers conclusions. Ancillary tables are included in the Appendix.

2 Literature Review

2.1 Energy Poverty

The concept of "insufficient" access to essential energy services emerged in the 1970s, initially termed *fuel poverty*, and gained prominence with the publication of the book *Fuel Poverty: From Cold Homes to Affordable Warmth* by Boardman (1991). The definition provided therein established the problem of fuel poverty in academia and decision-making. (Bouzarovski, 2018; Healy, 2017) As defined by Boardman (1991), fuel poverty was initially understood as a household's inability to afford adequate indoor-warmth. If required to spend more than 10% of its total income on fuel to maintain adequate warmth, a household was considered fuel poor. Although fuel poverty disproportionately affects income-poor households, it is not limited to them (Boardman, 1991). Factors such as a building's energy efficiency and fuel expenses in proportion to income also influence fuel poverty (Boardman, 2009). Therefore, alleviating households from fuel poverty cannot be achieved by just alleviating income poverty. Additional investments, for example, in the housing stock are required. (Healy, 2017) This clearly highlights why fuel poverty is a complex problem where energy and poverty interplay in a non-trivial manner (Bouzarovski, 2014).

Although initially the term fuel poverty was used to refer to a household's inability to afford sufficient energy services, energy poverty is often used interchangeably with it. In recent literature, the two terms are largely treated as synonymous. (Bouzarovski and Herrero, 2017; Thomson, Bouzarovski, and Snell, 2017) This paper uses the term energy poverty, in alignment with European and Portuguese policies. These policies further connect energy poverty to its consequences, the most significant of which are adverse effects on physical health and well-being. Inadequate heating causes prolonged exposure to cold indoor temperatures. This has been associated with cardiovascular and respiratory diseases in particular asthma and excess winter mortality. To prevent those negative health outcomes, the WHO has proposed a minimum indoor temperature of 18°C. (Braubach, Jacobs, and Ormandy, 2011; World Health Organization, 2018) Moreover, health risks are also associated with exposure to excessively hot indoor temperatures. In the scope of energy poverty, Thomson et al. (2019) examine the health and well-being effects of exposure to uncomfortably hot indoor temperatures, identifying general discomfort, fatigue, lethargy, and a reduced ability to perform daily activities under such conditions. Similarly, in Portugal, increased exposure to hot indoor temperatures during heat waves contributes to higher mortality rates among older people living in non-protected houses. Heller, Schittekatte, and Batlle (2024) connect these consequences to additional economic burdens on governments due to increased social and healthcare expenditures. In addition to physical health, energy poverty also negatively impacts mental health, such as by increasing depression rates (Oliveras et al., 2021).

This underlines the complexity of energy poverty and its interconnected environmental, economic, and social dimensions, highlighting the importance of addressing it to promote sustainable development.

2.2 Energy Poverty in Europe

Energy Poverty is gaining recognition in European policy making, as it is a prevalent problem in the European Union. 10.6% of the households in Europe lacked adequate access to indoor heating in 2023 (Eurostat, 2024a). The first directive to recognize energy poverty as a growing problem was the *Third Energy Package (TEP)*, which contains the *Directive 2009/72/EC* about the internal electricity market (Bouzarovski, 2018). It required member states to address energy poverty by implementing national action plans and to take measures to reduce the number of energy poor households (European Parliament, 2009). The most recent policies on energy poverty are set by the directives *2024/1275 on energy performance of buildings*, *2024/1711 on electricity market design* and the *recommendation 2023/2407 on energy poverty*. *Directive 2024/1275* emphasizes the importance of improving the energy efficiency of buildings to reduce greenhouse gas emissions and alleviate energy poverty (European Parliament, Council of the European Union, 2024). *Directive 2024/1711* reforms the European electricity market to strengthen it, foster sustainable development, and reduce price volatility. During the energy crises, price volatility disproportionately affected energy poor households, making clear how reducing it is key to prevent an energy poverty trap (European Parliament, Council of the European Union, 2024). *Recommendation 2023/2407 on energy poverty* identifies the three main causes of the multidimensional phenomenon, low income levels, high share of energy expenditure, and buildings and appliances with low energy performance (Directorate-General for Energy, 2023). Acknowledging the importance of assessing energy poverty and its impact, the European Commission mandated member states to assess the affected households in 2019.

European policies and the measures therein demonstrate that the European Union takes energy poverty and its mitigation seriously.

2.3 Measures of Energy Poverty

The question of how to properly measure energy poverty has been subject to academic debate. The literature generally distinguishes between two types: consensual and expenditure-based indicators (Heindl and Schüssler, 2015; Herrero, 2017). These are also referred to as subjective (consensual) versus objective (expenditure-based) indicators. While consensual indicators rely on qualitative data, expenditure-based metrics rely on quantitative data about household income and expenditure. (Churchill and Smyth, 2020; Romero, Linares, and López, 2018).

Consensual measures generally consider the affordability of certain energy services and goods socially regarded as ”necessities” [1], such as adequately heated homes. Consensual indicators encompass both self-reported responses to survey questions and objective measures, such as third-party observations of issues like leaking roofs, rot, or dampness in dwellings. (Healy, 2017; Heindl and Schüssler, 2015; Herrero, 2017)

In contrast to the qualitative nature of consensual indicators, expenditure-based indicators are calculated using quantitative data on a household's income and expenditure on energy services. The 10% indicator was the first established measure of energy poverty. It has been criticized by Healy (2017) for arbitrarily setting the expenditure threshold at 10% without scientific rationale. To address the shortcomings of the 10% indicator, numerous alternative expenditure-based indicators have been developed. A vast body of literature discusses the different indicators and their advantages and disadvantages[2] (Hills, 2011; Rademaekers et al., 2016). For an overview of the different subgroups within expenditure-based indicators, please refer to Appendix B.

The general conclusion is that both, consensual and expenditure-based indicators of energy poverty have advantages and limitations. One of the main advantages of expenditure-based indicators is that the underlying data allows for quantification and objectivity (Thomson, Bouzarovski, and Snell, 2017). A limitation, however, is that they are very sensitive to the choice of thresholds and income definitions. Legendre and Ricci (2015) illustrate this by identifying energy poor households using three different expenditure-based indicators. The share of energy poor households ranged from 20.9% to 9.2%, while the overlap of these indicators amounted to only 7.76%.

One main advantage of consensual indicators of energy poverty is that they consider the problem as directly experienced by households. This allows them to capture broader household experiences and perceived impacts. A disadvantage of consensual indicators is the variation in perceptions of adequacy regarding energy services and the reluctance of households to admit certain problems. Additionally, consensual measures have been criticized for lacking an income

1. Necessity goods are a type of normal goods with an income elasticity of demand lower than one. Income elasticity of energy demand, in turn, has recently been found to vary with levels of income and economic development (AlKathiri, Darandary, and Mikayilov, 2024).

2. This discussion, however, is not subject of this study.

perspective. (Hills, 2011; Rademaekers et al., 2016).

According to Herrero (2017), neither expenditure-based nor consensual indicators should be favored. Both consider important aspects of energy poverty, complement each other, and are therefore useful to address this multifaceted issue (Hills, 2011).

2.4 Energy Poverty in Portugal

Portugal is one of the countries with the highest share of energy poverty in Europe, despite having one of the mildest climates. (Eurostat, 2024b; Eurostat, 2024a). The high prevalence of energy poverty in Portugal has gained attention, from both academic literature and policy makers.

In this context, the Portuguese National Energy and Climate Plan (NECP) 2021-2030 outlines a vision to promote energy system transitions and achieve carbon neutrality. One strategic priority is to tackle energy poverty by renovating the housing stock and promoting energy efficiency as well as passive insulation. To ensure a just transition, the measures should prioritize the most vulnerable regions and households. (Directorate-General for Communication, 2023) In addition to the NECP the national long-term strategy to fight energy poverty, the *Estratégia Nacional de Longo Prazo para o Combate à Pobreza Energética 2023-2050 (ELPPE)*, was approved by the resolution of the Council of Ministers in January 2024. The ELPPE frames the methodology to fight energy poverty by identifying primary and complementary indicators to measure it. One of the primary indicators is the share of households unable to keep their homes adequately heated.[3] The goal set in the ELPPE is to eradicate energy poverty by 2050 through promoting an environmentally and energetically sustainable housing stock, universal access to essential energy services, regional integration and knowledge building for informed action. Progress toward the overall goal is assessed by setting sub-goals aligned with the main strategic indicators. For indicator *IP1.1*, the share of households not able to adequately heat home, the sub-goals are to reduce this share to 10% by 2030 and to less than 1% by 2050. One measure to achieve these goals is the establishment of a national energy poverty observatory (Observatório Nacional da Pobreza Energética), which will be essential to implement the strategy and to support various

3. The others are: The share of dwellings with energy performance efficiency class C or below, the share of households living in a dwelling with leak, damp or rot, the share of households not able to keep homes adequately cool in summer, and the share of households spending more than 10% of their income on energy expenditure.

public policy areas, such as energy, housing, and social security. (Presidência do Conselho de Ministros, 2024)

The ELPPE further describes programs to combat energy poverty. One such program is the *Vale Eficiência*, which targets economically vulnerable consumers. It enables them to invest in energy efficiency improvements of the building to improve thermal comfort. Another program, the *Programa de Apoio a Edifícios Mais Sustentáveis (PAEMS)* supports middle-income households by co-financing energy efficiency investments in their dwellings, thereby overcoming opportunity costs. The *Programa de Apoio a Condomínios Residenciais (PACR)* is a response to some difficulties faced under the PAEMS. It supports measures to improve thermal insulation of multi-family houses. The programs in the ELPPE are not limited to those described above and reflect a strong emphasis on combating energy poverty in national policies.

In addition to the policy prevalence of energy poverty, a body of academic literature has addressed the problem in Portugal. One of the first studies dedicated to energy poverty in the country aimed to identify consumer groups suffering from fuel poverty. Key factors found to influence fuel poverty include lower income and educational levels as well as dwelling characteristics such as construction year, dwelling size, and glazing material. (Gouveia, Seixas, and Long, 2018)

Contributing to a better understanding of energy poverty through vulnerability mapping, Horta et al. (2019) calculated the energy poverty vulnerability index at the civil parish level, complemented by qualitative interviews. The results indicate that living in urban areas is associated with lower vulnerability to energy poverty. The interviews conducted [4] reveal that the cost of heating is the main reason for households to suffer thermal discomfort. The poor quality of buildings is highlighted as another possible driver of the results.

Improving the quality and energy performance of existing buildings through retrofitting can reduce the energy needs of households, thereby lowering energy costs and the share of income spent on energy expenditure (Matos, Delgado, and Guimarães, 2022).

Another, more recent study by Peralta, Carvalho, and Fonseca (2023) aimed to identify population groups most affected by energy poverty in Portugal. The study found that employment status is a determining factor, with unemployed or inactive individuals most affected. Other

4. The sample size, however, is not representative.

determinants include lower education, household composition, and regional differences, with people living on the islands being particularly vulnerable to energy poverty.

The present study contributes to a better understanding of energy poverty in Portugal, by focusing on the household characteristics that influence poor household's likelihood to be energy poor. Households are identified as poor if their income is below the poverty line, which is 60% of the median income. It provides insights into energy poverty among households already living below the poverty line. This understanding is crucial for designing effective, sustainable public policies to alleviate energy poverty for disproportionately affected households.

3 Data

The dataset used in this paper is an unbalanced panel data set covering a time period of three years. The dataset was created by combining three cross-sectional sub datasets obtained from the *Inquérito às Condições de Vida e Rendimento (ICOR)*, the Portugese Survey on Income and Living Conditions conducted by the *Instituto National de Estatísticas*. The Portuguese survey is part of the EU statistics on income and living conditions (EU-SILC) and was established in 2004. The data is collected annually through sample surveys,with dwellings as the sample units. The survey is conducted through face-to face interviews. If the survey is conducted in year *n*, the income reference year is $n - 1$. Each household stays in the survey for 4 consecutive years. The rotation of sampled households after four years leads to an unbalanced panel when combining cross-sectional datasets for each year.

For the sample selection, a stratified multi-stage (the stages being area and dwelling) sampling scheme is applied. Although initially sized at national levels, the sample size was recalculated in 2015 to obtain an adequate representation of each region.

The analyzed dataset consists of three cross-sectional datasets corresponding to the survey years 2020, 2021, and 2022.[5] The final dataset used in the analysis includes 22,620 households and 28,719 individuals. The difference in the number of households and individuals across years is due to possible changes in the income structure of a household, resulting in a change in the breadwinner designation.

5. the most recent available.

4 Methodology

To analyze socio-economic, dwelling, and regional characteristics that influence the probability of households below the poverty line to be energy poor, this study applies a linear index model. The approach is based on the approach suggested by Legendre and Ricci (2015). The binary outcome variable used in this regression, *Energy Poverty*, is derived from households' self-reported financial ability to afford adequate indoor heating. Space heating serves as a good approximation of energy consumption, as in 2022, it accounted for the largest portion of final energy consumption among Portuguese households (Eurostat, 2024c). The choice of the energy poverty indicator, as well as the focus on households below the poverty line, is based on its policy relevance for Portugal. For some indicators, such as the share of the population living in households unable to keep their homes adequately heated, the ELPPE contains sub-indicators, including the share of population living in households unable to keep the house adequately heated. Sub-indicator *IP1.2* measures the share of people living below the poverty line and in households unable to keep their homes adequately heated. The designation of households below the poverty line is based on an indicator in the dataset that measures whether disposable income is above or below the poverty line. The poverty line is defined in accordance with the definition of the European Commission as a threshold of 60% of the median income. In Portugal, 19.43% of the surveyed households live below the poverty line. Of those households below the poverty line, 36.38% are also energy poor (see also Figure 2 in the Appendix). Since the logit regression is conducted only for households below the poverty line, any reference to *the sample* hereafter refers specifically to these households (see Appendix, Table 4 and 5 for descriptive statistics of the sample).

To model the conditional probability of poor households to be energy poor, a logit regression model is applied. Generally, logit and probit yield similar results, differing mainly in the distributional assumption of the error term, which is used to derive the response probability function. Logit was chosen over probit mainly due to the distribution of the binary outcome variable. For households living below the poverty line, 36.38% also live in energy poverty (binary outcome variable d_EP=1) and 63.32% do not live in energy poverty (binary outcome variable d_EP=0). Given that the logistic distribution underlying the logit model has fatter tails than the normal distribution underlying the probit model, a logistic distribution is slightly more adequate to model the data in the sample. Graphical analysis of error terms from both logit and probit regressions confirms that the logit model is perceived to provide a better fit (see Appendix Figure 1). To model the binary outcome variable y_{it} = $d_{EnergyPoverty}$ we assume that y_{it} is generated by a linear latent variable model where X_{it} is the vector of explanatory variables. The latent variable is denoted by y_{it}^* and is not observed. It is assumed that:

$$y_{it}^* = X_{it}\theta + e_{it},\ e_{it}|x_{it} \sim \text{Logistic} \tag{1}$$

$$d_{EnergyPoverty} = 1 \quad \text{if} \quad y_{it}^* > 0 \tag{2}$$

$$d_{EnergyPoverty} = 0 \quad \text{if} \quad y_{it}^* < 0 \tag{3}$$

The response probability function follows:

$$P(d_{EnergyPoverty} = 1|X_{it}) = P(y_{it}^* > 0|X_{it}) \tag{4}$$

$$P(X_{it}\theta + e_{it} > 0|X_{it}) = P(e_{it} > -X_{it}\theta|X_{it}) \tag{5}$$

Inserting the logistic distribution that underlies e_{it}, the response probability function is obtained:

$$P(d_{EnergyPoverty} = 1|X_{it}) = \frac{exp(X_{it}\theta)}{1 + exp(X_{it}\theta)} \in (0,1) \tag{6}$$

The vector of explanatory variables was chosen based on the existing literature. It includes household characteristics, socio-economic characteristics of the breadwinner, health status, dwelling characteristics and the location of the dwelling.

Household Characteristics: The household characteristics chosen to model the conditional response probability of being energy poor are household size, household composition and tenure status. Household size is included following Romero, Linares, and López (2018) who suggest that living in a large household with low income has a significant effect on the probability of being energy poor. A higher number of people in one household can usually be associated with higher energy use. Both household composition and tenure status have been found to influence energy poverty (Costa-Campi, Jové-Llopis, and Trujillo-Baute, 2019; Legendre and Ricci, 2015; Romero, Linares, and López, 2018). Tenure status, in particular, is related to the autonomy individuals have over their home, heating system, and the ability to make repairs or housing improvements (Healy, 2017).

Socio-economic characteristics: To analyze the impact of socio-economic characteristics on the probability of being energy poor, the breadwinner of the household was identified. This is the person in each household who earns the most, based on all income sources in the dataset (income from labor, capital, property, among others). Studies have found that the employment status and education level of the breadwinner are factors that significantly influence the probability of being energy poor (Costa-Campi, Jové-Llopis, and Trujillo-Baute, 2019; Legendre and Ricci, 2015; Romero, Linares, and López, 2018). Accordingly, these factors are included in the vector of explanatory variables. The health status of the breadwinner is also included as an explanatory variable to obtain a broader picture of households living in energy poverty. Energy poverty is known to have severe health consequences, so it could be argued that the inclusion of health dummies introduces reverse causality to the logit regression. Reverse causality in turn leads to an upward bias of the estimate. This has been accounted for and a regression excluding health characteristics has been run.[6] Even though reverse causality might exist, understanding the relation between health and energy poverty is relevant for policy implications.

Dwelling characteristics: The dwelling characteristics included as explanatory variables are the housing type and the number of rooms. The number of rooms is used to proxy dwelling size. (Costa-Campi, Jové-Llopis, and Trujillo-Baute, 2019; Romero, Linares, and López, 2018) To account for dwelling conditions, a proxy for poor housing, a dummy variable indicating no flushing indoor toilet in the household, has been included. This variable captures severe material deprivation, a poor state or old age of the building. Another variable for poor housing conditions is a dummy that identifies leak, rot or damp in a building, capturing the conditions of the building envelope (Matos, Delgado, and Guimarães, 2022). Poor conditions of the building envelope, in turn, typically result in low energy efficiency. The dummy, however, might be simultaneously determined with the dependent variable, causing the estimate to suffer from simultaneity bias and inconsistency. This is important to keep in mind when interpreting the results. A regression model excluding this dummy is run to ensure robustness of the results for the other explanatory variables. Nevertheless, the interplay between energy poverty and the characteristics of the

6. Model 3 and 4.

building stock is non-trivial, and understanding it is crucial for policy design.

Location: The location of a dwelling is another potential factor influencing energy poverty. Mostly, a distinction has been made between urban and rural locations of the dwelling (Costa-Campi, Jové-Llopis, and Trujillo-Baute, 2019; Romero, Linares, and López, 2018). This study also accounts for the effect of living in an urban area. Legendre and Ricci (2015) conducted a more granular regional analysis, dividing the sample into regions with different climatic conditions. Peralta, Carvalho, and Fonseca (2023) further found that in Portugal, households in some regions namely in Madeira, the Azores and the North of continental Portugal are more exposed to energy poverty. Therefore, the regions on a NUTS2 level have been included as explanatory variables. Lastly, a dummy for the year 2020 is included, as it was the year with the lowest number of heating degree days in the sample period (Eurostat, 2024b). The indicator therefore captures the influence of milder outdoor temperatures on the probability of being energy poor.

Inserting the vector of explanatory variables in (6), the modeled conditional response probability of poor households to be energy poor is specified as follows:

$$Pr(Y_{it} = \text{Energy Poor} \mid X_{it}) = \frac{\exp(\beta_0 + \beta_1 \text{household\_ch}_{it} + \beta_2 \text{socio-economic\_ch}_{it} + \beta_3 \text{dwelling\_ch}_{it} + \beta_4 \text{region}_i + \beta_5 \text{health}_{it} + \beta_6 \text{d\_urban}_i + \beta_7 \text{d\_2020})}{1 + \exp(\beta_0 + \beta_1 \text{household\_ch}_{it} + \beta_2 \text{socio-economic\_ch}_{it} + \beta_3 \text{dwelling\_ch}_{it} + \beta_4 \text{region}_i + \beta_5 \text{health}_{it} + \beta_6 \text{d\_urban}_i + \beta_7 \text{d\_2020})}$$

where

$household\_ch_{it}$ is a vector of variables that captures household characteristics for each household *i* at time *t*. It includes ***Household size***, a continuous variable that captures the number of people living in the household. Several dummies[7] represent household composition. $Kids_{it}$ is equal to 1 if children live in the household.[8] *Two adults of which 1 is old* is equal to 1 if a household consists of two adults, at least one aged 65 or older. $Single\ person\ household_{it}$ is 1 if a person lives alone. $Single\ parent\ household_{it}$ equals 1 if a single parent lives with at least one child. Tenure status is represented by several dummy variables. The dummy $Owner_{it}$ equals 1 if the household owns the dwelling. The dummy $Owner\ paying\ mortgage_{it}$ equals 1 if the owner pays mortgage. $Supported\ rent_{it}$ equals 1 if the rent is supported or capped.[9]

7. See Appendix Table 1 for reference points of the dummies.
8. Excludes single parents with kids.
9. Supported rent by the government, capped rent is capped at a legally established value.

$socio - economic\_ch_{it}$ is a vector of variables capturing the socio-economic characteristics of the breadwinner of household *i* at time *t*. Several dummy variables indicate the working status. The dummy $Working\ full\ time_{it}$ equals 1 if the breadwinner is working full time. The dummy $Unemployment_{it}$ equals 1 if the breadwinner of the household is unemployed. The dummy $Retirement_{it}$ takes a value of 1 if the breadwinner is retired. Two dummies are included to capture the educational attainment of the breadwinner. The dummy $Basic\ education_{it}$ is 1 if the highest level of education is either pre-primary or basic education. The dummy $Higher\ education_{it}$ takes a value of 1 if the breadwinner holds a university degree.

$dwelling\_ch_{it}$ is a vector of variables that captures the characteristics of the dwelling. It includes the continuous variable $Number\ of\ rooms_{it}$. To capture the housing type, two dummies are included. The dummy variable $Apartment\ in\ a\ big\ building_i$ takes the value 1 if the household lives in a building containing ten or more units. The dummy variable $House_i$ takes a value of 1 if the household lives in a detached or semi detached house. A dummy capturing living in an apartment has been omitted due to multicollinearity. To capture the condition of the building, two dummy variables are included. Capturing the condition of the building, or more broadly the building envelope is an important proxy for the energy efficiency of the building. The variable $leak_{it}$ is a dummy equal to 1 if household *i* lives in a home with a leak, damp or rot. The variable captures self-reported answers. The dummy variable $no\ indoor\ toilet_{it}$ takes the value 1 if a dwelling has no indoor toilet. In the sample, this is the case for 2.1% of the households. The answer is self-reported as well.

reg_i is a vector of dummies that capture the location of the household *i* at a NUTS2 level. The metropolitan region Lisbon is excluded due to multicollinearity.

d_urban_i is a dummy that indicates if a household lives in an urban area. This dummy is constructed based on the underlying data, which captures three different degrees of urbanization: densely populated, intermediate and sparsely populated. The dummy d_urban_i equals 1 if the dwelling is in a densely populated area.

$health_{it}$ is a vector of variables that capture the health characteristics of the breadwinner of household *i* at time *t*. The dummy $good\ health_{it}$ takes the value of 1 if the breadwinner declares her health status to be *very good*. The dummy $bad\ health_{it}$, on the other hand, takes the value of 1 if the breadwinner reports her health status to be either *poor* or *very poor*. The dummy

$health\ chronic_{it}$ takes the value one if the breadwinner declares to have chronic or prolonged health problems. Prolonged health problems last at least six months.

d_2020 is a dummy that takes the value 1 if the reference year is 2020. 2020 was the year with the highest number of cooling degree days and the lowest number of heating degree days in the sample. Thus, 2020 was the warmest year in the sample and the dummy captures this effect on energy poverty. Especially the low number of heating degree days might indicate a reduced energy need due to warmer temperatures in winter.

Binary outcome variables have heteroskedasticity, as the conditional variance of y is dependent on x. Therefore, heteroskedasticity is accounted for using robust standard errors.[10]

As mentioned in the data section, the sample is not based on random sampling. The primary sampling units are cells[11] of 1x1 kilometer. The observations on household locations are recorded at a broader level, the NUTS2 level. The sampling design applied leads to an over representation of less populated regions, especially the Azores and Madeira and to an under representation of populated areas, especially the regions Norte, Centro, and Lisboa. To account for the non-random sampling the dataset includes survey weights which are based on the inverse probability of selection. However, given that the stratification is on the exogenous variable region, weights are not included in the regression (Wooldridge, 2020).

For robustness, several post estimation tests were conducted. The results of these tests are reported in Table 3 in the Appendix. To check for multicollinearity between the independent variables, the variance inflation factors (VIFs) were calculated. None of the VIFs exceeds the threshold of 30, and the mean VIF is not significantly greater than one in any model. The Pearson χ^2 goodness-of-fit test tests for model fitness. If the p-value cannot be rejected, the test suggests that the model fits the data well. To further assess the fit of the model, classification statistics were taken into account. The overall rate of correct classification, sensitivity and specificity of the model are reported. Sensitivity indicates how much of the energy poor were correctly specified. Specificity, in contrast, indicates the rate of correctly classified non-energy poor households.

The logit estimates indicate only the direction of influence on the conditional probability of

10. Clustering standard errors is not feasible with the underlying data, as none of the variables suitable for clustering exceeds 20 unique values.

11. In accordance with the INSPIRE grid system.

being energy poor. To capture the average partial effect, marginal effects are estimated, averaging these effects across the explanatory variable's distribution in the sample. Table 2 in the Appendix presents both the logit regression estimates and the marginal effects.

5 Results

This section describes the regression results reported in Table 2 in the Appendix. The first column of each model displays the logit regression estimates and robust standard errors in parentheses. The second column displays the marginal effects of the respective model and robust standard errors in parentheses. The Baseline Model includes all explanatory variables, the dummy for leak, damp, or rot in the house as well as the dummies regarding the health conditions. The second model excludes the dummy for leak, damp or rot, while the third model excludes the dummies for good health, bad health and chronic health. The fourth model excludes both, the dummy for leak damp rot and the health dummies.

5.1 Baseline Model

The logit regression estimates in column 1 indicate the effects of household characteristics on the conditional probability of energy poverty. Owning the house and paying mortgage decreases the conditional probability of being energy poor, ceteris paribus. The estimate is significant at a 1% significance level. A possible explanation for the negative relationship is that properties with mortgages are likely to have been built more recently (Peralta, Carvalho, and Fonseca, 2023). Examining the linear correlation between disposable income and these variables reveals another possible explanation. The linear correlation with disposable income is negative for owning a house without a mortgage but positive for owning a house with a mortgage. This aligns with the findings of Peralta, Carvalho, and Fonseca (2023). Being in a supported rent regime, in contrast, increases the conditional probability of being energy poor, ceteris paribus. The corresponding estimated coefficient is significant at a 1% significance level. The marginal effect for the supported rent regime is considerably high. Ceteris paribus, the probability of being energy poor increases on average by 11.3% if a household is in a supported rent regime. A possible explanation can be that households under a supported rent regime have particularly low income. In the sample, however, disposable income shows no significant linear correlation with being in a supported rent regime. Although the correlation might be non-linear and more complex, this suggests that the estimate also captures other factors influencing the positive relationship between energy poverty and the supported rent regime. One factor possibly captured is the lack of financial incentives for landlords to maintain the dwelling in good condition and improve energy efficiency (Healy, 2017).[12] [13] Thus, dwellings rented in a supported or capped rent regime might be in poorer conditions. Moreover, the fact that supported rent regimes often protect older people from increasing rents may also be captured by that result. Indeed, with 7.46%, those aged 80 or above make up the largest age group living in a supported rent regime. Older people, in turn, are more affected by energy poverty and, due to more fragile health conditions more vulnerable (Peralta, Carvalho, and Fonseca, 2023).

The socio-economic characteristics of the breadwinner that significantly influence the conditional probability of being energy poor are full-time employment, basic education, and higher education. Full-time employment negatively influences the probability of being energy poor. The conditional probability of being energy poor decreases on average by 8.68% ceteris paribus when the breadwinner works full time. One possible explanation is that households where the breadwinner works full time have a higher disposable income. The different levels of education further influence the conditional probability of being energy poor. Having basic education increases the conditional probability of being energy poor, while having higher education, in turn, decreases it. Lower levels of educational attainment, in general, can be associated with higher prevalence of poverty and material deprivation (Healy, 2017). In the sample, however, the mean disposable incomes for the two groups do not differ much. For households with basic education mean disposable income is 7621.76€, while for those with higher education it is 7834.03€. This suggests the presence of other driving forces. It is likely that more educated individuals are more aware not only of the energy efficiency of their dwelling but also of the benefits of insulation (Legendre and Ricci, 2015).

The dwelling characteristics significantly influencing the conditional probability of being

12. The incentives that result from the "homeowner-renter" gap are well explained in Blumstein et al. (1980): "The economic benefits of energy conservation do not always accrue to the person who is trying to conserve. For example, if an apartment tenant pays the utility bill, the landlord has little incentive to make energy conserving improvements."

13. In Portugal, this is often the case for municipally owned houses, which are typically poorly maintained, energy inefficient and are rented under a supported rent regime.

energy poor are the number of rooms, having leak damp or rot in the dwelling and having no flushing indoor toilet. The number of rooms as a proxy for the living area decreases the conditional probability of being energy poor. This may seem counterintuitive, as a larger living area might be associated with a higher use of energy.[14] A possible explanation for this result is that, in the sample, more rooms are associated with higher income.[15] Another possible explanation is provided by Romero-Jordán and Río (2022), who found a positive relationship between electricity efficiency and the number of rooms in a dwelling. As the authors argue, the compartmentalization of electricity use is one of the main reasons. This could also be applied to energy use, explaining the finding that a higher number of rooms decreases the conditional probability of energy poverty.

The effect of having a leaking roof, damp walls or rot on the conditional probability of being energy poor is highly significant, and the marginal effects are comparably large. However, one should be cautious when interpreting these estimates, due to potential simultaneity bias.[16] To better understand the impact on energy poverty, it is important to understand what the dummy for the presence of leak, damp or rot in the wall is capturing. Firstly, it reflects the conservation state of the dwelling, which, in turn, indicates its energy performance (Energy Poverty Advisory Hub, 2022). Moreover, it may account for factors such as building deterioration and inefficient heating systems (Thomson, Bouzarovski, and Snell, 2017). Consequently, the dummy variable is linked to the energy efficiency of the dwelling and the conditions of the building envelop (Matos, Delgado, and Guimarães, 2022; Rademaekers et al., 2016). The positive impact of having a leak damp or rot on the conditional probability of energy poverty therefore indicates, that the state of conservation of the dwelling, its energy efficiency and the conditions of the building envelop significantly impact the probability of energy poverty.

Severe housing deprivation, captured by the dummy *no indoor toilet* increases the conditional probability of being energy poor. As with the dummy for energy efficiency, it is crucial to understand what the dummy captures. The absence of a flushing indoor toilet indicates lower

14. Costa-Campi, Jové-Llopis, and Trujillo-Baute (2019) as well as Legendre and Ricci (2015) found a positive and significant relationship between energy poverty and the living area.

15. There is a positive and significant linear correlation between the two variables.

16. The correlation between the dummy indicating leak, damp or rot and the dummy for energy poverty amounts to 0.1945. This low correlation indicates that their linear correlation is weak, which might decrease the risk of simultaneity. Simultaneity, however, might as well capture a complex, non-linear and non-trivial relationship between the two variables.

housing quality, often associated with outdated or missing basic sanitary infrastructure. It is typically linked to older buildings, which may lack thermal protection or have insulation below the standard, thus affecting energy efficiency (Matos, Delgado, and Guimarães, 2022). Houses built before 1980, in particular, tend to have poorly performing building envelopes, requiring higher energy use (Gouveia and Palma, 2019). The estimates for the two dummies indicate that poor building conditions and lower energy efficiency significantly increases the probability of being energy poor. Both dummies are intrinsically related to poor building conditions and lacking energy efficiency. Hence, the obtained results show the importance of dwelling characteristics when analyzing the probability of energy poverty.

The regional estimates indicate a disparity in the probability of being energy poor. Living in the North (continental Portugal) and the Autonomous Region of the Azores increases the conditional probability of being energy poor, ceteris paribus. In contrast, living in the Center (continental Portugal) decreases it, ceteris paribus. These results reflect the general trend of regional disparities in poverty rates and material deprivation. While in the North and the Autonomous Region of the Azores, the poverty risk rate is 20% or higher, it is lower in the Center.[17] (Peralta, Carvalho, and Fonseca, 2023)

Most striking are the estimates for Madeira Island and Alentejo, as they are highly significant with large marginal effects. Madeira is the region with the highest share of people at risk of poverty (Peralta, Carvalho, and Fonseca, 2023). This in turn may explain the positive impact on the conditional probability of energy poverty. In the sample, however, the mean and mode of disposable income are not significantly lower for Madeira compared to other regions (see Table 6 in the Appendix). The high prevalence of poverty in Madeira might therefore interact with other factors in influencing energy poverty. One possible factor is the prevalence of material deprivation (Peralta, Carvalho, and Fonseca, 2023). Another possible factor is that Madeira's housing stock is the most energy inefficient in Portugal, with dwellings lacking insulation and having only simple walls in a region where humidity is typically high due to its proximity to the ocean (Gouveia and Palma, 2019). The Madeira case [18] exemplifies the complex interplay between poverty and energy poverty. It indicates that energy poverty cannot be explained by low

17. However, given that the estimation sample consists of households living below the poverty line, this can only partly explain the estimates.

18. see Appendix C for further discussion.

disposable income alone but by more complex structural problems caused by poverty, such as insufficient investments in housing stock.[19]

The negative impact of living in Alentejo on the probability of being energy poor can be explained by the low material deprivation rate (Peralta, Carvalho, and Fonseca, 2023). Another explanation is the traditional architecture in Alentejo, with small windows designed to keep out summer heat and thick walls serving as insulation.

Living in an urban area decreases the conditional probability of being energy poor ceteris paribus. Similar results have been explained by the prevalence of isolated households that lack access to affordable energy in rural areas (Bouzarovski, 2018; Costa-Campi, Jové-Llopis, and Trujillo-Baute, 2019). The obtained estimate may also capture additional factors. While the share of people with higher education is higher in urban areas (8.24% in urban areas, 4.14% in non-urban areas), the share of those with basic education is larger in non-urban areas (84.63% in non-urban areas, 77.28% in urban areas). Given that urban areas are not homogeneous, an analysis at the parish level might provide a better understanding of the specific dynamics within urban areas. However, this is beyond the scope of this paper.

Regarding health the estimated coefficient indicate that households where the breadwinner reports poor health are more likely to experience energy poverty. Similarly, the estimates for chronic or prolonged illness increase the conditional probability of being energy poor. However, these findings should be interpreted with caution, as the direction of causality is uncertain. Thus, reversed causality may be present. Nevertheless, there is evidence of a significant relationship between health and energy poverty.[20] Nonetheless, these findings are important for policy design. Overall, the estimates align with the established negative relationship between energy poverty and the health conditions of the affected population, emphasizing the link between them and the need to address these issues.

The Baseline Model was assessed for goodness of fit. The p-value of the Pearson χ^2 goodness-of-fit test cannot be rejected. This suggests that the model fits the data well. Overall, the model correctly classifies 67.2% of the households. The model classifies 87.43% of the non energy poor and 31.87% of the energy poor households correctly. Given the sensitivity of the test statistics to the relative group size, classification into the larger group is favored and specificity is higher

19. Among those having no flushing indoor toilet, 48.23% are located in Madeira.
20. Although reverse causality might lead to overestimation.

than sensitivity.

5.2 *Alternative Models*

Model 2 excludes the dummy for leak, damp and rot due to possible simultaneity bias. The estimates from the logit regression are reported in column 3 with robust standard errors in parenthesis. Most estimates [21] from the Baseline Model did not change in magnitude, neither did the corresponding standard errors. The estimate for the dummy indicating having kids, however, turned significant at 10%. The estimate indicates a negative relationship between the conditional probability of being energy poor and having kids. The impact of children is ambiguous, as some previous studies found a positive relationship while others found a negative one (Healy, 2017; Legendre and Ricci, 2015). Having children in the household is likely to increase energy consumption. Healy (2017) associates this effect only with households with 4 or more children. This effect might therefore be captured by the continuous variable for household size. Another possible explanation can be found by looking at the data. The positive linear correlation between disposable income and having children is higher for households below the poverty line than for those above it.[22] The negative estimate might in part capture this positive correlation.

As for the Baseline Model, the Pearson χ^2 goodness-of-fit test indicates that Model 2 fits the data well. The overall rate of correct classification decreases to 65.53%, and the sensitivity decreases to 24.65%. This indicates that having a leak damp or rot in the dwelling influences the correct prediction of a household's probability to be energy poor. This in turn highlights the importance of dwelling characteristics, especially energy inefficiency and deprivation of the building envelope, when analyzing energy poverty.

Model 3 excludes the health characteristics, due to concerns about reverse causality. The estimate for having kids is negative and significant at a 10% significance level. For the other variables, the estimates and their standard errors are similar in magnitude to the Baseline Model. As for the other models, the Pearson χ^2 goodness-of-fit test indicates that Model 3 fits the data well. The overall rate of correct classification decreases to 66.38% when compared to the Baseline Model. The rate of correct classification decreases to 30.54%. This decrease, however, is less

21. That were interpreted in the section above, thus significant in the Baseline Model.
22. 0.497 for households below the poverty line and 0.224 for those above the poverty line.

pronounced than in Model 2, indicating that health characteristics are less important in correctly predicting the probability of being energy poor when compared to dwelling characteristics.

Model 4 excludes all potential sources of bias. Except for minor differences in the significance level of the dummy variables *Kids* and *North*, the estimates and standard errors for the other variables are similar to those of the Baseline Model. As for the other models, the Pearson χ^2 goodness-of-fit test indicates that Model 4 fits the data well. The overall rate of correct classification decreases to 65.3% as compared to the Baseline Model. Whereas the rate of correct classification of non energy poor households increases to 90.6%, the rate of correctly classified energy poor households decreases to 21.05%. This decrease in sensitivity indicates that the dummy for leak, damp and rot as well as those capturing health characteristics, are important factors in correctly predicting the conditional probability to be energy poor. The results obtained in the previous model indicate that the dummy for leak, damp and rot is a more important factor.

In conclusion, the significant estimates across all models highlight factors that influence the conditional probability of being energy poor, including tenure status, educational attainment, dwelling characteristics, and regional disparities.

6 Discussion

As explained in the previous section, some important characteristics that influence the probability to be energy poor have been identified in this study. Nevertheless, the study has some limitations. The simultaneity between the dummies for leak, damp, and rot, and energy poverty is a major one. While the estimates suggest a significant relationship, the causal path remains complex. However, dwelling characteristics such as energy inefficiency and a deprived, old building envelope significantly increase the conditional probability of being energy poor. The Portuguese building stock has indeed been found to be aged and to exhibit a low energy efficiency performance (Matos, Delgado, and Guimarães, 2022). Due to data limitations, dwelling characteristics at a more detailed level could not be included.[23] More detail, however, is important to rule out simultaneity and to better understand the impact of dwelling characteristics on the probability of being energy poor. Thus, future studies should

23. Detailed data on this dwelling characteristics does not match the households and time periods used and therefore cannot be included in this analysis.

include explanatory variables such as the construction year, insulation, window glazing, and building envelope features like construction material and wall thickness. To understand the impact of energy efficiency equipment on the probability of being energy poor, variables such as heat pumps or high efficiency thermal boilers should be included. Other variables potentially influencing the probability of being energy poor are the source of energy by consumption type and the existing heating system. Future studies should consider these variables.

Another limitation due to data availability is the measure of energy poverty based on one single indicator. As pointed out in the literature review, energy poverty is a complex problem which is hard to capture using one single indicator. Therefore, in addition to the consensual indicator *Financial Ability to Adequately Heat*, an expenditure based indicator, such as the *Low-Income High Cost Indicator*, should be used as a binary outcome variable in a second logit regression. A comparison of the estimates from the two regressions would provide a broader understanding of the household characteristics influencing the probability of being energy poor. A better understanding of these characteristics is crucial to combat energy poverty.

In addition to the inclusion of an expenditure-based indicator, another consensual indicator included in the ELPPE should be considered in future studies, namely, the ability to keep the house adequately cool during summer. To date, however, no data on this indicator were available. Given the changing climate, this indicator will undoubtedly gain importance. Characteristics that influence all three indicators of energy poverty would build a solid foundation to design effective and sustainable public policies to combat energy poverty in Portugal.

One of the main results of this study is the significant impact of some regions on the conditional probability of being energy poor. This study identified regional disparities for households below the poverty line. Similar results have been found for households across all income levels. To better understand drivers of regional disparities for households below the poverty line, regressions at the regional level with a larger sample size should be conducted.

The analysis of socio-economic, dwelling, and regional characteristics influencing the likelihood of poor households experiencing energy poverty provides valuable insights for policy design. Effective policies are essential to address energy poverty within this particularly vulnerable group. Key factors impacting the conditional probability of being energy poor include educational attainment, dwelling characteristics associated with energy inefficiency and housing deprivation, and regional disparities. Translating these findings into effective and equitable policies and programs to combat energy poverty is challenging. Rademaekers et al. (2016) suggest policy interventions to combat energy poverty: by (i) intervening financially to improve affordability in the short term, (ii) protecting vulnerable consumers (iii) improving energy efficiency (iv) engaging local communities to improve consumer awareness and enable informed action.

In this context, it is important to be aware of the existing policies to combat energy Poverty in Portugal. As discussed in the literature review, the ELPPE outlines several programs to combat energy poverty, among which is the *Tarifa Social de Energia*. It provides economically vulnerable consumers with discounted electricity and natural gas bills, as well as tax exemptions. This program targets the households analyzed in the sample and takes crucial measures to address concerns of disconnectedness and high levels of debt. It can therefore be categorized as short-term intervention to improve financial affordability. However, the program addresses only one of the main drivers of energy poverty, and if the household's income structure does not change, it is questionable whether energy poverty can be alleviated sustainably in the long term. Fontoura Gouveia and Félix (2024) reported that the cost of the program will be 136.5 million euros in 2024, borne by electricity producers and suppliers.

Another policy explicitly targeting economically vulnerable households is *Vale Eficiência*. It provides them with vouchers for interventions to improve the dwelling's energy efficiency. An eligible household can obtain up to three vouchers, valued at 1.300€ each. Interestingly, only residents in mainland Portugal are eligible for the *Vale Eficiência*, implying that Madeira is excluded. The findings of this study, however imply that households in Madeira are more likely to be energy poor. The second round of *Vale Eficiência* started in November 2023 with an expanded scope of eligibility, now including households in rented homes.[24] 104 million euros were allocated to this program (Fontoura Gouveia and Félix, 2024). The *Vale Eficiência* can be categorized as a program targeting energy efficiency and therefore structural energy poverty. However, the question arises of whether the vouchers provided through the program effectively contribute to improving energy efficiency. Households below the poverty line often lack the financial means to take complementary measures to those provided by the program.

24. One of the findings of this study is that tenure status significantly impacts energy poverty; therefore, this expansion of scope is an important step toward effectively combating energy poverty.

Poor building conditions cannot be improved, because substantial investment in the building stock is not feasible for the households below the poverty line. However, the results of this study indicate that such investments are crucial to address energy poverty in the long term. Given the severely deteriorated condition of some buildings, the vouchers provided by *Vale Eficiência* are unlikely to effectively tackle energy poverty sustainably. In this context substantial investments in improving building conditions, such as general refurbishment should be seriously considered as policy to combat energy poverty. In other words, the decisions about how to proceed should be supported by careful cost-benefit analysis and equity assessment given that resources are scarce, increasing the opportunity cost of any allocation decision.

Poor households can only be successfully lifted out of energy poverty when short-term measures improve energy affordability, while long-term measures sustainably address building conditions to break the energy poverty trap. Additionally, engaging with local populations to empower them to take informed action is essential for ensuring the success and equity of policies (Fontoura Gouveia and Félix, 2024).

7 Conclusion

As highlighted in this study, energy poverty is a multifaceted issue that is likely to intensify with climate change. Achieving the goals of the ELPPE will require substantial investments in improving energy efficiency within the building stock. Energy efficient buildings not only mitigate energy poverty but also reduce emissions and improve the health of affected individuals. The broader benefits include improved labor market outcomes through better workforce health and increased educational attainment for children. Since energy poverty intersects with both social and environmental dimensions, policies addressing energy poverty can simultaneously tackle broader societal and ecological challenges, contributing to a more sustainable future.

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Appendix

A

Regression Results

Table 1: Reference Points for Binary Variables

	Included in the Regression	Reference Point
Household Characteristics		
Household Composition	Having kids Single person Single parent with kids Two adults, of which 1 is old	Two or more adults under 65, without children
Dwelling characteristics		
Housing type	House Apartment in a building with 10 or more units	Apartment
Regions	North Center Alentejo Algarve Azores Madeira	Lisbon

Figure 1: Error Terms for Logit vs Probit Regressions

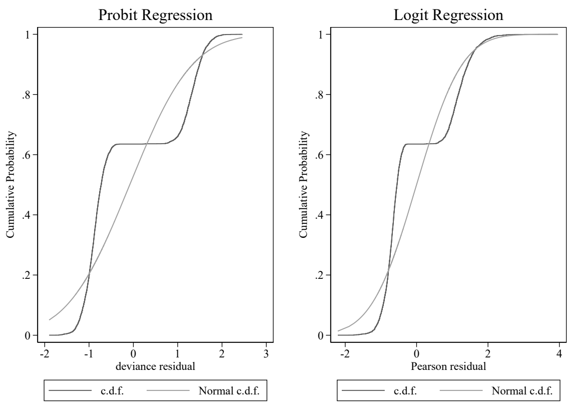


Table 2: Logit Regression Results for the Conditional Probability to be Energy Poor

	Model 1		Model 2		Model 3		Model 4	
	Coefficients	Marginal Effects	Coefficients	Marginal Effects	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Household characteristics:								
Household size	0.0146	0.00306	0.0382	0.00819	-0.0128	-0.00270	0.00886	0.00192
	(0.0502)	(0.0105)	(0.0504)	(0.0108)	(0.0491)	(0.0103)	(0.0493)	(0.0107)
Kids	-0.173	-0.0363	-0.177*	-0.0380*	-0.177*	-0.0373*	-0.187*	-0.0405*
	(0.106)	(0.0223)	(0.106)	(0.0227)	(0.105)	(0.0221)	(0.104)	(0.0225)
Two adults, of which 1 is old	-0.0906	-0.0190	-0.106	-0.0228	-0.100	-0.0211	-0.116	-0.0251
	(0.0965)	(0.0202)	(0.0956)	(0.0205)	(0.0960)	(0.0202)	(0.0949)	(0.0205)
Single person household	0.0905	0.0190	0.0911	0.0195	0.0738	0.0156	0.0747	0.0161
	(0.108)	(0.0227)	(0.108)	(0.0231)	(0.107)	(0.0226)	(0.107)	(0.0230)
Single parent household	0.0119	0.00249	0.0504	0.0108	-0.00766	-0.00162	0.0301	0.00651
	(0.137)	(0.0287)	(0.135)	(0.0290)	(0.137)	(0.0288)	(0.135)	(0.0292)
Owner	-0.0563	-0.0118	-0.0959	-0.0206	-0.0470	-0.00991	-0.0883	-0.0191
	(0.0732)	(0.0153)	(0.0723)	(0.0155)	(0.0730)	(0.0154)	(0.0720)	(0.0156)
Owner paying mortgage	-0.259***	-0.0543***	-0.304***	-0.0652***	-0.278***	-0.0587***	-0.333***	-0.0720***
	(0.0985)	(0.0206)	(0.0976)	(0.0209)	(0.0993)	(0.0207)	(0.0975)	(0.0210)
Supported Rent	0.540***	0.113***	0.599***	0.128***	0.569***	0.120***	0.641***	0.139***
	(0.118)	(0.0247)	(0.118)	(0.0251)	(0.117)	(0.0245)	(0.116)	(0.0250)
Socio-economic characteristics:								
Working full time	-0.414***	-0.0868***	-0.389***	-0.0835***	-0.518***	-0.109***	-0.520***	-0.112***
	(0.0922)	(0.0192)	(0.0915)	(0.0195)	(0.0899)	(0.0188)	(0.0889)	(0.0191)
Unemployment	0.120	0.0252	0.164	0.0352	0.0377	0.00795	0.0625	0.0135
	(0.123)	(0.0258)	(0.121)	(0.0259)	(0.121)	(0.0255)	(0.119)	(0.0257)
Retirement	-0.108	-0.0226	-0.116	-0.0248	-0.103	-0.0217	-0.109	-0.0235
	(0.0829)	(0.0174)	(0.0821)	(0.0176)	(0.0828)	(0.0174)	(0.0819)	(0.0177)
Basic Education	0.229**	0.0480**	0.269***	0.0577***	0.283***	0.0597***	0.339***	0.0732***
	(0.0923)	(0.0193)	(0.0919)	(0.0197)	(0.0917)	(0.0193)	(0.0912)	(0.0196)
Higher education	-0.418***	-0.0877***	-0.391**	-0.0837**	-0.443***	-0.0935***	-0.421***	-0.0911***
	(0.159)	(0.0334)	(0.160)	(0.0343)	(0.159)	(0.0336)	(0.160)	(0.0346)
Disposable income	7.23e-06	1.54e-06	4.90e-06	1.05e-06	1.09e-05	2.29e-06	8.91e-06	1.93e-06
	(1.16e-05)	(2.43e-06)	(1.15e-05)	(2.46e-06)	(1.15e-05)	(2.41e-06)	(1.13e-05)	(2.45e-06)
Dwelling characteristics:								
Number of rooms	-0.109***	-0.0229***	-0.122***	-0.0262***	-0.111***	-0.0235***	-0.126***	-0.0273***
	(0.0273)	(0.00569)	(0.0269)	(0.00574)	(0.0272)	(0.00570)	(0.0268)	(0.00576)
House	-0.0323	-0.00677	-0.00366	-0.000786	-0.0127	-0.00268	0.0241	0.00522
	(0.0800)	(0.0168)	(0.0791)	(0.0169)	(0.0797)	(0.0168)	(0.0787)	(0.0170)
Apartment in a big building	-0.0250	-0.00524	-0.107	-0.0228	-0.00384	-0.000809	-0.0867	-0.0188
	(0.114)	(0.0239)	(0.113)	(0.0242)	(0.113)	(0.0239)	(0.112)	(0.0243)
Leak	0.653***	0.137***			0.700***	0.147***		
	(0.0559)	(0.0113)			(0.0552)	(0.0111)		
No indoor toilet	0.615***	0.129***	0.777***	0.167***	0.607***	0.128***	0.782***	0.169***
	(0.186)	(0.0389)	(0.186)	(0.0397)	(0.187)	(0.0393)	(0.188)	(0.0403)
Location:								
Norte	0.203*	0.0425*	0.161	0.0345	0.219*	0.0461*	0.177	0.0383
	(0.118)	(0.0248)	(0.118)	(0.0252)	(0.118)	(0.0248)	(0.117)	(0.0253)
Centro	-0.244*	-0.0512*	-0.269**	-0.0576**	-0.233*	-0.0491*	-0.254**	-0.0548**
	(0.127)	(0.0266)	(0.126)	(0.0270)	(0.126)	(0.0266)	(0.125)	(0.0271)
Alentejo	-0.580***	-0.122***	-0.668***	-0.143***	-0.575***	-0.121***	-0.665***	-0.144***
	(0.139)	(0.0289)	(0.138)	(0.0294)	(0.138)	(0.0289)	(0.137)	(0.0294)
Algarve	-0.0774	-0.0162	-0.140	-0.0300	-0.0883	-0.0186	-0.159	-0.0343
	(0.127)	(0.0266)	(0.126)	(0.0270)	(0.127)	(0.0267)	(0.125)	(0.0271)
Azores	0.223*	0.0468*	0.228*	0.0490*	0.226*	0.0477*	0.233*	0.0505*
	(0.128)	(0.0268)	(0.126)	(0.0271)	(0.127)	(0.0269)	(0.126)	(0.0272)
Madeira	0.341***	0.0714***	0.382***	0.0818***	0.339***	0.0714***	0.385***	0.0834***
	(0.112)	(0.0234)	(0.111)	(0.0237)	(0.111)	(0.0234)	(0.110)	(0.0237)
Good Health	-0.173	-0.0364	-0.195	-0.0419				
	(0.149)	(0.0313)	(0.148)	(0.0318)				
Bad Health	0.288***	0.0604***	0.351***	0.0753***				
	(0.0677)	(0.0141)	(0.0665)	(0.0141)				
Chronic Health	0.134**	0.0282**	0.181***	0.0387***				
	(0.0649)	(0.0136)	(0.0641)	(0.0137)				
Urban	-0.201***	-0.0423***	-0.212***	-0.0463***	-0.214***	-0.0451***	-0.227***	-0.0490***
	(0.0717)	(0.0150)	(0.0707)	(0.0151)	(0.0715)	(0.0150)	(0.0704)	(0.0152)
Dummy 2020	-0.0695	-0.0146	-0.0401	-0.00859	-0.0657	-0.0138	-0.0323	-0.00698
	(0.0573)	(0.0120)	(0.0567)	(0.0121)	(0.0572)	(0.0120)	(0.0564)	(0.0122)
Constant	-0.527**		-0.314		-0.364*		-0.0854	
	(0.223)		(0.221)		(0.217)		(0.214)	
Observations	6,695	6,695	6,695	6,695	6,723	6,723	6,723	6,723

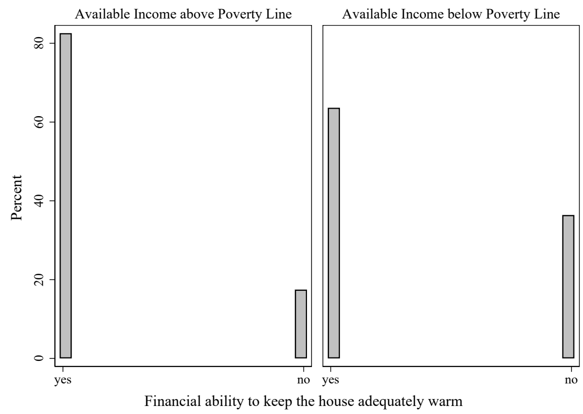
Robust standard errors are reported in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Model Test Results

	Model 1	Model 2	Model 3	Model 4
Pearson χ^2 Goodness of Fit				
Prob $>$ chi2	0.5222	0.4307	0.5393	0.4456
Classification				
Correctly Classified	67.2%	65.53%	66.38%	65.3%
Sensitivity	31.87%	24.65%	30.54%	21.05%
Specificity	87.43%	88.94%	86.88%	90.60%
Variance Inflation Factors				
Mean VIF	4.22	4.29	4.40	4.49

Descriptive Statistics

Figure 2: Financial Ability to Heat



Note: For households with available income above the poverty line, 82.56% do and 17.44% do not have the financial ability to heat. For households with available income below the poverty line, 63.62% do and 36.38% do not have the financial ability to heat.

Table 4: Descriptive Statistics for Continuous Variables

Variable	Mean	Mode	Minimum	Maximum
Household size	2.35	2	1	10
Disposable income	7 784.144	7 419.176	174.72	29 476
Number of rooms	4.08694	4	1	6

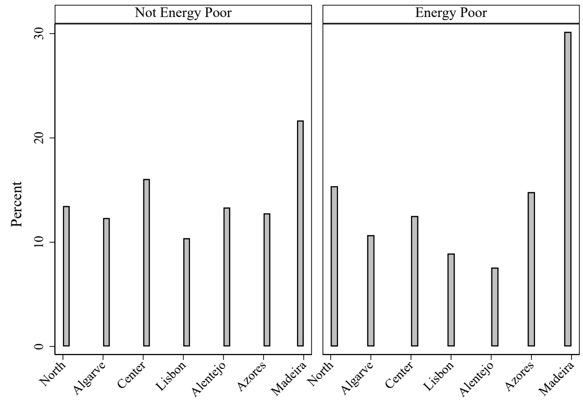
The descriptive statistics displayed in this table refer to the housheolds below the poverty line.

Table 5: Descriptive Statistics for Binary Variables

Variable 1	Energy poor	Not Energy poor
Household composition		
Single person household	31.60%	25.67%
Two or more adults without children	21.59 %	21,23%
Two adults, at least one 65 or older	22.12%	21.04%
Single parent household	4.74%	5.4%
Kids	19.95%	26.66%
Tenure status		
Owner	57.87%	56.43%
Owner paying mortgage	10.22%	17.94%
Tenant	9.57%	9.38%
Supported or conditional rent tenant	10.03%	4.93%
Accommodation provided free of charge	12.31%	11.32%
Employment Status		
Full-time employment	25.72%	38.23%
Retired	47.83%	41.36%
Unemployed	7.73%	6.2%
Educational Attainment		
Basic education	88.43%	79.28%
Secondary education	8.87%	13.98%
Higher education	2.7%	6.74%
Self-declared Health Status		
Very good	2.71%	5.31%
Good	15.72%	26.00%
Fair	46.41%	45.81%
Bad	25.81%	17.52%
Very bad	9.36%	5.36
Chronic or prolonged illness	68.01%	55.63%
Urbanization		
Densely populated	27.15 %	27.59%
Intermediate	31.81%	28.81%
Sparsely populated	41.04%	43.61%
Leak, damp or rot	51.1%	31.42%
No flushing indoor toilet	3.72%	1.17%

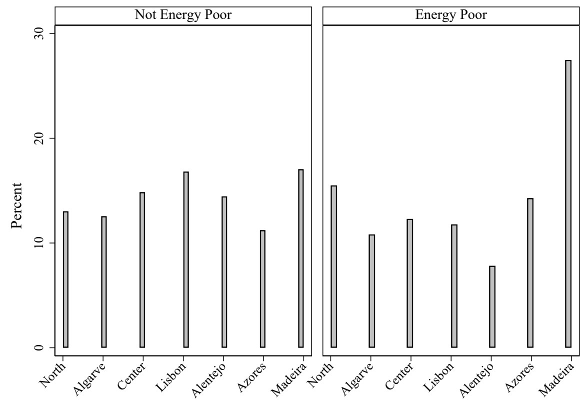
The descriptive statistics displayed in this table refer to the housheolds below the poverty line.

Figure 3: Regional Distribution by Energy Poverty for Households below the Poverty Line



Note: Regional distribution of non energy poor households: North 13.47%, Algarve 12.32%, Center 16.06%, Lisbon 10.38%, Alentejo 13.33%, Azores 12.77%, Madeira 21.67%
Regional distribution of energy poor households: North 15.37%, Algarve 10.67%, Center 12.51%, Lisbon 8.91%, Alentejo 7.57%, Azores 14.8%, Madeira 30.17%

Figure 4: Regional Distribution by Energy Poverty for all Households



Note: Regional distribution of non energy poor households: North 13.02%, Algarve 12.56%, Center 14.86%, Lisbon 16.82%, Alentejo 14.46%, Azores 11.23%, Madeira 17.05%
Regional distribution of energy poor households: North 15.50%, Algarve 10.82%, Center 12.30%, Lisbon 11.78%, Alentejo 7.83%, Azores 14.29%, Madeira 27,48%

Table 6: Descriptive Statistics for Selected Variables by Region

	Norte	Algarve	Centro	Lisboa	Alentejo	Azores	Madeira
Mean disposable income	7768.10€	7783.65€	7367.11€	7418.24€	7276.79€	8392.91€	8085.83€
Mode of disposable income	7601.33€	7071.5€	6860€	6613€	6600€	8040€	7886.08€
Share of population with higher education	4.62%	7.36%	6.55%	9.97%	4.64%	2.75%	3.66 %
Share of population with basic education	82.25 %	77.92%	83.59%	71.15 %	82.91%	87.78%	86.07 %
Share of households with leak, damp or rot	35.50%	29.82%	36.25%	35.20%	27.68%	43.61%	49.43%

The descriptive statistics displayed in this table refer to the housheolds below the poverty line.

Appendix

B

Overview of Subgroups of Expenditure-Based Indicators

Expenditure-based indicators can generally be divided into three sub-groups. The first sub-group focuses on absolute energy expenditure and aims at detecting ”hidden energy poverty” by identifying households with energy spending below a threshold considered as necessary to meet basic needs. An example of such an indicator is the *half the median expenditure indicator*. The second sub-group measures the excess burden of energy expenditure and identifies households with energy expenditures above a certain threshold as energy poor. Measures such as the *10% indicator* and *twice the national median share* fall within this group. The third sub-group measures the residual disposable household income after deducting domestic energy expenses. This approach detects households with low incomes and high energy expenditures. A prominent indicator within this sub-group is the *low income high costs (LIHC)* indicator. (Biermann, 2016; Herrero, 2017; Rademaekers et al., 2016)

The choice of thresholds and income definitions for expenditure-based indicators is subject to debate. A range of income definitions has been suggested, such as disposable income before or after housing costs. Thresholds for energy expenditure levels should either not be exceeded (sub-group two) or be undercut (sub-group one). These thresholds can be absolute, like the *10% threshold*, or relative, like the *twice the median share threshold*. (Rademaekers et al., 2016)

Hills (2011) discusses the advantages and disadvantages of different thresholds and income definitions. However, there is no consensus about the optimal threshold and income level to use.

Appendix

C

Brief Analysis of Madeira

Madeira is the region with the highest share of households living in energy poverty within the sample (1,665 households). To better understand the factors influencing energy poverty in this region a separate regression was conducted for Madeira. Separate regressions were not performed for other regions, as their sample sizes did not exceed 1,000 households. Additionally, the results for Madeira should be interpreted with caution due to the small sample size.

In this analysis, Model 1 excludes the dummy variable for having leak, damp, or rot in the dwelling, while Model 2 includes this variable. Health characteristics are excluded in both models. The methodology used aligns with that of the Baseline Model, and the results are displayed in Table 7.

The estimates that significantly influence the conditional probability of being energy poor in Madeira are broadly consistent with those of the Baseline Model. The only exception is that, in Madeira, the estimated coefficient for retirement is negative and significant. Thus, being retired decreases the conditional probability of being energy poor, ceteris paribus. Owning a property with a mortgage and working full time significantly reduce the conditional probability of being energy poor. Conversely, housing deprivation and energy inefficiency, as indicated by the dummy variables for leaks, dampness, or rot and the absence of a flushing indoor toilet, significantly increase the probability of being energy poor.

It is important to note that this regression serves only as an indication. To confirm these results, further analysis using a larger sample size is necessary. However, this regression appears to support the interpretation in section 5 that the high prevalence of energy poverty in Madeira is linked to structural issues of poverty, such as low investment and material deprivation.

Table 7: Logit Regression Results for the Conditional Probability to be Energy Poor in Madeira

	Model 1	Model 2
Household characteristics:		
Household size	-0.133	-0.139
	(0.0888)	(0.0875)
Having kids	-0.0563	-0.0816
	(0.188)	(0.189)
Two adults, one old	-0.106	-0.0815
	(0.188)	(0.189)
Single person	-0.240	-0.249
	(0.209)	(0.208)
Single parent with kids	-0.00661	-0.0446
	(0.272)	(0.272)
Owner	-0.0838	-0.0667
	(0.140)	(0.141)
Owner paying mortgage	-0.568***	-0.528**
	(0.213)	(0.212)
Supported Rent	0.350	0.318
	(0.230)	(0.234)
Socio-economic characteristics:		
Working full time	-0.676***	-0.711***
	(0.171)	(0.172)
Unemployment	0.0669	-0.0272
	(0.224)	(0.226)
Retirement	-0.419**	-0.457***
	(0.168)	(0.168)
Basic Education	0.355*	0.300
	(0.183)	(0.183)
Higher education	-0.0300	-0.0236
	(0.343)	(0.338)
Disposable income	4.98e-06	4.63e-06
	(2.09e-05)	(2.11e-05)
Dwelling characteristics:		
Number of rooms -0.0843	-0.0600	
	(0.0529)	(0.0534)
House	0.201	0.127
	(0.175)	(0.177)
Apartment, big building	-0.221	-0.133
	(0.255)	(0.258)
Leak, damp or rot		0.583***
		(0.106)
No indoor toilet	0.562**	0.475*
	(0.258)	(0.256)
Urban	-0.505***	-0.509***
	(0.119)	(0.120)
Dummy 2020	0.137	0.120
	(0.112)	(0.113)
Constant	0.655*	0.416
	(0.393)	(0.397)
Observations	1,665	1,665

Robust standard errors are reported in parenthesis.
**** p<0.01, ** p<0.05, * p<0.1*